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Auteurs


Olivier CARDI, Romain RESTOUT

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jaoulgrammare@beta-cnrs.unistra.fr

WHY HOURS WORKED DECLINE LESS AFTER TECHNOLOGY SHOCKS? *

Olivier CARDI[†]

Lancaster University Management School

Romain RESTOUT[‡]

Université de Lorraine BETA (CNRS UMR 7522)

Abstract

The contractionary effect of aggregate technology shocks on hours worked has shrunk over time in OECD countries. Our estimates suggest that this finding can be attributed to the increasing share of the variance of technology improvements driven by asymmetric technology shocks across sectors. While technology improvements uniformly distributed across sectors are found empirically to give rise to a dramatic decline in total hours worked, asymmetric technology shocks do the opposite. By depreciating non-traded prices, symmetric technology shocks generate a contractionary effect on non-traded labor and thus on total hours. In contrast, by appreciating non-traded prices, technological change concentrated toward traded industries puts upward pressure on wages which has a strong expansionary effect on total hours worked. A two-sector open economy model with frictions into the movements of inputs can reproduce the time-increasing response of both total and sectoral hours worked we estimate empirically once we allow for factor-biased technological change and we let the share of asymmetric technology shocks increase over time. A model with endogenous technology decisions reveals that two-third of the progression of asymmetric technology shocks is driven by greater exposition of traded industries to the international stock of knowledge.

Keywords: Sector-biased technology shocks; Endogenous technological change; Factor-augmenting efficiency; Open economy; Labor reallocation; CES production function; Labor income share.

JEL Classification: E25; E62; F11; F41; O33

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[†]Olivier Cardi. Correspondence address: Lancaster University Management School, Bailrigg, Lancaster LA1 4YX. E-mail: o.cardi@lancaster.ac.uk.

[‡]Romain Restout. Correspondence address: Université de Lorraine, BETA, CNRS, INRA, 54000, Nancy, France. Phone: +33 03 54 50 43 72. Fax: +33 03 54 50 43 51. E-mail: romain.restout@univ-lorraine.fr.

1 Introduction

A major question in macroeconomics is whether technology improvements lead to a fall or a rise in inputs, especially labor. We find empirically that total hours worked decline following a permanent increase in utilization-adjusted total factor productivity (TFP henceforth). When estimating the response on rolling sub-samples (with a window of the same length), our evidence also shows that the response of total hours worked to a technology improvement is increasing over time, moving from large to small negative values. In this paper, we show that the time-increasing response of hours worked is driven by the rise in the contribution of asymmetric technology shocks across sectors to technology improvements in an open economy.

These findings for a panel of seventeen OECD countries over 1970-2017 corroborate the evidence by Galí and Gambetti [2009], Cantore et al. [2017], Galí and Van Rens [2021] on U.S. data who report a time-increasing response of hours worked following a permanent increase in productivity. In contrast to these papers which put forward the change in the monetary policy rule, a greater substitutability between capital and labor, or a reduction in labor market frictions, we offer a new explanation which is based on the open economy aspect and the multi-sector dimension. Financial openness eases the increase in leisure and the reduction in hours worked following a technology shock while the dispersion in technology improvements across industries has an expansionary effect on hours by fostering labor demand in low productivity growth industries.

As shown in Fig. 1(a) which plots impact responses of hours to a permanent technology improvement against the averaged current balance (in % of GDP) for seventeen OECD countries, economies which borrow from abroad also experience a decline in hours worked.¹ In contrast, as displayed by Fig. 1(b) which plots impact responses of hours to a technology shock against the (value added) share of tradables, a greater contribution of exporting industries to GDP is associated with an increase in hours worked following a permanent technology improvement. Intuitively, a greater share of tradables implies that the variations in utilization-adjusted-aggregate-TFP are further driven by technological change in traded industries. Because technological change is more pronounced in traded than in non-traded industries, aggregate technological change tends to be more asymmetric across sectors. As detailed later below, because asymmetric technology shocks have a strong expansionary effect on total hours worked, the impact response of hours is increasing in the share of asymmetric technology shocks and thus in the share of tradables.

¹Countries with low mobility costs can meet higher demand for traded goods by importing goods from abroad and meet higher demand for non-traded goods by shifting productive resources away from traded and toward non-traded industries. According to our model's predictions detailed in the quantitative part, when factors' mobility costs between sectors are too high, imports shrink and leisure increases less. Imports will further decline and labor supply might increase as home- and foreign-produced traded goods become imperfect substitutes.

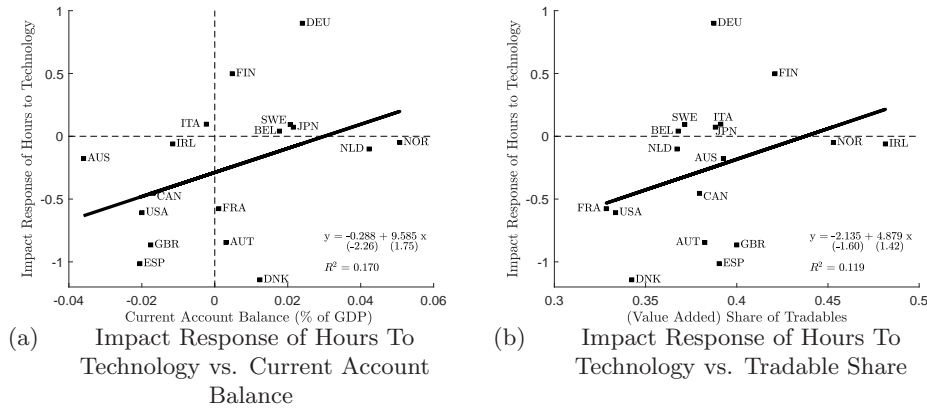


Figure 1: Impact Responses of Hours Worked to a Permanent Technology Improvement: Role of Financial Openness and Tradable Share. *Notes:* Fig. 1(a) and Fig. 1(b) show the impact response of total hours worked to a 1% permanent increase in utilization-adjusted-aggregate-TFP. We first identify the technology shock by estimating a VAR which includes utilization-adjusted-aggregate-TFP, real GDP, total hours worked, and the real consumption wage and by imposing long-run restrictions for each country of our sample. Then in a second step, we estimate the impact response of hours worked by means of local projections. In Fig. 1(a), we plot impact response of hours worked (on vertical axis) against the current account balance (as a percentage of GDP) averaged over 1970-2017. Data for the current account balance are taken from Lane and Milesi-Ferretti [2007]. In Fig. 1(b), we plot impact response of hours worked (on vertical axis) against the value added share of tradables (as a percentage of GDP) averaged over 1970-2017. Data are taken from EU KLEMS. Sample: 17 OECD countries, annual data, 1970-2017.

In an open economy with an exporting (i.e., a traded) vs. a non-exporting (i.e., non-traded) sector, technology improvements are driven by technological change which is both common to both sectors and concentrated toward traded industries. To decompose aggregate technology improvements into symmetric and asymmetric technology shocks in an open economy, we adapt the standard long-run SVAR identification of technology shocks. While both symmetric and asymmetric technology shocks increase utilization-adjusted-aggregate-TFP, only asymmetric technology improvements increase permanently the utilization-adjusted-TFP of tradables relative to non-tradables. The dynamic responses obtained from Jordà's [2005] local projections reveal that symmetric and asymmetric technology shocks have very distinct (and opposite) effects on hours worked. We find that symmetric technology shocks drive down dramatically hours worked on impact (i.e., by -0.47%) and reallocate labor toward the traded sector. Conversely, asymmetric technology shocks increase significantly hours (i.e., by 0.31%) in the short-run and reallocate labor toward the non-traded sector. Estimating the impact labor effects on rolling sub-samples (of fixed window length), hours worked are found empirically to decline by 0.26% the first thirty periods and by 0.11% only the last thirty periods of our sample period. During the same period, the share of the forecast error variance of technology improvements driven by asymmetric technology shocks has increased from 10% to 40%.

To investigate whether the growing role of asymmetric technology improvements is responsible for the reduction of the contractionary effects of technology shocks on hours, we develop an open economy model with tradables and non-tradables by adding several elements to the setup pioneered by Kehoe and Ruhl [2009]. We find that five key elements are essential to account for the labor market effects of a permanent technology shock: financial and trade openness, barriers to factors' mobility between sectors, imperfect substitutabil-

ity between home- and foreign-produced traded goods, factor-biased technological change (FBTC henceforth), and the mix of symmetric and asymmetric technology shocks. In a RBC model with flexible prices, a permanent technology improvement leads hours worked to increase if the economy is closed or to fall dramatically if the economy is financially open (and if home- and foreign-produced traded goods are perfect substitutes).² Intuitively, while a closed economy needs more labor to meet additional demand for consumption and investment goods, a small open economy can work less by importing goods from abroad and running a current account deficit. A model producing tradables and non-tradables is halfway between these two extreme cases as the demand for non-traded goods must be met by domestic firms.

However, a two-sector open economy model without any mobility costs will overstate considerably the decline in traded labor and thereby in total hours worked as imports are perfect substitutes for home-produced traded goods and productive resources shift massively toward the non-traded sector. When we allow for labor and capital mobility costs, traded and thus total hours worked fall by a smaller amount because less resources are moved toward the non-traded sector and thus households must mitigate the increase in leisure to meet higher demand for non-traded goods. If we further assume imperfect substitutability between home- and foreign-produced traded goods, the fall in both traded and total hours worked further shrink because households are now reluctant to substitute foreign- for home-produced traded goods and thus the economy needs more labor to produce home-produced traded goods. Even with mobility costs and a price-elastic demand for home-produced traded goods, the model still overstates the reallocation of labor toward the non-traded sector and the decline in total hours worked. It is only once we allow for technological change biased toward labor that the model can account quantitatively for the labor market effects of a technology shock. Because technological change is more biased toward labor in the traded than in the non-traded sector, the rise in the demand for labor in the traded sector neutralizes the incentives to shift resources toward the non-traded sector which leads the model to generate a decline in hours worked in line with our estimates.

While quantitatively our open economy model with the specific elements mentioned above generates a decline in hours worked in line with what we estimate empirically, such a fall is the result of a mix of symmetric and asymmetric technology shocks across sectors. Both shocks produce distinct effects on the economy, especially on labor. By reducing sectoral prices and putting downward pressure on sectoral wages, symmetric technology shocks lower total hours worked. The depreciation in non-traded good prices lowers the

²As shown by Dotsey [1999], a closed economy model with sticky prices with standard monetary policy rules will produce a rise in hours worked. When we extend our model to sticky prices in the non-traded goods sector, we also find that the model produces an increase in hours worked instead of a decline because a technology improvement is associated with a small increase in non-traded productivity which generates an excess demand for non-traded goods which cannot be eliminated by an appreciation in non-traded good prices and thus non-traded hours worked must increase.

share of expenditure spent on non-tradables because traded and non-traded goods are complements, in line with our estimates and the evidence documented by Mendoza [1992] and Stockman and Tesar [1995], which has a strong negative impact on non-traded hours worked. Because home- and foreign-produced traded goods are high substitutes, as evidence suggests, see e.g., Bajzik et al. [2020], the terms of trade depreciation leads labor to shift toward traded industries. As a result, the dramatic decline in total hours worked is concentrated in the non-traded sector. The negative response of hours to a technology improvement common to both sectors is amplified because symmetric technology shocks are biased toward capital. Conversely, when technology improvements are asymmetric, the concentration of productivity growth in traded industries leads non-traded industries to increase their prices to compensate for their higher marginal cost. Because the price-elasticity of demand for non-traded goods is lower than one, the non-tradable content of expenditure increases. While hiring gets more profitable, non-traded firms must pay higher wages to encourage workers (who experience mobility costs) to switch. By putting upward pressure on wages, asymmetric technology shocks lead households to supply more labor. The positive response of hours worked is further amplified as technology improvements concentrated in traded industries are biased toward labor. Only the baseline model can generate an initial rise in hours by 0.28% (close to the evidence) when technological change is asymmetric between sectors and can produce a decline in hours by 0.40% on impact (close to the evidence) when technological change is uniformly distributed across sectors.

To assess the ability of our baseline model to account for the time-varying effects we estimate empirically, we let the share of symmetric technology shocks fall from 90% to 60% in line with our estimates. We find that the increasing importance of asymmetric technology shocks can rationalize the time-increasing response of total hours worked to aggregate technology shocks. By putting upward pressure on wages and making production more labor intensive, technology improvements concentrated toward traded industries offset the negative impact of symmetric technology shocks. Our model with barriers to factors' mobility and imperfect substitutability between home- and foreign-produced traded goods can generate the shrinking contractionary effects on traded and non-traded hours worked caused by a permanent technology improvement as long as we allow for FBTC. When we impose Hicks-neutral technological change, the restricted model generates a time-decreasing impact response of traded hours worked in contradiction with our evidence. Intuitively, asymmetric technology shocks have a strong expansionary effect on non-traded hours worked at the expense of traded hours worked which tend to fall more on impact as the share of asymmetric shocks increases because more labor shifts toward non-traded industries. We can reproduce the time-increasing impact response of traded and non-traded hours worked to a permanent technology improvement only once technological change is significantly biased toward labor. A model imposing Hicks-neutral technological change generates a time-decreasing impact

response of traded hours worked, in contradiction with our evidence.

Because technological change concentrated toward traded industries is growing over time, it is important to understand the key driver behind this phenomenon and its pattern. By extending our two-sector open economy setup to endogenous technology decisions, we find that two-third of the progression of asymmetric technology shocks is driven by the greater exposition of traded industries to the international stock of knowledge. Because only the estimated value of the elasticity of utilization-adjusted-TFP of tradables w.r.t. the stock of R&D is substantial and statistically significant, the combined effect of the increase in the world stock of ideas and the growing intensity of traded technology in the international stock of knowledge amplifies the dispersion of technology improvements between the traded and the non-traded sector and further increases the share of the variance of technological change driven by asymmetric technology improvements. One additional key finding is that asymmetric technology shocks give rise to an increase in the stock of R&D but only in traded industries, thus suggesting that such technology improvements are driven by innovation. Conversely, the stock of R&D remains unchanged in both sectors after symmetric technology shocks, technology improvement thus reflecting either improved work organization, better management practices, or adoption of existing technologies.

The article is structured as follows. In section 2, we contrast the effects of symmetric technology shocks with those caused by asymmetric technology shocks and investigate the time-varying effects of technology improvements on hours worked. In section 3, we develop a semi-small open economy model with tradables and non-tradables, frictions into factors' mobility and sectoral factor-augmenting efficiency with a symmetric and an asymmetric component. In section 4, we assess numerically the role of each element of our model by considering restricted versions of our setup and compare the predictions of the baseline model with the dynamic effects from local projections. In section 5, we extend the baseline model in two directions. We differentiate between workers' skills and allow for endogenous technology decisions to quantify the share of asymmetric technology change driven by the access to the international stock of ideas. The Online Appendix contains more empirical results, conducts robustness checks, details the solution method, and shows extensions of the baseline model.

Related Literature. Our paper fits into several different literature strands, as we bring several distinct threads in the existing literature together.

Impact response of hours to a technology shocks. There is a vast literature investigating whether a technology improvement increases or lowers hours worked. While the response of hours worked to a technology shock is still debatable as the identification of technology shocks has been subject to criticisms, see e.g., Erceg et al. [2005], Dupaigne et al. [2007], Chari et al. [2008], the literature has put forward a set of solutions to deal with

both the lag-truncation and the small sample biases, among others. These solutions include the number of lags, see e.g., De Graeve and Westermarck [2013], the measure of technology, see e.g., Chaudourne et al. [2014], Dupaigne and Fève [2009], the VAR specification, see e.g., Fève and Guay [2010], the behavior of hours worked (i.e., stationary or free of low-frequency movements), see e.g., Christiano et al. [2006], Francis and Ramey [2009], or econometric methods of identification, see e.g., Francis et al. [2014], Li [2022]. Most of the aforementioned works find that positive technology shocks, identified with long-run restrictions, lead to a short-run decrease in hours worked.

Technology shocks and time-varying response of hours worked. Galí and Gambetti [2009] attribute the shrinking contractionary effect of technology improvements on hours worked to the greater effectiveness of monetary policy to stabilize the economy. Indeed, Dotsey [1999] shows that a sufficiently procyclical monetary policy can induce a positive correlation between output and employment following a technology shock. Galí and Van Rens [2021] put forward the decline in labor regulation leading to a greater outward shift of labor demand. Nucci and Riggi [2013] attribute shrinking contractionary effects on hours worked of positive technology shocks to an increase in performance-related pay schemes. Our work is complementary to these studies as we focus on both financial openness and multi-sector aspects of industrialized countries and show that the time-increasing impact response of hours is not limited to the US.

Closely related to our work, Cantore et al. [2017] base their explanation of the time-varying pattern of hours on increases in the magnitude of the degree of capital-labor substitution. Intuitively, when the production function is of the CES type with an elasticity of substitution between capital and labor lower than one, as evidence suggests, and if technological change is biased toward capital, technology improvements are associated with a fall in labor demand which lowers hours worked. As the elasticity of substitution between capital and labor (smaller than one) takes higher values, technological change turns out to be less biased toward capital. Like the authors, we allow sectoral goods to be produced by means of CES production functions and assume FBTC. In contrast to them, we are able to quantify the extent of technological change biased toward product factors by recovering the dynamics of FBTC by adapting the methodology pioneered by Caselli and Coleman [2006]. Because asymmetric technology shocks across sectors are biased toward labor, the time-increasing contribution of asymmetric technology shocks across sectors tend to raise the labor intensity of production but the trigger mechanism is the growing role of technological change concentrated toward traded industries.

Drivers of technology improvements and effects of technology shocks on labor. Shea [1999] and Alexopoulos [2011] find that technology shocks driven by innovation increase employment. In this paper, we show that symmetric technology shocks lower

dramatically hours worked while asymmetric technology shocks increase significantly labor. Since asymmetric technology shocks are driven by innovation, our work can reconcile the evidence documented by Shea [1999] and Alexopoulos [2011] who focus exclusively on shocks to innovation and those documented by the literature pioneered by Gali [1999] reporting negative effects of labor productivity shocks on hours worked.

Multi-Sector setup, labor reallocation, and total hours worked. Like Garin et al. [2018], we put forward the increasing contribution of asymmetric technology shocks across sectors in driving changes in the labor market together with the importance of barriers to factors' mobility. In contrast to the authors who focus on the labor productivity which has switched from strongly procyclical to mildly countercyclical, we are interested in the response of hours to technology improvements. In this regard, we show that the sectoral dimension is not sufficient on its own to account for the evidence as the open economy aspect also plays a crucial role together with the gross substitutability between home- and foreign produced traded goods and the gross complementarity between traded and non-traded goods. More specifically, our evidence reveals that the variations in hours worked on impact mostly originate from the non-traded sector and to account for this aspect, we have to assume an elasticity of substitution between traded and non-trade goods smaller than one (in line with our estimates) which echoes the findings documented by the structural change literature pioneered by Ngai and Pissarides [2007]. The complementarity between traded and non-traded goods ensures a decline in non-traded hours worked after symmetric technology shocks and an increase following asymmetric technology shocks. To generate the magnitude of the variations in hours we observe in the data, we have to consider an open economy which can borrow after symmetric technology improvement and lend to abroad after asymmetric technology shocks.³ In contrast to the structural change literature which restricts attention to asymmetric technology shocks, we consider a technology improvement driven by both symmetric and asymmetric technology shocks across sectors. We also show that mobility costs are crucial to account for our evidence as they put upward pressure on wages and prevent from a dramatic decline in hours caused by financial openness.

2 Technology and Hours Worked: Evidence

In this section, we document evidence for seventeen OECD countries about the link between technology and labor by highlighting the sectoral dimensions. Below, we denote the percentage deviation from initial steady-state (or the rate of change) with a hat. Robustness checks related to several aspects of our identification of technology shocks and measures of

³Intuitively, after symmetric technology shocks, the rise in imports more than offsets the increase in exports thus leading to a current account deficit because the terms of trade depreciation is not large enough. In contrast, technology improvements concentrated within traded industries give rise to a dramatic terms of trade depreciation in the terms of trade which increases significantly exports and mitigates the decline in traded hours worked.

technology are discussed in section 2.7.

2.1 The Response of Hours Worked across Model Variants

To discipline and guide our empirical investigation, we derive below a formal expression for the equilibrium total hours worked which enables us to discuss the link between technology and labor. Since this relationship involves different elements, we build intuition on each ingredient by considering the simplest model and by adding one ingredient at a time. These ingredients include: i) financial openness, ii) capital adjustment costs, iii) the production of tradables and non-tradables, iv) frictions into the movements of inputs by considering imperfect substitutability between sectoral hours worked and between sectoral capital, v) imperfect substitutability between home- and foreign-produced traded goods, vi) the relative risk aversion parameter, vii) FBTC, viii) and sectoral endogenous capital utilization rates.

Households. To conduct this analysis, we consider the general class of preferences proposed by Shimer [2009] which imply that utility is non-separable in consumption C and leisure with functional form

$$\Lambda \equiv \frac{C(t)^{1-\sigma} V(L(t))^\sigma - 1}{1-\sigma}, \quad \text{if } \sigma \neq 1, \quad V(L(t)) \equiv \left(1 + (\sigma - 1) \gamma \frac{\sigma_L}{1 + \sigma_L} L(t)^{\frac{1+\sigma_L}{\sigma_L}} \right) \quad (1)$$

and

$$\Lambda \equiv \log C(t) - \gamma \frac{\sigma_L}{1 + \sigma_L} L(t)^{\frac{1+\sigma_L}{\sigma_L}}, \quad \text{if } \sigma = 1. \quad (2)$$

where L is total hours worked. These preferences are characterized by two crucial parameters: σ_L is the Frisch elasticity of labor supply, and $\sigma > 0$ determines the substitutability between consumption and leisure and collapses to relative risk aversion. Denoting by $\lambda(t)$, $P_C(t)$, and $W(t)$ the marginal utility of wealth, the consumption price index, and the aggregate wage rate, first-order conditions for consumption and labor supply are $\Lambda_C(C(t), L(t)) = \lambda(t)P_C(t)$ and $-\Lambda_L(C(t), L(t)) = \lambda(t)W(t)$. Rearranging the FOC for consumption, i.e., $C(t) = \left(\frac{\Lambda_C}{V^\sigma} \right)^{-\frac{1}{\sigma}}$, and plugging the latter equation into the FOC for labor supply, the optimal decision on total hours worked reads:

$$\gamma L(t)^{\frac{1}{\sigma_L}} = W_C(t) \frac{(\Lambda_C(t))^{\frac{1}{\sigma}}}{\sigma}, \quad (3)$$

where $W_C(t) = \frac{W(t)}{P_C(t)}$ is the real consumption wage.

Firms. On the production side, perfectly competitive firms produce a final good by using capital ($K^j(t)$) and labor ($L^j(t)$) services i.e., $Y^j(t) = F^j \left[A^j(t)L^j(t), B^j(t)\tilde{K}^j(t) \right]$ where $Y^j(t)$ is the value added in sector j , $A^j(t)$ and $B^j(t)$ are labor- and capital-augmenting technological change and $\tilde{K}^j(t) = u^{K,j}(t)K^j(t)$ where $u^{K,j}(t)$ is the capital utilization rate chosen by households. Denoting the capital rental rate by $R^j(t)$, and the wage rate by $W^j(t)$, the demand for capital and labor read $R^j(t) = \frac{\partial F^j}{\partial K^j}$ and $W^j(t) = \frac{\partial F^j}{\partial L^j}$, respectively.

In Table 3 which is relegated to Online Appendix A, we consider eleven variants of a RBC model to investigate the role of each element for the link between hours and technology. In each variant, we assume that aggregate utilization-adjusted aggregate TFP increases by 1% initially and remains permanently to this level. When we consider a two-sector economy, we assume that traded and non-traded technology improves by 1.7% and 0.6% respectively, in line with our evidence. When we relax the assumption of Hicks-neutral technological change (HNTC henceforth), we let technological change to be biased toward labor in the traded sector (by 1.60%) and the non-traded sector (by 0.29%), in line with our estimates.

Moving from a closed to a small open economy. In order to understand the role played by each element we first assume that the production function is Cobb-Douglas and technological change is Hicks-neutral (i.e., $A^j(t) = B^j(t) = Z^j(t)$). We assume that capital utilization rate is fixed. In a closed economy model where households consume one unique final good, the consumption price index P_C collapses to 1. Assuming that the parameter σ is equal to one, the equilibrium level for hours worked (3) collapses to: $\gamma L(t)^{\frac{1}{\sigma_L}} = W(t)C(t)^{-1}$. By increasing the wage rate, a technology shock encourages agents to supply more labor through the substitution channel. A technology shock also produces a positive wealth effect which encourages households to consume more goods and more leisure and to lower their labor supply. As is well-known, in a closed economy, a technology shock leads to an increase in hours worked on impact which is necessary to meet higher demand for consumption and investment goods. As shown in the first row of Table 3, total hours worked increase by 0.075%.

When we consider a two-sector closed economy model which produces goods and services, the relative price of leisure collapses to the real consumption wage denoted $W_C(t)$. As shown in the second row of Table 3, a technology improvement further increases total hours worked by 0.11%. Intuitively, in line with the evidence, technology improvements are more pronounced in Manufacturing than in Services which leads the latter sector to charge higher prices to compensate for its higher marginal cost. Because goods and services are complements, the appreciation in the relative price of services disproportionately increases the share of services in total expenditure which leads labor to shift toward the service sector. Since worker experience mobility costs, firms in the service sector must pay higher wages which amplifies the substitution effect and further increases labor supply.

Moving from a closed to a small open economy. We now assume that the economy has perfect access to world capital markets. For pedagogical purposes, we consider first a one-sector economy with no capital adjustment costs. As shown in the third row of Table 3, total hours worked decline dramatically in a small open economy by -0.492%. Intuitively, because domestic goods and foreign goods are perfect substitutes, the open economy finds it optimal to work less and import goods and services from abroad by running a current

account deficit. As shown in the last column Table 3, consumption increases less once we allow for capital adjustment costs (see the fourth row), leading labor supply to fall less (i.e., by 0.418%) because domestic capital and foreign bonds are no longer perfect substitutes in the short-run which mitigates the current account deficit.

Moving from a one-sector to a two sector open economy. We now consider an economy which produces traded goods that can be exported and non-traded goods for domestic absorption only. The decline in labor supply 0.348% is less pronounced than in a one-sector small open economy because the economy must produce non-traded goods which cannot be imported from abroad. While traded hours worked decline by almost the same amount as in one-sector economy, labor now shifts toward non-traded industries. Note that by raising the marginal revenue product of labor, the appreciation in the relative price of non-tradables increases the wage rate which leads agents to supply more labor.

As shown in the sixth row, when we allow for labor mobility costs. hours worked fall by a smaller magnitude, i.e., by 0.219%. Intuitively, in a model where workers experience switching costs, less labor can move toward the non-traded sector. Therefore workers must reduce their labor supply by a smaller magnitude so that the production of non-traded goods meets additional demand.

Moving from a small to a semi-small open economy. We now assume that home- and foreign-produced traded goods are imperfect substitutes. As shown in the seventh row of Table 3, total hours worked decline less following a technology improvement, i.e., $\hat{L}(0) = -0.110$. Intuitively, households are now reluctant to substitute foreign- for home-produced traded which in turn leads the traded sector to produce more to meet higher demand. Because the open economy reduces its imports, the decline in hours worked must be less pronounced. As displayed by the eight row of Table 3, capital mobility costs slightly mitigate the magnitude of the decline in total hours worked.

Factor-biased technological change and preferences. We now add a new element by allowing production to be more intensive in one specific input. Under the assumptions of perfectly competitive markets and constant returns to scale in production, labor is paid its marginal product. Denoting the labor income share by s_L^j , the marginal revenue product of labor, $s_L^j \frac{P^j Y^j}{L^j}$, must equate the wage rate W^j . The same logic applies at an aggregate level, i.e., $s_L \frac{Y}{L} = W$ where s_L is the aggregate labor income share (LIS henceforth) and Y is GDP at current prices. Plugging labor demand $s_L \frac{Y}{L} = W$ into labor supply (3) to eliminate W and solving leads to the equilibrium level of total hours worked:

$$\gamma L(t)^{\frac{1+\sigma_L}{\sigma_L}} = s_L(t) \frac{Y(t)}{P_C(t)} \frac{(\Lambda_C(t))^{\frac{1}{\sigma}}}{\sigma}. \quad (4)$$

If we assume that production functions are of the CES type and technological change is factor-biased, the aggregate LIS varies following a permanent technology improvement which in turn influences the equilibrium level of total hours worked. Column 4 in the ninth

row indicates that technological change biased toward labor mitigates the magnitude of the decline in hours worked from 0.106% to 0.096%. Formally, technological change biased toward labor is reflected into an increase in s_L which raises the marginal revenue product of labor, pushes up labor demand and increases wages.

More specifically, technological change biased toward labor implies that production in both sectors turns out to be more intensive in labor which has an expansionary effect on hours worked.⁴ In the tenth row, we assume that consumption and leisure are substitutes so that the coefficient of relative risk aversion σ collapses to two. The decline in total hours worked is more pronounced, passing from 0.096% to 0.140%. Because the marginal utility of consumption declines more rapidly as consumption increases, households allocate a greater share of their additional wealth to leisure time which amplifies the decline in total hours worked. In the last row, we allow for an endogenous capital utilization at a sectoral level. The decline in L slightly shrinks at -0.13%. On one hand, capital utilization falls substantially in the traded sector because technological change is strongly biased toward labor which has a negative impact on traded hours worked. On the other hand, capital utilization increases in the non-traded sector because non-traded prices appreciate which has a positive effect on non-traded hours worked. The latter effect more than offsets the former.

2.2 Data Construction

Before presenting evidence on the effects of a permanent technology improvement, we briefly discuss the dataset we use. Our sample contains annual observations and consists of a panel of 17 OECD countries. The period runs from 1970 to 2017.

Classification of industries as tradables or non-tradables. Since our primary objective is to quantify the implications of the dispersion in technology improvements across sectors, we describe below how we construct time series at a sectoral level. Our sample covers eleven 1-digit ISIC-rev.3 industries. Following De Gregorio et al. [1994], we define the tradability of an industry by constructing its openness to international trade given by the ratio of total trade (imports plus exports) to gross output, see Online Appendix M.2 for more details. Data for trade and output are taken from WIOD [2013], [2016]. "Agriculture, Hunting, Forestry and Fishing", "Mining and Quarrying", "Total Manufacturing" and "Transport, Storage and Communication" exhibit high openness ratios and are thus classified as tradables. At the other end of the scale, "Electricity, Gas and Water Supply", "Construction", "Wholesale and Retail Trade" and "Community Social and Personal Services" are considered as non-tradables since the openness ratio in this group of industries is low (i.e., less than 10% for most of the countries in our sample). For the three remaining in-

⁴The effect looks small because an aggregate technology shock is a mix of symmetric and asymmetric technology shocks. Although asymmetric technology improvements are strongly biased toward labor, symmetric technology shocks which are predominant and biased toward capital.

dustries "Hotels and Restaurants", "Financial Intermediation", "Real Estate, Renting and Business Services" the results are less clearcut since the openness ratio averages (across countries) 14% for the former and 20% for the last two sectors. In the benchmark classification, we adopt the standard classification of De Gregorio et al. [1994] by treating "Real Estate, Renting and Business Services" and "Hotels and Restaurants" as non-traded industries. Given the dramatic increase in financial openness that OECD countries have experienced since the end of the eighties, we allocate "Financial Intermediation" to the traded sector. This choice is also consistent with the classification of Jensen and Kletzer [2006] who categorize "Finance and Insurance" as tradable.⁵

In Online Appendix G, we detail the source and the construction of time series for sectoral value added at constant prices, Y_{it}^j , sectoral hours worked, L_{it}^j , the hours worked share of sector j , $\nu_{it}^{L,j}$, the value added share at constant prices, $\nu_{it}^{Y,j}$. While we mainly focus on the sectoral hours and sectoral value added effects of technology shocks, we also build intuition about the transmission mechanism of a technology improvement in a two-sector open economy by analyzing the movements in relative wages and relative prices. The relative wage of non-tradables is constructed as the ratio of the non-traded wage to the aggregate wage, W_{it}^N/W_{it} , the relative price of non-tradables is computed as the ratio of the non-traded value added deflator to the traded value added deflator, $P_{it} = P_{it}^N/P_{it}^H$, and the terms of trade are constructed as the ratio of the traded value added deflator of the home country i to the geometric average of the traded value added deflator of the seventeen trade partners of the corresponding country i , the weight being equal to the share $\alpha_i^{M,k}$ of imports from the trade partner k (averaged over 1970-2017).

Utilization-adjusted sectoral TFPs. Sectoral TFPs are Solow residuals calculated from constant-price (domestic currency) series of value added, Y_{it}^j , capital stock, K_{it}^j , and hours worked, L_{it}^j , i.e., $\hat{\text{TFP}}_{it}^j = \hat{Y}_{it}^j - s_{L,i}^j \hat{L}_{it}^j - (1 - s_{L,i}^j) \hat{K}_{it}^j$ where $s_{L,i}^j$ is the LIS in sector j averaged over the period 1970-2017. To obtain series for the capital stock in sector j , we first compute the overall capital stock by adopting the perpetual inventory approach, using constant-price investment series taken from the OECD's Annual National Accounts. Following Garofalo and Yamarik [2002], we split the gross capital stock into traded and non-traded industries by using sectoral valued added shares.⁶ Once we have constructed the Solow residual for the traded and the non-traded sectors, we construct a measure

⁵Because "Financial Intermediation" and "Real Estate, Renting and Business Services" are made up of sub-sectors which display a high heterogeneity in terms of tradability, and "Hotels and Restaurants" has experienced a large increase in tradability over the last fifty years, we perform a sensitivity analysis with respect to the classification for the three aforementioned sectors in Online Appendix M.2. Treating "Financial Intermediation" as non-tradables or classifying "Hotels and Restaurants" or "Real Estate, Renting and Business Services" as tradables does not affect our main results.

⁶Due to limited data availability, in the line of Garofalo and Yamarik [2002], we split the aggregate capital stock into tradables and non-tradables in accordance with their value added share. In Online Appendix M.3, we use EU KLEMS [2011], [2017] which provide disaggregated capital stock data (at constant prices) at the 1-digit ISIC-rev.3 level for thirteen countries of our sample over the period 1970-2015. Our estimates show that our empirical findings are robust and insensitive to the way the sectoral capital stocks are constructed in the data.

for technological change by adjusting the Solow residual with the capital utilization rate, denoted by $u_{it}^{K,j}$:

$$\hat{Z}_{it}^j = \widehat{\text{TFP}}_{it}^j - \left(1 - s_{L,i}^j\right) \hat{u}_{it}^{K,j}, \quad (5)$$

where we follow Imbs [1999] in constructing time series for $u_{it}^{K,j}$, see Online Appendix H, as utilization-adjusted TFP is not available at a sectoral level for most of the OECD countries of our sample. In Online Appendix N.4, we find that our results are little sensitive to the use of alternative measures of technology which include i) Basu's [1996] approach which has the advantage of controlling for unobserved changes in both capital utilization and labor effort, ii) and the use of time series for utilization-adjusted-TFP from Huo et al. [2023] and Basu et al. [2006].

Factor-Biased Technological Change (FBTC). Within each sector, we allow for labor- and capital-augmenting efficiency to increase at different rates so that technological change can potentially be factor-biased. To investigate empirically whether technological change is biased toward capital or labor, we have to construct time series for FBTC within sector $j = H, N$. We draw on Caselli and Coleman [2006] and Caselli [2016] to construct time series for FBTC which must be adjusted with the capital utilization rate, as explained in section 2.3. Denoting the elasticity of substitution between capital and labor by σ_i^j , capital- and labor-augmenting efficiency by B_{it}^j and A_{it}^j , respectively, our measure of capital-utilization-adjusted-FBTC, denoted by FBTC_{it}^j , reads (see Online Appendix E for a formal derivation):

$$\text{FBTC}_{it}^j = \left(\frac{B_{it}^j / \bar{B}_i^j}{A_{it}^j / \bar{A}_i^j} \right)^{\frac{1-\sigma_i^j}{\sigma_i^j}} = \frac{S_{it}^j}{\bar{S}_i^j} \left(\frac{k_{it}^j}{\bar{k}_i^j} \right)^{-\frac{1-\sigma_i^j}{\sigma_i^j}} \left(\frac{u_{it}^{K,j}}{\bar{u}_i^{K,j}} \right)^{-\frac{1-\sigma_i^j}{\sigma_i^j}}, \quad (6)$$

where a bar refers to averaged values of the corresponding variable over 1970-2017. To construct time series for FBTC_{it}^j , we plug time series for the ratio of the labor to the capital income share, $S_{it}^j = s_{L,it}^j / (1 - s_{L,it}^j)$, the capital-labor ratio, k_{it}^j , the capital utilization rate defined later, $u_{it}^{K,j}$. We also plug values for σ_i^j we have estimated for each country of our sample, see Online Appendix J.6 for a detailed exposition of our empirical strategy. As shown in Table 1, we find values for σ_i^j smaller than one for the whole sample (and most of countries/sectors), thus corroborating the gross complementarity between capital and labor documented by Klump et al. [2007], Herrendorf et al. [2015], Oberfield and Raval [2021], Chirinko and Mallick [2017]. When FBTC_{it}^j increases, technological change is biased toward labor while a fall indicates that technological change is biased toward capital. To compute aggregate FBTC, we calculate the labor compensation share weighted sum of sectoral FBTC adjusted with the capital income share, i.e., $\widehat{\text{FBTC}}_{it}^A = \sum_{j=H,N} \alpha_{L,i}^j \left(1 - s_{L,i}^j\right) \widehat{\text{FBTC}}_{it}^j$.

2.3 Identification of Asymmetric vs. Symmetric Technology Shocks

To conduct our empirical study, we compute the responses of selected variables by using a two-step estimation procedure. We first identify a permanent technology improvement by adopting the identification pioneered by Gali [1999]. Like Gali, we impose long-run restrictions in the VAR model to identify permanent technology shocks as shocks that increase permanently the level of our measure of technology. Because Erceg et al. [2005] and Chari et al. [2008] have shown that persistent non-technology shocks can disturb the identification of permanent technology shocks, we adjust TFP with the capital utilization rate. Chaudourne et al. [2014] demonstrate that the use of 'purified' TFP to measure technological change ensures the robustness of the identification of technology shocks. In the second step, we trace out the dynamic effects of the identified shock to utilization-adjusted TFP by using Jordà's [2005] single-equation method.

First step. To explore empirically the dynamic effects of a shock to aggregate productivity, we consider a vector denoted by X_{it} which includes utilization-adjusted aggregate TFP, Z_{it}^A , real GDP, $Y_{R,it}$, total hours worked, L_{it} , the real consumption wage, $W_{C,it}$. In the sequel, all quantities are divided by the working age population and all variables enter the VAR model in rate of growth. In the first step, we identify the permanent technology shocks ε_{it}^Z by estimating a reduced-form VAR model in panel format on annual data

$$\hat{X}_{it} = B(L)A_0\varepsilon_{it}^Z, \quad (7)$$

where $B(L) = C(L)^{-1}$ with $C(L) = I_n - \sum_{k=1}^p C_k L^k$ a p -order lag polynomial. The matrices C_k and the variance-covariance matrix Σ are assumed to be invariant across time and countries and the VAR is estimated with two lags, country fixed effects and time dummies; we assume a linear relationship between reduced form residuals η_{it} and structural technology shocks ε_{it}^Z

$$\eta_{it} = A_0\varepsilon_{it}^Z, \quad (8)$$

where A_0 the matrix that describes the instantaneous effects of structural shocks on observables. Let us denote $A(L) = B(L)A_0$ with $A(L) = \sum_{k=0}^{\infty} A_k L^k$. To identify permanent technology improvements, ε_{it}^Z , we use the restriction that the unit root in utilization-adjusted-TFP originates exclusively from technology shocks which implies that the upper triangular elements of the long-run cumulative matrix $A(1) = B(1)A_0$ must be zero. Once the reduced form has been estimated using OLS, structural shocks can then be recovered from $\varepsilon_{it}^Z = A(1)^{-1}B(1)\eta_{it}$ where the matrix $A(1)$ is computed as the Cholesky decomposition of $B(1)\Sigma B(1)'$.

Second step. Once we have identified technology shocks, in the second step, we estimate the effects on selected variables (detailed later) by using Jordà's [2005] single-equation method. The local projection method amounts to running a series of regressions of each

variable of interest on a structural identified shock for each horizon $h = 0, 1, 2, \dots$:

$$x_{i,t+h} = \alpha_{i,h} + \alpha_{t,h} + \beta_{i,h}t + \psi_h(L) z_{i,t-1} + \gamma_h \varepsilon_{i,t}^Z + \eta_{i,t+h}, \quad (9)$$

where $\alpha_{i,h}$ are country fixed effects, $\alpha_{t,h}$ are time dummies, and we include country-specific linear time trends; x is the logarithm of the variable of interest, z is a vector of control variables (i.e., past values of utilization-adjusted-TFP and of the variable of interest), $\psi_h(L)$ is a polynomial (of order two) in the lag operator and $\varepsilon_{i,t}^Z$ is the identified technology shock.

VAR identification of symmetric vs. asymmetric technology shocks across sectors. The starting point of the identification of symmetric and asymmetric technology shocks is the sectoral decomposition of the percentage deviation of utilization-adjusted-aggregate-TFP (i.e., Z_{it}^A) relative to its initial steady-state:

$$\hat{Z}_{it}^A = \nu_i^{Y,H} \hat{Z}_{it}^H + (1 - \nu_i^{Y,H}) \hat{Z}_{it}^N, \quad (10)$$

where \hat{Z}_{it}^H and \hat{Z}_{it}^N measure technology improvements in the traded and the non-traded sector, respectively. Eq. (10) can be rearranged as follows

$$\hat{Z}_{it}^A = \hat{Z}_{it}^N + \nu_i^{Y,H} (\hat{Z}_{it}^H - \hat{Z}_{it}^N), \quad (11)$$

which enables us to decompose technological change into technology improvements which are common and asymmetric between sectors. When technology improves at the same rate in the traded and the non-traded sector, i.e., $\hat{Z}_{it}^H = \hat{Z}_{it}^N$, then the second term on the RHS of eq. (11) vanishes and technological change collapses to its symmetric component (indexed by the the subscript S), i.e., $\hat{Z}_{S,it}^A = \hat{Z}_{S,it}^H = \hat{Z}_{S,it}^N$. In contrast, the asymmetric component of aggregate technological change is captured by the second term on the RHS, i.e., $\hat{Z}_{D,it}^A = \nu_i^{Y,H} (\hat{Z}_{D,it}^H - \hat{Z}_{D,it}^N)$, which reflects the excess of technology improvements in the traded sector over those in the non-traded sector weighted by the value added share of tradables.

We assume that technology in sector j is made up of a symmetric and an asymmetric component, i.e., $Z_{it}^j = (Z_{S,it}^j)^{\eta_i} (Z_{D,it}^j)^{1-\eta_i}$, where we denote by η the share of technological change which is common across sectors. Log-linearizing this expression of technology in sector j and plugging the result into eq. (10) leads to the decomposition of aggregate technological change into a symmetric and an asymmetric component:

$$\hat{Z}_{it}^A = \eta_i \hat{Z}_{S,it}^A + (1 - \eta_i) \hat{Z}_{D,it}^A. \quad (12)$$

We consider two versions of the VAR model. In the first version, we estimate a VAR model which includes utilization-adjusted-aggregate-TFP, real GDP, total hours worked and the real consumption wage where all variables enter the VAR model in growth rates. We impose long-run restrictions to identify aggregate technology shocks as shocks which increase permanently Z_{it}^A . In the second version, we augment the VAR model with the

ratio of traded to non-traded utilization-adjusted-TFP ordered first. Building on our above discussion based on eq. (11), we impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z_{it}^A while only asymmetric technology shocks increase permanently Z_{it}^H/Z_{it}^N in the long-run. Technically the long-run cum matrix is lower triangular which implies that only asymmetric technology shocks in the first row increases both the ratio of traded to non-traded technology and aggregate technology while symmetric technology shocks leave the relative productivity of tradables unaffected.

2.4 Sectoral Effects of Aggregate Technology Shocks

We first investigate the effects of a 1% permanent increase in utilization-adjusted aggregate TFP. We generated impulse response functions by means of local projections. The dynamic adjustment of variables to an exogenous increase in Z_{it}^A by 1% is displayed by the solid blue line in Fig. 2. The shaded areas indicate 90% confidence bounds. The horizontal axis of each panel measures the time after the shock in years and the vertical axis measures deviations from trend. Responses of sectoral value added and sectoral hours worked are re-scaled by the sample average of sectoral value added to GDP and sectoral labor compensation share, respectively. As such, the sum of variations in Y_{it}^j and L_{it}^j collapses to the change in real GDP and total hours worked, respectively.

Technology. The first row of Fig. 2 shows the effects of a technology improvement by 1% in the long-run on aggregate TFP, traded relative to non-traded TFP, aggregate FBTC. As shown in Fig. 2(a), the technology shock is hump-shaped and peaks after one year. Inspection of Fig. 2(c) indicates that the adjustment of aggregate TFP remains flat because capital utilization rates fall in the short run in both sectors and display a U-shaped pattern. Fig. 2(b) reveals that technology improvements are not evenly distributed across sectors since technology shocks are associated with a significant technology differential between tradables and non-tradables. Quantitatively, the long-run elasticities of utilization-adjusted TFP in traded and non-traded industries w.r.t. utilization-adjusted-aggregate-TFP averages 1.6 and 0.4, respectively.⁷ Fig. 2(d) shows that utilization-adjusted aggregate FBTC increases which suggests that technological change is biased toward labor but the response is not statistically significant.

Total hours and real GDP. We now turn to the aggregate effects of a permanent technology improvement which are displayed by the first column of Fig. 2. We find that hours worked decrease by 0.15% on impact and remain below trend, the long-run elasticity of hours w.r.t. utilization-adjusted-aggregate-TFP averaging -0.12 . The contractionary effect on hours worked of a technology improvement is mitigated as technological change is (slightly) biased toward labor, see Fig. 2(d). The fall in hours worked leads to a long-run

⁷To estimate the long-run elasticity of variable X w.r.t. to aggregate technology Z_t^A , we consider a ten year-horizon and calculate $\frac{\int_0^{10} \dot{X}_t dt}{\int_0^{10} \dot{Z}_t^A dt}$.

elasticity of real GDP w.r.t. to Z_{it}^A which averages 0.87.

Sectoral hours and value added. The second and the third row of Fig. 2 shows the sectoral composition effects of a technology shock. Fig. 2(f) shows that the decline in total hours worked is concentrated in the non-traded sector in the short-run while the situation is reversed from $t = 4$ as labor is reallocated toward the non-traded sector as can be seen in Fig. 2(g).

The deindustrialization trend movement is driven by the productivity growth differential between tradables and non-tradables which averages 1.2% as displayed by Fig. 2(b). As technology improvements are concentrated in the traded sector, non-traded industries charge higher prices to compensate for the higher marginal cost, as can be seen in Fig. 2(k) which shows that the relative price of non-tradables appreciates. Because the demand for non-traded relative to traded goods is little sensitive to the relative price of non-tradables (see e.g., Mendoza [1992], Stockman and Tesar [1995]), the non-tradable content of expenditure increases which causes labor to shift toward the non-traded sector. However, labor reallocation toward the non-traded sector materializes only in the long-run. As shown later in section 4.3, there are a number of factors which prevents labor from shifting in the short-run such as mobility costs, imperfect substitutability between home- and foreign-produced traded goods and technological change biased toward labor in the traded sector.

More specifically, as displayed by Fig. 2(h), traded output becomes more intensive in labor as the traded LIS increases above trend in the short-run which neutralizes the incentives for labor to shift toward non-traded industries. In addition, as can be seen in Fig. 2(l), the terms of trade depreciate because traded value added increases disproportionately relative to non-traded value added. Because home- and foreign-produced traded goods are high substitutes, as evidence suggests, e.g., Bajzik et al. [2020]), the terms of trade depreciation mitigates the decline in the share of tradables by increasing both domestic and foreign demand for home-produced traded goods.

Because productivity growth is concentrated in traded industries, two-thirds of real GDP growth originates from the traded sector which accounts for only one-third of GDP. This leads the value added share of tradables at constant prices to increase permanently by 0.2 ppt of GDP, as displayed by Fig. 2(j).

2.5 The Time-Varying Response of Hours Worked

Like Gali and Gambetti [2009], Cantore et al. [2017], Li [2022] on U.S. data, our evidence reveals that a permanent technology improvement has a contractionary effect on total hours worked in the short-run in OECD countries. We now investigate whether this decline has changed over the last fifty years. To conduct this analysis, we re-estimate the effect of a permanent technology improvement on hours worked by running the regression eq. (9) on

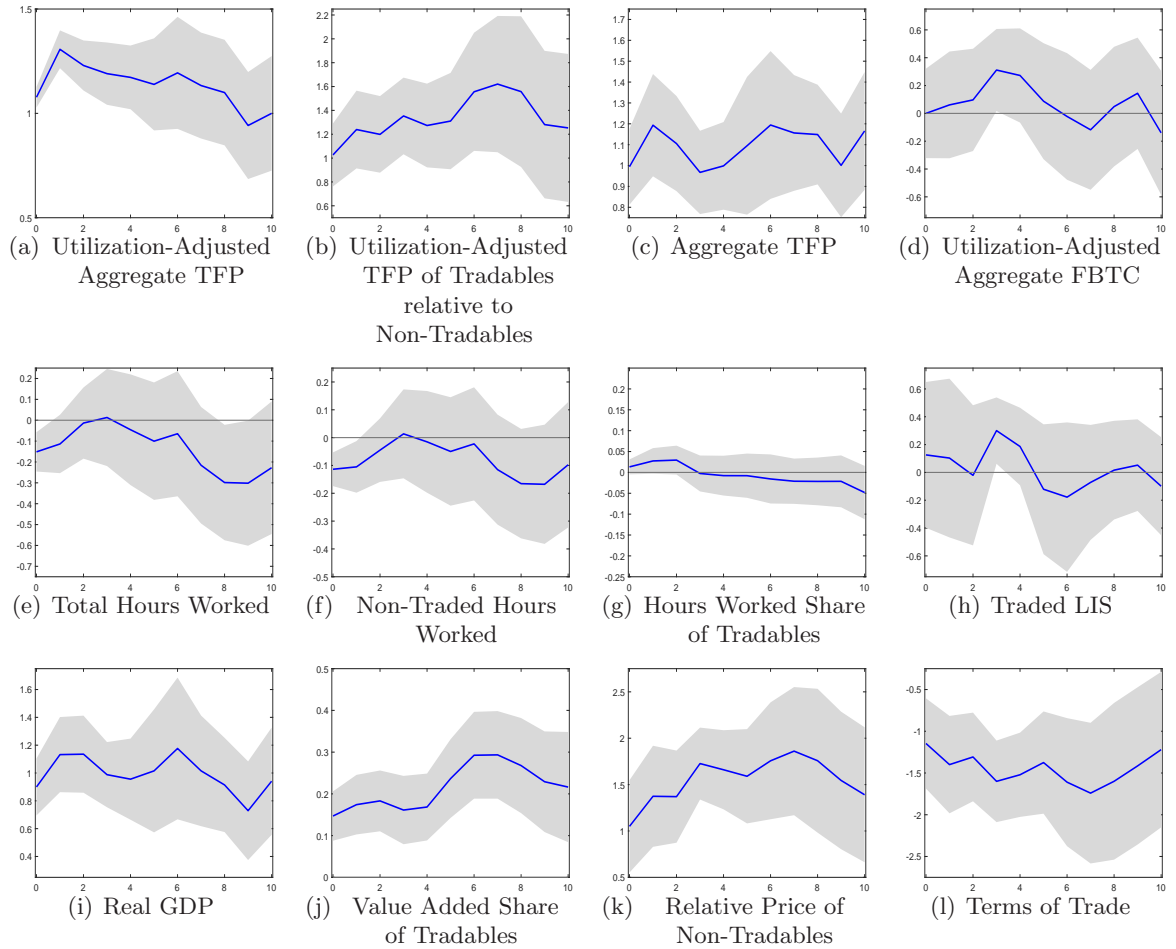


Figure 2: Labor Market Effects of a Technology Shock. *Notes:* The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (sectoral value added share, labor income share), percentage deviation from trend in total hours worked units (sectoral hours worked, labor share), percentage deviation from trend (utilization-adjusted TFPs, utilization-adjusted FBTC). Sample: 17 OECD countries, 1970-2017, annual data.

rolling windows of fixed length. We focus on the impact effect captured by the estimated value γ_0 and consider a window of thirty years. More specifically, we estimate γ_0 , starting from 1970-2000, repeating the estimation by moving the starting date by one year until we estimate the response over the last thirty years of the sample, i.e., over 1987-2017.⁸ As shown in Fig. 3(a), a 1% permanent increase in utilization-adjusted aggregate TFP lowers total hours worked by 0.26% on impact over the period 1970-2000 and by 0.11% over the last thirty years. As shown in Fig. 3(e), the shrinking impact labor response is concomitant to the rise in the share of technology improvements driven by asymmetric technology shocks. When we estimate the VAR model on rolling sub-periods, the FEVD reveals that the contribution of asymmetric technology shocks to the variance of aggregate technology improvements has increased substantially over time from 10% the first thirty years to 40% over the recent period.

Our hypothesis that the time-increasing response of total hours worked to a technology improvement is driven by the growing share of asymmetric technology shocks is correct as long as the elasticity of hours worked to symmetric and asymmetric technology shocks remains stable over time. To clarify this point, we decompose the impact response of total hours worked to an aggregate technology shock into impact responses of hours to symmetric and asymmetric technology shocks, i.e.,

$$\gamma_0 = \eta\gamma_{S,0} + (1 - \eta)\gamma_{D,0}, \quad (13)$$

where $\gamma_0 = \frac{\hat{L}_0}{\hat{Z}_0^A}$ and $\gamma_{X,0} = \frac{\hat{L}_{X,0}}{\hat{Z}_{X,0}^A}$ with $X = S, D$. According to our hypothesis, the time-declining share η of symmetric technology shocks leads γ_0 to move from larger to smaller negative values over time while $\gamma_{S,0}$ and $\gamma_{D,0}$ are assumed to remain constant over time. To test this assumption, in column 2 of Fig. 3, we plot the impact responses of hours worked to symmetric and asymmetric technology shocks which are estimated over rolling sub-samples. Two conclusions emerge. The first conclusion is that as discussed in the next subsection, symmetric technology shocks exert a strong negative impact on hours worked while asymmetric technology shocks increase hours worked on impact. The second conclusion which emerges from the inspection of Fig. 3(b) is that the elasticity of labor to symmetric technology shocks is increasing over time which could potentially rationalize smaller negative values of γ_0 . However, as displayed by Fig. 3(f), asymmetric technology shocks tend to produce smaller positive effects on total hours worked which thus lead to larger negative values of γ_0 . To quantify the role of time-varying elasticities of hours worked to symmetric and asymmetric technology shocks in driving γ_0 , we plug the time-varying estimated values of $\gamma_{S,0}$ and $\gamma_{D,0}$ into (13) and find that the contractionary effect on hours

⁸When estimating the impact effect of a technology shock on hours worked as captured by the estimated value of γ_0 , we run the same regression as in eq. (9), except that we consider overlapping subperiods of a fixed length, i.e., $T = 30$. More specifically, for $T = 30$, we estimate eq. (9) over 1970-2000, 1971-2001, ..., 1987-2017. We have considered windows of alternative length such as $T = 20$ and $T = 25$ and find that all the conclusions hold.

shrinks from -0.26 to -0.22 when we keep the share of symmetric technology shocks constant over time. Therefore these changes in the responses of hours to symmetric and asymmetric technology shocks cannot rationalize the time-increasing impact response of hours to tech shocks which thus suggests that the cause should lie in the rise in the share of asymmetric tech shocks.

Columns 3 and 4 of Fig. 3 show additional evidence which corroborate the role of the increasing share of asymmetric shocks in driving the time-increasing impact response of hours worked. In column 3, we plot impact responses of the relative price of non-tradable and the terms of trade to an aggregate technology shock over rolling windows. Because technology improvements are not uniformly distributed across sectors and instead are concentrated toward traded industries, a technology shock produces an excess demand for non-traded goods which appreciates the relative price of non-tradables as displayed by Fig. 3(c). Conversely, an excess supply on the traded goods market shows up which leads to a depreciation in the terms of trade as can be seen in Fig. 3(g). As shown in Fig. 3(c), the appreciation in the relative price of non-tradables tends to more pronounced while Fig. 3(g) reveals that the terms of trade depreciate more over time. The greater appreciation in the relative price of non-tradables and the more pronounced depreciation in the terms of trade suggest that aggregate technology shocks are increasingly driven by asymmetric technology improvements between sectors.

By increasing the share of expenditure spent on non-tradables, the appreciation in the relative price of non-tradables has a strong expansionary effect on labor demand in the non-traded sector. Therefore, by raising the appreciation in the relative price of non-tradables over time, the rise in the share of asymmetric technology shocks, as displayed by Fig. 3(e), should increase the impact response of non-traded hours worked to aggregate technology shocks. Fig. 3(d) which shows that the decline in non-traded hours worked shrinks over time corroborates this assumption. However, by giving rise to incentives to shift labor toward the non-traded sector, the greater appreciation in the relative price of non-tradables should lead to larger negative values for the response of traded hours worked to an aggregate technology improvement. In contrast, Fig. 3(h) shows that the decline in traded hours worked also shrinks over time. Such a finding is driven by two factors. First, as detailed later in section 4.3, the terms of trade depreciation stimulates labor demand in the traded sector which partly offsets the incentives to shift labor toward the non-traded sector. This factor is not sufficient on its own to generate the time-increasing impact response of L^H . As shown in section 4.5, it is only once we allow for technological change biased toward labor that the model can generate the response of traded hours worked displayed by Fig. 3(h).

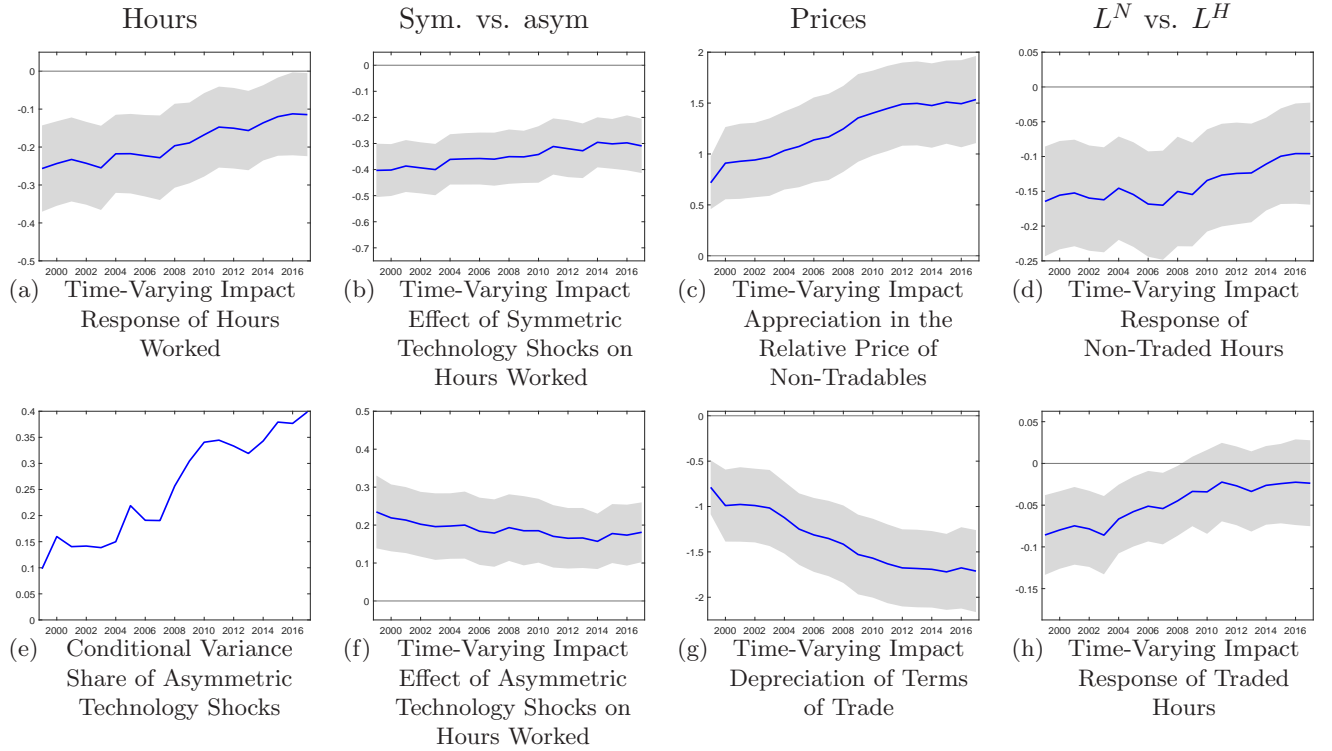


Figure 3: Time-Varying Impact Response of Hours Worked to a Technology Shock. *Notes:* In Fig. 3(a), we estimate the effects of a 1% permanent increase in utilization-adjusted aggregate TFP on hours worked by using Jordà's [2005] single-equation method. We run the regression (9) in rolling sub-samples by considering a fixed window length of thirty years. Because we are interested in the impact effect of technology on hours worked, we consider an horizon $h = 0$ into (9). The horizontal axis shows the end year of the period of the sub-sample and the vertical line displays the point estimate of the impact effect of technology on total hours worked. In Fig. 3(e), we show the fraction of the (conditional) variance of utilization-adjusted TFP growth which is attributable to the variance of asymmetric technology shocks across sectors. While in column 1, we focus on aggregate technology shocks, in column 2 of Fig. 3, we estimate the impact response of total hours worked to a 1% permanent increase in utilization-adjusted aggregate TFP driven by symmetric technology shocks (Fig. 3(b)) while in Fig. 3(f), we consider a rise in utilization-adjusted aggregate TFP driven by asymmetric technology shocks. To identify symmetric vs. asymmetric technology shocks, we estimate the VAR model $[\hat{Z}_{it}^H - \hat{Z}_{it}^N, \hat{Z}_{it}^A, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}]$. We impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z_{it}^A while only asymmetric technology shocks increase permanently Z_{it}^H/Z_{it}^N in the long-run. In column 3, we show the impact responses estimated on rolling windows (of fixed length of thirty years) of the relative price of non-tradables (see Fig. 3(c)) and the terms of trade (see Fig. 3(g)). In column 4, we show time-varying impact responses of non-traded and traded hours worked to an aggregate technology shock. Sample: 17 OECD countries, 1970-2017, annual data.

2.6 Symmetric vs. Asymmetric Technology Shocks across Sectors

We have shown above that an aggregate technology shock produces a contractionary effect on hours worked which shrinks over time. To rationalize the shrinking contractionary effect on hours worked, we put forward the increasing contribution of asymmetric technology shocks. Intuitively, symmetric technology shocks have a strong negative impact on hours worked while asymmetric technology shocks have an expansionary effect. Because symmetric technology shocks are predominant, permanent technology shocks give rise to a fall in hours worked on impact. Because the share of asymmetric technology shocks increases over time, the contractionary effect on hours shrinks over time.

In Fig. 4, we investigate empirically the effects of symmetric technology shocks shown in the black lines and contrast their impact with those caused by asymmetric technology shocks displayed by solid blue lines. While both shocks lead to a technology improvement by 1% in the long-run, see Fig. 4(a), the behavior of sectoral TFPs are distinct. As can be seen in Fig. 4(b), asymmetric technology shocks generate a significant increase in utilization-adjusted-TFP of tradables relative to non-tradables while productivity growth is uniformly distributed across sectors after a symmetric technology shock since the ratio Z^H/Z^N remains unchanged at all horizons.

Effects of symmetric technology shocks. Importantly, Fig. 4(e) reveals that symmetric and asymmetric technology shocks produce distinct effects on labor as hours worked decline dramatically (by 0.47% on impact) after symmetric technology shocks while hours increase (by 0.31% on impact) after asymmetric technology shocks. These distinct effects are the result of the impact of productivity on sectoral prices. As shown in the black lines in Fig. 4(k) and Fig. 4(l), both non-traded and traded prices depreciate after symmetric technology shocks which in turn put downward pressure on wages and exert a negative impact on labor supply. This negative impact is amplified by the fact that technological change is biased toward capital as the black line in Fig. 4(h) reveals that utilization-adjusted-FBTC declines in the traded sector, thus leading to an increase in the capital intensity of production.

As can be seen in the black line Fig. 4(f), the decline in total hours worked is mostly driven by the fall in hours worked in the non-traded sector. Because the elasticity of substitution between traded and non-traded goods is low (i.e., less than one), the fall in non-traded prices drives down the share of expenditure spent on non-traded goods which reduces labor demand in the non-traded sector. By contrast, because home- and foreign-produced traded goods are high substitutes, the terms of trade depreciation raises the share of home-produced traded goods and thus further increases the share of tradables. This has an expansionary effect on labor demand in the traded sector as can be seen in Fig. 4(g). By providing more incentives to shift labor toward traded industries, the terms of trade

depreciation further depresses non-traded labor thus leading the fall in hours worked to be concentrated in the non-traded sector.

Effects of asymmetric technology shocks. Asymmetric technology shocks produce very distinct effects. Because technology improvements are concentrated in traded industries, see the blue line in Fig. 4(b), the value added share of tradables (at constant prices) increases disproportionately, as can be seen in Fig. 4(j). It gives rise to an excess supply for home-produced traded goods and an excess demand for non-traded goods. As shown in the blue line in Fig. 4(k), the excess demand puts upward pressure on non-traded goods prices. Because traded and non-traded goods are gross complements, the appreciation in non-traded prices increases the share of non-tradables which has a positive impact on non-traded hours worked, as displayed by the blue line in Fig. 4(f).

The rise in L^N is amplified by the shift of labor toward the non-traded sector. As shown in the blue line of Fig. 4(g), the hours worked share of tradables declines dramatically on impact by 0.1 ppt of total hours worked before recovering gradually. The first four years, the reallocation of labor toward the non-traded sector accounts for one-third of the rise in non-traded hours worked. To encourage workers to shift, non-traded firms must pay higher wages which put upward pressure on non-traded wages and thus on the aggregate wage which has a strong expansionary effect on total hours worked as shown in the blue line of Fig. 4(e). On impact, the rise in total hours worked mostly originates from non-traded industries and is amplified by the fact that asymmetric technology improvements are significantly biased toward labor, as displayed by the blue line of Fig. 4(d).

Both the terms of trade deterioration displayed by the blue line in Fig. 4(l) and the rise in the labor intensity of traded production prevents traded hours worked from decreasing although the decline in the capital utilization rate shown in Fig. 4(c) partially offsets the positive impact of technological change biased toward labor in the traded sector.

Do asymmetric technology shocks increase innovation? Asymmetric technology shocks are technology improvements which are concentrated within traded industries. As shown in Online Appendix M.5, only these shocks give rise to a significant and positive increase in the stock of R&D which reflects cumulated investment devoted to innovative activity. In Online Appendix R.4, we run the regression of utilization-adjusted-TFP in sector j on the stock of R&D at constant prices in sector j by using cointegration techniques. The FMOLS estimated value reveals that the elasticity of traded technology w.r.t. to the stock of R&D in the traded sector amounts to 0.23 while it is virtually zero in the non-traded sector. These evidence thus underlines that asymmetric technology improvements are shocks which are associated with innovation. In this regard, in Online Appendix M.5, we detect a positive cross-country relationship between the share of the FEV of aggregate technology shocks driven by asymmetric technology improvements and the ratio of R&D

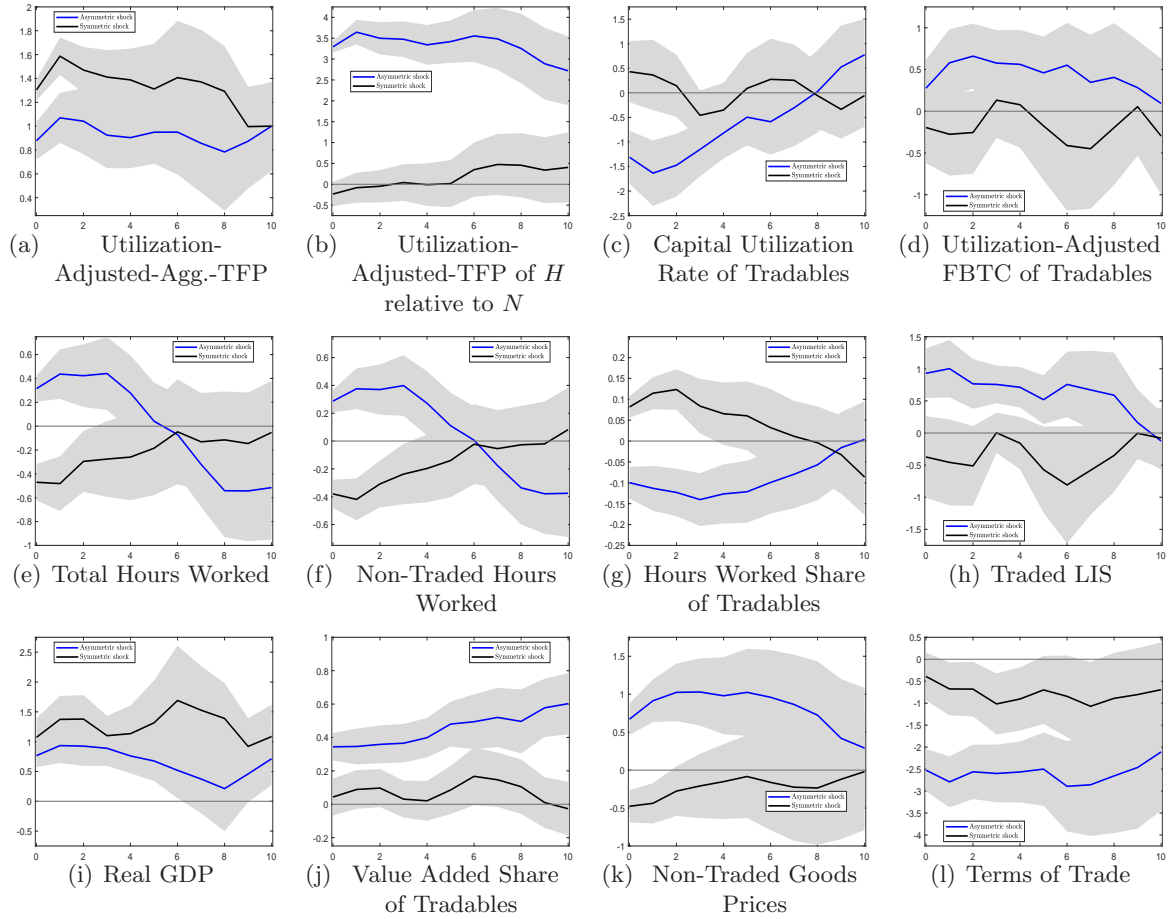


Figure 4: Labor Market Effects of an Asymmetric vs. Symmetric Technology Shocks. *Notes:* The solid lines shows the responses to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. The blue line shows responses when the technology shock is asymmetric and increases the ratio of utilization-adjusted TFP of tradables relative to non-tradables by 1%. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in GDP units (sectoral value added share, labor income share), percentage deviation from trend in total hours worked units (sectoral hours worked, labor share), percentage deviation from trend (utilization-adjusted TFPs, utilization-adjusted FBTC). Sample: 17 OECD countries, 1970-2017, annual data.

investment to value added in the traded sector. In contrast, symmetric technology shocks do not increase the stock of R&D significantly and should capture better management practices and improvements in firm's organization.

2.7 Robustness checks

We have conducted several robustness checks detailed in Online Appendices M and N w.r.t. the SVAR identification of technology shocks, and the measure of technology. We summarize the main results below.

SVAR critique and remedies. Galí's [1999] has pioneered the identification of permanent technology improvement through long-run restrictions. Because the SVAR estimation allows for a limited number of lags (2 lags on annual data), the SVAR critique has formulated some reservations with regard to the ability of the SVAR model to disentangle pure technology shocks from other shocks (which have long-lasting effects on productivity) when capital adjusts sluggishly, see e.g., Erceg et al. [2005], Dupaigne et al. [2007], Chari et al. [2008].

The literature has proposed different methods to mitigate the lag-truncation bias and avoid persistent non-technology shocks disturbing the identification of permanent technology shocks. Chari et al. [2008] recommend to increase the number of lags. To avoid a potential contamination of technology shocks by country-specific non-technology shocks, Dupaigne and Fève [2009] suggest the use of the world component of TFP while Fève and Guay [2010] propose to adopt a two-step SVARs-based procedure where hours worked is removed for the identification of technology shocks in the first step. Chaudourne et al. [2014] demonstrate that the use of 'purified' TFP to measure technology ensures the robustness of the identification of technology shocks.

SVAR identification and exogeneity test. The identified technology shocks should not in principle be correlated with other exogenous non-technology shifts nor with lagged endogenous variables. A mean to test whether the identified shocks are really technology improvements is to test whether non-technology variables are correlated with the identified shocks to technology. We consider three types of non-technology variables: government spending shocks, monetary policy shocks and tax shocks. Long-lasting non-technology shocks can potentially contaminate the SVAR identification of permanent technology shocks as they impinge on hours worked and thus on (labor) productivity. Since we use the TFP and also control for capital utilization, a potential contamination is less likely. To run the exogeneity test, we identify government spending shocks and tax shocks by assuming that the implementation of fiscal policy is subject to lags, in the lines of Blanchard and Perotti [2002]. Like Christiano et al. [2005], we identify monetary policy shocks as the innovation to the federal funds rate under a recursive ordering, with the policy rate ordered last. See Online Appendix N.2 for further details. Following Francis and Ramey [2005], we run the

regression of identified technology shocks to utilization-adjusted-TFP on shocks to government spending, monetary policy and taxation. To identify technology shocks, we consider three measures of technology: utilization-adjusted-TFP (like Chaudourne et al. [2014]), TFP (like Chang and Hong [2006]), and labor productivity (like Galí [1999]). We test the null hypothesis that all of the coefficients on explanatory variables are jointly equal to zero. The p -value for the F -test shows that none of the variables is significant in explaining our identified technology shocks only once we use utilization-adjusted-TFP to measure technology. Technology shocks identified on the basis of the Solow residual and labor productivity are instead correlated with the demand shocks. Because we estimate a VAR model including utilization-adjusted-TFP, real GDP, hours worked, the real consumption wage and technology shocks are shocks which increase permanently the first variable, shocks to real GDP are more likely to be correlated with persistent demand shocks. Indeed, the p -value for the F -test shows that non-technology shocks are correlated with demand shocks and tax shocks.

Lags. Erceg et al. [2005], Chari et al. [2008] have shown that persistent non-technology shocks can disturb the identification of permanent technology shocks if they account for a large fraction of output fluctuations. De Graeve and Westermark [2013] find that raising the number of lags may be a viable strategy to achieve identification when long-run restrictions are imposed on the VAR model. In Online Appendix N.2, we increase the lags from two to eight and find that all of our conclusions stand, in particular a permanent technology improvement lowers hours worked and shifts gradually labor toward the non-traded industries.

World technology. Because world permanent technology shocks are not affected by country-specific persistent non-technology shocks, identifying technology shocks by using technological change common to all countries can eliminate the problem of identification raised by Erceg et al. [2005], Dupaigne et al. [2007], Chari et al. [2008]. As detailed in Online Appendix N.5, we adapt the method of Dupaigne and Fève [2009], and replace the country-level-utilization-adjusted-TFP with two alternative measures of world TFP in the VAR. Assuming that ideas diffuse through international trade, we construct a stock of world technology specific to country i as an import-share-weighted-average of utilization-adjusted-TFPs of trade partners of country i denoted by Z_{it}^W . Because this measure varies across countries, it allows us to estimate the VAR model in panel format. Replacing \hat{Z}_{it}^A with the world utilization-adjusted-TFP growth rate in the VAR model, we find that the response of hours worked is muted on impact and declines after one year below trend but lies within the confidence bounds of the point estimate of the baseline VAR model. World technology shocks do not drive hours below trend on impact because they are further driven by asymmetric technology shocks compared with shocks to country-level utilization-adjusted-TFP. The reason to this is intuitive as world technology shocks capture increases

in technology which diffuse across borders and are common across countries and therefore mostly originate from the traded sector. Because technology improvements originating from traded industries are more pronounced than in the non-traded sector, world technology improvements are characterized by a greater dispersion in technology improvements between the traded and the non-traded sector.

Two-step method. On the basis of evidence documented by Christiano et al. [2006], Fève and Guay [2010] propose to identify technology shocks by adopting a two-step approach so that a VAR model with a finite number of lags can more easily approximate the true underlying dynamics of the data. In the first step, the rate of growth of hours worked must be excluded from the SVAR and replaced by the (logged) ratio of (private and public) consumption to GDP. Since we consider open economies, we augment consumption with net exports, the sum being divided by nominal GDP. In Online Appendix N.7, we estimate a VAR model which includes the rate of change in utilization-adjusted-TFP and the log ratio of consumption plus net exports to GDP. Then in the second step, we estimate the dynamic effects by using local projections. We find empirically that the difference between ours and the point estimate obtained from Fève and Guay’s [2010] approach is negligible and the latter estimates lie within the confidence bounds of the baseline estimate.

Measure of technology. Chang and Hong [2006] have shown that labor productivity is not the correct measure from which to identify technology shocks. The reason to this is that labor productivity reflects both improved efficiency and changes in the input mix (i.e., in the capital-labor ratio). In support of their argument, the authors show that labor productivity and TFP are not cointegrated, therefore the long-run component of labor productivity does not truly identify technology shocks. By using three different measures of productivity (used for long-run identification): labor productivity, TFP, adjusted-TFP, Chaudourne, Fève and Guay [2014] estimate the short-run responses of hours worked in various (bivariate) SVARs on (actual) U.S. data. It is found that when technological change is properly measured, i.e., by using TFP or adjusted-TFP, consistent VAR estimates are obtained. In Online Appendix, we use three alternative measures of technology to our measure based on Imbs [1999]. We construct time series of utilization-adjusted-TFP at a sectoral level by adopting Basu’s [1996] approach and alternatively use directly time series from Huo et al. [2023] and Basu et al. [2006] which are available for sixteen OECD countries over a limited period of time. We find that all of our conclusions hold after aggregate, symmetric and asymmetric technology shocks for all measures of technology.

Max share identification. Erceg, Gust and Guerrieri [2005], Chari et al. [2008] argue that allowing for a limited number of lags causes a lag-truncation bias which lead estimated IRFs to be biased, in magnitude for the former and in sign for the latter. Francis et al. [2014] offer an alternative approach to the identification of technology shocks with the intent of

addressing the shortcoming associated with long-run restriction in small-sample estimation. The Maximum Forecast Error Variance (Max FEV) approach extracts the shock that best explains the FEV at a long but finite horizon of the measure of technology. Because we focus on the labor market effects, we re-estimate the baseline VAR model together with a VAR model which includes the utilization-adjusted-aggregate-TFP, traded and non-traded hours worked. We contrast the responses when imposing long-run restrictions, all variables entering the VAR model in rate of growth, with those obtained when we adopt the Max FEV identification of technology shocks, all variables entering the VAR model in log-level. We find that all responses lie within the confidence bounds of the point estimate of the baseline identification, except for Austria, Belgium and Denmark. When we compare the response from the panel VAR model with LR restriction and the median of estimates from Max FEV, we find that the difference between the two is not statistically different.

3 A Semi-Small Open Economy Model with Tradables and Non-Tradables

We consider a semi-small open economy that is populated by a constant number of identical households and firms that have perfect foresight and live forever. Like Kehoe and Ruhl [2009], Chodorow-Reich et al. [2021], the country is assumed to be semi-small in the sense that it is a price-taker in international capital markets, and thus faces a given world interest rate, r^* , but is large enough on world good markets to influence the price of its export goods. The open economy produces a traded good which can be exported, consumed or invested and imports consumption and investment goods. While the home-produced traded good, denoted by the superscript H , faces both a domestic and a foreign demand, a non-traded sector produces a good, denoted by the superscript N , for domestic absorption only. The foreign good is chosen as the numeraire. Time is continuous and indexed by t . More details about the model can be found on Online Appendices O and P.

3.1 Firms

We denote value added in sector j by Y^j . Both the traded and non-traded sectors use physical capital (inclusive of capital utilization chosen by households), denoted by $\tilde{K}^j(t) = u^{K,j}(t)K^j(t)$, and labor, L^j , according to a constant returns-to-scale technology described by a CES production function:

$$Y^j(t) = \left[\gamma^j (A^j(t)L^j(t))^{\frac{\sigma^j-1}{\sigma^j}} + (1 - \gamma^j) (B^j(t)\tilde{K}^j(t))^{\frac{\sigma^j-1}{\sigma^j}} \right]^{\frac{\sigma^j}{\sigma^j-1}}, \quad (14)$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology and σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$. We allow for labor- and capital-augmenting efficiency denoted by $A^j(t)$ and $B^j(t)$. Factor-augmenting productivity

is made up of a symmetric component (across sectors) denoted by the subscript S and an asymmetric component denoted by the subscript D :

$$A^j(t) = \left(A_S^j(t)\right)^\eta \left(A_D^j(t)\right)^{1-\eta}, \quad B^j(t) = \left(B_S^j(t)\right)^\eta \left(B_D^j(t)\right)^{1-\eta}, \quad (15)$$

where the elasticity of factor-augmenting productivity w.r.t. to its symmetric component is denoted by η which is assumed to be symmetric across sectors. This parameter determines the share of technology improvements which are symmetric across sectors.

Firms rent capital $\tilde{K}^j(t)$ and labor $L^j(t)$ services from households. We assume that the movements in capital and labor across sectors are subject to frictions which imply that the capital rental cost equal to $R^j(t)$, and the wage rate $W^j(t)$, are sector-specific. Both sectors are assumed to be perfectly competitive and thus choose capital services and labor by taking prices P^j as given. Because markets are perfectly competitive, marginal revenue products of labor and capital equate the corresponding factor's cost:

$$P^j(t)\gamma^j \left(A^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(L^j(t)\right)^{-\frac{1}{\sigma^j}} \left(Y^j(t)\right)^{\frac{1}{\sigma^j}} \equiv W^j(t), \quad (16a)$$

$$P^j(t) (1 - \gamma^j) \left(B^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(u^{K,j}(t)K^j(t)\right)^{-\frac{1}{\sigma^j}} \left(Y^j(t)\right)^{\frac{1}{\sigma^j}} = R^j(t). \quad (16b)$$

Demand for inputs can be rewritten in terms of their respective cost in value added; for labor, we have $s_L^j(t) = \gamma^j (A^j(t)/y^j(t))^{\frac{\sigma^j-1}{\sigma^j}}$. Applying the same logic for capital and denoting the ratio of labor to capital income share by $S^j(t) \equiv \frac{s_L^j(t)}{1-s_L^j(t)}$, we have:

$$S^j(t) \equiv \frac{s_L^j(t)}{1-s_L^j(t)} = \frac{\gamma^j}{1-\gamma^j} \text{FBTC}^j(t) \left(\frac{u^{K,j}(t)K^j(t)}{L^j(t)} \right)^{\frac{1-\sigma^j}{\sigma^j}}, \quad (17)$$

where $\text{FBTC}^j(t) = \left(B^j(t)/A^j(t)\right)^{\frac{1-\sigma^j}{\sigma^j}}$ is utilization-adjusted factor-biased technological change. According the evidence documented in the literature, e.g., Klump et al. [2007], Herrendorf et al. [2015], Oberfield and Raval [2021], Chirinko and Mallick [2017]), capital and labor are gross complements in production, i.e., $\sigma^j < 1$. Under this assumption, a rise in $B^j(t)/A^j(t)$ generates technological change biased toward labor (as captured by an increase in FBTC^j) which has an expansionary on the LIS in sector j .

3.2 Technology Frontier

Firms within each sector $j = H, N$ decide about the split of capital-utilization-adjusted-TFP, denoted by $Z^j(t)$, between labor- and capital-augmenting efficiency. Following Caselli and Coleman [2006] and Caselli [2016], we assume that firms choose a mix of $A^j(t)$ and $B^j(t)$ along a technology frontier (which is assumed to take a CES form):

$$\left[\gamma_Z^j \left(A^j(t)\right)^{\frac{\sigma_Z^j-1}{\sigma_Z^j}} + \left(1 - \gamma_Z^j\right) \left(B^j(t)\right)^{\frac{\sigma_Z^j-1}{\sigma_Z^j}} \right]^{\frac{\sigma_Z^j}{\sigma_Z^j-1}} \leq Z^j(t), \quad (18)$$

where $Z^j(t) > 0$ is the height of the technology frontier, $0 < \gamma_Z^j < 1$ is the weight of labor efficiency in utilization-adjusted-TFP and $\sigma_Z^j > 0$ corresponds to the elasticity of substitution between labor- and capital-augmenting productivity. Firms choose labor and capital efficiency, A^j and B^j , along the technology frontier described by eq. (18) that minimizes the unit cost function. The unit cost minimization requires that the contribution of labor-augmenting productivity to technological change collapses to the LIS (see Online Appendix C)

$$s_L^j = \gamma_Z^j \left(\frac{A^j(t)}{Z^j(t)} \right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}}. \quad (19)$$

Inserting this equality into the log-linearized version of the technology frontier (18) shows that technological change in sector j is a factor-income-share-weighted sum of changes in factor-augmenting efficiency:

$$\hat{Z}^j(t) = s_L^j \hat{A}^j(t) + (1 - s_L^j) \hat{B}^j(t). \quad (20)$$

While the technological frontier imposes a structure on the mapping between the utilization-adjusted-TFP and factor-augmenting efficiency, as described by (20), it has the advantage of ensuring a consistency between the theoretical and the empirical approach where we used the utilization-adjusted-Solow residual to measure technological change whilst allowing for technological change to be factor-biased at the same time. Adding the change in the capital utilization rate weighted by the capital income share leads to the rate of change in sectoral TFP:

$$\text{TFP}^j(t) = s_L^j \hat{A}^j(t) + (1 - s_L^j) \left(\hat{B}^j(t) + \hat{u}^{K,j}(t) \right). \quad (21)$$

Totally differentiating (15), plugging the outcome into (20) and using the fact that aggregate technology improvement is a weighted average of sectoral technology improvements, i.e. $\hat{Z}^A(t) = \nu^{Y,H} \hat{Z}^H(t) + (1 - \nu^{Y,H}) \hat{Z}^N(t)$, shows that utilization-adjusted TFP growth can be decomposed into symmetric and asymmetric components across sectors:

$$\hat{Z}^A(t) = \eta \hat{Z}_S^A(t) + (1 - \eta) \hat{Z}_D^A(t), \quad (22)$$

where $\hat{Z}_S^A(t) = \hat{Z}_S^H(t) = \hat{Z}_S^N(t)$ and $\hat{Z}_D^A(t) = \nu^{Y,H} \hat{Z}_D^H(t) + (1 - \nu^{Y,H}) \hat{Z}_D^N(t)$. In the quantitative analysis, we will explore the effect of an increase in the asymmetric component captures by higher values of $1 - \eta$. The decomposition of technological change into a symmetric and an asymmetric component implies that the movements in the capital technology utilization rate must have both a symmetric and asymmetric component, i.e.,

$$u^{K,j}(t) = \left(u_S^{K,j}(t) \right)^\eta \left(u_D^{K,j}(t) \right)^{1-\eta}. \quad (23)$$

Plugging (23) into (15), i.e., $u^{K,j}(t) B^j(t) = \left(u_S^{K,j}(t) B_S^j(t) \right)^\eta \left(u_D^{K,j}(t) B_D^j(t) \right)^{1-\eta}$, totally differentiating and inserting the outcome into (21) allows us to decompose sectoral TFP growth into a symmetric and an asymmetric component, i.e.,

$$\text{TFP}^j(t) = \eta \text{TFP}_S^j(t) + (1 - \eta) \text{TFP}_D^j(t). \quad (24)$$

3.3 Households

At each instant the representative household consumes traded and non-traded goods denoted by $C^T(t)$ and $C^N(t)$, respectively, which are aggregated by means of a CES function:

$$C(t) = \left[\varphi^{\frac{1}{\phi}} (C^T(t))^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}} (C^N(t))^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}, \quad (25)$$

where $0 < \varphi < 1$ is the weight of the traded good in the overall consumption bundle and ϕ corresponds to the elasticity of substitution between traded goods and non-traded goods. The traded consumption index $C^T(t)$ is defined as a CES aggregator of home-produced traded goods, $C^H(t)$, and foreign-produced traded goods, $C^F(t)$:

$$C^T(t) = \left[(\varphi^H)^{\frac{1}{\rho}} (C^H(t))^{\frac{\rho-1}{\rho}} + (1-\varphi^H)^{\frac{1}{\rho}} (C^F(t))^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \quad (26)$$

where $0 < \varphi^H < 1$ is the weight of the home-produced traded good and ρ corresponds to the elasticity of substitution between home- and foreign-produced traded goods.

The representative household supplies labor to the traded and non-traded sectors, denoted by $L^H(t)$ and $L^N(t)$, respectively. To put frictions into the movement of labor between the traded sector and the non-traded sector, we assume that sectoral hours worked are imperfect substitutes, in lines with Horvath [2000]:

$$L(t) = \left[\vartheta_L^{-1/\epsilon_L} (L^H(t))^{\frac{\epsilon_L+1}{\epsilon_L}} + (1-\vartheta_L)^{-1/\epsilon_L} (L^N(t))^{\frac{\epsilon_L+1}{\epsilon_L}} \right]^{\frac{\epsilon_L}{\epsilon_L+1}}, \quad (27)$$

where $0 < \vartheta_L < 1$ parametrizes the weight attached to the supply of hours worked in the traded sector and ϵ is the elasticity of substitution between sectoral hours worked. Like labor, we generate imperfect capital mobility by assuming that traded $K^H(t)$ and non-traded $K^N(t)$ capital stock are imperfect substitutes:

$$K(t) = \left[\vartheta_K^{-1/\epsilon_K} (K^H(t))^{\frac{\epsilon_K+1}{\epsilon_K}} + (1-\vartheta_K)^{-1/\epsilon_K} (K^N(t))^{\frac{\epsilon_K+1}{\epsilon_K}} \right]^{\frac{\epsilon_K}{\epsilon_K+1}}, \quad (28)$$

where $0 < \vartheta_K < 1$ is the weight of capital supply to the traded sector in the aggregate capital index $K(\cdot)$ and ϵ_K measures the ease with which sectoral capital can be substituted for each other and thereby captures the degree of capital mobility across sectors.

The representative agent is endowed with one unit of time, supplies a fraction $L(t)$ as labor, and consumes the remainder $1 - L(t)$ as leisure. At any instant of time, households derive utility from their consumption and experience disutility from working and maximizes the following objective function:

$$\mathcal{U} = \int_0^{\infty} \Lambda(C(t), L(t)) e^{-\beta t} dt, \quad (29)$$

where $\beta > 0$ is the discount rate and we consider the utility specification proposed by Shimer [2009]:

$$\Lambda(C, L) \equiv \frac{C^{1-\sigma} V(L)^\sigma - 1}{1-\sigma}, \quad \text{if } \sigma \neq 1, \quad V(L) \equiv \left(1 + (\sigma-1) \gamma \frac{\sigma_L}{1+\sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}} \right). \quad (30)$$

These preferences are characterized by two crucial parameters: σ_L is the Frisch elasticity of labor supply, and $\sigma > 0$ determines the substitutability between consumption and leisure; if $\sigma > 1$, the marginal utility of consumption is increasing in hours worked. The inverse of σ collapses to the intertemporal elasticity of substitution for consumption. When we let σ equal to one, the felicity function is additively separable in consumption and labor,

Households supply labor $L(t)$ and capital services $K(t)$ and, in exchange, receive a wage rate $W(t)$ and a capital rental rate $R^K(t)$. Households choose the level of capital utilization in sector j , which includes both a symmetric and an asymmetric component, see eq. (23), i.e., $u_S^{K,j}(t)$ and $u_D^{K,j}(t)$. Both components of the capital utilization rate collapse to one at the steady-state. The capital utilization adjustment costs are assumed to be an increasing and convex function of the capital utilization rate:

$$C_S^{K,j}(t) = \xi_{1,S}^j \left(u_S^{K,j}(t) - 1 \right) + \frac{\xi_{2,S}^j}{2} \left(u_S^{K,j}(t) - 1 \right)^2, \quad C_D^{K,j}(t) = \xi_{1,S}^j \left(u_D^{K,j}(t) - 1 \right) + \frac{\xi_{2,D}^j}{2} \left(u_D^{K,j}(t) - 1 \right)^2, \quad (31)$$

where $\xi_{2,S}^j > 0$, $\xi_{2,D}^j > 0$, are free parameters. When we let $\xi_{2,c}^j \rightarrow \infty$, capital utilization is fixed at unity and TFP growth collapses to technological change.

Households can accumulate internationally traded bonds (expressed in foreign good units), $N(t)$, that yield net interest rate earnings of $r^*N(t)$. Denoting lump-sum taxes by $T(t)$, the household's flow budget constraint states that real disposable income can be saved by accumulating traded bonds, $\dot{N}(t)$, can be consumed, $P_C(t)C(t)$, invested, $P_J(t)J(t)$, or cover utilization adjustment costs:

$$\begin{aligned} \dot{N}(t) &+ P_C(t)C(t) + P_J(t)J(t) + \sum_{j=H,N} P^j(t) \left(C_S^{K,j}(t) + C_D^{K,j}(t) \right) \nu^{K,j}(t) K(t) \\ &= r^*N(t) + W(t)L(t) + R^K(t)K(t) \sum_{j=H,N} \alpha_K^j(t) \left(u_S^{K,j}(t) \right)^\eta \left(u_D^{K,j}(t) \right)^{1-\eta} - T(t), \end{aligned} \quad (32)$$

where we denote the share of sectoral capital in the aggregate capital stock by $\nu^{K,j}(t) = K^j(t)/K(t)$ and the capital compensation share in sector $j = H, N$ by $\alpha_K^j(t) = \frac{R^j(t)K^j(t)}{R^K(t)K(t)}$.

The investment good is (costlessly) produced using inputs of the traded good and the non-traded good by means of a CES technology:

$$J(t) = \left[\varphi_J^{\frac{1}{\phi_J}} \left(J^T(t) \right)^{\frac{\phi_J-1}{\phi_J}} + (1 - \varphi_J)^{\frac{1}{\phi_J}} \left(J^N(t) \right)^{\frac{\phi_J-1}{\phi_J}} \right]^{\frac{\phi_J}{\phi_J-1}}, \quad (33)$$

where $0 < \varphi_J < 1$ is the weight of the investment traded input and ϕ_J corresponds to the elasticity of substitution between investment traded goods and investment non-traded goods. The index $J^T(t)$ is defined as a CES aggregator of home-produced traded inputs, $J^H(t)$, and foreign-produced traded inputs, $J^F(t)$:

$$J^T(t) = \left[(\iota^H)^{\frac{1}{\rho_J}} \left(J^H(t) \right)^{\frac{\rho_J-1}{\rho_J}} + (1 - \iota^H)^{\frac{1}{\rho_J}} \left(J^F(t) \right)^{\frac{\rho_J-1}{\rho_J}} \right]^{\frac{\rho_J}{\rho_J-1}}, \quad (34)$$

where $0 < \iota^H < 1$ is the weight of the home-produced traded input and ρ_J corresponds to the elasticity of substitution between home- and foreign-produced traded inputs.

Installation of new investment goods involves convex costs, assumed to be quadratic. Thus, total investment $J(t)$ differs from effectively installed new capital:

$$J(t) = I(t) + \frac{\kappa}{2} \left(\frac{I(t)}{K(t)} - \delta_K \right)^2 K(t), \quad (35)$$

where the parameter $\kappa > 0$ governs the magnitude of adjustment costs to capital accumulation. Denoting the fixed capital depreciation rate by $0 \leq \delta_K < 1$, aggregate investment, $I(t)$, gives rise to capital accumulation according to the dynamic equation:

$$\dot{K}(t) = I(t) - \delta_K K(t). \quad (36)$$

Households choose consumption, worked hours, capital and technology utilization rates, investment in physical capital by maximizing lifetime utility (29) subject to (32) and (36). Denoting by λ and Q' the co-state variables associated with the budget constraint and law of motion of physical capital, the first-order conditions characterizing the representative household's optimal plans are:

$$C(t)^{-\sigma} V(t)^\sigma = P_C(t) \lambda(t), \quad (37a)$$

$$C(t)^{1-\sigma} V(t)^\sigma \gamma L(t)^{\frac{1}{\sigma_L}} = \lambda(t) W(t), \quad (37b)$$

$$Q(t) = P_J(t) \left[1 + \kappa \left(\frac{I(t)}{K(t)} - \delta_K \right) \right], \quad (37c)$$

$$\dot{\lambda}(t) = \lambda(\beta - r^*), \quad (37d)$$

$$\begin{aligned} \dot{Q}(t) = & (r^* + \delta_K) Q(t) - \left\{ \sum_{j=H,N} \alpha_K^j(t) u^{K,j}(t) R^K(t) \right. \\ & \left. - \sum_{j=H,N} P^j(t) \left(C_S^{K,j}(t) + C_D^{K,j}(t) \right) \nu^{K,j}(t) - P_J(t) \frac{\partial J(t)}{\partial K(t)} \right\}, \end{aligned} \quad (37e)$$

$$\frac{R^j(t)}{P^j(t)} \eta \frac{u^{K,j}(t)}{u_S^{K,j}(t)} = \xi_{1,S}^j + \xi_{2,S}^j \left(u_S^{K,j}(t) - 1 \right), \quad j = H, N, \quad (37f)$$

$$\frac{R^j(t)}{P^j(t)} (1 - \eta) \frac{u^{K,j}(t)}{u_D^{K,j}(t)} = \xi_{1,D}^j + \xi_{2,D}^j \left(u_D^{K,j}(t) - 1 \right), \quad j = H, N, \quad (37g)$$

and the transversality conditions $\lim_{t \rightarrow \infty} \bar{\lambda} N(t) e^{-\beta t} = 0$ and $\lim_{t \rightarrow \infty} Q(t) K(t) e^{-\beta t} = 0$. To derive (37c) and (37e), we used the fact that $Q(t) = Q'(t)/\lambda(t)$. In an open economy model with a representative agent having perfect foresight, a constant rate of time preference and perfect access to world capital markets, we impose $\beta = r^*$ in order to generate an interior solution. Setting $\beta = r^*$ into (37d) implies that the shadow value of wealth is constant over time, i.e., $\lambda(t) = \lambda$. When new information about the fiscal shock arrives, λ jumps (to fulfill the intertemporal solvency condition determined later) and remains constant afterwards.

Once households have determined aggregate consumption, they allocate consumption expenditure between traded and non-traded goods according to the following optimal rule:

$$1 - \alpha_C(t) = \frac{P^N(t) C^N(t)}{P_C(t) C(t)} = (1 - \varphi) \left(\frac{P^N(t)}{P_C(t)} \right)^{1-\phi}. \quad (38)$$

According to (38), a depreciation in non-traded goods prices $P^N(t)$ drives down the share of expenditure allocated to non-traded goods while an appreciation in $P^N(t)$ increases $1 - \alpha_C$ as long as $\phi < 1$, as evidence suggests. This assumption ensures that symmetric technology shocks have a negative impact on $L^N(t)$ while asymmetric technology improvements has a strong expansionary effect on non-traded hours worked. However, the assumption $\phi < 1$ alone without frictions leads the model to considerably overstate the shift of labor between sectors. The first friction comes from capital adjustment costs which mitigate the investment boom in the non-traded sector following a technology shock. The second source of frictions comes from labor and capital mobility costs across sectors as captured by finite values (in line with our estimates) of the elasticity of labor supply (ϵ_L) and capital supply (ϵ_K):

$$L^j = \vartheta_L^j \left(\frac{W^j}{W} \right)^{\epsilon_L} L, \quad K^j = \vartheta_K^j \left(\frac{R^j}{R^K} \right)^{\epsilon_K} K. \quad (39)$$

The third source of friction which hampers the movement of productive resources across sectors is captured by the assumption of imperfect substitutability between home- and foreign-produced traded goods as reflected into price-elasticities of demand for home-produced traded goods ρ and ρ_J which also take finite values. In line with the evidence documented by the literature, see e.g., Bajzik et al. [2020], home- and foreign-produced traded goods are assumed to be gross substitutes, i.e., ρ and ρ_J are larger than one. One key implication of this assumption is that the terms of trade depreciation following a technology shock stimulates the demand fore home-produced traded goods which mitigates the decline in the share of tradables $\alpha_C(t)$ and $\alpha_J(t)$ when the relative price of non-tradables appreciates. To see it formally, we log-linearize the demand for home-produced traded consumption goods:

$$\hat{\alpha}_C(t) = - (1 - \phi) (1 - \alpha_C) \left[\hat{P}(t) + (1 - \alpha^H) \hat{P}^H(t) \right]. \quad (40)$$

While an appreciation in the relative price of non-traded goods, $P(t) \equiv P^N(t)/P^H(t)$ lowers $\alpha_C(t)$ because $\phi < 1$, a decrease in the terms of trade $P^H(t)$ mitigates the fall in $\alpha_C(t)$ and thus the shift of labor toward the non-traded sector.

3.4 Government

The final agent in the economy is the government. Government spending includes expenditure on non-traded goods, G^N , home- and foreign-produced traded goods, G^H and G^F , respectively. The government finances public spending, G , by raising lump-sum taxes, T , and assume without loss of generality that government budget is balanced at each instant:

$$G(t) \equiv P^N(t)G^N(t) + P^H(t)G^H(t) + G^F(t) = T(t). \quad (41)$$

3.5 Model Closure and Equilibrium

To fully describe the equilibrium, we impose goods market clearing conditions for non-traded and home-produced traded goods:

$$Y^N(t) = C^N(t) + J^N(t) + G^N(t) + \left(C_S^{K,N}(t) + C_D^{K,N}(t) \right) K^N(t), \quad (42a)$$

$$Y^H(t) = C^H(t) + J^H(t) + G^H(t) + X^H(t) + \left(C_S^{K,H}(t) + C_D^{K,H}(t) \right) K^H(t), \quad (42b)$$

where X^H stands for exports of home-produced goods; exports are assumed to be a decreasing function of terms of trade, P^H .⁹

$$X^H(t) = \varphi_X \left(P^H(t) \right)^{-\phi_X}, \quad (43)$$

where $\varphi_X > 0$ is a scaling parameter, and ϕ_X is the elasticity of exports w.r.t. P^H . Using the properties of constant returns to scale in production, identities $P_C(t)C(t) = \sum_g P^g(t)C^g(t)$ and $P_J(t)J(t) = \sum_g P^g(t)J^g(t)$ (with $g = F, H, N$) along with market clearing conditions (42), the current account equation (16a) can be rewritten as a function of the trade balance:

$$\dot{N}(t) = r^* N(t) + P^H(t)X^H(t) - M^F(t), \quad (44)$$

where $M^F(t) = C^F(t) + G^F(t) + J^F(t)$ stands for imports of foreign-produced consumption and investment goods.

Setting the dynamics of factor-augmenting productivity. We drop the time index below to denote steady-state values. Eq. (20) shows that sectoral TFPs dynamics are driven by the dynamics of labor- and capital-augmenting efficiency, i.e., $\hat{Z}^j(t) = s_L^j \hat{A}^j(t) + (1 - s_L^j) \hat{B}^j(t)$. Like Galí [1999], we abstract from trend growth and consider a technology shock that increases permanently utilization-adjusted-aggregate-TFP.¹⁰ Because we consider symmetric and asymmetric technology shocks, we have to set the dynamics of labor- and capital-augmenting efficient for both technology shocks. Denoting the factor-augmenting efficiency by $X_S = A_S, B_S$ and $X_D = A_D, B_D$ for symmetric and asymmetric technology shocks, respectively, the adjustment of $X_S^j(t)$ and $X_D^j(t)$ toward their long-run (higher) level expressed in percentage deviation from initial steady-state is governed by the

⁹Domestic exports are the sum of foreign demand for the domestically produced tradable consumption goods and investment inputs denoted by $C^{F,*}$ and $J^{F,*}$, and we assume that the rest of the world have similar preferences. Since we abstract from trend labor-augmenting technological change, foreign prices remain fixed so that domestic exports are decreasing in the terms of trade, $P^H(t)$.

¹⁰We assume that the economy starts from an initial steady-state and is hit by a permanent technology improvement just like in the empirical part where we estimate the dynamic adjustment following a permanent increase in utilization-adjusted-TFP. In the same spirit as Galí [1999], the accumulation of permanent technology shocks gives rise to a unit root in the time series for utilization-adjusted-aggregate TFP, an assumption we use implicitly to identify a permanent technology shock in the empirical part. We do not characterize the convergence of the economy toward a balanced growth path which is supposed to exist, in line with the theoretical findings by Kehoe et al. [2018] who allow labor income shares to vary across sectors.

following continuous time process:

$$\hat{X}_S^j(t) = \hat{X}_S^j + e^{-\xi_{X,S}^j t} - (1 - x_S^j) e^{-\chi_{X,S}^j t}, \quad (45a)$$

$$\hat{X}_D^j(t) = \hat{X}_D^j + e^{-\xi_{X,D}^j t} - (1 - x_D^j) e^{-\chi_{X,D}^j t}, \quad (45b)$$

where x_S^j and x_D^j are parameters, and $\xi_{X,S}^j > 0$, $\xi_{X,D}^j > 0$, $\chi_{X,S}^j > 0$, $\chi_{X,D}^j > 0$, measures the speed at which productivity closes the gap with its long-run level. When $\xi_{X,c}^j \neq \chi_{X,c}^j$ (with $c = S, D$), the above law of motion allows us to generate hump-shaped adjustment of factor-augmenting productivity. Once $X_S^j(t)$ and $X_D^j(t)$ have completed their adjustment, they increase permanently to a new higher level, i.e., letting time tend toward infinity into (45a)-(45b) leads to $\hat{X}_S^j(\infty) = \hat{X}_S^j$ and $\hat{X}_D^j(\infty) = \hat{X}_D^j$ where \hat{X}_S^j and \hat{X}_D^j are steady-state (permanent) changes in factor-augmenting efficiency in percentage. Inserting (45) into the log-linearized version of the technology frontier allows us to recover the dynamics of utilization-adjusted TFP in sector j $\hat{Z}_c^j(t) = s_L^j \hat{A}_c^j(t) + (1 - s_L^j) \hat{B}_c^j(t)$ which converges toward its new higher steady-state level.

Solving the model. The adjustment of the open economy toward the steady state is described by a dynamic system which comprises four equations that are functions of $K(t)$, $Q(t)$, and the vector of factor-augmenting productivity $V_S(t) = (A_S^H(t), B_S^H(t), A_S^N(t), B_S^N(t))$ and $V_D(t) = (A_D^H(t), B_D^H(t), A_D^N(t), B_D^N(t))$:

$$\dot{K}(t) = \Upsilon(K(t), Q(t), V_S(t), V_D(t)), \quad (46a)$$

$$\dot{Q}(t) = \Sigma(K(t), Q(t), V_S(t), V_D(t)). \quad (46b)$$

Linearizing the dynamic equations (46a)-(46b) in the neighborhood of the steady-state and inserting the law of motion of symmetric and asymmetric components of factor-augmenting efficiency (45a)-(45b) leads to a system of first-order linear differential equations which can be solved by applying standard methods. See Online Appendix Q which details the solution method by Buiter [1984] for continuous time models adapted to our case.

4 Quantitative Analysis

In this section, we take the model to the data. For this purpose we solve the model numerically.¹¹ Therefore, first we discuss parameter values before turning to the effects of a technology shock biased toward the traded sector.

4.1 Calibration

Calibration strategy. At the steady-state, capital utilization rates, $u^{K,j}$, collapse to one so that $\tilde{K}^j = K^j$. We consider an initial steady-state with Hicks-neutral technological

¹¹Technically, the assumption $\beta = r^*$ requires the joint determination of the transition and the steady state since the constancy of the marginal utility of wealth implies that the intertemporal solvency condition depends on eigenvalues' and eigenvectors' elements, see e.g., Turnovsky [1997].

change and normalize $A^j = B^j = Z^j$ to 1. To ensure that the initial steady-state with CES production functions is invariant when σ^j is changed, we normalize CES production functions by choosing the initial steady-state in a model with Cobb-Douglas production functions as the normalization point. Once we have calibrated the initial steady-state with Cobb-Douglas production functions, we assign values to σ^j in accordance with our estimates and the CES economy is endogenously calibrated to reproduce the ratios of the Cobb-Douglas economy, including the sectoral LISs.

To calibrate the reference model that we use to normalize the CES economy, we have estimated a set of ratios and parameters for the eighteen OECD economies in our dataset, see Table 7 relegated to Online Appendix J.1. Our reference period for the calibration corresponds to the period 1970-2017. Because we calibrate the reference model to a representative OECD economy, we take unweighted average values of ratios and parameters which are summarized in Table 1. Among the 25 parameters that the model contains, 13 have empirical counterparts while the remaining 12 parameters plus initial conditions must be endogenously calibrated to match ratios.

Twelve parameters plus initial conditions must be set to target ratios. Parameters including φ , ι , φ^H , ι^H , ϑ_L , ϑ_K , δ_K , G , G^N , G^H and initial conditions (N_0 and K_0), must be set to target a tradable content of consumption and investment expenditure of $\alpha_C = 43\%$ and $\alpha_J = 32\%$, respectively, a home content of consumption and investment expenditure in tradables of $\alpha^H = 66\%$ and $\alpha_J^H = 42\%$, respectively, a weight of labor supply and capital supply to the traded sector of $L^H/L = 36\%$, $K^H/K = 39\%$, respectively, an investment-to-GDP ratio of $\omega_J = 23\%$, a ratio of government spending to GDP of $\omega_G = 20\%$ ($= G/Y$), a tradable and home-tradable share of government spending of $\omega_{GT} = 16\%$ ($= 1 - (P^N G^N/G)$), and $\omega_{GH} = 12\%$ ($= P^H G^H/G$), and we choose initial conditions so as trade is balanced, i.e., $v_{NX} = \frac{NX}{P^H Y^H} = 0$ with $NX = P^H X^H - C^F - I^F - G^F$. Because $u^{K,j} = 1$ at the steady-state, two parameters related to adjustment cost functions of capital utilization, i.e., ξ_1^H and ξ_1^N , are set to be equal to real capital rental rates in the traded and the non-traded sector, i.e., $\frac{R^H}{P^H}$ and $\frac{R^N}{P^N}$, respectively.

Six parameters are assigned values which are taken directly or estimated from our own data. We choose the model period to be one year. In accordance with the last column of Table 1, the world interest rate, r^* , which is equal to the subjective time discount rate, β , is set to 2.7%. In line with mean values shown in columns 11 and 12 of Table 1, the shares of labor income in traded and non-traded value added, s_L^H and s_L^N , are set to 0.63 and 0.69, respectively, which leads to an aggregate LIS of 66%.

Because barriers to factors' mobility play a key role in our model and estimates for OECD countries are not available, we have estimated empirically the elasticity of labor supply across sectors, ϵ_L , for each OECD economy. As shown in Online Appendix J.2,

we pin down ϵ_L from a testable equation obtained by combining labor supply and labor demand and run the regression in panel format on annual data of the percentage change in the labor share of sector j on the percentage change in the relative share of value added paid to workers in sector j over 1970-2017. Building on our estimates, the degree of labor mobility across sectors is set to 0.8, in line with the average of our estimates (see the last line of column 15 of Table 1). Note that this value is close to the value of 1 estimated by Horvath [2000] on U.S. data over 1948-1985 and commonly chosen in the literature allowing for imperfect mobility of labor. We have also estimated the degree of mobility of capital across sectors by running the regression of the percentage change in K_{it}^j/K_{it} on the percentage change in the relative share of value added paid to capital in sector j over 1970-2017. Building on our estimates, the degree of capital mobility across sectors is set to 0.15, in line with the average of our estimates (see the last line of column 16 of Table 1).

While there is a consensus in the open-economy macroeconomics literature that C^T and C^N are gross complements and thus ϕ should take a value lower than one, precise estimates for OECD countries are still lacking. To pin down ϕ , we use the first-order condition for C^N and run the regression of the logged share of non-tradables $1 - \alpha_C(t)$ on logged $P^N(t)/P_C(t)$. Time series for $1 - \alpha_C(t)$ are constructed by using the market clearing condition for non-tradables. Building on our panel data estimates, the elasticity of substitution ϕ between traded and non-traded goods is set to 0.35, since this value corresponds to our panel data estimates, see Online Appendix J.5. It is worth mentioning that our value is close to the estimated elasticity by Stockman and Tesar [1995] who report a value of 0.44 by using cross-section data for the year 1975.

Seven parameters are taken from external research works. In Shimer [2009] preferences, the relative risk aversion coefficient collapses to the coefficient which parameterizes the substitutability between consumption and leisure. We choose a value of $\sigma = 2$ which implies that consumption and leisure are substitutes and the intertemporal elasticity of substitution for consumption is equal to 0.5.¹² In line with the estimates recently documented Peterman [2016], we set the Frisch elasticity of labor supply σ_L to 3. We choose the value of parameter κ which captures the magnitude of capital adjustment costs so that the elasticity of I/K with respect to Tobin's q , i.e., Q/P_J , is equal to the value implied by estimates in Eberly et al. [2008]. The resulting value of κ is equal to 17.

In line with the empirical findings documented by Bems [2008] who finds that the non-tradable content of investment expenditure is stable in OECD countries, we set the elasticity of substitution, ϕ_J , between J^T and J^N to 1. We set the elasticity of substitution in consumption (investment), ρ (ρ_J), between home- and foreign-produced traded goods

¹²As pointed out recently by Best et al. [2020], there exists no consensus on a reasonable value for the intertemporal elasticity of substitution for consumption as estimates in the literature range between 0 and 2.

Table 1: Data to Calibrate the Two Open Economy Sector Model

Tradable share						Home share				Labor Share	
GDP	Cons.	Inv.	Gov.	Labor	Capital	X^H	C^H	I^H	G^H	LIS ^H	LIS ^N
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
0.36	0.43	0.32	0.20	0.36	0.39	0.13	0.66	0.42	0.12	0.63	0.69
Elasticities								Aggregate ratios			
ϕ	ρ	ϵ_L	ϵ_K	σ^H	σ^N	σ_L^H	σ_L^N	LIS	I/Y	G/Y	r
(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
0.35	1.30	0.80	0.15	0.81	0.87	0.77	0.69	0.66	0.23	0.20	0.027

Notes: Columns 1-5 show the GDP share of non-tradables, the non-tradable content of consumption, investment and government expenditure, the share of non-tradables in labor. Column 6 gives the ratio of exports of final goods and services to GDP; columns 7 and 8 show the home share of consumption and investment expenditure in tradables and column 9 shows the content of government spending in home-produced traded goods; ϕ is the elasticity of substitution between traded and non-traded goods in consumption; estimates of the elasticity of substitution between home- and foreign-produced traded goods ρ (with $\rho = \rho_J = \phi_X$) is taken from Bertinelli et al. [2022]; ϵ_L is the elasticity of labor supply across sectors; ϵ_K is the elasticity of capital supply across sectors; σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$; σ_L^j is the elasticity of substitution between skilled labor and unskilled labor in production in sector $j = H, N$. LIS ^{j} stands for the labor income share in sector $j = H, N$ while LIS refers to the aggregate LIS; I/Y is the investment-to-GDP ratio and G/Y is government spending as a share of GDP. The real interest rate is the real long-term interest rate calculated as the nominal interest rate on 10 years government bonds minus the rate of inflation which is the rate of change of the Consumption Price Index.

(inputs) to 1.3 which fits estimates by Bertinelli et al. [2022] who find a value of 1.3 for $\rho = \rho_J$ from a panel of seventeen OECD countries which is close to the value of 1.5 chosen by Backus et al. [1994]. Assuming that all countries have the same elasticities, since the price elasticity of exports is a weighted average of ρ and ρ_J , we set $\phi_X = 1.3$. A value larger than one fits well the structural estimates of the price elasticities of aggregate exports documented by Imbs and Mejean [2015].

Calibrating the CES economy. To calibrate the CES economy, we proceed as follows. First, we choose the same values for the thirteen parameters which have empirical counterparts as above, except for the labor income shares which are now endogenously calibrated. Thus in addition to σ , σ_L , κ , ϕ_J , ρ , ρ_J , ϕ_X , r^* , ϵ_L , ϵ_K , ϕ , we have to choose values for the elasticity of substitution between capital and labor for tradables and non-tradables, σ^H and σ^N . We estimate σ^H and σ^N over 1970-2017 on panel data so as to have consistent estimates in accordance with our classification of industries as tradables and non-tradables and sample composition. Drawing on Antràs [2004], we run the regression of value added per hours worked on the real wage in sector j by adopting cointegration methods. In line with our panel data estimates, we choose $\sigma^H = 0.81$ and $\sigma^N = 0.88$ (see the last line of columns 17 and 18 of Table 1).

Given the set of elasticities above, the remaining parameters are set so as to maintain the steady-state of the CES economy equal to the normalization point. Therefore, we calibrate the model with CES production functions so that fifteen parameters φ , ι , φ^H , ι^H , ϑ_L , ϑ_K , δ_K , G , G^N , G^H , N_0 , K_0 , Z^H , Z^N , γ^H , γ^N are endogenously set to target $1 - \bar{\alpha}_C$, $1 - \bar{\alpha}_J$, $\bar{\alpha}^H$, $\bar{\alpha}_J^H$, \bar{L}^N/\bar{L} , $\bar{\omega}_J$, $\bar{\omega}_G$, $\bar{\omega}_{GN}$, $\bar{\omega}_{GH}$, \bar{v}_{NX} , \bar{K} , \bar{y}^H , \bar{y}^N , $\bar{s}_L^H = \theta^H$, $\bar{s}_L^N = \theta^N$, respectively, where a bar indicates that the ratio is obtained from the Cobb-Douglas economy. In addition, we have to set the dynamic processes of technology improvements, capital utilization rates and factor-augmenting-efficiency and the share of symmetric technology shocks across sectors.

4.2 Factor-Augmenting Efficiency and Sectoral Technology Improvements Dynamics

In this subsection, we detail how we calibrate the endogenous responses of $A^j(t)$, $B^j(t)$, $u^{K,j}(t)$, to a technology improvement. We proceed as follows. Once we have identified symmetric and asymmetric technology shocks across sectors empirically, we calibrate the dynamic processes of factor-augmenting-efficiency and capital utilization rates so as to reproduce their empirical counterpart for both their symmetric and asymmetric components.

Share of symmetric technology shocks across sectors. Before calibrating the dynamic processes of technology variables, we have to calibrate the share η of symmetric technology shocks across sectors. By using the fact that $\hat{Z}^A(t) = \eta \hat{Z}_S^A(t) + (1 - \eta) \hat{Z}_D^A(t)$, we pin down the value of η which minimizes the discrepancy between the response of $Z^A(t)$ after an aggregate technology shock and its response calculated as a weighted average of the responses of symmetric and asymmetric utilization-adjusted-aggregate-TFP. We find that $\eta = 0.6$ and thus 60% of technology improvements are driven by technology shocks which are symmetric across sectors, see Online Appendix J.8 for more details.

Factor-augmenting efficiency. As detailed in section 3.1 (see eq. (15)), factor-augmenting productivity is made up of a symmetric and an asymmetric component across sectors. To set the adjustment of factor-augmenting efficiency, we first recover their dynamics in the data in the same spirit as Caselli and Coleman [2006]. Log-linearizing the demand for labor relative to the demand for capital (17), this equation together with the log-linearized version of the technology frontier (20) can be solved for deviations of $A_c^j(t)$ and $B_c^j(t)$ relative to their initial values (where the subscript $c = S, D$ refers to either the symmetric or asymmetric component):

$$\hat{A}_c^j(t) = \hat{A}_c^j(t) - (1 - s_L^j) \left[\left(\frac{\sigma^j}{1 - \sigma^j} \right) \hat{S}^j(t) - \hat{k}^j(t) - \hat{u}_c^{K,j}(t) \right], \quad (47a)$$

$$\hat{B}_c^j(t) = \hat{B}_c^j(t) + s_L^j \left[\left(\frac{\sigma^j}{1 - \sigma^j} \right) \hat{S}^j(t) - \hat{k}^j(t) - \hat{u}_c^{K,j}(t) \right]. \quad (47b)$$

Plugging estimated values for σ^j and empirically estimated responses for $s_L^j(t)$, $k^j(t)$, $u_S^{K,j}(t)$ following a symmetric technology shock across sectors into above equations enables us to recover the dynamics for $A_S^j(t)$ and $B_S^j(t)$ consistent with the demand for factors of production (17) and the technology frontier (20). The same logic applies to asymmetric technology shocks across sectors as we insert empirically estimated responses for $s_L^j(t)$, $k^j(t)$, $u_D^{K,j}(t)$ into (47a) and (47b) to recover the dynamics for $A_D^j(t)$ and $B_D^j(t)$. Then we choose values for exogenous parameters x_c^j (for $x = a, b, c = S, D$), $\xi_{X,c}^j$ and $\chi_{X,c}^j$ (for $X = A, B, c = S, D$) of the continuous time paths (45) within sector $j = H, N$, which are consistent with the estimated paths (47a)-(47b) for $A_c^j(t)$ and $B_c^j(t)$. Once we have recovered the dynamics of $A_c^j(t)$ and $B_c^j(t)$, we can infer the dynamics of utilization-adjusted-TFP in sector j by using the technology frontier, i.e., $\hat{Z}_c^j(t) = s_L^j \hat{A}_c^j(t) + (1 - s_L^j) \hat{B}_c^j(t)$ (see eq.

(20)).

Capital utilization adjustment costs. We also calibrate the parameters for the adjustment costs function of capital utilization. Log-linearizing (37f)-(38) shows that it is profitable to increase $u^{K,j}(t)$ when the real capital rental rate goes up

$$\hat{u}_c^{K,j}(t) = \frac{\xi_{1,c}^j}{\xi_{2,c}^j} \left(\hat{R}^j(t) - \hat{P}^j(t) \right), \quad (48)$$

The parameter $\xi_{2,c}^j$ determines the magnitude of the adjustment in the capital utilization rate in sector j following a symmetric ($c = S$) or an asymmetric ($c = D$) technology shock across sectors. We set $\xi_{2,S}^H = 0.5$ and $\xi_{2,S}^N = 0.6$, and $\xi_{2,D}^H = 0.03$ and $\xi_{2,D}^N = 0.5$, so as to account for empirical responses of $u_S^{K,j}(t)$ and $u_D^{K,j}(t)$, respectively, conditional on symmetric and asymmetric technology shocks across sectors.

4.3 Decomposition of Model's Performance

In this subsection, we analyze the role of the model's ingredients in driving the labor effects of a permanent technology improvement. We show that both the two-sector dimension and the open economy aspect of our model matter in determining the dynamic effects of a technology shock on hours worked.

Our baseline model includes four sets of elements. The first set is related to the biasedness of technology improvements toward traded industries together with the gross complementarity between traded and non-traded goods (i.e., $\phi < 1$). The second set of elements is related to barriers to factors' mobility which include labor mobility costs and costs of switching capital from one sector to another (i.e., $0 < \epsilon_L < \infty$ and $0 < \epsilon_K < \infty$). The third set of factors are related to trade openness, as reflected into imperfect substitutability between home- and foreign-produced traded goods (i.e., $0 < \rho < \infty$, $0 < \rho_J < \infty$, $0 < \phi_X < \infty$) which influences the extent of foreign borrowing. The fourth set of elements is related to an endogenous intensity in the use of physical capital (i.e., $0 < \xi_{2,c}^j < \infty$), and technology improvements which are factor-biased at a sector level (i.e., $\hat{A}_c^j(t) \neq \hat{B}_c^j(t)$).

To understand (and quantify) the role of each element, we first consider the simplest version of our model and add one ingredient at a time. This restricted version shown in column 7 of Table 2 collapses to the international RBC model by Fernández de Córdoba and Kehoe [2000] (FK henceforth) who consider a small open economy setup with tradables and non-tradables together with capital adjustment costs. In column 6, we allow for both labor and capital mobility costs across sectors. In column 5, we assume that home- and foreign-produced traded goods are imperfect substitutes. In column 2, we allow for CES production functions, FBTC and endogenous capital utilization. This model collapses to our baseline setup. We will discuss later the effects of symmetric and asymmetric technology shocks which are displayed by columns 3 and 4.

Table 2: Impact Labor Effects of a Technology Improvement: Baseline vs. Restricted Models

	Data	CES: FBTC and uK			CD: IM & TOT	CD: IML& IMK	CD: PM
	LP	AGG	SYM	ASYM	AGG	AGG	AGG
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A.Technology							
Aggregate technology, $dZ^A(t)$	0.93	0.94	1.19	0.58	0.95	0.95	0.95
T technology, $dZ^H(t)$	1.53	1.66	1.06	2.57	1.66	1.66	1.66
NT technology, $dZ^N(t)$	0.55	0.56	1.26	-0.50	0.56	0.56	0.56
T capital utilization, $du^{K,H}(t)$	-0.24	-0.11	0.09	-1.81	0.00	0.00	0.00
NT capital utilization, $du^{K,N}(t)$	0.12	0.03	0.11	0.00	0.00	0.00	0.00
B.Hours							
Hours, $dL(t)$	-0.15	-0.07	-0.40	0.28	-0.26	-0.42	-0.70
Traded Hours, $dL^H(t)$	-0.04	-0.03	-0.11	-0.02	-0.15	-0.28	-0.57
Non-Traded Hours, $dL^N(t)$	-0.11	-0.05	-0.30	0.29	-0.12	-0.14	-0.13
Hours Share of Tradables, $d\nu^{L,H}(t)$	0.01	-0.00	0.03	-0.11	-0.06	-0.14	-0.33
C.Relative Prices							
Relative price of NT, $d(P^N/P^H)(t)$	1.05	1.63	-0.43	4.69	1.56	2.11	1.15
Terms of trade, $dP^H(t)$	-1.15	-1.09	-0.44	-1.99	-0.93	0.00	0.00
D.VA Shares							
VA share of T (constant prices) $d\nu^{Y,H}(t)$	0.18	0.23	-0.02	0.47	0.22	0.14	-0.08
VA share of N (current prices) $d\omega^{Y,N}(t)$	n.a.	0.13	-0.07	0.57	0.13	0.34	0.34
E.Current Account							
Current Account, $dCA(t)$	n.a.	-0.02	-0.06	0.04	-0.02	-0.18	-0.38

Notes: This table shows impact effects of a 1% permanent increase in government consumption in the baseline model (columns 2-4) and in restricted versions of the model (columns 5-13). 'T' refers to traded industries while 'NT' refers to non-tradables. Panel A shows the impact effects for technology variables, panel B displays the impact effects for hours worked, panel C shows the relative price effects while panel D reports the change on impact in the current account (in percentage point of GDP). Across all scenarios, we consider a 1% permanent increase in utilization-adjusted-aggregate-TFP. In column 1, we show impact responses of the corresponding variables. Columns 2, 5, 6, 7 show numerical results following a technology improvement which increases the utilization-adjusted-aggregate-TFP by 1% in the long-run. Column 3 shows numerical results following a symmetric technology shock across sectors which increases the utilization-adjusted-aggregate-TFP by 1% in the long-run. Column 4 shows numerical results following an asymmetric technology shock across sectors which increases the utilization-adjusted-aggregate-TFP by 1% in the long-run. Column 7 shows numerical results for an open economy model with tradables and non-tradables with capital adjustment costs, perfect mobility of labor and capital, perfect substitutability between home- and foreign-produced traded goods. In column 6, we augment the previous model with imperfect mobility of labor and capital. In column 5, we augment the previous model with imperfect substitutability between home- and foreign-produced traded goods so that terms of trade are endogenous. In columns 2-4, we consider the baseline model which allows for endogenous capital utilization rate and assumes that sectoral goods are produced by means of CES production functions and we let technological change to be factor-biased.

Table 2 reports the impact effect of selected variables, including total hours worked, $L(t)$, traded and non-traded hours worked, $L^H(t)$ and $L^N(t)$, the hours worked share of tradables, $\nu^{L,H}(t)$, the relative price of non-tradables and the terms of trade, $P(t)$ and $P^H(t)$, and the current account $CA(t)$. To further illustrate the transmission mechanism, we also show the adjustment in the real value added share of tradables, $d\nu^{Y,H}(t)$, and the value added share of non-tradables, $d\omega^{Y,N}(t)$. For comparison purposes, the first column displays the impact response of the corresponding variable which is estimated empirically by means of local projections which should be contrasted with the responses computed numerically shown in columns 2,5,6,7.

While we normalize the technology improvement to 1% in the long-run, panel A of Table 2 shows the adjustment of aggregate, traded and non-traded utilization-adjusted-TFP on impact. As shown in columns 2, 5, 6, 7, all model variants generate an increase in utilization-adjusted-aggregate-TFP by 0.94% on impact in line with the evidence and gives rise to a technology improvement of 1.66% and 0.56% close to our estimates.

First ingredient: Barriers to factors' mobility. In column 7 of Table 2, we report

results from a restricted version of the baseline model where we consider a two-sector small open economy model with capital adjustment costs which collapses to the FK model. In this model's version, home- and foreign-produced traded goods are perfect substitutes so that terms of trade are exogenous (and constant over time). Labor and capital can move freely across sectors. Production functions are Cobb-Douglas so that technological change is Hicks-neutral. We also abstract from endogenous capital utilization rates. Contrasting the model's predictions shown in column 7 with empirically estimated values reported in column 1, the restricted version of the model substantially overstates the decline in total hours worked.

As long as home- and foreign-produced goods are perfect substitutes, it is optimal to import traded goods and reallocate labor (and capital) toward the non-traded sector. Because labor and capital are not subject to mobility costs, the hours worked share of tradables falls dramatically by 0.33 percentage point of total hours worked, thus leading the restricted model to generate a decline in traded hours worked by 0.57 ppt of total hours worked while we find empirically a fall by 0.03 ppt. The corollary of the shift of resources toward the non-traded sector and the surge of imports is that the open economy runs a large current deficit (see panel E). Under these assumptions, households find it optimal to lower hours worked (see the first line of panel B) by 0.7% which considerably overstates the decline estimated in the data (i.e., -0.15%).

In column 6, we consider the same model as in column 7 except that we allow for both labor and capital mobility costs. The frictions into the movements of factors substantially mitigate the shift of productive resources toward the non-traded sector. In particular, as shown in the last line of panel B, the decline in the hours worked share of tradables shrinks from -0.33 ppt of total hours worked (column 7) to -0.14 ppt (column 6). Because less productive resources move toward the non-traded sector, households must cut the rise in leisure, thus resulting in a shrinking decline in total hours worked to meet the demand for non-traded goods. The fall in $L(0)$ by 0.42% is still too large compared with what we estimate empirically (i.e., -0.15%).

Second ingredient: Imperfect substitutability between home- and foreign-produced traded goods. While putting frictions into the movements of labor and capital between sectors improves the fit of the model to the data, the model still overstates the decline in total hours worked and the fall in the hours worked share of tradables. As shown in column 5, the ability of the model to account for the evidence improves once we allow for imperfect substitutability between home- and foreign-produced traded goods. More specifically, as households are getting more reluctant to substitute imported goods for domestic goods, there is a shift toward home-produced traded goods which leads traded firms to produce more. The reallocation of labor toward non-traded industries further

shrinks from 0.14 ppt to 0.06 ppt of total hours worked (see the fourth row of panel B). Therefore traded hours worked fall less because as shown in the second row of panel C, the terms of trade depreciate by 1.15% (close to what we estimate empirically) which stimulates the demand for home-produced traded goods. Imports increase less which results in a smaller current account deficit as can be seen in panel E. Because the economy must meet the demand for home-produced traded goods, the decline in total hours worked further shrinks from -0.42% to -0.26% but the magnitude is still larger what we estimate empirically.

Third ingredient: Factor-biased technological change. The model's predictions square well with our evidences once we let technological change to be factor-biased and allow physical capital to be used more intensively. As shown in panel B, labor no longer shifts toward the non-traded sector (see the fourth row) while the decline in total hours worked is much less pronounced than in restricted versions of the model. Intuitively, once we let sectoral goods to be produced by means of CES production functions and because technological change is biased toward labor in the traded sector, traded production becomes more labor intensive which prevents labor from shifting toward non-traded industries and thus mitigates the decline in traded hours worked. The baseline model generates a fall in $L^H(t)$ by -0.03 ppt of total hours worked close to what we estimate empirically (i.e., -0.04 ppt). Although our model slightly understates the fall in total hours (-0.07% vs. -0.15% in the data) because it understates the decline in non-traded hours on impact, the model reproduces well the dynamics of hours worked as shown later.

Fourth ingredient: Aggregate technology shocks are a mix of symmetric and asymmetric technology shocks. So far, we have seen that the model must include frictions into the movement of inputs across sectors to account for the labor effects of a permanent technology improvement. We now highlight the necessity to consider a mix of symmetric and asymmetric technology shocks. To stress this aspect, columns 3 and 4 of Table 2 shows the impact effects of symmetric and asymmetric technology shocks separately.

We first focus on the effects of a symmetric technology shock displayed by column 3. As shown in panel A, technology improvements are uniformly distributed between the traded and the non-traded sector. As can be seen in the first row of panel B, a symmetric technology shock generates a decline in hours worked by -0.40% close to to what we estimate empirically (-0.47% in the data). Intuitively, a symmetric technology shock across sectors lowers the marginal cost in both sectors which leads both traded and non-traded firms to cut prices. Lower prices put downward pressure on wages which generates a dramatic fall in hours worked. As shown in panel E, a symmetric technology shock gives rise to a current deficit which amplifies the decline in total hours worked.

In line with the evidence, the fall in total hours worked mostly originates from the non-traded sector. Because the elasticity of substitution between traded and non-traded

goods is smaller than one (i.e., $\phi < 1$), the decline in non-traded prices lowers the share of expenditure allocated to non-traded goods (see the second row of panel D) and depresses labor demand in the non-traded sector. The terms of trade depreciation further tilts the demand toward traded goods which leads to a shift of labor toward the traded sector, as reflected by $d\nu^{L,H}(0) = 0.03$ ppt. While traded hours worked fall (see the second line of panel B), the decline in hours is concentrated in the non-traded sector which experiences a labor outflow.

Asymmetric technology shocks generate opposite effects. As shown in the first line of panel B in column 4, an asymmetric shock produces an increase in hours by 0.28% close to what we estimate empirically (i.e., 0.31% in the data). In contrast to a symmetric technology shock, panel A shows that technology improvements are concentrated in the traded sector. To compensate for the rise in the marginal cost, non-traded firms set higher prices (see the first row of panel C). The share of non-tradables increases (see the second row of panel D) which has an expansionary effect on labor demand in the non-traded sector and leads to a shift of labor away from traded industries. This results in a decline in traded hours worked which is mitigated by technological change biased toward labor in the traded sector.

Relegated to Online Appendix K for reasons of space, we show impact responses computed numerically for symmetric and asymmetric technology shocks across restricted versions of the baseline model. Numerical estimates reveal that it is only once we allow for FBTC and endogenous capital utilization at a sectoral level that the open economy model can account for the magnitude of the rise in hours worked we estimate after asymmetric technology shocks.¹³ By making the production in the traded sector more labor intensive, technological change biased toward labor in the traded sector mitigates the shift of labor toward non-traded industries and thus prevents L^H from declining dramatically which allows the model to generate a rise in total hours worked. However, by increasing labor demand in the traded relative to the non-traded sector, the model understates the reallocation of labor toward the non-traded sector. To account for the decline in $\nu^{L,H}$ and reproduce the rise in total hours worked we estimate, we have to assume endogenous capital utilization. More specifically, if endogenous capital utilization rates were shut down, technological change biased toward labor would increase total hours worked by 0.50% (far beyond what we estimate empirically) and importantly, the hours worked share of tradables would decline by only 0.025 ppt which is four times below what we find empirically. By reducing the traded wage rate, the dramatic decline in the capital utilization rate of tradables on impact

¹³Restricted versions imposing perfect substitutability between home- and foreign-produced traded goods generate a decline in hours worked on impact instead of an increase because under this assumption, it is optimal to shift productive resources toward the non-traded sector to meet higher demand for non-traded goods and import traded goods by running a (large) current account deficit. Once home- and foreign-produced traded goods are assumed to be imperfect substitutes, the model can generate an increase in hours worked but its magnitude is six times smaller what we estimate empirically.

amplifies the shift of labor toward the non-traded sector and generates an increase in labor supply by 0.28% close to our evidence. In line with the evidence, labor growth originates from the non-traded sector (see the third row of panel B).

Because technology shocks uniformly distributed across sectors produce a dramatic decline in $L(0)$ and technology shocks concentrated toward the traded sector have an expansionary effect on hours worked, they cannot account separately for the moderate decline in hours worked we estimate after an aggregate technology shock. Therefore, it is only one we consider a mix of symmetric and asymmetric technology shocks that we can account for the labor market effects of an aggregate technology shock.

4.4 Dynamic Effects of a Permanent Technology Improvement

While in Table 2, we restrict our attention to impact effects, in Fig. 5, we contrast theoretical (displayed by solid black lines with squares) with empirical (displayed by solid blue lines) dynamic responses with the shaded area indicating the 90% confidence bounds.¹⁴ We also contrast theoretical responses from the baseline model with the predictions of a restricted model which imposes HNTC shown in dashed red lines. As shown in Fig. 5(a), models experience the same technology improvement.

Dynamics. As displayed by Fig. 5(c), both models generate a decline in hours worked but only the baseline model with technological change biased toward labor can account for the dynamics of total hours worked. The reason for this is that as shown in Fig. 5(e), the model imposing HNTC overstates the decline in traded hours worked by generating a strong reallocation of labor away from traded industries displayed by Fig. 5(k). More specifically, as can be seen in Fig. 5(l), technological change is concentrated within traded industries which in turn leads non-traded industries to set higher prices. As the appreciation in the relative price of non-tradables builds up over time, as displayed by Fig. 5(m), more labor shifts toward non-traded industries as households allocate a greater share of their expenditure to non-traded goods.

However, the so-called deindustrialization movement reflected into the decline in the labor share of tradables is gradual and shows up only in the long-run. The reason is that the reallocation of productive resources across sectors is subject to frictions. First, the terms of trade depreciation displayed by Fig. 5(n) mitigates the rise in the share of non-tradables. Second, as shown in Fig. 5(o), the technology improvement increases non-traded relative to aggregate wage which points at the presence of labor labor mobility costs which further hampers the reallocation of labor. Third, as shown in Fig. 5(f) and Fig. 5(i), traded output becomes more labor intensive than non-traded output, especially in the short-run, which hampers the shift of labor away from traded industries. By imposing HNTC, the

¹⁴For reasons of space, we relegate to Online Appendix J.10 the dynamics of utilization-adjusted-TFP, capital utilization rates and FBTC for tradables and non-tradables following a symmetric and an asymmetric technology shock together with an aggregate technology shock.

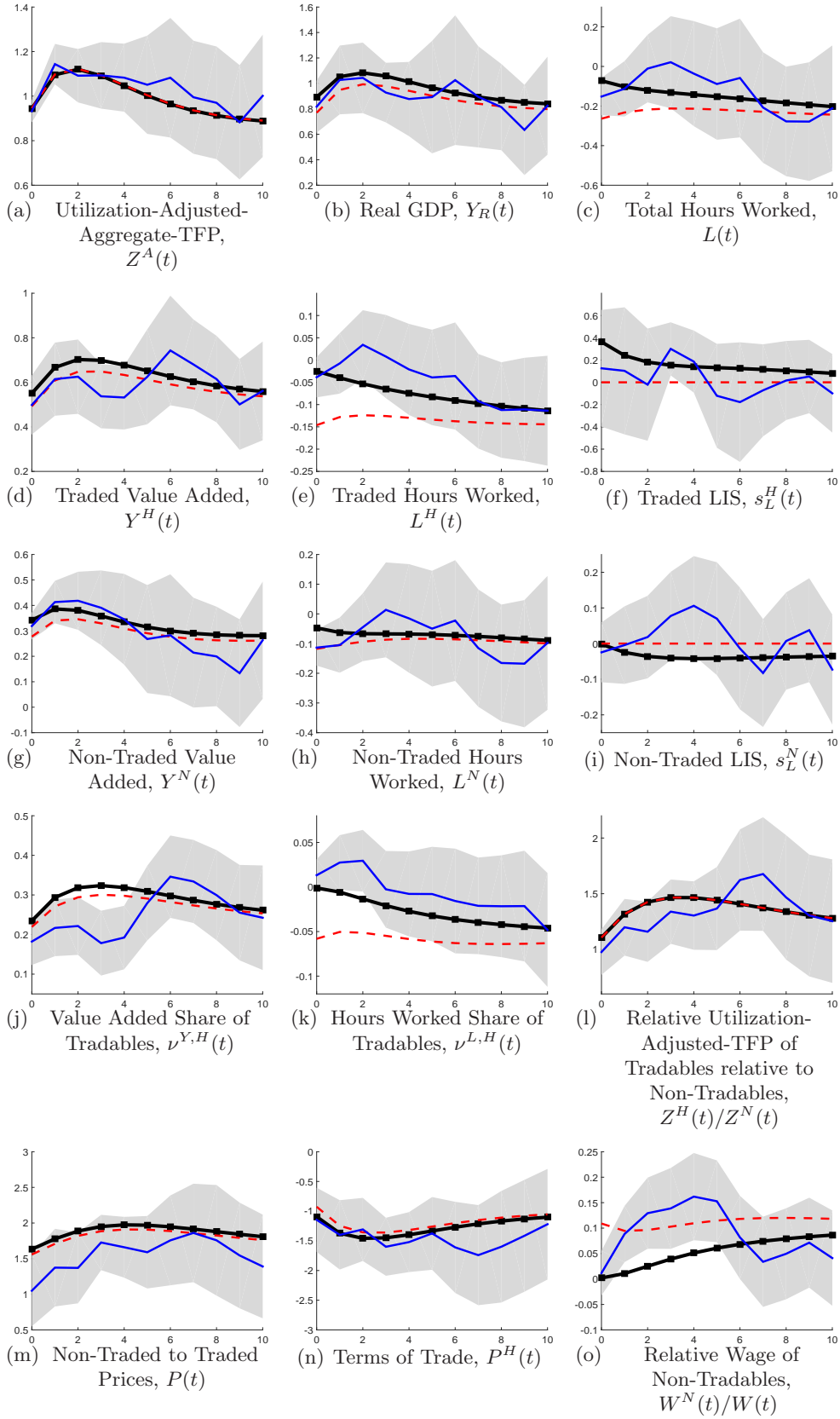


Figure 5: Theoretical vs. Empirical Responses Following a Technology Shock: Hours and Value Added Effects. **Notes:** The solid blue line which displays point estimate from local projections with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario with capital utilization rates together with FBTC, while the dashed red line shows predictions of a model with Cobb-Douglas production functions (which amount to shutting down FBTC) and abstracting from endogenous capital utilization. The relative wage of non-tradables is constructed as the ratio of the non-traded wage to the aggregate wage, the relative price of non-tradables is computed as the ratio of the non-traded value added deflator to the traded value added deflator, and the terms of trade are constructed as the ratio of the traded value added deflator of the home country i to the geometric average of the traded value added deflator of the seventeen trade partners of the corresponding country i , the weight being equal to the share of imports from the trade partner k (averaged over 1970-2017).

model assuming Cobb-Douglas production functions overstates the decline in traded hours worked in the short-run, see Fig. 5(e), and therefore in total hours worked, see Fig. 5(c).

Finally, inspection of Fig. 5(b) reveals that real GDP growth mimics the hump-shaped adjustment in utilization-adjusted-TFP. As displayed by Fig. 5(d) and Fig. 5(g), both the baseline model and its variant reproduce well the dynamics of traded and non-traded value added. While both labor and capital shift toward the non-traded sector, the model generates an increase in the value added share of tradables (which slightly overstates what we estimate empirically) as can be seen in Fig. 5(j), as a result of the positive productivity growth differential between tradables and non-tradables.

4.5 Time-Varying Impact Effects of a Permanent Technology Shock

Time-increasing response of hours worked. The main objective of our paper is to rationalize the time-increasing impact response of hours worked to a 1% permanent technology improvement we document empirically as shown in the blue line in Fig. 6(a). The explanation we put forward is the growing contribution of asymmetric of technology shocks to the variations in utilization-adjusted-aggregate-TFP.

To assess the ability of our open economy model with tradables and non-tradables to account for the time-increasing response of hours worked we estimate empirically, we keep the same calibration and estimate the impact response of hours worked to a 1% permanent technology improvement by letting the share of symmetric technology shocks η increase over time in line with our empirical estimates over rolling windows (see Fig. 3(e)). As shown in the black line in Fig. 6(a), as we lower the share of technology shocks uniformly distributed across sectors from 90% to 60%, the baseline model can generate the shrinking contractionary effect of technology improvements on hours we estimate empirically shown in the blue line.¹⁵

Sectoral decomposition of the time-varying response of hours worked. In Fig. 6(b) and Fig. 6(c), we investigate the ability of the baseline model shown in the black line to account for the shrinking contractionary effect (on impact) of a 1% permanent technology improvement on both traded and non-traded hours worked. As it stands out, the model reproduces well the time-increasing impact response of traded hours worked as it generates a shrinking decline from -0.086 ppt (-0.086 ppt in the data) the first thirty years to -0.025 ppt (-0.024 ppt in the data) the last thirty years. The performance of the model lies in FBTC.

Relegated to Online Appendix K.2 for reasons of space, a model imposing HNTC would produce a time-decreasing impact response of L^H , traded hours worked declining on impact

¹⁵Quantitatively, we find numerically that increasing the contribution of asymmetric technology shocks from 10% to 40% reduces the magnitude of the decline in hours worked from -0.32% to -0.07% which slightly overstates what we estimate empirically as the decline in hours worked shown in the blue line increase from -0.26% to -0.11%.

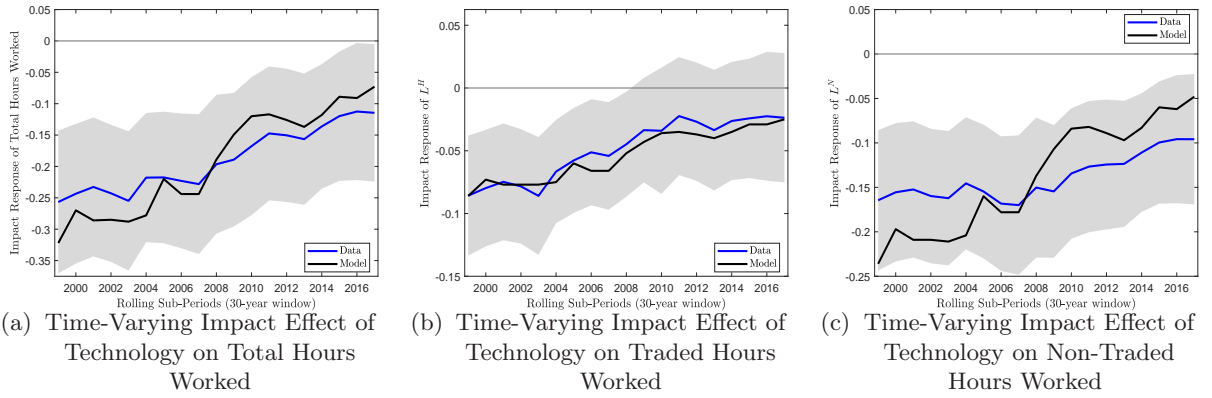


Figure 6: Time-Varying Impact Effects of a Technology Shock. *Notes:* The figure shows impact responses of total, traded and non-traded hours worked to a 1% permanent increase in utilization-adjusted aggregate TFP. The solid blue line shows the impact response we estimate empirically on rolling sub-periods by using Jordà’s [2005] single-equation impact method. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. The solid black line shows the impact response we compute numerically by letting the share of technology improvements driven by asymmetric technology shocks vary across sub-periods, i.e., we set the share of asymmetric technology shocks one minus the value estimated empirically by means of FEVD as shown in Fig. 3(e). Note that we have normalized the rise in utilization-adjusted aggregate TFP to 1% on impact as we focus on The horizontal axis shows the end year of the period of the sub-sample and the vertical line displays the point estimate of the impact effect of technology on total hours worked.

by -0.12 ppt over 70-00 and by -0.15 ppt over 87-17 because asymmetric technology shocks reallocate labor toward non-traded industries and exert a strong negative impact on L^H . By allowing for technological change strongly biased toward labor in the traded sector which neutralizes the incentives to shift labor away from traded industries in the short-run, the baseline model can account for the shrinking contractionary effect of a technology improvement on L^H .

We may notice that our model can also generate the time-increasing impact response of L^N in line with the data as the black line lies within the confidence bounds of the empirical point estimate. It is worth noting that our model predicts that on average, the decline in non-traded hours worked contributes 75% to the fall in total hours worked while in the data, the contribution is slightly lower as it averages 71%.

5 Extensions

In this section, we extend our analysis in two directions to answer two questions:

- So far, we have considered that workers’ skills were homogenous across sectors. One key question is whether the decline in total hours worked is uniformly distributed across workers’ skills and if not, how does the skill composition effect drive the time-increasing response of hours?
- We have shown that the growing contribution of asymmetric technology shocks across sectors to technology improvements is responsible for the time-increasing response of total hours worked. One important question is: why technology improvements are increasingly driven by asymmetric technology shocks across sectors over time?

5.1 Skill Composition Effect of a Permanent Technology Improvement

In this subsection, we analyze the hours worked effects of a permanent technology improvement by differentiating between skilled and unskilled labor. Our objective is twofold. First, we assess the ability of our model to account for the labor composition effects across workers' skills of a permanent technology improvement. Second, we investigate whether the model can generate the rise in impact responses of skilled and unskilled hours worked on rolling sub-periods.

Framework. The framework we have in mind which is detailed in Online Appendix S is a model where a representative household supplies both skilled and unskilled labor. We assume that skilled and unskilled hours worked are imperfect substitutes, thus giving rise to a costly transition from unskilled to skilled labor. Both skilled and unskilled workers experience costs of switching sectors. As described by eq. (14), we assume that sectoral goods are produced with labor and capital by means of a CES production function. We relax the assumption that labor is homogenous and suppose that efficient labor is a CES aggregator of skilled and unskilled labor. In addition to assuming that firms within each sector $j = H, N$ decide about the split of capital-utilization-adjusted-TFP $Z^j(t)$ between labor- and capital-augmenting efficiency, we also assume that firms choose a mix of skilled- and unskilled-labor-augmenting productivity $A^{S,j}(t)$ and $A^{U,j}(t)$ along a technology frontier whose height is measured by labor efficiency $A^j(t)$.

Data and Calibration. The calibration strategy is identical to that described in section 4.1. To disentangle the labor effects of a technology improvement across workers' skills, we use time series from EU KLEMS [2008] which are available for eleven OECD countries over a maximum period of time 1970-2017. We aggregate high- and medium-skilled labor as their responses are similar and distinct from those of low-skilled workers, see Online Appendix L. In accordance with the evidence documented by Kambourov and Manovskii [2009] which reveals that industry (and occupational) mobility declines with education, our empirical findings indicate that the elasticity of labor supply across sectors is twice larger for unskilled than skilled workers. More specifically, we set $\epsilon_S = 0.63$ and $\epsilon_U = 1.13$, in line with our panel data estimates, see Online Appendix J.4 for further details about the data and the empirical strategy. As detailed in Online Appendix J.7, we estimate an elasticity of substitution in production between skilled and unskilled labor of $\sigma_L^H = 0.77$ for tradables and an elasticity of $\sigma_L^N = 0.69$ for non-tradables. While there is a debate about whether the elasticity of substitution between skilled and unskilled labor is smaller or larger than one, our evidence corroborates the findings by Bazcik et al. [2020] who are conducting a meta-analysis on the subject. By using the fact that technology improvements are a weighted average of symmetric and asymmetric technology shocks, we find that a value of $\eta = 80\%$ minimizes the discrepancy between the empirical response of $Z^A(t)$

following a permanent technology improvement and its response computed from $\hat{Z}^A(t) = \eta \hat{Z}_S^A(t) + (1 - \eta) \hat{Z}_D^A(t)$. In line with the evidence for the eleven countries of our sample, we let $\xi_{2,S}^j, \xi_{2,D}^j$ tend toward infinity so that the capital utilization rates are muted in both sectors. Finally, we allow for skill-biased technological change (SBTC henceforth) in our model and construct time series for SBTC at a sectoral level by adapting the methodology pioneered by Caselli and Coleman [2006], more details can be found in Online Appendix S.3.

Labor composition effects across workers' skills. In Fig. 7, we contrast the dynamic effects of a 1% permanent technology improvement we estimate empirically (shown in the solid blue line) with the responses we compute numerically in the baseline model (shown in black line with squares). To give a sense of the role of FBTC and SBTC in driving the effects of a permanent technology improvement, we also consider a restricted version of our model shown in dashed red lines where we shut down these two elements.

A permanent increase in utilization-adjusted-aggregate-TFP shown in Fig. 7(a) leads agents to work less as displayed by Fig. 7(e). Quantitatively, hours worked decline by 0.45% on impact (in accordance with the evidence) and such a dramatic decline comes from the dominance of symmetric technology shocks which account for 80% of technology improvements. As mentioned above, when technological change is uniformly distributed across sectors, higher productivity puts downward pressure on sectoral prices which curbs the increase in sectoral wages. In addition, symmetric technology shocks are strongly biased toward capital, especially in the traded sector.

Skilled and unskilled labor are not impacted uniformly by a technology improvement. More specifically, as displayed by Fig. 7(b), a permanent technology improvement significantly lowers the ratio of skilled labor compensation to total labor compensation over time. The gradual decline in the skilled labor income share is driven by the decrease in the skilled labor income shares in both the traded and the non-traded sector (see Fig. 7(c) and Fig. 7(d)) which reveal that the demand for labor is tilted toward unskilled workers in both sectors. Intuitively, the combined effect of the rise in the skilled workers efficiency and the complementarity between skilled and unskilled labor leads to an increase in the demand for unskilled labor and therefore causes a decrease in the skilled labor intensity of production of both sectors. As shown in the dashed red lines, a model abstracting from SBTC predicts a flat skilled labor income share in contrast to our evidence. As displayed by Fig. 7(f), the restricted model tends to understate the fall in skilled labor. In contrast, a model with FBTC and SBTC reproduces well the adjustment in skilled labor. Importantly, the decline in skilled labor (by -0.31 ppt of total hours in the model) contributes 70% to the fall in total hours worked. On its own, the decline in non-traded skilled labor by 0.21 ppt (see Fig. 7(g) accounts for almost half of the decline in total hours worked.

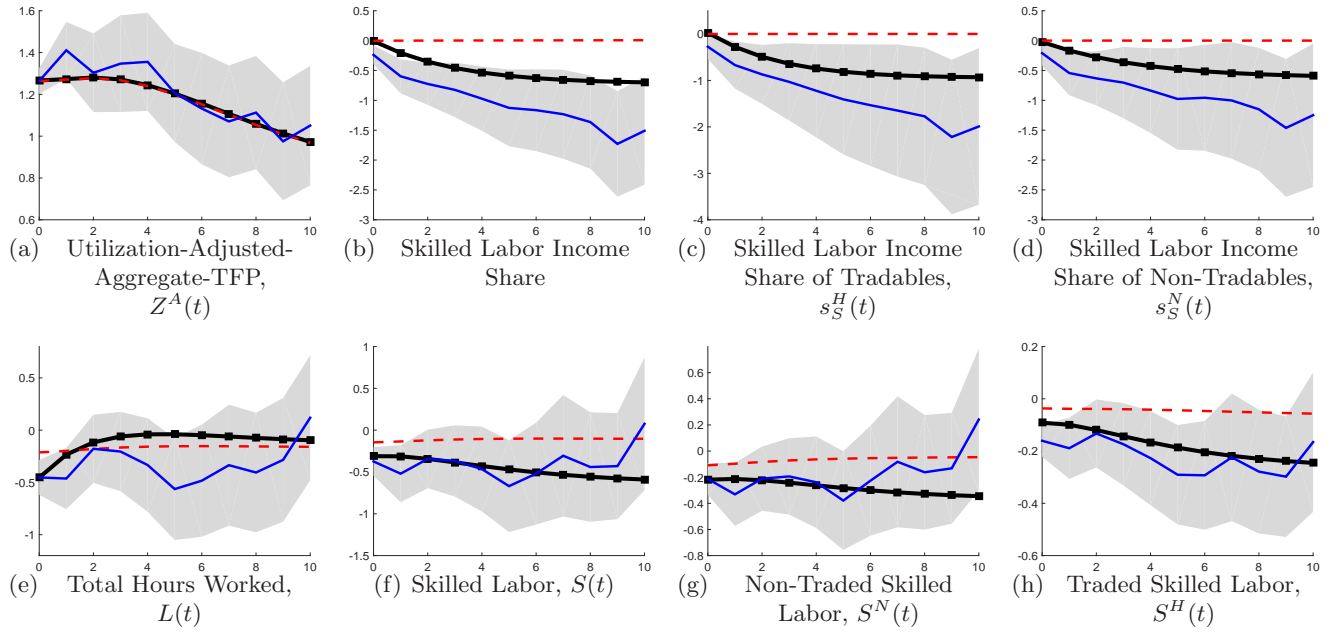


Figure 7: Theoretical vs. Empirical Responses Following a Technology Shock: Labor Composition Effects across Workers' Skills. *Notes:* The solid blue line which displays point estimate from local projections with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario with FBTC and SBTC, while the dashed red line shows predictions of a model with Cobb-Douglas production functions (which amount to shutting down FBTC and SBTC).

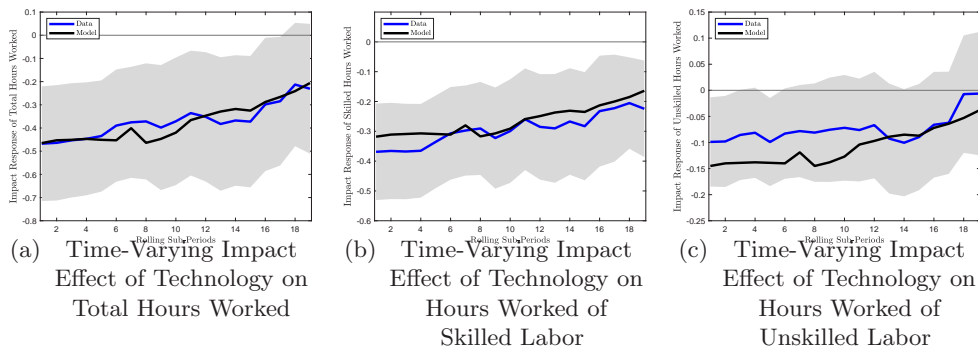


Figure 8: Time-Varying Impact Effects of a Technology Shock. *Notes:* Fig. 8(a)-8(c) show the impact responses on total hours worked together with its skilled vs. unskilled components to a 1% permanent increase in utilization-adjusted aggregate TFP. The solid blue line shows the impact response we estimate empirically on rolling sub-periods by using Jordà's [2005] single-equation method. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. The solid black line shows the impact response we compute numerically by calibrating the contribution of symmetric technology shocks to variations in utilization-adjusted-aggregate-TFP to what we estimate empirically. Note that we have normalized the rise in utilization-adjusted aggregate TFP to 1% at time $t = 0$ as we focus on impact effect. The horizontal axis shows the end year of the period of the sub-sample and the vertical line displays the of the impact effect of technology expressed in ppt of total hours worked. Sample: 11 OECD countries, 1970-2017

Time-increasing impact response of hours worked across workers' skills. As in section 4.5, we assess the ability of the model to account for the time-increasing response of hours worked by letting the share of asymmetric technology shocks increase over time. For the eleven countries of our sample, the share of asymmetric technology shocks increases from 19% to 39% in line with our empirical estimates for the sample of eleven OECD countries. As displayed by Fig. 8(a), the model reproduces well the shrinking contractionary effect of a permanent technology improvement on total hours worked. Fig. 8(b) and Fig. 8(c) reveal that both skilled labor and unskilled labor experience a time-increasing impact response to an aggregate technology shock and our model predictions shown in the black lines can account for these time-varying effects. More specifically, we find that 59% of the rise in the impact response of hours worked is driven by skilled hours worked which is close to the contribution of 61% we estimate empirically. Intuitively, asymmetric technology shocks have a strong expansionary effect on non-traded hours worked. Although technological change is biased toward unskilled labor, technological change biased toward labor together with a high intensity of non-traded industries in skilled labor leads skilled labor to contribute significantly to the time-increasing impact response of total hours worked. In Online Appendix K.3, we relax the assumptions of FBTC and SBTC. By abstracting from technological change biased toward capital, a model imposing HNTC significantly understates the decline in total hours worked.¹⁶

5.2 Why Technology Shocks are More Asymmetric across Sectors

We have shown that hours worked decline less over time because technology improvements are increasingly driven by asymmetric technology shocks across sectors over time. In this subsection, we put forward the greater exposition of traded industries to the international stock of knowledge to rationalize the growing contribution of asymmetric technological change to the variance of aggregate technology improvements.

To conduct a decomposition of the (unconditional) variance of aggregate technological change, we first rearrange eq. (10) so that the productivity growth differential shows up, i.e., $\hat{Z}^A(t) = \hat{Z}^N(t) + \nu^{Y,H} (\hat{Z}^H(t) - \hat{Z}^N(t))$. When technology increases by the same amount across sectors, i.e., $\hat{Z}^N(t) = \hat{Z}^H(t)$, the second term on the RHS vanishes so that the rate of change of utilization-adjusted-aggregate TFP collapses to its symmetric component, i.e., $\hat{Z}^A(t) = \hat{Z}_S^A(t)$. The second term on the RHS thus reflects the technology dispersion between sectors. Taking the variance of both sides, subtracting the covariance between symmetric and asymmetric technological change from the variance of aggregate technology improvements and denoting the adjusted variance by $\text{Var}'(\hat{Z}^A(t))$, we find a formal expression for the share of the variance of the rate of growth of utilization-adjusted-

¹⁶For the eleven countries which have time series for skilled and unskilled labor, aggregate technology improvements are biased toward capital instead of being biased toward labor.

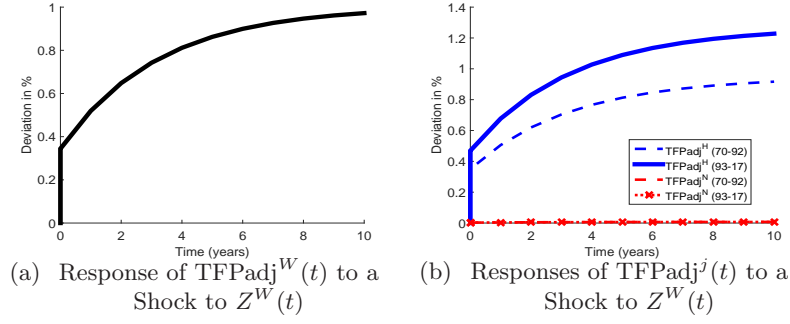


Figure 9: Technology Effects of a Permanent Increase in the International Stock of R&D.

Notes: Fig. 9(a) and Fig. 9(b) show the adjustment of utilization-adjusted-TFP to a permanent increase in the international stock of R&D which increases the international component of utilization-adjusted-TFP by 1% in the long-run. Fig. 9(a) displays the endogenous adjustment of the world component of the utilization-adjusted-aggregate-TFP to a permanent. The IRF for $\text{TFP}_{adj}^W(t)$ is obtained when we estimate a VAR model which includes the world utilization-adjusted-TFP, real GDP, total hours worked, the real consumption wage. Fig. 9(b) displays the response of utilization-adjusted-TFP in sector j , i.e., $\text{TFP}_{adj}^j(t)$, following a 1% permanent increase in $\text{TFP}_{adj}^W(t)$. The blue lines in Fig. 9(b) show the responses of technology of tradables while the red lines show the responses of technology of non-tradables. The dashed blue line and the dashed red line display the responses when the domestic component of $\text{TFP}_{adj}^H(t)$ and $\text{TFP}_{adj}^N(t)$ stands at 63.4% and 65.5% over the period 1970-1992, respectively. The solid blue line and the dashed-dotted red line with a cross display the responses when the domestic component of $\text{TFP}_{adj}^H(t)$ and $\text{TFP}_{adj}^N(t)$ stands at 51% and 67.3% over the period 1993-2017, respectively.

aggregate-TFP driven by asymmetric technology improvements across sectors:

$$\frac{\text{Var}\left(\hat{Z}_D^A(t)\right)}{\text{Var}'\left(\hat{Z}^A(t)\right)} = (\nu^{Y,H})^2 \frac{\text{Var}\left(\hat{Z}^H(t) - \hat{Z}^N(t)\right)}{\text{Var}'\left(\hat{Z}^A(t)\right)}, \quad (49)$$

where $\hat{Z}_D^A(t) = \nu^{Y,H} \left(\hat{Z}^H(t) - \hat{Z}^N(t)\right)$. Using the fact that $\text{Var}\left(\hat{X}(t)\right) = \left[\hat{X}(t) - \hat{X}\right]^2$ where $X = Z^A, Z_S^A, Z_D^A, Z^j$, eq. (49) says that the contribution of asymmetric technology shocks to the variance of technological change is increasing in both the value added share of tradables, $\nu^{H,H}$, and the dispersion in technology improvement between the traded and the non-traded sector. As shown below, by amplifying the asymmetry in technological change between tradables and non-tradables, the growing exposition of traded industries to innovation abroad can rationalize a (significant) fraction of the rise in the share of the variance of technological change driven by asymmetric technology shocks between sectors.

To guide our analysis, we have to specify the production function and the factors driving technological change. Because we are interested in estimating the impact of an increase in the international stock of R&D on utilization-adjusted-sectoral-TFP, we abstract from FBTC and thus assume a Cobb-Douglas production technology by augmenting the production function with the stock of knowledge $Z^j(t)$ which has an impact measured by ν^j on the utilization-adjusted-TFP in sector j , i.e., $Y^j(t) = (Z^j(t))^{\nu^j} (L^j(t))^{\theta^j} \left(\tilde{K}^j(t)\right)^{1-\theta^j}$. The stock of knowledge that sector j uses to improve technology is made up of the domestic stock of R&D, $Z^j(t)$, and an international stock of R&D, $Z^W(t)$. Formally, the aggregate stock of knowledge is a geometric weighted average of the domestic and international stock of knowledge, as described by $Z^j(t) = (Z^j(t))^{\zeta^j} (Z^W(t))^{1-\zeta^j}$ where ζ^j captures the country-specific content of the stock of knowledge while $1 - \zeta^j$ captures its international component. In Online Appendix R.1-R.3, we detail the steps to extend the model laid out in section 3 to endogenous technology decisions in the same spirit as Corhay et al. [2020] where households decide about investment in tangible and intangible assets. In contrast to

the authors, we consider a two-sector model where the stocks of physical capital and R&D are allocated across sectors in accordance to their return.

In this regard, one key parameter is ν^j which measures the impact of 1% increase in the stock of R&D in sector j on utilization-adjusted-TFP in sector j . We have run the regression of the logged utilization-adjusted-TFP in sector j on the logged stock of R&D at constant prices by using cointegration techniques. We find a FMOLS estimate of the long-term relationship of 0.1499 for the traded sector and 0.0007 for the non-traded sector. Both are significant at 5% and 10% level, respectively. Using data from Stehrer et al. [2019] (EU KLEMS database) we construct time series for both gross fixed capital formation and capital stock in R&D in the traded and non-traded sectors. Data are available for thirteen countries over 1995-2017. In estimating ν^j , we implicitly assume that the domestic and the international stock of R&D both produce the same effect on utilization-adjusted-TFP.¹⁷

In Fig. 9(b), we plot the dynamic adjustment of utilization-adjusted-TFP of tradables (displayed by the blue line) and non-tradables (displayed by the red line) following a shock to the international stock of knowledge $Z^W(t)$ which increases the world utilization-adjusted-TFP by 1% in the long-run. Because ν^N is close to zero, a shock to $Z^W(t)$ has no effect on utilization-adjusted-TFP of non-tradables. In contrast, a shock to $Z^W(t)$ increases utilization-adjusted-TFP of tradables by 0.92% at horizon $t = 10$ (dashed blue line) when we set the international component of traded technology to 37% which corresponds to its value over 1970-1992 and by 1.24% at horizon $t = 10$ (solid blue line) when $1 - \eta^H = 49\%$ when we consider the sub-period 1993-2017. As traded industries are more exposed to the international stock of knowledge $Z^W(t)$, a permanent rise in the stock of ideas leads to greater technology improvements in traded industries and importantly amplifies the productivity growth differential between the traded and the non-traded sector.

Once we have estimated by how much utilization-adjusted-TFP increases in sector j when the world utilization-adjusted-TFP increases by 1% in the long-run, we construct artificial time series for utilization-adjusted-TFP predicted by the progression in the world utilization-adjusted-TFP. By using eq. (49), the share of the variance of aggregate technological change driven by asymmetric technological change has increased from 18.7% (over 70-92) to 38.9% in the post-1992 period. As detailed in Online Appendix R.4, we derive a formula to disentangle the share attributable to asymmetric technology improvements into a country-specific and an international components. We find that the share of the variance

¹⁷Because this assumption may be viewed as strong, we have constructed an international stock of knowledge as a (geometric) import-share-weighted-average of trade partners' stock of R&D at constant prices. We find an elasticity of utilization-adjusted-TFP which is smaller at 0.077 for the traded sector and negative for the non-traded sector at -0.002. If we assumed that the domestic and the international stocks of R&D were producing distinct effects on utilization-adjusted-TFP of sector j , then the production function would be modified as follows: $Y^j(t) = (Z^j(t))^{\nu^j \zeta^j} (Z^W(t))^{\nu^j_w (1-\zeta^j)} (L^j(t))^{\theta^j} (\tilde{K}^j(t))^{1-\theta^j}$. To find the value for ν^H_W , we have to divide the estimated value of the coefficient 0.077 by $1 - \eta^H = 0.369$ which leads to $\nu^H_W = 0.209$ which is close to $\nu^j = 0.238$.

of technological change driven by the access to the international stock of ideas has almost tripled, passing from 7.7% before 1992 to 22.1% in the post-1992 period. More specifically, by amplifying the dispersion of technology improvements between the traded and the non-traded sector, the progression of the international stock of ideas and the greater exposition of traded industries to these ideas has led the share of technological change driven by asymmetric technology improvements which are attributable to the progression of the stock of knowledge to increase from 41% to 57%. While the greater exposition to the international stock of ideas does not fully explain the increase in the share of asymmetric technology by 20 ppt, it can account for two-third of this progression, i.e., 14 ppt.

6 Conclusion

In this paper, we investigate the effects of technology improvements on hours worked across time. More specifically, we find that a 1% permanent increase in utilization-adjusted-aggregate-TFP produces a decline in total hours worked which tends to vanishes over time. To rationalize the time-increasing impact response of hours to an improvement in technology, we put forward the contribution of asymmetric technology shocks in driving the variations in utilization-adjusted-aggregate-TFP. We identify asymmetric technology shocks as shocks which increase both utilization-adjusted-aggregate-TFP and utilization-adjusted-TFP of tradables relative to non-tradables while symmetric technology shocks leave the ratio of sectoral technology unaffected. Our evidence reveals that technology shocks which are symmetric across sectors give rise to a dramatic decline in hours worked on impact while asymmetric technology shocks across sectors do the opposite as they significantly increase hours worked. The forecast error variance decomposition on rolling sub-periods shows a gradual increase over time in the share of asymmetric technology shocks in driving technology improvements from 10% to almost 40% over the last thirty years. The growing importance of technology improvements concentrated within traded industries suggests that structural change is responsible for the shrinking contractionary effect of technological change on hours.

To rationalize these evidence, we put forward an open economy model with tradables and non-tradables and shows that four sets of elements are key to generating the magnitude of the decline in hours worked, including barriers to factors' mobility, imperfect substitutability between home- and foreign-produced traded goods, factor-biased technological change and a combination of symmetric and asymmetric technology shocks across sectors. In a model with no frictions to factors' mobility and where home- and foreign-produced traded goods are perfect substitutes, it is optimal to enjoy leisure and consume more by importing more goods from abroad and running a large current account deficit. This results in a dramatic decline in hours worked which considerably overstates the magnitude

that we estimate empirically. Because technology improvements are more pronounced in traded industries, labor (and capital) shifts toward non-traded industries. In a model with factors' mobility frictions, non-traded firms must pay higher wages to encourage workers to shift which puts upward pressure on aggregate wages and thus leads households to mitigate the decline in labor supply. When home- and foreign-produced traded goods are imperfect substitutes, households are more reluctant to substitute foreign- for home-produced traded goods which has a positive impact on the demand for labor in the traded sector and mitigates the decline in hours worked. It is only once we allow for technological change biased toward labor in traded industries (in line with our evidence) that our model can account for the magnitude of the decline in hours worked we estimate empirically.

A fourth key ingredient is that technology improvements are not uniformly distributed across sectors but instead are concentrated within exporting industries. If technological change were evenly spread out across sectors, hours worked would decline by a magnitude which is beyond our SVAR estimates. Intuitively, when technology improves at the same rate across sectors, both sectors cut prices which put downward pressure on wages and results in a dramatic decline in hours worked. Such a decline is concentrated in non-traded industries because non-traded and traded goods are gross complements in consumption and the fall in non-traded good prices shifts labor toward traded industries by driving down the share of non-tradables. On the contrary, when technology improvements are concentrated toward traded industries, non-traded prices appreciate which has an expansionary effect on labor demand in the non-traded sector and puts upward pressure on wages. The positive impact on hours is amplified by technological change biased toward labor. While neither symmetric nor asymmetric technology shocks considered separately can account for the labor effects we estimate empirically, the model can account for the magnitude of the decline in hours once we allow for a mix of both shocks.

When we increase the contribution of asymmetric shocks to technology improvements from 10% to almost 40%, the model can generate the shrinking contractionary effect of a permanent technology improvement on hours we estimate empirically. The baseline model can also account for the time-increasing impact responses of traded and non-traded hours worked and this performance lies in the assumption of FBTC. If we impose Hicks-neutral technological change, the model generates a time-decreasing response of traded hours worked as asymmetric technology shocks have a strong expansionary impact on non-traded labor. It is only once we allow for technological change biased toward labor in the traded sector which neutralizes the incentives to shift labor toward the non-traded sector that the model can account for the time-varying labor effects of a technology shock.

One key question is why technology improvements are increasingly driven by asymmetric technology shocks across sectors over time? By extending our model to endogenous

technology decisions, we find quantitatively that two-thirds of the rise in the variance of aggregate technological change attributable to asymmetric technology improvements between sectors are driven by the greater exposition of traded industries to the international stock of knowledge in the post-1992 period.

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A Response of Total Hours Worked to a Technology Shock across Variants of the RBC Model

In order to have a better understanding of the contribution of each element of our model to the impact response of total hours worked to a permanent technology improvement, we consider several variants of the RBC model, both in closed and open economy, and with one or two sectors.

Households. We assume non-separable preferences between consumption and leisure in the lines of Shimer [2009]:

$$\Lambda \equiv \frac{C^{1-\sigma}V(L)^\sigma - 1}{1-\sigma}, \quad \text{if } \sigma \neq 1, \quad V(L) \equiv \left(1 + (\sigma - 1)\gamma \frac{\sigma_L}{1 + \sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}}\right) \quad (50)$$

and

$$\Lambda \equiv \log C - \gamma \frac{\sigma_L}{1 + \sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}}, \quad \text{if } \sigma = 1. \quad (51)$$

These preferences are characterized by two crucial parameters: σ_L is the Frisch elasticity of labor supply, and $\sigma > 0$ determines the substitutability between consumption and leisure; it is worthwhile noticing that if $\sigma > 1$, the marginal utility of consumption is increasing in hours worked. Such preferences imply that the Frisch elasticity of labor supply is constant.

Households can accumulate internationally traded bonds (expressed in foreign good units), N_t , that yield net interest rate earnings of r^*N_t . Denoting lump-sum taxes by T_t , household's flow budget constraint states that real disposable income (on the RHS of the equation below) can be saved by accumulating traded bonds, consumed, $P_{C,t}C_t$, invested, $P_{J,t}J_t$ or is used to cover adjustment costs of capital utilization:

$$\begin{aligned} \dot{N}_t + P_{C,t}C_t + P_{J,t}J_t + \sum_{j=H,N} P_t^j C_t^{K,j} \nu_t^{K,j} K_t \\ = r^*N_t + W_t L_t - T_t + R_t^K K_t \sum_{j=H,N} \alpha_{K,t}^j u_t^{K,j}, \end{aligned} \quad (52)$$

where we denote the share of sectoral capital in the aggregate capital stock by $\nu_t^{K,j} = K_t^j / K_t$ and the capital compensation share in sector $j = H, N$ by $\alpha_{K,t}^j = \frac{R_t^j K_t^j}{R_t^K K_t}$.

Partial derivatives of (50) w.r.t. C and L read:

$$\Lambda_C = C^{-\sigma} V(L)^\sigma, \quad (53a)$$

$$\Lambda_L = -C^{1-\sigma} \sigma V(L)^{\sigma-1} \gamma L^{\frac{1}{\sigma_L}}, \quad (53b)$$

$$\Lambda_{CL} = -\frac{\Lambda_L (\sigma - 1)}{C}, \quad (53c)$$

where $\Lambda_C = \frac{\partial \Lambda}{\partial C}$ and $\Lambda_L = \frac{\partial \Lambda}{\partial L}$. According to eq. (53c), the marginal utility of consumption is increasing in labor supply as long as $\sigma > 1$, i.e., if consumption and leisure are gross substitutes.

The representative household chooses C_t and L_t so as to maximize his/her lifetime utility with an instantaneous utility given by (50) subject to (52) and $\dot{K}_t = I_t - \delta_K K_t$. Because we are only interested in investigating the role of each ingredient in influencing the impact response of total hours worked, we will restrict ourselves to optimal decisions about consumption and labor supply:

$$\Lambda_C(C_t, L_t) = P_{C,t} \lambda_t, \quad (54a)$$

$$-\Lambda_L(C_t, L_t) = W \lambda_t, \quad (54b)$$

where $\Lambda_C = C^{-\sigma} V(L)^\sigma$ and $-\Lambda_L = C^{1-\sigma} \sigma \gamma L^{1/\sigma_L} V(L)^{\sigma-1}$.

First, eliminating the marginal utility of wealth λ from (54b) by using (54a), i.e., $\lambda = \frac{\Lambda_C}{P_C}$, leads to

$$-\frac{\Lambda_L}{\Lambda_C} = \frac{\sigma}{\sigma - 1} \frac{C V_L}{V} = \frac{W}{P_C},$$

where $V_L = \frac{\partial V(L)}{\partial L} = \gamma L^{\frac{1}{\sigma_L}}$. Rearranging the FOC for consumption (54a), i.e., $C_t = \left(\frac{\Lambda_C}{V^\sigma}\right)^{-\frac{1}{\sigma}}$, and plugging the latter equation into the above equation leads us to rearrange the optimal decision on total hours worked (54b) as follows:

$$\gamma L_t^{\frac{1}{\sigma_L}} = \frac{W_t}{P_{C,t}} \frac{(\Lambda_{C,t})^{\frac{1}{\sigma}}}{\sigma}. \quad (55)$$

Firms. Both the traded and non-traded sectors use physical capital (inclusive of capital utilization), denoted by $\tilde{K}_t^j = u_t^{K,j} K_t^j$, and labor, L^j , according to a constant returns-to-scale technology

described by a CES production function:

$$Y_t^j = \left[\gamma^j \left(A_t^j L_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} + (1-\gamma^j) \left(B_t^j \tilde{K}_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} \right]^{\frac{\sigma^j}{\sigma^j-1}}, \quad (56)$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology, respectively, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, and A_t^j and B_t^j are labor- and capital-augmenting efficiency.

We denote the wage rate and capital rental rate by W^j and R^j which are sector-specific as we allow for labor and capital mobility costs. Because goods and factor markets are perfect competitive and the production function displays constant returns to scale, these assumptions imply that the elasticity of value added w.r.t. labor and capital is equal to the cost of these factors in value added:

$$\frac{\partial Y^j}{\partial L^j} \frac{L^j}{Y^j} = s_L^j, \quad \frac{\partial Y^j}{\partial K^j} \frac{K^j}{Y^j} = 1 - s_L^j, \quad (57)$$

where $s_L^j = \frac{W^j L^j}{P^j Y^j}$ is the labor income share. Dividing the demand for labor by the demand for capital leads to a relationship between the labor income share in sector j and technological change biased toward labor (last term on the RHS):

$$\frac{s_{L,t}^j}{1 - s_{L,t}^j} = \frac{\gamma^j}{1 - \gamma^j} \left(u_t^{K,j} k_t^j \right)^{\frac{1-\sigma^j}{\sigma^j}} \left(\frac{B_t^j}{A_t^j} \right)^{\frac{1-\sigma^j}{\sigma^j}}. \quad (58)$$

When the term $\left(\frac{B_t^j}{A_t^j} \right)^{\frac{1-\sigma^j}{\sigma^j}}$ increases, firms tilt their demand toward labor, thus leading to a rise in the labor income share.

Equilibrium total hours worked. Using the fact $W^j L^j = s_L^j P^j Y^j$ and summing across sectors leads to $\sum_j W^j L^j = \sum_j s_L^j P^j Y^j = WL$. Denoting the aggregate labor income share by s_L , by definition, we have $WL = s_L Y$ where Y is nominal GDP. Making use of this expression to eliminate the wage rate from the labor supply decision and solving leads to the equilibrium level for total hours worked:

$$\gamma L_t^{\frac{1+\sigma_L}{\sigma_L}} = s_{L,t} \frac{Y_t}{P_{C,t}} \frac{(\Lambda_{C,t})^{\frac{1}{\sigma}}}{\sigma}. \quad (59)$$

Eq. (59) corresponds to eq. (8) in the main text. Column 4 of Table 3 shows the impact response of total hours worked for the baseline model (11th row) which is contrasted with the responses for ten versions. Across all variants, we consider a permanent increase in utilization-adjusted-aggregate-TFP by 1% and we assume that technology adjusts instantaneously to its new long-run level.

B Unit Cost for Producing

In this section, we derive the expression for the unit cost for producing.

Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given:

$$\max_{\tilde{K}_t^j, L_t^j} \Pi_t^j = \max_{K_t^j, L_t^j} \left\{ P_t^j Y_t^j - W_t^j L_t^j - R_t^j \tilde{K}_t^j \right\}. \quad (60)$$

Because we assume labor and capital mobility costs, the value of marginal products in the traded and non-traded sectors equalizes while costly labor mobility implies a differential in wage rates and capital rental rates across sectors:

$$P_t^j \gamma^j \left(A_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} \left(L_t^j \right)^{-\frac{1}{\sigma^j}} \left(Y_t^j \right)^{\frac{1}{\sigma^j}} \equiv W_t^j, \quad (61a)$$

$$P_t^j (1 - \gamma^j) \left(B_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} \left(\tilde{k}_t^j \right)^{-\frac{1}{\sigma^j}} \left(y_t^j \right)^{\frac{1}{\sigma^j}} \equiv R_t^j, \quad (61b)$$

where we denote by $\tilde{k}_t^j \equiv \tilde{K}_t^j / L_t^j$ the capital-labor ratio for sector $j = H, N$, and $y_t^j \equiv Y_t^j / L_t^j$ value added per hours worked described by

$$y_t^j = \left[\gamma^j \left(A_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} + (1 - \gamma^j) \left(B_t^j \tilde{k}_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} \right]^{\frac{\sigma^j}{\sigma^j-1}}. \quad (62)$$

Table 3: Impact Response of Total Hours Worked to A Permanent Technology Improvement across Variants of the RBC Model

Model Variants		Tech. Change		Relative Risk		Impact effects			
Variant		HNTC		Aversion		Hours	Wage	Real Wage	Cons.
(1)		vs. FBTC		σ		$\hat{L}(0)$	$\hat{W}(0)$	$\hat{W}_C(0)$	$dC(0)$
		(2)		(3)		(4)	(5)	(6)	(7)
Closed Economy without CAC	1	HNTC		$\sigma = 1$		0.075	0.96	0.96	0.50
Two-Sector Closed Economy without CAC	2	HNTC		$\sigma = 1$		0.110	1.99	1.05	0.53
Small Open Economy (SOE) without CAC	3	HNTC		$\sigma = 1$		-0.492	1.17	1.18	0.92
Small Open Economy (SOE) with CAC	4	HNTC		$\sigma = 1$		-0.418	1.14	1.15	0.87
Two-Sector SOE with PML	5	HNTC		$\sigma = 1$		-0.348	1.83	1.18	0.86
Two-Sector SOE with IML	6	HNTC		$\sigma = 1$		-0.219	2.03	1.17	0.79
Two-Sector SSOE with IML	7	HNTC		$\sigma = 1$		-0.110	0.76	0.93	0.60
Two-Sector SSOE with IML & IMK	8	HNTC		$\sigma = 1$		-0.106	0.82	0.95	0.60
Two-Sector SSOE with IML & IMK	9	FBTC		$\sigma = 1$		-0.096	0.92	1.09	0.68
Two-Sector SSOE with IML & IMK	10	FBTC		$\sigma = 2$		-0.140	1.01	1.11	0.67
Two-Sector SSOE with IML & IMK & Cap Ut	11	FBTC		$\sigma = 2$		-0.130	1.01	1.12	0.67

Notes: Column 1 indicates the variant of the model which is considered. In column 2, we specify whether technological change is Hicks-Neutral (HNTC) or factor-biased (FBTC). Column 3 gives the value of the coefficient of relative risk aversion which collapses to the degree of substitutability between consumption and leisure. Column 4 reports the numerically estimated impact response of total hours worked following a permanent increase in total factor productivity. Columns 5-7 show the responses of the aggregate wage rate, W , of the real consumption wage, W/P_C , and consumption. An increase in the aggregate wage rate or in the real consumption wage has a positive impact on total hours worked by encouraging households to supply more labor through the substitution effect. Because a technology shock produces a positive wealth effect which encourages households to increase both consumption and leisure and thus to reduce labor supply. Note that the impact response of consumption shown in column 7 is measured in percentage point of GDP.

Dividing (87) by (88) leads to a positive relationship between the relative cost of labor and the capital-labor ratio in sector j :

$$\frac{W^j}{R} = \frac{\gamma^j}{1 - \gamma^j} \left(\frac{B^j}{A^j} \right)^{\frac{1 - \sigma^j}{\sigma^j}} \left(\frac{\tilde{K}^j}{L^j} \right)^{\frac{1}{\sigma^j}}, \quad (63)$$

where $\tilde{K}^j = u^{K,j} K^j$. We manipulate (63) To to determine the conditional demands for both inputs:

$$L^j = \tilde{K}^j \left(\frac{\gamma^j}{1 - \gamma^j} \right)^{\sigma^j} \left(\frac{B^j}{A^j} \right)^{1 - \sigma^j} \left(\frac{W^j}{R} \right)^{-\sigma^j}, \quad (64a)$$

$$\tilde{K}^j = L^j \left(\frac{1 - \gamma^j}{\gamma^j} \right)^{\sigma^j} \left(\frac{B^j}{A^j} \right)^{\sigma^j - 1} \left(\frac{W^j}{R} \right)^{\sigma^j}. \quad (64b)$$

Inserting eq. (64a) (eq. (64a) resp.) in the CES production function (56) and solving for L^j (\tilde{K}^j resp.) leads to the conditional demand for labor (capital resp.):

$$\gamma^j (A^j L^j)^{\frac{\sigma^j - 1}{\sigma^j}} = (Y^j)^{\frac{\sigma^j - 1}{\sigma^j}} (\gamma^j)^{\sigma^j} \left(\frac{W^j}{A^j} \right)^{1 - \sigma^j} (X^j)^{-1}, \quad (65a)$$

$$(1 - \gamma^j) (B^j \tilde{K}^j)^{\frac{\sigma^j - 1}{\sigma^j}} = (Y^j)^{\frac{\sigma^j - 1}{\sigma^j}} \left(\frac{R}{B^j} \right)^{\sigma^j} (X^j)^{\frac{\sigma^j}{1 - \sigma^j}}, \quad (65b)$$

where X^j is given by:

$$X^j = (\gamma^j)^{\sigma^j} (A^j)^{\sigma^j - 1} (W^j)^{1 - \sigma^j} + (1 - \gamma^j)^{\sigma^j} (B^j)^{\sigma^j - 1} R^{1 - \sigma^j}. \quad (66)$$

Total cost is equal to the sum of the labor and capital cost:

$$C^j = W^j L^j + R \tilde{K}^j. \quad (67)$$

Inserting conditional demand for inputs (65) into total cost (67), we find that C^j is homogenous of degree one with respect to value added:

$$C^j = c^j Y^j, \quad \text{with} \quad c^j = (X^j)^{\frac{1}{1 - \sigma^j}}, \quad (68)$$

where the unit cost for producing is:

$$c^j = \left[(\gamma^j)^{\sigma^j} \left(\frac{W^j}{A^j} \right)^{1 - \sigma^j} + (1 - \gamma^j)^{\sigma^j} \left(\frac{R}{B^j} \right)^{1 - \sigma^j} \right]^{\frac{1}{1 - \sigma^j}}. \quad (69)$$

C Technology Frontier and FBTC

Following Caselli and Coleman [2006] and Caselli [2016], the menu of possible choices of production functions is represented by a set of possible (A^j, B^j) pairs. These pairs are chosen along the technology frontier which is assumed to take a CES form:

$$\left[\gamma_Z^j (A^j(t))^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} + (1 - \gamma_Z^j) (B^j(t))^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} \right]^{\frac{\sigma_Z^j}{\sigma_Z^j - 1}} \leq Z^j(t), \quad (70)$$

where $Z^j > 0$ is the height of the technology frontier, $0 < \gamma_Z^j < 1$ is the weight of labor efficiency along the technology frontier and $\sigma_Z^j > 0$ corresponds to the elasticity of substitution between labor and capital efficiency. Log-linearizing (70) leads to

$$0 = \gamma_Z^j (A^j(t))^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} \hat{A}^j(t) + (1 - \gamma_Z^j) (B^j(t))^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} \hat{B}^j(t),$$

$$\frac{\hat{B}^j(t)}{\hat{A}^j(t)} = - \frac{\gamma_Z^j}{1 - \gamma_Z^j} \left(\frac{B^j(t)}{A^j(t)} \right)^{\frac{1 - \sigma_Z^j}{\sigma_Z^j}}. \quad (71)$$

Firms choose A^j and B^j along the technology frontier so that minimizes the unit cost function described by (69) subject to (70) which holds as an equality. Differentiating (69) w.r.t. A^j and B^j (while keeping W^j and R^j fixed) leads to:

$$\hat{c}^j(t) = - (\gamma^j)^{\sigma^j} \left(\frac{W^j(t)}{A^j(t)} \right)^{1 - \sigma^j} (c^j(t))^{\sigma^j - 1} \hat{A}^j(t) - (1 - \gamma^j)^{\sigma^j} \left(\frac{R^j(t)}{B^j(t)} \right)^{1 - \sigma^j} (c^j(t))^{\sigma^j - 1} \hat{B}^j(t). \quad (72)$$

Using the fact that $(\gamma^j)^{\sigma^j} \left(\frac{W^j(t)}{A^j(t)} \right)^{1-\sigma^j} (c^j(t))^{\sigma^j-1} = s_L^j(t)$, eq. (72) can be rewritten as $-s_L^j \hat{A}^j(t) - (1 - s_L^j) \hat{B}^j(t) = \hat{c}^j(t)$. Setting this equality to zero and inserting (71) leads to:

$$\frac{\gamma_Z^j}{1 - \gamma_Z^j} \left(\frac{B^j(t)}{A^j(t)} \right)^{\frac{1-\sigma_Z^j}{\sigma_Z^j}} = \frac{s_L^j(t)}{1 - s_L^j(t)} \equiv S^j(t). \quad (73)$$

Solving (73) for s_L^j leads to:

$$s_L^j = \gamma_Z^j \left(\frac{A^j}{Z^j} \right)^{\frac{\sigma_Z^j-1}{\sigma_Z^j}}. \quad (74)$$

Inserting (74) into (71) allows us to rewrite the log-linearized version of the technology frontier as follows:

$$\hat{Z}_t^j = s_L \hat{A}_t^j + (1 - s_L^j) \hat{B}_t^j. \quad (75)$$

Eq. (75) corresponds to eq. (8) in the main text.

D Sectoral Decomposition of Aggregate TFP

We consider an open economy which produces domestic traded goods, denoted by a superscript H , and non-traded goods, denoted by a superscript N . The foreign-produced traded good is the numeraire and its price is normalized to 1. We consider an initial steady-state where prices are those at the base year so that initially real GDP, denoted by Y_R , and the value added share at constant prices, denoted by $\nu^{Y,j}$, collapse to nominal GDP (i.e., Y) and the value added share at current prices, respectively.

Summing value added at constant prices across sectors gives real GDP:

$$Y_{R,t} = P^H Y_t^H + P^N Y_t^N, \quad (76)$$

where P^H and P^N stand for the price of home-produced traded goods and non-traded goods, respectively, which are kept fixed since we consider value added at constant prices.

Log-linearizing (76), and denoting the percentage deviation from initial steady-state by a hat leads to:

$$\hat{Y}_{R,t} = \nu^{Y,H} \hat{Y}_t^H + (1 - \nu^{Y,H}) \hat{Y}_t^N, \quad (77)$$

where $\nu^{Y,H} = \frac{P^H Y^H}{Y}$ is the value added share of home-produced traded goods evaluated at the initial steady-state. We drop the time index below as long as it does not cause confusion.

Sectoral goods are produced from CES production functions (56). Log-linearizing (56) and invoking the property of constant returns to scale together with the assumptions of perfect competition in goods and factor market are perfectly competitive, i.e., inserting eq. (57), leads to:

$$\hat{Y}_t^j = s_L \left(\hat{A}_t^j + \hat{L}_t^j \right) + (1 - s_L^j) \left(\hat{B}_t^j + \hat{u}_t^{K,j} + \hat{K}_t^j \right). \quad (78)$$

We assume that firms choose a mix of labor- and capital-augmenting efficiency, A^j and B^j , along a technology frontier whose height is measured by capital-utilization-TFP. The technology frontier is described by eq. (70). Inserting the log-linearized version of the technology frontier (75) implies that the log-linearized version of the CES production function (78) now reads:

$$\hat{Y}_t^j = \hat{Z}_t^j + s_L \hat{L}_t^j + (1 - s_L^j) \left(\hat{u}_t^{K,j} + \hat{K}_t^j \right). \quad (79)$$

Since TFP growth, $\hat{\text{TFP}}_t^j$, includes both technology improvement \hat{Z}_t^j and the adjustment in capital utilization $(1 - s_L^j) \hat{u}_t^{K,j}$, the change in value added can be rewritten as follows:

$$\hat{Y}_t^j = \hat{\text{TFP}}_t^j + s_L \hat{L}_t^j + (1 - s_L^j) \hat{K}_t^j. \quad (80)$$

Summing capital income and labor income across sectors and denoting the aggregate capital rental rate by R and the aggregate wage rate by W implies:

$$\sum_j W_t^j L_t^j = W_t L_t, \quad (81a)$$

$$\sum_j R_t^j K_t^j = R_t K_t, \quad \sum_j R_t^j \tilde{K}_t^j = R_t \tilde{K}_t, \quad (81b)$$

where $\tilde{K}^j = u^{K,j} K^j$ and $\tilde{K} = u^K K$. Log-linearizing (81a)-(81b) while keeping factor prices constant and dividing by nominal GDP leads to:

$$s_L \hat{L}_t = \sum_j \nu^{Y,j} s_L^j \hat{L}_t^j, \quad (82a)$$

$$(1 - s_L) \hat{K}_t = \sum_j \nu^{Y,j} (1 - s_L^j) \hat{K}_t^j. \quad (82b)$$

Inserting (80) into (77) allows us to rewrite the percentage deviation of real GDP as follows:

$$\hat{Y}_{R,t} = \sum_j \nu^{Y,j} \left[\text{TFP}_t^j + s_L^j \hat{L}_t^j + (1 - s_L^j) \hat{K}_t^j \right]. \quad (83)$$

Making use of (82a) and (82b), eq. (83) can be rewritten in the following form:

$$\hat{Y}_{R,t} = T \hat{F} P_t^A + s_L \hat{L}_t + (1 - s_L^j) \hat{K}_t^j, \quad (84)$$

where

$$T \hat{F} P_t^A = \nu^{Y,H} T \hat{F} P_t^H + (1 - \nu^{Y,H}) T \hat{F} P_t^N. \quad (85)$$

Log-linearizing $\sum_j R_t^j \tilde{K}_t^j = R_t \tilde{K}_t$ w.r.t. $u^{K,j}$ and divided by nominal GDP leads to:

$$(1 - s_L) \hat{u}_t^K = \sum_j (1 - s_L^j) \nu^{Y,j} \hat{u}_t^{K,j}. \quad (86)$$

Inserting the definition of TFP growth

$$T \hat{F} P_t^j = \hat{Z}^j + (1 - s_L^j) \hat{u}_t^{K,j}, \quad (87)$$

and using (86) allows us to rewrite (85) as follows:

$$\hat{Z}^A = \nu^{Y,H} \hat{Z}^H + (1 - \nu^{Y,H}) \hat{Z}^N. \quad (88)$$

E Construction of Time Series for FBTC

In this section, we detail the methodology to construct time series for capital-utilization-adjusted-FBTC in sector $j = H, N$. We choose the initial steady-state in a model with Cobb-Douglas production functions as the normalization point. When we calibrate the model with Cobb-Douglas production functions to the data, the ratios we target are averaged values over 1970-2017.

The starting point is the ratio of the labor to the capital income share in sector j given by eq. (17) which can be solved for capital-utilization-adjusted-FBTC in sector j :

$$\text{FBTC}_t^j \equiv \left(\frac{B_t^j}{A_t^j} \right)^{\frac{1-\sigma^j}{\sigma^j}} = S_t^j \frac{1-\gamma^j}{\gamma^j} (k_t^j)^{-\frac{1-\sigma^j}{\sigma^j}} (u_t^{K,j})^{-\frac{1-\sigma^j}{\sigma^j}}, \quad (89)$$

where $u_t^{K,j}$ is constructed by using the formula (106).

Since we normalize CES production functions so that the relative weight of labor and capital is consistent with the labor and capital income share in the data, solving for γ^j leads to:

$$\gamma^j = \left(\frac{\bar{A}^j}{\bar{y}^j} \right)^{\frac{1-\sigma^j}{\sigma^j}} \bar{s}_L^j, \quad (90a)$$

$$1 - \gamma^j = \left(\frac{\bar{B}^j \bar{u}^{K,j} \bar{k}^j}{\bar{y}^j} \right)^{\frac{1-\sigma^j}{\sigma^j}} (1 - \bar{s}_L^j). \quad (90b)$$

Dividing (90a) by (90b) leads to:

$$\bar{S}^j = \frac{\gamma^j}{1 - \gamma^j} \left(\frac{\bar{B}^j \bar{u}^{K,j} \bar{k}^j}{\bar{A}^j} \right)^{\frac{1-\sigma^j}{\sigma^j}}, \quad (91)$$

where variables with a bar are averaged values of the corresponding variables over 1970-2017.

The methodology adopted to calculate γ^j amounts to using averaged values as the normalization point to compute time series for FBTC. Dividing (89) by (91) yields:

$$\left(\frac{B_t^j / \bar{B}^j}{A_t^j / \bar{A}^j} \right)^{\frac{1-\sigma^j}{\sigma^j}} = \frac{S_t^j}{\bar{S}^j} \left(\frac{k_t^j}{\bar{k}^j} \right)^{-\frac{1-\sigma^j}{\sigma^j}} \left(\frac{u_t^{K,j}}{\bar{u}^{K,j}} \right)^{-\frac{1-\sigma^j}{\sigma^j}}. \quad (92)$$

Eq. (92) corresponds to eq. (6) in the main text. To construct time series for $FTBC_t^j$, we plug estimates for the elasticity of substitution between capital and labor, σ^j , and time series for the ratio of the labor to the capital income share, S_t^j , the capital-labor ratio, k_t^j , and the capital utilization rate, $u_t^{K,j}$, in sector $j = H, N$. Next we divide yearly data by averaged values of the corresponding variable over 1970-2017.

To get estimates of σ^j at a sectoral level, following Antràs [2004], we run the regression of logged real value added per hours worked on the logged real wage in this sector with country-specific linear trends over 1970-2017. Since all variables display unit root process, we use the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000] to estimate the cointegrating relationship. Columns 17 and 18 of Table 7 report estimates for σ^H and σ^N we use to recover FBTC from (92). FMOLS estimated values for the whole sample, i.e., $\sigma^H = 0.81$ and $\sigma^N = 0.87$, reveal that capital and labor are gross complements in both sectors.¹⁸ Once we have values for σ^j , we plug time series for k^j and s_L^j into the RHS of eq. (92) to recover time series for FBTC in sector j .

F Identification of Technology Shocks

In this section we detail the identification strategy of technology shocks.

Empirical identification of technology shocks. To identify a permanent technology improvement, we consider a vector of n observables $\hat{X}_{it} = [\hat{Z}_{it}, \hat{V}_{it}]$ where \hat{Z}_{it} consists of the first difference of the (logarithm of the) utilization-adjusted TFP (as defined in eq. (5)) and \hat{V}_{it} denotes the $n - 1$ variables of interest (in growth rate) detailed later. Let us consider the following reduced form of the VAR(p) model:

$$C(L)\hat{X}_{it} = \eta_{it}, \quad (93)$$

where $C(L) = I_n - \sum_{k=1}^p C_k L^k$ is a p -order lag polynomial and η_{it} is a vector of reduced-form innovations with a variance-covariance matrix given by Σ . We estimate the reduced form of the VAR model by panel OLS regression with country and time fixed effects which are omitted in (98) for expositional convenience. The matrices C_k and Σ are assumed to be invariant across time and countries and all VARs have two lags. The vector of orthogonal structural shocks $\varepsilon_{it} = [\varepsilon_{it}^Z, \varepsilon_{it}^V]$ is related to the vector of reduced form residuals η_{it} through:

$$\eta_{it} = A_0 \varepsilon_{it}, \quad (94)$$

which implies $\Sigma = A_0 A_0'$ with A_0 the matrix that describes the instantaneous effects of structural shocks on observables. The linear mapping between the reduced-form innovations and structural shocks leads to the structural moving average representation of the VAR model:

$$\hat{X}_{it} = B(L)A_0 \varepsilon_{it}, \quad (95)$$

where $B(L) = C(L)^{-1}$. Let us denote $A(L) = B(L)A_0$ with $A(L) = \sum_{k=0}^{\infty} A_k L^k$. To identify a permanent technology improvement, ε_{it}^Z , we use the restriction that the unit root in utilization-adjusted TFP originates exclusively from technology shocks which implies that the upper triangular elements of the long-run cumulative matrix $A(1) = B(1)A_0$ must be zero. Once the reduced form has been estimated using OLS, structural shocks can then be recovered from $\varepsilon_{it} = A(1)^{-1}B(1)\eta_{it}$ where the matrix $A(1)$ is computed as the Cholesky decomposition of $B(1)\Sigma B(1)'$.

G Data Description for Empirical Analysis

Sources: Our primary sources for sectoral data are the OECD and EU KLEMS databases. We use data from EU KLEMS ([2011], [2017]) March 2011 and July 2017 releases. The EU KLEMS dataset covers all countries of our sample, with the exceptions of Canada and Norway. For these two countries, sectoral data are taken from the Structural Analysis (STAN) database provided by the OECD ([2011], [2017]). For both EU KLEMS and STAN databases, the March 2011 release provides data for eleven 1-digit ISIC-rev.3 industries over the period 1970-2007 while the July 2017 release provides data for thirteen 1-digit-rev.4 industries over the period 1995-2017.

The construction of time series for sectoral variables over the period 1970-2017 involves two steps. First, we identify tradable and non-tradable sectors. We adopt the classification proposed by De Gregorio et al. [1994]. Following Jensen and Kletzer [2006], we have updated this classification by treating the financial sector as a traded industry. We map the ISIC-rev.4 classification into the

¹⁸Online Appendices J.6 provide more details about our empirical strategy to estimate σ^j . All FMOLS estimated coefficients are positive and statistically significant except the estimated value for σ^H for Ireland which is negative. As in Antràs [2004], we alternatively run the regression of the ratio of value added to capital stock at constant prices on the real capital cost R/P^j in sector j and replace the inconsistent estimate for σ^H obtained from labor demand with that obtained from the demand of capital.

Table 4: Sample Range for Empirical and Numerical Analysis

Country	Code	Period	Obs.
Australia	(AUS)	1970 - 2017	48
Austria	(AUT)	1970 - 2017	48
Belgium	(BEL)	1970 - 2017	48
Canada	(CAN)	1970 - 2017	48
Germany	(DEU)	1970 - 2017	48
Denmark	(DNK)	1970 - 2017	48
Spain	(ESP)	1970 - 2017	48
Finland	(FIN)	1970 - 2017	48
France	(FRA)	1970 - 2017	48
Great Britain	(GBR)	1970 - 2017	48
Ireland	(IRL)	1970 - 2017	48
Italy	(ITA)	1970 - 2017	48
Japan	(JPN)	1974 - 2017	44
Netherlands	(NLD)	1970 - 2017	48
Norway	(NOR)	1970 - 2017	48
Sweden	(SWE)	1970 - 2017	48
United States	(USA)	1970 - 2017	48
Total number of obs.			812
Main data sources		EU KLEMS & OECD STAN	

Notes: Column 'period' gives the first and last observation available. Obs. refers to the number of observations available for each country.

ISIC-rev.3 classification in accordance with the concordance Table 5. Once industries have been classified as traded or non-traded, for any macroeconomic variable X , its sectoral counterpart X^j for $j = H, N$ is constructed by adding the X_k of all sub-industries k classified in sector $j = H, N$ as follows $X^j = \sum_{k \in j} X_k$. Second, series for tradables and non-tradables variables from EU KLEMS [2011] and OECD [2011] databases (available over the period 1970-2007) are extended forward up to 2017 using annual growth rate estimated from EU KLEMS [2017] and OECD [2017] series (available over the period 1995-2017).

Table 5: Summary of Sectoral Classifications

Sector	ISIC-rev.4 Classification (sources: EU KLEMS [2017] and OECD ([2017]))		ISIC-rev.3 Classification (sources: EU KLEMS [2011] and OECD ([2011]))	
	Industry	Code	Industry	Code
Tradables (H)	Agriculture, Forestry and Fishing	A	Agriculture, Hunting, Forestry and Fishing	AtB
	Mining and Quarrying	B	Mining and Quarrying	C
	Total Manufacturing	C	Total Manufacturing	D
	Transport and Storage	H	Transport, Storage and Communication	I
	Information and Communication	J		
	Financial and Insurance Activities	K	Financial Intermediation	J
Non Tradables (N)	Electricity, Gas and Water Supply	D-E	Electricity, Gas and Water Supply	E
	Construction	F	Construction	F
	Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles	G	Wholesale and Retail Trade	G
	Accommodation and Food Service Activities	I	Hotels and Restaurants	H
	Real Estate Activities	L	Real Estate, Renting and Business Services	K
	Professional, Scientific, Technical, Administrative and Support Service Activities	M-N		
	Community Social and Personal Services	O-U	Community Social and Personal Services	LtQ

Construction of sectoral variables. Once industries have been classified as traded or non-traded, we construct sectoral variables by taking time series from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. These two databases provide data, for each industry and year, on value added at current and constant prices, permitting the construction of sectoral deflators of value added, as well as details on labor compensation and hours worked data, allowing the construction of sectoral wage rates. Time and countries are indexed by subscripts i and t below while the sector is indexed by the superscript $j = H, N$.

All quantity variables are scaled by the working age population (15-64 years old). Source: OECD ALFS Database for the working age population (data coverage: 1970-2017). We describe below the construction for the sectoral data employed in the main text (mnemonics are given in parentheses):

- **Sectoral value added**, Y_{it}^j : sectoral value added at constant prices in sector $j = H, N$ (VA_QI). Series for sectoral value added in current (constant) prices are constructed by adding

value added in current (constant) prices for all sub-industries k in sector $j = H, N$, i.e., $P_{it}^j Y_{it}^j = \sum_k P_{k,it}^j Y_{k,it}^j$ ($\bar{P}_{it}^j Y_{it}^j = \sum_k \bar{P}_{k,it}^j Y_{k,it}^j$ where the bar indicates that prices P^j are those of the base year), from which we construct price indices (or sectoral value added deflators), P_{it}^j . Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

- **Sectoral value added share**, $\nu_{it}^{Y,j}$, is constructed as the ratio of value added at constant prices in sector j to GDP at constant prices, i.e., $Y_{it}^j / (Y_{it}^H + Y_{it}^N)$ for $j = H, N$.
- **Relative price of non-tradables**, P_{it} . Normalizing base year price indices \bar{P}^j to 1, the relative price of non-tradables, P_{it} , is constructed as the ratio of the non-traded value added deflator to the traded value added deflator (i.e., $P_{it} = P_{it}^N / P_{it}^H$). The sectoral value added deflator P_{it}^j for sector $j = H, N$ is calculated by dividing value added at current prices (VA) by value added at constant prices (VA_QI) in sector j . Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Terms of trade**, $TOT_{it} = P_{it}^H / P_{it}^{H,*}$, is computed as the ratio of the traded value added deflator of the home country i , P_{it}^H , to the geometric average of the traded value added deflator of the seventeen trade partners of the corresponding country i , $P_{it}^{H,*}$, the weight being equal to the share $\alpha_i^{M,k}$ of imports from the trade partner k . We use the traded value added deflator to approximate foreign prices as it corresponds to a value-added concept. The Direction of Trade Statistics (DOTS, IMF) gives the share of imports $\alpha_i^{M,k}$ of country i by trade partner k for all countries of our sample over 1970-2017. The traded value added deflator P_{it}^H is calculated by dividing value added at current prices (VA) by value added at constant prices (VA_QI) in sector H . Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) for P^H . Prices of foreign goods and services are calculated as follows: $P_{it}^{H,*} = \prod_{k \neq i} \left(P_{it}^{H,k} \right)^{\alpha_i^{M,k}}$. While the seventeen trade partners of a representative home country do not fully account for the totality of trade between country i and its trade partners $k \neq i$, it covers 58% of total trade on average for a representative OECD country of our sample. Source: Direction of Trade Statistics [2017]. Period: 1970-2017 for all countries except for Belgium (1997-2017).
- **Sectoral hours worked**, L_{it}^j , correspond to hours worked by persons engaged in sector j (H.EMP). Likewise sectoral value added, sectoral hours worked are constructed by adding hours worked for all sub-industries k in sector $j = H, N$, i.e., $L_{it}^j = \sum_k L_{k,it}^j$. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Sectoral labor share**, $\nu_{it}^{L,j}$, is constructed as the ratio of hours worked in sector j to total hours worked, i.e., $L_{it}^j / (L_{it}^H + L_{it}^N)$ for $j = H, N$.
- **Sectoral nominal wage**, W_{it}^j is calculated as the ratio of the labor compensation (compensation of employees plus compensation of self-employed) in sector $j = H, N$ (LAB) to total hours worked by persons engaged (H.EMP) in that sector. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Relative wage**, W_{it}^j / W_{it} , is constructed as the ratio of the nominal wage in the sector j to the aggregate nominal wage W .
- **Labor income share (LIS)**, $s_{L,it}^j$, is constructed as the ratio of labor compensation (compensation of employees plus compensation of self-employed) in sector $j = H, N$ (LAB) to value added at current prices (VA) of that sector. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

We detail below the data construction for aggregate variables (mnemonics are in parentheses). For all variables, the reference period is running from 1970 to 2017:

- **Real gross domestic product**, $Y_{R,it}$, is the sum of traded and non-traded value added at constant prices. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Total hours worked**, L_{it} , are total hours worked by persons engaged (H.EMP). By construction, total hours worked is the sum of traded and non-traded hours worked. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.
- **Real consumption wage**, $W_{C,it} = W_{it} / P_{C,it}$, is constructed as the nominal aggregate wage divided by the consumer price index (CPI). Source: OECD Prices and Purchasing Power Parities Database [2017] for the consumer price index. The nominal aggregate wage is calculated by dividing labor compensation (LAB) by total hours worked by persons engaged (H.EMP). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

- **Aggregate total factor productivity**, TFP_{it} , is constructed as the Solow residual from constant-price domestic currency series of GDP, capital, LIS $s_{L,i}$, and total hours worked. In Appendix D, we detail the procedure to construct time series for the aggregate capital stock. The aggregate LIS, $s_{L,i}$, is the ratio of labor compensation (compensation of employees plus compensation of self-employed) (LAB) to GDP at current prices (VA) in sector averaged over the period 1970-2017 (except Japan: 1974-2017). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

H Construction of Utilization-Adjusted-TFP Time Series at a Sectoral Level

We construct time-varying capital utilization series using the procedure discussed in Imbs [1999] to construct our own series of utilization-adjusted TFP. We assume perfectly competitive factor and product markets; We also abstract from capital adjustment costs and capital mobility costs across sectors. Both the traded and non-traded sectors use physical capital, K^j , and labor, L^j , according to constant returns to scale production functions which are assumed to take a CES form:

$$Y_t^j = \left[\gamma^j \left(A_t^j L_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} + (1-\gamma^j) \left(B_t^j u_t^{K,j} K_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} \right]^{\frac{\sigma^j}{\sigma^j-1}}. \quad (96)$$

We denote the capital utilization rate by $u_t^{K,j}$. Because more intensive capital use depreciates the capital more rapidly, we assume the following relationship between capital use and depreciation:

$$\delta_{K,t}^j = \delta_K \left(u_t^{K,j} \right)^{\phi_K}, \quad (97)$$

where δ_K is the capital depreciation rate and ϕ_K is the parameter which must be determined. At the steady-state, we have $u^{K,j} = 1$ and thus capital depreciation collapses to δ_K which is assumed to be symmetric across sectors. Firms also choose A^j and B^j along the technology frontier that we assume to be Cobb-Douglas without loss of generality:

$$Z_t^j = \left(A_t^j \right)^{s_{L,t}^j} \left(B_t^j \right)^{1-s_{L,t}^j}. \quad (98)$$

While in the main text, we assume that the technology frontier is CES and above we assume it is Cobb-Douglas, it leads to the same outcome, i.e., $\hat{Z}_t^j = s_L^j \hat{A}_t^j + (1-s_L^j) \hat{B}_t^j$.

Denoting the capital rental cost by $R_t = P_{J,t} (\delta_{K,t} + r^*)$, and the labor cost by W_t^j , firms choose the capital stock, capital utilization and labor so as the maximize profit:

$$\Pi_t^j = P_t^j Y_t^j - W_t^j L_t^j - R_t K_t^j. \quad (99)$$

Profit maximization leads to first order conditions on K^j , $u^{K,j}$, L^j :

$$P_t^j (1-\gamma^j) \left(B_t^j u_t^{K,j} \right)^{\frac{\sigma^j-1}{\sigma^j}} \left(K_t^j \right)^{-\frac{1}{\sigma^j}} \left(Y_t^j \right)^{\frac{1}{\sigma^j}} = R_t, \quad (100a)$$

$$P_t^j (1-\gamma^j) \left(B_t^j K_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} \left(u_t^{K,j} \right)^{-\frac{1}{\sigma^j}} \left(Y_t^j \right)^{\frac{1}{\sigma^j}} = P_{J,t} \delta_K \phi_K \left(u_t^{K,j} \right)^{\phi_K-1} K^j, \quad (100b)$$

$$P_t^j \gamma^j \left(A_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} \left(L_t^j \right)^{-\frac{1}{\sigma^j}} \left(Y_t^j \right)^{\frac{1}{\sigma^j}} = W_t^j. \quad (100c)$$

Multiplying both sides of the first equality by K^j and dividing by sectoral value added leads to the capital income share:

$$1 - s_{L,t}^j = (1-\gamma^j) \left(\frac{B_t^j u_t^{K,j} K_t^j}{Y_t^j} \right)^{\frac{\sigma^j-1}{\sigma^j}}. \quad (101)$$

By using the definition of the capital income share above and inserting the expression for the capital rental cost, first-order conditions can be rewritten as follows:

$$(1-s_L^j) \frac{P_t^j Y_t^j}{P_{J,t} K_t^j} = (\delta_{K,t} + r^*), \quad (102a)$$

$$(1-s_L^j) \frac{P_t^j Y_t^j}{P_{J,t} K_t^j} = \delta_{K,t} \phi_K, \quad (102b)$$

$$s_{L,t}^j \frac{P_t^j Y_t^j}{L_t^j} = W_t^j. \quad (102c)$$

Evaluating (102a) and (102b) at the steady-state and rearranging terms leads to:

$$(r^* + \delta_K) = \delta_K \phi_K, \quad (103)$$

which allows us to pin down ϕ_K . We let the capital depreciation rate δ_K and the real interest rate r^* (long-run interest rate minus CPI inflation rate) vary across countries to compute ϕ_K .

In the line of Garofalo and Yamarik [2002], we use the value added share at current prices to allocate the aggregate capital stock to sector j :

$$K_t^j = \omega_t^{Y,j} K_t, \quad (104)$$

where K_t is the aggregate capital stock at constant prices and $\omega_t^{Y,j} = \frac{P_t^j Y_t^j}{P_t Y_{R,t}}$ is the value added share of sector $j = H, N$ at current prices. The methodology by Garofalo and Yamarik [2002] is based on the assumption of perfect mobility of capital across sectors and a small discrepancy in the LIS across sectors, i.e., $s_L^H \simeq s_L^N$. Inserting (104) into (102a)-(102b), first order conditions on K^j and $u^{K,j}$ now read as follows:

$$\left(1 - s_{L,t}^j\right) \frac{P_t Y_{R,t}}{P_{J,t} K_t} = (\delta_{K,t} + r^*), \quad (105a)$$

$$\left(1 - s_{L,t}^j\right) \frac{P_t Y_{R,t}}{P_{J,t} K_t} = \delta_{K,t} \phi_K. \quad (105b)$$

Solving (105b) for $u_t^{K,j}$ leads to:

$$u_t^{K,j} = \left[\frac{\left(1 - s_{L,t}^j\right) \frac{P_t Y_{R,t}}{P_{J,t} K_t}}{\delta_K \phi_K} \right]^{\frac{1}{\phi_K}}, \quad (106)$$

where $\phi_K = \frac{r^* + \delta_K}{\delta_K}$ (see eq. (103)). Dropping the time index to denote the steady-state value, the capital utilization rate is:

$$u^{K,j} = \left[\frac{\left(1 - s_L^j\right) \frac{P Y_R}{P_J K}}{\delta_K \phi_K} \right]^{\frac{1}{\phi_K}}. \quad (107)$$

Dividing (106) by (107) leads to the capital utilization rate relative to its steady-state:

$$\frac{u_t^{K,j}}{u^{K,j}} = \left[\frac{\left(1 - s_{L,t}^j\right) \frac{P_t Y_{R,t}}{P_{J,t} K_t}}{\left(1 - s_L^j\right) \frac{P Y_R}{P_J K}} \right]^{\frac{1}{\phi_K}}, \quad (108)$$

We denote total factor productivity in sector $j = H, N$ by TFP^j which is defined as follows:

$$\text{TFP}_t^j = \frac{Y_t^j}{\left[\gamma^j \left(L_t^j\right)^{\frac{\sigma^j - 1}{\sigma^j}} + (1 - \gamma^j) \left(K_t^j\right)^{\frac{\sigma^j - 1}{\sigma^j}} \right]^{\frac{\sigma^j}{\sigma^j - 1}}}. \quad (109)$$

Log-linearizing (109), the Solow residual is:

$$T\hat{F}P_t^j = \hat{Y}_t^j - s_L^j \hat{L}_t^j - \left(1 - s_L^j\right) \hat{K}_t^j. \quad (110)$$

Log-linearizing the production function (96) shows that the Solow residual can alternatively be decomposed into utilization-adjusted TFP and capital utilization correction:

$$T\hat{F}P_t^j = \hat{Z}_t^j + \left(1 - s_L^j\right) \hat{u}_t^{K,j}, \quad (111)$$

where utilization-adjusted TFP denoted by Z^j is equal to:

$$\hat{Z}_t^j = s_L^j \hat{A}_t^j + \left(1 - s_L^j\right) \hat{B}_t^j. \quad (112)$$

Construction of time series for sectoral capital stock, K_t^j . To construct the series for the sectoral capital stock, we proceed as follows. We first construct time series for the aggregate capital stock for each country in our sample. To construct K_t , we adopt the perpetual inventory approach. The inputs necessary to construct the capital stock series are a i) capital stock at the beginning of the investment series, K_{1970} , ii) a value for the constant depreciation rate, δ_K , iii) real

gross capital formation series, I_t . Real gross capital formation is obtained from OECD National Accounts Database [2017] (data in millions of national currency, constant prices). We construct the series for the capital stock using the law of motion for capital in the model:

$$K_{t+1} = I_t + (1 - \delta_K) K_t. \quad (113)$$

for $t = 1971, \dots, 2017$. The value of δ_K is chosen to be consistent with the ratio of capital depreciation to GDP observed in the data and averaged over 1970-2017:

$$\frac{1}{46} \sum_{t=1970}^{2017} \frac{\delta_K P_{J,t} K_t}{Y_t} = \frac{CFC}{Y}, \quad (114)$$

where $P_{J,t}$ is the deflator of gross capital formation series, Y_t is GDP at current prices, and CFC/Y is the ratio of consumption of fixed capital at current prices to nominal GDP averaged over 1970-2017. Deflator of gross capital formation, GDP at current prices and consumption of fixed capital are taken from the OECD National Account Database [2017]. The second column of Table 6 shows the value of the capital depreciation rate obtained by using the formula (114). The capital depreciation rate averages to 5%.

To have data on the capital stock at the beginning of the investment series, we use the following formula:

$$K_{1970} = \frac{I_{1970}}{g_I + \delta_K}, \quad (115)$$

where I_{1970} corresponds to the real gross capital formation in the base year 1970, g_I is the average growth rate from 1970 to 2017 of the real gross capital formation series. The system of equations (113), (114) and (115) allows us to use data on investment to solve for the sequence of capital stocks and for the depreciation rate, δ_K . There are 47 unknowns: K_{1970} , δ_K , K_{1971} , \dots , and K_{2017} , in 47 equations: 45 equations (113), where $t = 1971, \dots, 2017$, (114), and (115). Solving this system of equations, we obtain the sequence of capital stocks and a calibrated value for depreciation, δ_K . Following Garofalo and Yamarik [2002], the gross capital stock is then allocated to traded and non-traded industries by using the sectoral value added share, see eq. (104).

Construction of time series for sectoral TFPs. Sectoral TFPs, TFP_t^j , at time t are constructed as Solow residuals from constant-price (domestic currency) series of value added, Y_t^j , capital stock, K_t^j , and hours worked, L_t^j , by using eq. (110). The LIS in sector j , s_L^j , is the ratio labor compensation (compensation of employees plus compensation of self-employed) to nominal value added in sector $j = H, N$, averaged over the period 1970-2017 (except Japan: 1974-2017). Data for the series of constant price value added (VA_QI), current price value added (VA), hours worked (H_EMP) and labor compensation (LAB) are taken from the EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

Construction of time series for real interest rate, r^* . The real interest rate is computed as the real long-term interest rate which is the nominal interest rate on 10 years government bonds minus the rate of inflation which is the rate of change of the Consumption Price Index (CPI). Sources: OECD Economic Outlook Database [2017] for the long-term interest rate on government bonds and OECD Prices and Purchasing Power Parities Database [2017] for the CPI. Data coverage: 1970-2017 except for IRL (1990-2017) and KOR (1983-2017). The first column of Table 6 shows the value of the real interest rate which averages 3% over the period 1970-2017.

Construction of time series for capital utilization, $u_t^{K,j}$. To construct time series for the capital utilization rate, $u_t^{K,j}$, we proceed as follows. We use time series for the real interest rate, r^* and for the capital depreciation rate, δ_K to compute $\phi = \frac{r^* + \delta_K}{\delta_K}$ (see eq. (103)). Once we have calculated ϕ for each country, we use time series for the LIS in sector j , s_L^j , GDP at current prices, $P_t Y_{R,t} = Y_t$, the deflator for investment, $P_{J,t}$, and times series for the aggregate capital stock, K_t to compute time series for $u_t^{K,j}$ by using the formula (106).

Construction of time series for utilization-adjusted TFP, Z_t^j . According to (111), capital utilization-adjusted sectoral TFP expressed in percentage deviation relative to the steady-state reads:

$$\begin{aligned} \hat{Z}_t^j &= \hat{TFP}_t^j - \left(1 - s_L^j\right) \hat{u}_t^{K,j}, \\ \ln Z_t^j - \ln \bar{Z}_t^j &= \left(\ln TFP_t^j - \ln \bar{TFP}_t^j\right) - \left(1 - s_L^j\right) \left(\ln u_t^{K,j} - \ln \bar{u}_t^{K,j}\right). \end{aligned} \quad (116)$$

The percentage deviation of variable X_t from initial steady-state is denoted by $\hat{X}_t = \ln X_t - \ln \bar{X}_t$ where we let the steady-state varies over time; the time-varying trend $\ln \bar{X}_t$ is obtained by applying a HP filter with a smoothing parameter of 100 to logged time series. To compute $T\hat{F}P_t^j$, we take the log of TFP_t^j and subtract the trend component extracted from a HP filter applied to logged TFP_t^j ,

Table 6: Data on Real Interest Rate (r^*) and Fixed Capital Depreciation Rate (δ_K)

Country	r^*	δ_K
AUS	0.028	0.058
AUT	0.029	0.040
BEL	0.031	0.041
CAN	0.031	0.100
DEU	0.022	0.062
DNK	0.044	0.036
ESP	0.020	0.048
FIN	0.024	0.043
FRA	0.031	0.031
GBR	0.023	0.042
IRL	0.033	0.029
ITA	0.025	0.050
JPN	0.017	0.061
NLD	0.028	0.035
NOR	0.025	0.102
SWE	0.029	0.038
USA	0.025	0.026
OECD	0.027	0.050

i.e., $\ln \text{TFP}_t^j - \ln \bar{\text{TFP}}_t^j$. The same logic applies to $u_t^{K,j}$. Once we have computed the percentage deviation $\ln Z_t^j - \ln \bar{Z}_t^j$, we reconstruct time series for $\ln Z_t^j$:

$$\ln Z_t^j = \left(\ln Z_t^j - \ln \bar{Z}_t^j \right) + \ln \bar{Z}_t^j. \quad (117)$$

The construction of time series of logged sectoral TFP, $\ln \text{TFP}_t^j$, capital utilization-adjusted sectoral TFP, $\ln Z_t^j$, is consistent with the movement of capital utilization along the business cycle.

I Construction of Non-Traded Demand Components

In this section, we detail the construction of time series for non-traded government consumption, G_t^N , non-traded consumption, C_t^N , and non-traded investment, J_t^N . We use the World Input-Output Databases ([2013], [2016]). The 2013 release provides data for eleven 1-digit ISIC-rev.3 industries over the period 1995-2011 while the 2016 release provides data for thirteen 1-digit-rev.4 industries over the period 2000-2014. As sectoral data are classified using identical ISIC revisions in both the EU KLEMS and WIOD datasets, we map the WIOD ISIC-rev.4 classification (the 2016 release) into the WIOD ISIC-rev.3 classification (the 2013 release) in accordance with the concordance Table 5. Consistent with the methodology we used to extend series taken from the EU KLEMS ([2011], [2017]), time series for traded and non-traded variables from the WIOD [2013] dataset (available over the period 1995-2011) are extended forward up to 2014 using annual growth rate estimated from WIOD [2016] series (available over the period 2000-2014). Coverage: 1995-2014 except for NOR (2000-2014).

To compute non-traded demand components, we have to overcome two difficulties. While the input-output WIOD dataset gives purchases of non-traded goods and services from the private sector, data also includes purchases of imported goods and services. Whereas consumption and investment expenditure can be split into traded and non-traded expenditure, this split does not exist for government spending for most of the countries in our sample. We detail below how we overcome the two aforementioned difficulties.

To begin with, the non traded and the home-produced traded goods markets must clear such that:

$$Y^N = C^N + J^N + G^N + X^N - M^N, \quad (118a)$$

$$Y^H = C^H + J^H + G^H + X^H - M^H, \quad (118b)$$

where Y^j is value added at constant prices in sector $j = H, N$, C^j consumption in good j , J^j investment in good j , G^j government consumption in good j and X^j stands for exports. Imports (by households, firms, and the government) in good j denoted by M^j can be broken into three components:

$$M^N = C^{N,F} + J^{N,F} + G^{N,F}, \quad (119a)$$

$$M^H = C^{H,F} + J^{H,F} + G^{H,F}, \quad (119b)$$

where $C^{H,F}$, $J^{H,F}$ and $G^{H,F}$ are foreign-produced traded good for consumption, investment and government spending respectively, and $C^{N,F}$, $J^{N,F}$ and $G^{N,F}$ denote consumption, investment and government spending domestic demand for non-traded goods produced by the rest of the world respectively. Next, each demand component C^j , J^j , G^j of sector $j = H, N$ can be split into a domestic demand for home-produced good (denoted by $C^{j,D}$, $J^{j,D}$, $G^{j,D}$) and a domestic demand for foreign-produced good (denoted by $C^{j,F}$, $J^{j,F}$, $G^{j,F}$) by the rest of the world. This decomposition yields the following identities:

$$C^N = C^{N,D} + C^{N,F}, \quad (120a)$$

$$J^N = J^{N,D} + J^{N,F}, \quad (120b)$$

$$G^N = G^{N,D} + G^{N,F}, \quad (120c)$$

$$C^H = C^{H,D} + C^{H,F}, \quad (120d)$$

$$J^H = J^{H,D} + J^{H,F}, \quad (120e)$$

$$G^H = G^{H,D} + G^{H,F}. \quad (120f)$$

We denote total imports by M which consist of imports of consumption goods by households and the government and imports of capital goods by firms:

$$M = M^N + M^H. \quad (121)$$

Total exports to the rest of the world include exports of non-traded and traded goods:

$$X = X^N + X^H. \quad (122)$$

Obviously, we are aware that non-traded goods are not subject to international trade but we use this terminology to avoid confusion between the model's annotations and the data.

Combining (118a) and (118b) and using (121)-(122) leads to the standard accounting identity between the sum of sectoral value added and final expenditure:

$$\begin{aligned} P^H Y^H + P^N Y^N &= P_C C + P_J J + G + P_X X - P_M M, \\ Y &= P_C C + P_J J + G + N X, \end{aligned} \quad (123)$$

where we normalize P_G to one in (123) to be consistent with the model's annotations. Dividing (123) by GDP implies that consumption expenditure, investment expenditure, government spending, and net exports as a share of GDP must sum to one:

$$1 = \omega_C + \omega_J + \omega_G + \omega_{NX}. \quad (124)$$

We focus first on components of government spending. We use the accounting identity (118a) to compute time series for G^N :

$$P^N G^N = P^N Y^N - P^N C^N - P^N J^N - P^N X^N + P^N M^N \quad (125)$$

We divide both sides by nominal GDP, i.e., $P^H Y^H + P^N Y^N = Y$. The LHS of eq. (125) divided by nominal GDP reads:

$$\begin{aligned} \frac{P^N G^N}{Y} &= \frac{P^N G^N}{G} \frac{G}{Y}, \\ &= \omega_{G^N} \omega_G. \end{aligned} \quad (126)$$

Making use of (125)-(126), we can calculate time series for ω_{G^N} as follows:

$$\omega_{G^N} = \frac{1}{\omega_G} \left[\frac{P^N Y^N}{Y} - \frac{P^N C^N - P^N J^N - P^N X^N + P^N M^N}{Y} \right]. \quad (127)$$

While in the model, we assume that non-traded industries do not trade with the rest of the world, the definition of a non-traded industry in the data is based on an arbitrary rule. Industries whose the sum of exports plus imports in percentage of GDP is lower than 20% are treated as non-tradables; since these industries trade, we have to split G^N into $G^{N,D}$ and $G^{N,F}$ so as to calculate time series for $\omega_{G^{N,D}}$. According to (119a), total imports of non-traded goods and services include imports by households, firms and the government, i.e., $M^N = C^{N,F} + J^{N,F} + G^{N,F}$. Thus, $G^{N,F} = M^N - C^{N,F} - J^{N,F}$, from which we get $\omega_{G^{N,F}} = G^{N,F}/G$. By using (120c), $G^{N,D}$ can be computed as $G^{N,D} = G^N - G^{N,F}$. This allows us to recover the share of non-traded government consumption which excludes imports: $\omega_{G^{N,D}} = \omega_{G^N} - \omega_{G^{N,F}}$. Next, government spending on foreign-produced traded goods $G^{H,F}$ can be calculated by using the definition of imports of final traded goods and

services: $M^F = C^{H,F} + J^{H,F} + G^{H,F}$, where $C^{H,F}$ and $J^{H,F}$ are consumption and investment in home-produced traded goods. Rearranging the last equation give $G^{H,F} = M^H - C^{H,F} - J^{H,F}$. It follows that $\omega_{G^{H,F}} = G^{H,F}/G$. Once we have time series for $G^{N,D}$, $G^{N,F}$, $G^{H,F}$, we can recover time series for government spending in home-produced traded goods, $G^{H,D}$ by using the accounting identity which says that total government spending is equal to the sum of four components: $G = G^{N,D} + G^{N,F} + G^{H,D} + G^{H,F}$. Dividing both sides by G gives:

$$\begin{aligned} 1 &= \omega_{G^{N,D}} + \omega_{G^{N,F}} + \omega_{G^{H,F}} + \omega_{G^{H,D}}, \\ 1 &= \omega_{G^{N,D}} + \omega_{G^F} + \omega_{G^{H,D}}, \\ \omega_{G^{H,D}} &= 1 - \omega_{G^{N,D}} - \omega_{G^F}, \end{aligned} \quad (128)$$

where $\omega_{G^{N,F}} + \omega_{G^{H,F}} = \omega_{G^F}$ is the import content of government spending

Since data taken from WIOD allows to differentiate between domestic demand for home- and foreign-produced goods, we are able to construct time series for the home content of consumption and investment in traded goods as follows:

$$\alpha^H = \frac{P^H C^{H,D}}{P^T C^T} = \frac{(P^T C^T - C^{H,F})}{P^T C^T}, \quad (129a)$$

$$\alpha_J^H = \frac{P^H J^{H,D}}{P_J^T J^T} = \frac{(P_J^T J^T - J^{H,F})}{P_J^T J^T}. \quad (129b)$$

To compute time series for non-traded consumption, $C^{N,D}$, and non-traded investment, $J^{N,D}$, we make use of imports of final consumption and investment goods, and then we divide by total consumption and investment expenditure, respectively, to obtain their non-tradable content:

$$1 - \alpha_C = \frac{P^N C^{N,D}}{P_C C} = \frac{P^N (C^N - C^{N,F})}{P_C C}, \quad (130a)$$

$$1 - \alpha_J = \frac{P^N J^{N,D}}{P_J J} = \frac{P^N (J^N - J^{N,F})}{P_J J}. \quad (130b)$$

We obtain data on GDP and its demand components (consumption, investment, government spending, exports and imports) from the World Input-Output Databases ([2013], [2016]) for all years between 1995 and 2014 and all 1-digit ISIC rev.3 and rev.4 industries. Indexing the sector with a superscript $j = H, N$ and indexing the origin of demand of goods and services with a superscript $k = D, F$ where D refers to domestic demand of home-produced goods and services and F refers to domestic demand of foreign-produced goods and services, we provide below details about data construction:

- Consumption $C^{j,k}$ for $j = H, N$ and $k = D, F$: total consumption expenditure (at current prices) by households and by non-profit organizations serving households on good j produced by firms from country k . Data coverage: 1995-2014 except for NOR (2000-2014).
- Investment $I^{j,k}$ for $j = H, N$ and $k = D, F$: total gross fixed capital formation plus changes in inventories and valuables (at current prices) on good j produced by firms from country k . Data coverage: 1995-2014 except for NOR (2000-2014).
- Government spending $G^{j,k}$ for $j = H, N$ and $k = D, F$: total consumption expenditure (at current prices) by government on good j produced by firms from country k . Data coverage: 1995-2014 except for NOR (2000-2014).
- Exports $X^{j,k}$ for $j = H, N$ and $k = D, F$: total exports (at current prices) of final and intermediate good j produced by firms from country k . Data coverage: 1995-2014 except for NOR (2000-2014).
- Imports $M^{j,k}$ for $j = H, N$ and $k = D, F$: total imports (at current prices) of final and intermediate good j produced by firms from country k . Data coverage: 1995-2014 except for NOR (2000-2014).

Finally, when we use (125) to obtain the time series for G^N , the valuation of output Y^N and imports M^N include taxes and subsidies on products and trade and transport margins respectively. These adjustments are necessary to achieve consistency and to balance resources and uses.

J Data for Calibration

J.1 Non-Tradable Content of GDP and its Demand Components

Table 7 shows the non-tradable content of GDP, consumption, investment, government spending, labor and labor compensation (columns 1 to 6). The home content of consumption and investment

expenditure in tradables and the home content of government spending are reported in columns 8 to 10. Column 7 shows the ratio of exports to GDP. Columns 11 and 12 shows the labor income share in the traded and non-traded sector. Columns 13-14 display the investment-to-GDP ratio and government spending in % of GDP, respectively. Our sample covers the 17 OECD countries displayed by Table 4. The reference period for the calibration of labor variables is 1970-2017 while the reference period for demand components is 1995-2014 due to data availability, as detailed below. When we calibrate the model to a representative economy, we use the last line which shows the (unweighted) average of the corresponding variable.

Aggregate ratios. Columns 13-14 show the investment-to-GDP ratio, ω_J and government spending as a share of GDP, ω_G . To calculate ω_J , we use time series for gross capital formation at current prices and GDP at current prices, both obtained from the OECD National Accounts Database [2017]. Data coverage: 1970-2017 for all countries. To calculate ω_G , we use time series for final consumption expenditure of general government (at current prices) and GDP (at current prices). Source: OECD National Accounts Database [2017]. Data coverage: 1970-2017 for all countries. We consider a steady-state where trade is initially balanced and we calculate the consumption-to-GDP ratio, ω_C by using the accounting identity between GDP and final expenditure:

$$\omega_C = 1 - \omega_J - \omega_G. \quad (131)$$

As displayed by the last line of Table 7, investment expenditure (see column 13) and government spending (see column 14) as a share of GDP average to 23% and 20%.

Non-traded demand components. Columns 2 to 4 show non-tradable content of consumption (i.e., $1 - \alpha_C$), investment (i.e., $1 - \alpha_J$), and government spending (i.e., ω_{GN}), respectively. These demand components have been calculated by adopting the methodology described in eqs. (130a)-(130b), and eq. (127). Sources: World Input-Output Databases ([2013], [2016]). Data coverage: 1995-2014 except for NOR (2000-2014). The non-tradable content of consumption, investment and government spending shown in column 2 to 4 of Table 7 averages to 57%, 69% and 84%, respectively.

In the empirical analysis, we use data from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases for constructing sectoral value added over the period running from 1970 to 2017. Since the demand components for non-tradables are computed over 1995-2014 by using the WIOD dataset, to ensure that the value added is equal to the sum of its demand components, we have calculated the non-tradable content of value added shown in column 1 of Table 7 as follows:

$$\begin{aligned} \omega^{Y,N} &= \frac{P^N Y^N}{Y}, \\ &= \omega_C (1 - \alpha_C) + \omega_J (1 - \alpha_J) + \omega_{GN} \omega_G, \end{aligned} \quad (132)$$

where $1 - \alpha_C$ and $1 - \alpha_J$ are the non-tradable content of consumption and investment expenditure shown in columns 2 and 3, ω_{GN} is the non-tradable content of government spending shown in column 4, ω_C and ω_J are consumption- and investment-to-GDP ratios, and ω_G is government spending as a share of GDP.

Non-tradable content of hours worked and labor compensation. To calculate the non-tradable share of labor shown in column 5 and labor compensation shown in column 6, we split the eleven industries into traded and non-traded sectors by adopting the classification detailed in section M.2. Details about data construction for sectoral output and sectoral labor are provided above. We calculate the non-tradable share of labor compensation as the ratio of labor compensation in the non-traded sector (i.e., $W^N L^N$) to overall labor compensation (i.e., $W L$). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2017 for all countries (except Japan: 1974-2017). The non-tradable content of labor and labor compensation, shown in columns 5 and 6 of Table 7, average to 64% and 63% respectively.

Home content of consumption and investment expenditure in tradables. Columns 8 to 9 of Table 7 show the home content of consumption and investment in tradables, denoted by α^H and α_J^H in the model. These shares are obtained from time series calculated by using the formulas (129a)-(129b). Sources: World Input-Output Databases [2013], [2016]. Data coverage: 1995-2014 except for NOR (2000-2014). Column 10 shows the content of government spending in home-produced traded goods. Taking data from the WIOD dataset, time series for ω_{GH} are constructed by using the formula (128). Data coverage: 1995-2014 except for NOR (2000-2014). As shown in the last line of columns 8 and 9, the home content of consumption and investment expenditure in traded goods averages to 66% and 42%, respectively, while the share of home-produced traded goods in government spending averages 12%. Since the non-tradable content of government spending averages 84% (see column 4), the import content of government spending is 4% only.

Since we set initial conditions so that the economy starts with balanced trade, export as a share of GDP, ω_X , shown in column 7 of Table 7 is endogenously determined by the import content of consumption, $1 - \alpha^H$, investment expenditure, $1 - \alpha_J^H$, and government spending, ω_{GF} , along with the consumption-to-GDP ratio, ω_C , the investment-to-GDP ratio, ω_J , and government spending as

a share of GDP, ω_G . More precisely, dividing the current account equation at the steady-state by GDP, Y , leads to an expression that allows us to calculate the GDP share of exports of final goods and services produced by the home country:

$$\omega_X = \frac{P^H X^H}{Y} = \omega_C \alpha_C (1 - \alpha^H) + \omega_J \alpha_J (1 - \alpha^H) + \omega_G \omega_{G^F}, \quad (133)$$

$\omega_{G^F} = 1 - \omega_{G^{N,D}} - \omega_{G^{H,D}}$. The last line of column 7 of Table 7 shows that the export to GDP ratio averages 13%.

Sectoral labor income shares. The labor income share for the traded and non-traded sector, denoted by s_L^H and s_L^N , respectively, are calculated as the ratio of labor compensation of sector j to value added of sector j at current prices. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2017 for all countries (except Japan: 1974-2017). As shown in columns 11 and 12 of Table 7, s_L^H and s_L^N averages 0.63 and 0.68, respectively.

Estimated elasticities. Columns from 15 to 20 of Table 7 display estimates of the elasticity of substitution between tradables and non-tradables in consumption, ϕ , the elasticity of labor supply across sectors, ϵ_L , the elasticity of capital supply across sectors, ϵ_K , the elasticity of substitution between capital and labor in the traded and the non-traded sector, i.e., σ^H and σ^N , and the elasticity of substitution between skilled and unskilled labor in the traded and the non-traded sector, i.e., σ_L^H and σ_L^N ,

J.2 Estimates of ϵ_L Empirical Strategy and Estimates

Framework. The economy consists of M distinct sectors, indexed by $j = 0, 1, \dots, M$ each producing a different good. Along the lines of Horvath [2000], the aggregate labor index is assumed to take the form:

$$L = \left[\int_0^M (\vartheta^j)^{-\frac{1}{\epsilon}} (L^j)^{\frac{\epsilon+1}{\epsilon}} dj \right]^{\frac{\epsilon}{\epsilon+1}}, \quad (134)$$

The agent seeks to maximize her labor income

$$\int_0^M W^j L^j dj = X, \quad (135)$$

for given utility loss; L^j is labor supply to sector j , W^j the wage rate in sector j and X total labor income. The form of the aggregate labor index (134) implies that there exists an aggregate wage index $W(\cdot)$, whose expression will be determined later. Thus equation (135) can be rewritten as follows:

$$\int_0^M W^j L^j dj = WL. \quad (136)$$

Writing down the Lagrangian and denoting by μ the Lagrangian multiplier to the constraint, the first-order reads as:

$$(\vartheta^j)^{-\frac{1}{\epsilon}} (L^j)^{\frac{1}{\epsilon}} L^{-\frac{1}{\epsilon}} = \mu W^j. \quad (137)$$

Left-multiplying both sides of eq. (137) by L^j , summing over the M sectors and using eqs. (134) and (136) implies that $\mu = \frac{1}{W}$. Plugging the expression for the Lagrangian multiplier into (137) and rearranging terms leads to optimal labor supply L^j to sector j :

$$L^j = \vartheta^j \left(\frac{W^j}{W} \right)^\epsilon L. \quad (138)$$

Each sector consists of a large number of identical firms which use labor, L^j , and physical capital, K^j , according to a constant returns to scale technology described by a CES production function. The representative firm faces two cost components: a capital rental cost equal to R^j , and a wage rate equal to W^j , respectively. Since each sector is assumed to be perfectly competitive, the representative firm chooses capital and labor by taking prices as given:

$$\max_{K^j, L^j} \Pi^j = \max_{K^j, L^j} \{ P^j Y^j - W^j L^j - R^j K^j \}. \quad (139)$$

First-order conditions lead to the demand for labor and capital which read as follows:

$$s_L^j \frac{P^j Y^j}{L^j} = W^j, \quad (140a)$$

$$\left(1 - s_L^j \right) \frac{P^j Y^j}{K^j} = R^j. \quad (140b)$$

Table 7: Data to Calibrate the Two-Sector Model

Countries	Non-tradable share						Home share			LIS		Aggregate ratios			Elasticities				Interest r (21)		
	GDP (1)	Cons. (2)	Inv. (3)	Gov. (4)	Labor (5)	Lab. comp. (6)	X^H (7)	C^H (8)	I^H (9)	G^H (10)	LIS ^H (11)	LIS ^N (12)	I/Y (13)	G/Y (14)	ϵ_L (15)	ϵ_K (16)	σ^H (17)	σ^N (18)		σ^L (19)	σ^N (20)
AUS	0.62	0.58	0.76	0.54	0.65	0.64	0.09	0.76	0.49	0.17	0.58	0.67	0.27	0.18	0.48	0.06	0.52	0.83	n.a.	n.a.	0.028
AUT	0.64	0.56	0.60	0.91	0.61	0.62	0.17	0.56	0.42	0.11	0.68	0.68	0.25	0.18	1.10	0.18	0.95	1.21	0.25	0.29	0.029
BEL	0.65	0.53	0.63	0.97	0.65	0.64	0.22	0.44	0.20	0.00	0.66	0.68	0.23	0.22	0.60	0.23	0.75	1.15	0.90	0.58	0.031
CAN	0.62	0.49	0.66	0.95	0.67	0.66	0.14	0.68	0.31	0.20	0.54	0.63	0.22	0.21	0.36	0.11	0.89	0.95	1.07	0.78	0.031
DEU	0.63	0.53	0.61	0.94	0.61	0.58	0.14	0.69	0.43	0.09	0.75	0.64	0.23	0.20	1.00	0.04	0.72	1.09	n.a.	n.a.	0.022
DNK	0.68	0.60	0.73	0.83	0.67	0.68	0.16	0.49	0.22	0.22	0.64	0.70	0.21	0.25	0.27	n.a.	0.56	0.94	1.53	0.60	0.044
ESP	0.64	0.59	0.77	0.65	0.61	0.63	0.11	0.73	0.38	0.15	0.59	0.65	0.24	0.16	0.95	0.00	0.98	0.54	0.99	0.70	0.020
FIN	0.66	0.57	0.73	0.81	0.59	0.61	0.12	0.67	0.41	0.17	0.64	0.74	0.25	0.20	0.42	0.10	0.73	0.84	0.86	0.77	0.024
FRA	0.71	0.57	0.76	0.98	0.65	0.66	0.10	0.71	0.46	0.00	0.72	0.69	0.23	0.22	1.31	0.09	0.87	1.33	n.a.	n.a.	0.031
GBR	0.65	0.58	0.70	0.81	0.66	0.61	0.12	0.66	0.42	0.19	0.69	0.74	0.20	0.20	0.62	0.09	0.61	0.58	0.00	0.70	0.023
IRL	0.62	0.50	0.74	0.87	0.59	0.61	0.21	0.48	0.19	0.15	0.49	0.68	0.23	0.18	0.10	n.a.	0.65	0.82	n.a.	n.a.	0.033
ITA	0.64	0.55	0.64	0.98	0.59	0.59	0.09	0.79	0.60	0.08	0.73	0.67	0.22	0.18	1.63	0.00	0.93	0.71	0.35	0.36	0.025
JPN	0.67	0.66	0.71	0.61	0.62	0.64	0.04	0.85	0.82	0.16	0.59	0.66	0.30	0.16	0.96	0.60	0.95	0.40	0.63	0.65	0.017
NLD	0.66	0.52	0.69	0.97	0.68	0.68	0.18	0.55	0.25	0.00	0.61	0.74	0.22	0.23	0.22	0.03	1.14	0.83	0.79	1.28	0.028
NOR	0.62	0.53	0.63	0.86	0.63	0.63	0.14	0.66	0.49	0.16	0.50	0.68	0.25	0.20	0.17	0.00	0.94	0.72	n.a.	n.a.	0.025
SWE	0.67	0.56	0.60	0.97	0.66	0.65	0.15	0.63	0.38	0.06	0.67	0.74	0.24	0.25	0.55	0.00	0.64	0.80	n.a.	n.a.	0.029
USA	0.67	0.69	0.61	0.63	0.71	0.67	0.06	0.83	0.68	0.16	0.61	0.62	0.22	0.16	2.89	0.13	0.92	0.97	1.11	0.91	0.025
OECD	0.65	0.57	0.68	0.84	0.64	0.63	0.13	0.66	0.42	0.12	0.63	0.68	0.23	0.20	0.80	0.15	0.81	0.86	0.77	0.69	0.027

Notes: Columns 1-6 show the GDP share of non-tradables, the non-tradable content of consumption, investment and government expenditure, the share of non-tradables in labor, and the non-tradable content of labor compensation. Column 7 gives the ratio of exports of final goods and services to GDP; columns 8 and 9 show the home share of consumption and investment expenditure in tradables and column 10 shows the content of government spending in home-produced traded goods; LIS^j stands for the labor income share in sector $j = H, N$; I/Y is the investment-to-GDP ratio and G/Y is government spending as a share of GDP; ϕ is the elasticity of substitution between traded and non-traded goods in consumption; estimates of the elasticity of substitution between home- and foreign-produced traded goods ρ (with $\rho = \rho_j = \phi X$) is taken from Bertinelli et al. [2022]; ϵ_L is the elasticity of labor supply across sectors; ϵ_K is the elasticity of capital supply across sectors; σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$; σ^j is the elasticity of substitution between skilled labor and unskilled labor in production in sector $j = H, N$. The real interest rate is the nominal interest rate on 10 years government bonds minus the rate of inflation which is the rate of change of the Consumption Price Index.

Table 8: Baseline Parameters (Representative OECD Economy)

Definition	Value		Reference
	CD	year	
Period of time		year	data frequency
A. Preferences			
Subjective time discount rate, β	2.7%	2.7%	equal to the world interest rate
Intertemporal elasticity of substitution for consumption, σ	2	2	Shimer [2009]
Intertemporal elasticity of substitution for labor, σ_L	3	3	Peterman [2016]
Elasticity of substitution between C^T and C^N , ϕ	0.35	0.35	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Elasticity of substitution between J^T and J^N , ϕ_J	1	1	Bems [2008]
Elasticity of substitution between C^H and C^F , ρ	1.3	1.3	Bertinelli, Cardi, and Restout [2022]
Elasticity of substitution between J^H and J^F , ρ_J	1.3	1.3	Bertinelli, Cardi, and Restout [2022]
Elasticity of labor supply across sectors, ϵ_L	0.80	0.80	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Elasticity of capital supply across sectors, ϵ_K	0.15	0.15	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
B. Non-tradable share			
Weight of consumption in non-traded goods, $1 - \varphi$	0.49	0.49	set to target $1 - \alpha_C = 57\%$ (United Nations, COICOP [2017])
Weight of labor supply to the non-traded sector, $1 - \vartheta_L$	0.62	0.62	set to target $L^N/L = 64\%$ (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Weight of capital supply to the non-traded sector, $1 - \vartheta_K$	0.61	0.61	set to target $K^N/K = 61\%$ (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Weight of non-traded investment, $1 - \iota$	0.68	0.68	set to target $1 - \alpha_J = 69\%$ (OECD Input-Output database [2017])
Non-tradable content of government expenditure, ω_{G^N}	0.84	0.84	our estimates (Input-Output dataset, WIOD [2013])
C. Home share			
Weight of consumption in home traded goods, φ^H	0.71	0.71	set to target $\alpha^H = 66\%$ (Input-Output dataset, WIOD [2013])
Weight of home traded investment, ι^H	0.49	0.49	set to target $\alpha_J^H = 42\%$ (Input-Output dataset, WIOD [2013])
Home traded content of government expenditure, ω_{G^H}	0.12	0.12	our estimates (Input-Output dataset, WIOD [2013])
Export price elasticity, ϕ_X	1.3	1.3	Bertinelli, Cardi, and Restout [2022]
C. Production			
Labor income share in the non-traded sector, θ^N	0.68	0.68	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Labor income share in the traded sector, θ^H	0.63	0.63	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Elasticity of substitution between K^H and L^H , σ^H	1	0.81	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Elasticity of substitution between K^N and L^N , σ^N	1	0.86	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
D. GDP demand components			
Physical capital depreciation rate, δ_K	6.2%	6.2%	set to target $\omega_J = 23\%$ (Source: OECD Economic Outlook Database)
Parameter governing capital adjustment cost, κ	17	17	set to match the elasticity I/K to Tobin's q (Eberly et al. [2008])
Government spending as a ratio of GDP, ω_G	20%	20%	our estimates (Source: OECD Economic Outlook Database)
E. Capital utilization adjustment costs			
Parameter governing capital utilization cost, $\xi_{2,S}^H$	0.50	∞	set to reproduce IRF for $u_S^{K,H}(t)$
Parameter governing capital utilization cost, $\xi_{2,S}^{N,N}$	0.60	∞	set to reproduce IRF for $u_S^{K,N}(t)$
Parameter governing capital utilization cost, $\xi_{2,D}^H$	0.03	∞	set to reproduce IRF for $u_D^{K,H}(t)$
Parameter governing capital utilization cost, $\xi_{2,D}^{N,N}$	0.50	∞	set to reproduce IRF for $u_D^{K,N}(t)$

Notes: 'CD' refers to the Cobb-Douglas model which is taken as the reference point; 'CES' refers to the baseline model where production functions are of the CES type with $\sigma^j < 1$.

Table 9: Calibration of Dynamics of Symmetric and Asymmetric Technology Shocks

Parameters	Symmetric Technology shock				Asymmetric Technology Shock			
	Tradables		Non-Tradables		Tradables		Non-Tradables	
	$A_S^H(t)$	$B_S^H(t)$	$A_S^N(t)$	$B_S^N(t)$	$A_D^H(t)$	$B_D^H(t)$	$A_D^N(t)$	$B_D^N(t)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exogenous technology shock, x_c^j	-0.03	-0.70	-0.78	3.18	-8.20	14.46	-0.42	-1.12
Impact effect, $\hat{X}_c^j(0)$	1.68	0.00	1.84	0.00	-4.64	14.79	-1.20	1.00
Long-run effect, \hat{X}_c^j	1.71	0.70	2.62	-3.18	3.56	0.33	-0.78	2.12
Persistence and shape of $\hat{X}^j(t)$, $\xi_{X,c}^j$	0.38	0.38	0.50	0.50	0.19	0.20	0.10	0.10
Persistence and shape of $\hat{X}^j(t)$, $\chi_{X,c}^j$	0.41	0.35	0.51	0.50	0.18	0.24	0.10	0.10

Notes: Denoting the factor-augmenting efficiency by $X_c^j = A_c^j, B_c^j$ for technology shock $c = S, D$ in sector j , the adjustment of $X_c^j(t)$ toward its long-run level expressed in percentage deviation from initial steady-state is governed by the following continuous time process: $\hat{X}_c^j(t) = \hat{X}_c^j + e^{-\xi_{X,c}^j t} - (1 - x_c^j) e^{-\chi_{X,c}^j t}$. The first row is an exogenous parameter which determines the magnitude of the change in $X_c^j(t)$ on impact (see the second row) given its rate of change in the long-run \hat{X}_c^j (see the third row). The last two rows display the values of parameters $\xi_{X,c}^j$ and $\chi_{X,c}^j$ which determines the shape and the persistence of the technology shock.

Inserting labor demand (140a) into labor supply to sector j (138) and solving leads the share of sector j in aggregate labor:

$$\frac{L^j}{L} = (\vartheta^j)^{\frac{1}{\epsilon+1}} \left(\frac{s_L^j P^j Y^j}{\int_0^M s_L^j P^j Y^j dj} \right)^{\frac{\epsilon}{\epsilon+1}}, \quad (141)$$

where we combined (136) and (140a) to rewrite the aggregate wage as follows:

$$W = \frac{\int_0^M s_L^j P^j s_L^j dj}{L}. \quad (142)$$

We denote by β^j the fraction of labor's share of value added accumulating to labor in sector j :

$$\beta^j = \frac{s_L^j P^j Y^j}{\sum_{j=1}^M s_L^j P^j Y^j}. \quad (143)$$

Using (143), the labor share in sector j (141) can be rewritten as follows:

$$\frac{L^j}{L} = (\vartheta^j)^{\frac{1}{\epsilon+1}} (\beta^j)^{\frac{\epsilon}{\epsilon+1}}. \quad (144)$$

Introducing a time subscript and taking logarithm, eq. (144) reads as:

$$\ln \left(\frac{L^j}{L} \right)_t = \frac{1}{\epsilon+1} \ln \vartheta^j + \frac{\epsilon}{\epsilon+1} \ln \beta_t^j. \quad (145)$$

Totally differentiating (145), denoting the rate of growth of the variable with a hat, including country fixed effects captured by country dummies, f_i , sector dummies, f_j , and common macroeconomic shocks by year dummies, f_t , leads to:

$$\hat{L}_{it}^j - \hat{L}_{it} = f_i + f_t + \gamma_i \hat{\beta}_{it}^j + \nu_{it}^j, \quad (146)$$

where

$$\hat{L}_{it} = \sum_{j=1}^M \beta_{i,t-1}^j \hat{L}_{i,t}^j. \quad (147)$$

and

$$\beta_{it}^j = \frac{s_{L,i}^j P^j Y_{it}^j}{\sum_{j=1}^M s_{L,i}^j P^j Y_{it}^j}, \quad (148)$$

where $s_{L,i}^j$ is the labor income share in sector j in country i which is averaged over 1970-2017. Y^j is value added.

Elasticity of labor supply across sectors. We use panel data to estimate (146) where $\gamma_i = \frac{\epsilon_i}{\epsilon_i+1}$ and $\hat{\beta}_{it}^j$ is given by (143). The LHS term of (146) is calculated as the difference between changes (in percentage) in hours worked in sector j , $\hat{L}_{i,t}^j$, and in total hours worked, $\hat{L}_{i,t}$. The RHS term β^j corresponds to the fraction of labor's share of value added accumulating to labor

Table 10: Estimates of Elasticity of Labor Supply across Sectors (ϵ)

Country	Elasticity of labor supply across Sectors (ϵ)
AUS	0.480 ^a (3.84)
AUT	1.096 ^a (3.08)
BEL	0.599 ^a (3.66)
CAN	0.362 ^a (4.24)
DEU	0.998 ^a (3.62)
DNK	0.273 ^b (2.55)
ESP	0.950 ^a (3.84)
FIN	0.417 ^a (4.52)
FRA	1.309 ^a (3.03)
GBR	0.616 ^a (4.14)
IRL	0.105 ^a (3.17)
ITA	1.628 ^a (3.14)
JPN	0.961 ^a (3.67)
NLD	0.221 ^b (2.25)
NOR	0.166 ^a (2.77)
SWE	0.547 ^a (4.57)
USA	2.889 ^b (2.03)
Countries	17
Observations	794
Data coverage	1971-2017
Country fixed effects	yes
Time dummies	yes
Time trend	no

Notes: ^a, ^b and ^c denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

in sector j . Denoting by $P_t^j Y_t^j$ value added at current prices in sector $j = H, N$ at time t , β_t^j is computed as $\frac{s_L^j P_t^j Y_t^j}{\sum_{j=H}^N s_L^j P_t^j Y_t^j}$ where s_L^j is the LIS in sector $j = H, N$ defined as the ratio of the compensation of employees to value added in the j th sector, averaged over the period 1970-2017. Because hours worked are aggregated by means of a CES function, percentage change in total hours worked, $\hat{L}_{i,t}$, is calculated as a weighted average of sectoral hours worked percentage changes, i.e., $\hat{L}_t = \sum_{j=H}^N \beta_{t-1}^j \hat{L}_t^j$. The parameter we are interested in, say the degree of substitutability of hours worked across sectors, is given by $\epsilon_i = \gamma_i / (1 - \gamma_i)$. In the regressions that follow, the parameter γ_i is assumed to be different across countries when estimating ϵ_i for each economy ($\gamma_i \neq \gamma_{i'}$ for $i \neq i'$).

To construct \hat{L}_t^j and β_t^j we combine raw data on hours worked L^j , nominal value added $P^j Y^j$ and labor compensation $W^j L^j$. All required data are taken from the EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. The sample includes the 17 OECD countries mentioned above over the period 1971-2017 (except for Japan: 1975-2017).

Table 10 reports empirical estimates that are consistent with $\epsilon > 0$. All values are statistically significant at 10%. Since the estimated value for ϵ is not statistically significant for Norway, we run the same regression as in eq. (146) but use the output instead of value added to construct β^j . We find a value of 0.17, as reported in column 17 of Table 10, and this estimated value is statistically significant. Overall, we find that ϵ ranges from a low of 0.1 of Ireland and 0.2 for Norway to a high of 2.89 for USA.

J.3 Estimates of ϵ_K Empirical Strategy and Estimates

Framework. The economy consists of M distinct sectors, indexed by $j = 0, 1, \dots, M$ each producing a different good. Along the lines of Horvath [2000], the aggregate capital index is assumed to take

the form:

$$K = \left[\int_0^M \left(\vartheta_K^j \right)^{-\frac{1}{\epsilon^K}} \left(K^j \right)^{\frac{\epsilon^K+1}{\epsilon^K}} dj \right]^{\frac{\epsilon^K}{\epsilon^K+1}}, \quad (149)$$

The agent seeks to maximize capital income

$$\int_0^M R^j K^j dj = X^K, \quad (150)$$

for given utility level $K(\cdot)$; K^j is capital supply to sector j , R^j the capital rental rate in sector j and X^K total capital income. The form of the aggregate capital index (149) implies that there exists an aggregate capital rental rate index $R^K(\cdot)$, whose expression will be determined later. Thus equation (150) can be rewritten as follows:

$$\int_0^M R^j K^j dj = R^K K. \quad (151)$$

Writing down the Lagrangian and denoting by μ^K the Lagrangian multiplier to the constraint, the optimal decision for capital supply to sector j reads as follows:

$$\left(\vartheta_K^j \right)^{-\frac{1}{\epsilon^K}} \left(K^j \right)^{\frac{1}{\epsilon^K}} K^{-\frac{1}{\epsilon^K}} = \mu^K R^j. \quad (152)$$

Left-multiplying both sides of eq. (152) by K^j , summing over the M sectors and using eqs. (149) and (151) implies that $\mu^K = \frac{1}{R^K}$. Plugging the expression for the Lagrangian multiplier into (152) and rearranging terms leads to optimal labor supply K^j to sector j :

$$K^j = \vartheta_K^j \left(\frac{R^j}{R^K} \right)^{\epsilon^K} K. \quad (153)$$

Each sector consists of a large number of identical firms which use labor, L^j , and physical capital, K^j , according to a constant returns to scale technology described by a CES production function. The representative firm faces two cost components: a capital rental cost equal to R^j , and a wage rate equal to W^j , respectively. Since each sector is assumed to be perfectly competitive, the representative firm chooses capital and labor by taking prices as given:

$$\max_{L^j, K^j} \Pi^j = \max_{L^j, K^j} \{ P^j Y^j - W^j L^j - R^j K^j \}. \quad (154)$$

First-order conditions lead to the demand for labor and capital which can be rewritten as follows:

$$s_L^j \frac{P^j Y^j}{L^j} = W^j, \quad (155a)$$

$$\left(1 - s_L^j \right) \frac{P^j Y^j}{K^j} = R^j. \quad (155b)$$

Inserting labor demand (155a) into capital supply to sector j (153) and solving leads the share of sector j in aggregate labor:

$$\frac{K^j}{K} = \left(\vartheta_K^j \right)^{\frac{1}{\epsilon^K+1}} \left(\frac{\left(1 - s_L^j \right) P^j Y^j}{\int_0^M \left(1 - s_L^j \right) P^j Y^j dj} \right)^{\frac{\epsilon^K}{\epsilon^K+1}}, \quad (156)$$

where we combined (151) and (155a) to rewrite the aggregate capital rental rate as follows:

$$R^K = \frac{\int_0^M \left(1 - s_L^j \right) P^j Y^j dj}{K}. \quad (157)$$

We denote by $\beta^{K,j}$ the ratio of capital income in sector j to overall capital income:

$$\beta^{K,j} = \frac{\left(1 - s_L^j \right) P^j Y^j}{\sum_{j=1}^M \left(1 - s_L^j \right) P^j Y^j}. \quad (158)$$

Using (158), the share of capital in sector j (156) can be rewritten as follows:

$$\frac{K^j}{K} = \left(\vartheta_K^j \right)^{\frac{1}{1+\epsilon^K}} \left(\beta^{K,j} \right)^{\frac{\epsilon^K}{\epsilon^K+1}}. \quad (159)$$

Introducing a time subscript and taking logarithm, eq. (159) reads as:

$$\ln \left(\frac{K^j}{K} \right)_t = \frac{1}{\epsilon^K + 1} \ln \vartheta_K^j + \frac{\epsilon^K}{\epsilon^K + 1} \ln \beta_t^{K,j}. \quad (160)$$

We denote the rate of growth of the variable with a hat. We totally differentiate (160) and include country fixed effects captured by country dummies, g_i , sector dummies, g_j , and common macroeconomic shocks captured by year dummies, g_t :

$$\hat{K}_{it}^j - \hat{K}_{it} = g_i + g_t + g_j + \gamma_i^K \hat{\beta}_{it}^{K,j} + \nu_{it}^{K,j}, \quad (161)$$

We use panel data to estimate (161). We run the regression of the percentage change in the share of capital in sector j on the percentage change in the capital income share of sector j relative to the aggregate economy. Intuitively, when the demand for capital rises in sector j , $\beta^{K,j}$ increases which provides incentives for households to shift capital toward this sector. To calculate $\beta_{it}^{K,j}$ for sector j , in country i at time t , we proceed as follows:

$$\hat{K}_{it} = \sum_{j=1}^M \beta_{i,t-1}^{K,j} \hat{K}_{i,t}^j. \quad (162)$$

and

$$\beta_{it}^{K,j} = \frac{(1 - s_{L,i}^j) P_{it}^j Y_{it}^j}{\sum_{j=1}^M (1 - s_{L,i}^j) P_{it}^j Y_{it}^j}, \quad (163)$$

where $(1 - s_{L,i}^j)$ is the capital income share in sector j in country i which is averaged over 1970-2017. Y^j is value added and P^j is the value added deflator.

Data: Source and Construction. We take capital stock series from the EU KLEMS [2011] and [2017] databases which provide disaggregated capital stock data (at constant prices) at the 1-digit ISIC-rev.3 level for up to 11 industries, but only for thirteen countries of our sample which include Australia, Canada, Denmark, Finland, Italy, Spain, the United Kingdom, the Netherlands over the entire period 1970-2017, plus Austria (1976-2017), France (1978-2017), Japan (1973-2006), Korea (1970-2014). In efforts to have time series of a reasonable length, we exclude Belgium (1995-2017) and Sweden (1993-2017) because the period is too short while Ireland, and Norway do not provide disaggregated capital stock series. To construct \hat{K}_{it}^j and $\hat{\beta}_{it}^{K,j}$ we combine raw data on capital stock K^j , nominal value added $P^j Y^j$ and labor compensation $W^j L^j$ to calculate $1 - s_{L,i}^j$.

Degree of capital mobility across sectors. We use panel data to estimate (162) where $\gamma_i^K = \frac{\epsilon_{K,i}}{\epsilon_{K,i} + 1}$ and $\beta_{it}^{K,j}$ is given by (158). Table 11 reports empirical estimates that are consistent with $\epsilon_K > 0$. We average positive values for ϵ_K and exclude negative values as they are inconsistent. We find an average value for ϵ_K of 0.15 which suggests high capital mobility costs across sectors in OECD countries.

J.4 Estimates of ϵ_S and ϵ_U : Empirical Strategy and Estimates

Framework. The economy consists of M distinct sectors, indexed by $j = 0, 1, \dots, M$ each producing a different good. Along the lines of Horvath [2000], the aggregate skilled labor index is assumed to take the form:

$$S = \left[\int_0^M \left(\vartheta_S^j \right)^{-\frac{1}{\epsilon^S}} (L^j)^{\frac{\epsilon^S + 1}{\epsilon^S}} dj \right]^{\frac{\epsilon^S}{\epsilon^S + 1}}, \quad (164)$$

The agent seeks to maximize her labor income

$$\int_0^M W^{S,j} S^j dj = X^S, \quad (165)$$

for given utility loss; S^j is the supply of skilled labor to sector j , $W^{S,j}$ the wage rate paid in exchange for each hour of skilled labor services in sector j and X^S stands for total skilled labor income. The form of the aggregate skilled labor index (164) implies that there exists an aggregate wage index $W^S(\cdot)$, whose expression will be determined later. Thus equation (165) can be rewritten as follows:

$$\int_0^M W^{S,j} S^j dj = W^S S. \quad (166)$$

Writing down the Lagrangian and denoting by μ^S the Lagrangian multiplier to the constraint, the first-order reads as:

$$\left(\vartheta_S^j \right)^{-\frac{1}{\epsilon^S}} (S^j)^{\frac{1}{\epsilon^S}} S^{-\frac{1}{\epsilon^S}} = \mu^S W^{S,j}. \quad (167)$$

Table 11: Elasticity of Capital Supply across Sectors (ϵ_K)

Country	Elasticity of capital supply across Sectors (ϵ_K)
AUS	0.065 (1.10)
AUT	0.178 ^c (1.71)
BEL	0.229 ^c (1.69)
CAN	0.107 ^b (2.50)
DEU	0.041 (0.62)
DNK	-0.145 ^a (-3.88)
ESP	-0.045 (-1.01)
FIN	0.101 ^b (2.38)
FRA	0.090 (1.07)
GBR	0.087 ^c (1.72)
IRL	-0.156 ^a (-9.54)
ITA	-0.028 (-0.54)
JPN	0.597 ^a (4.59)
NLD	0.034 (0.62)
NOR	-0.007 (-0.32)
SWE	-0.038 (-0.59)
USA	0.128 (1.43)
Countries	17
Observations	699
Data coverage	1970-2017
Country fixed effects	yes
Time dummies	yes
Time trend	no

Notes: ^a, ^b and ^c denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

Left-multiplying both sides of eq. (167) by S^j , summing over the M sectors and using eqs. (164) and (166) implies that $\mu^S = \frac{1}{W^S}$. Plugging the expression for the Lagrangian multiplier into (167) and rearranging terms leads to optimal labor supply S^j to sector j :

$$S^j = \vartheta_S^j \left(\frac{W^{S,j}}{W^S} \right)^{\epsilon^S} S. \quad (168)$$

We assume that within each sector, there is a large number of identical firms which produces Y^j by using labor L^j and capital K^j according to constant returns to scale in production. Labor is made up of skilled S^j and unskilled U^j workers. The representative firm faces two cost components: a capital rental cost equal to R^j , a skilled labor wage rate $W^{S,j}$, and an unskilled labor wage rate $W^{U,j}$. Since each sector is assumed to be perfectly competitive, the representative firm chooses capital and labor by taking prices as given:

$$\max_{K^j, S^j, U^j} \Pi^j = \max_{K^j, S^j, U^j} \{P^j Y^j - W^{S,j} S^j - W^{U,j} U^j - R^j K^j\}. \quad (169)$$

Since the production function displays constant returns to scale and using the fact that factors are paid their marginal product, the demand for labor and capital are: $\partial Y^j / \partial L^j = W^j / P^j$ and $\partial Y^j / \partial K^j = R / P^j$, respectively; denoting the LIS in sector j by s_L^j , the demand for capital and labor can be rewritten as follows:

$$s_L^j P^j \frac{\partial Y^j}{\partial L^j} \frac{\partial L^j}{\partial S^j} = W^{S,j}, \quad (170a)$$

$$s_L^j P^j \frac{\partial Y^j}{\partial L^j} \frac{\partial L^j}{\partial U^j} = W^{U,j}, \quad (170b)$$

$$(1 - s_L^j) \frac{P^j Y^j}{K^j} = R^j, \quad (170c)$$

where $s_L^j P^j \frac{\partial Y^j}{\partial L^j} = W^j$. By inserting the latter equation into eqs. (170a)-(170b), multiplying both sides of eq. (170a) by S^j / L^j and both sides of eq. (170b) by U^j / L^j leads to:

$$\frac{\partial L^j}{\partial S^j} \frac{S^j}{L^j} = s_S^j = \frac{W^{S,j} S^j}{W^j S^j}, \quad (171a)$$

$$\frac{\partial L^j}{\partial U^j} \frac{U^j}{L^j} = 1 - s_S^j = \frac{W^{U,j} U^j}{W^j L^j}. \quad (171b)$$

Inserting labor demand for skilled labor, i.e., using (171a) to replace $W^{S,j}$ with $s_S^j \frac{W^j L^j}{S^j}$, into skilled labor supply to sector j (168) and solving leads to the share of sector j in aggregate skilled labor:

$$\begin{aligned} \frac{S^j}{S} &= \vartheta_S^j \left(\frac{S}{S^j} \frac{s_S^j s_L^j P^j Y^j}{\int_0^M s_S^j s_L^j P^j Y^j dj} \right)^{\epsilon^S}, \\ \frac{S^j}{S} &= \left(\vartheta_S^j \right)^{\frac{1}{\epsilon^S + 1}} \left(\frac{s_S^j s_L^j P^j Y^j}{\int_0^M s_S^j s_L^j P^j Y^j dj} \right)^{\frac{\epsilon^S}{\epsilon^S + 1}}, \end{aligned} \quad (172)$$

where we combined (166) and used the fact that $W^S S = \int_0^M W^{S,j} S^j dj = \int_0^M s_S^j s_L^j P^j Y^j dj$ to rewrite the aggregate skilled labor wage rate as follows:

$$W^S = \frac{\int_0^M s_S^j s_L^j P^j Y^j dj}{S}. \quad (173)$$

We denote by $\beta^{S,j}$ the fraction of skilled labor income in sector j relative to aggregate skilled labor income:

$$\beta^{S,j} = \frac{s_S^j s_L^j P^j Y^j}{\sum_{j=1}^M s_S^j s_L^j P^j Y^j}. \quad (174)$$

Using (174), the skilled hours worked share in sector j (172) can be rewritten as follows:

$$\frac{S^j}{S} = \left(\vartheta_S^j \right)^{\frac{1}{\epsilon^S + 1}} (\beta^{S,j})^{\frac{\epsilon^S}{\epsilon^S + 1}}. \quad (175)$$

Introducing a time subscript and taking logarithm, eq. (175) reads as:

$$\ln \left(\frac{S^j}{S} \right)_t = \frac{1}{\epsilon^S + 1} \ln \vartheta_S^j + \frac{\epsilon^S}{\epsilon^S + 1} \ln \beta_t^{S,j}. \quad (176)$$

Totally differentiating (176) and denoting the rate of change of the variable with a hat, we find that the change in skilled hours worked in sector j caused by labor reallocation across sectors is driven by the change in the skilled labor income share in sector j :

$$\hat{S}_t^j - \hat{S}_t = \gamma^S \hat{\beta}_t^{S,j}, \quad (177)$$

where $\gamma^S = \frac{\epsilon_i^S}{\epsilon_i^S + 1}$.

We use panel data to estimate (177). Including country fixed effects captured by country dummies, h_i , common macroeconomic shocks by year dummies, h_t , sector dummies, h_j , (177) can be rewritten as follows:

$$\hat{S}_{it}^j - \hat{S}_{it} = h_i + h_j + h_t + \gamma_i^S \hat{\beta}_{it}^{S,j} + \nu_{it}^{S,j}, \quad (178)$$

where $\gamma_i^S = \frac{\epsilon_i^S}{\epsilon_i^S + 1}$ and $\beta_{it}^{S,j}$ is given by (174); j indexes the sector, i the country, and t indexes time (i.e., years). The LHS and RHS variables are defined as follows:

$$\hat{S}_{it} = \sum_{j=1}^M \beta_{i,t-1}^{S,j} \hat{S}_{i,t}^j. \quad (179)$$

and

$$\beta_{it}^{S,j} = \frac{s_{S,i}^j s_{L,i}^j P_{it}^j Y_{it}^j}{\sum_{j=1}^M s_{S,i}^j s_{L,i}^j P_{it}^j Y_{it}^j}, \quad (180)$$

where $s_{S,i}^j$ is the share of skilled labor compensation in labor compensation in sector j , in country i averaged over 1970-2017, $s_{L,i}^j$ is the labor income share in sector j in country i which is averaged over 1970-2017. When exploring empirically (178), the coefficient γ^S is alternatively assumed to be identical, i.e., $\gamma_i^S = \gamma^S$, or to vary across countries. The LHS term of (178), i.e., $\hat{S}_{it}^j - \hat{S}_{it}$, gives the percentage change in skilled hours worked in sector j driven by the pure reallocation of skilled labor across sectors.

The same logic applies to derive the empirical strategy for estimating the degree of labor mobility of unskilled labor. Including country fixed effects and year dummies:

$$\hat{U}_{it}^j - \hat{U}_{it} = n_i + n_j + n_t + \gamma_i^U \hat{\beta}_{it}^{U,j} + \nu_{it}^{U,j}, \quad (181)$$

where $\gamma_i^U = \frac{\epsilon_i^U}{\epsilon_i^U + 1}$ and $\beta_{it}^{U,j}$ is given by (183); j indexes the sector, i the country, and t indexes time (i.e., years). The LHS and RHS variables are defined as follows:

$$\hat{U}_{it} = \sum_{j=1}^M \beta_{i,t-1}^{U,j} \hat{U}_{i,t}^j. \quad (182)$$

and

$$\beta_{it}^{U,j} = \frac{s_{U,i}^j s_{L,i}^j P_{it}^j Y_{it}^j}{\sum_{j=1}^M s_{U,i}^j s_{L,i}^j P_{it}^j Y_{it}^j}, \quad (183)$$

where $s_{U,i}^j$ is the share of unskilled labor compensation in labor compensation in sector j , in country i averaged over 1970-2017. When exploring empirically (181), the coefficient γ^U is alternatively assumed to be identical, i.e., $\gamma_i^U = \gamma^U$, or to vary across countries. The LHS term of (181), i.e., $\hat{U}_{it}^j - \hat{U}_{it}$, gives the percentage change in unskilled hours worked in sector j driven by the pure reallocation of unskilled labor across sectors.

Source and Coverage. Time series about high- (denoted by the superscript S), medium- (denoted by the superscript M), and low-skilled labor (denoted by the superscript U) are taken from EU KLEMS Database, Timmer et al. [2008]. Data are available for all countries except Norway. The baseline period is running from 1970 to 2017 but is different and shorter for several countries as indicated in braces for the corresponding countries: Austria (1980-2017), Belgium (1980-2017), Canada (1970-2005), Denmark (1980-2017), Finland (1970-2017), Ireland (2008-2017), Italy (1970-2017), Japan (1973-2017), the Netherlands (1979-2017), Spain (1980-2017), the United Kingdom (1970-2017), and the United States (1970-2005). We calculate the share of labor compensation in industry j for skilled labor as the ratio of the sum of labor compensation of high- and medium-skilled labor to total labor compensation in sector j , i.e., $s_S^j = \frac{W^{S,j} S^j + W^{M,j} M^j}{W^j L^j}$.

Estimates. We average consistent positive values which are statistically significant. We find $\epsilon_S = 0.63$ and $\epsilon_U = 1.13$. In accordance with the evidence documented by Kambourov and Manovskii [2009] which reveals that industry (and occupational) mobility declines with education, our empirical findings reveal that the elasticity of labor supply across sectors is twice larger for unskilled than skilled workers.

Table 12: Elasticity of Labor Supply across Sectors for Skilled Workers (ϵ_S) and for Unskilled Workers (ϵ_U)

Country	Skilled Workers (ϵ_S)	Unskilled Workers (ϵ_U)
AUT	0.975 ^b (2.55)	1.783 (1.52)
BEL	0.202 ^c (1.82)	0.551 ^c (1.86)
CAN	0.386 ^a (3.65)	0.249 ^c (1.83)
DNK	0.122 (1.47)	0.250 (1.57)
ESP	0.344 ^a (2.98)	0.928 ^b (2.52)
FIN	0.337 ^a (4.39)	0.506 ^a (3.38)
GBR	0.553 ^a (4.33)	0.655 ^a (2.95)
ITA	0.821 ^a (3.59)	1.440 ^b (2.28)
JPN	0.627 ^a (3.82)	0.892 ^a (2.57)
NLD	0.065 (0.89)	0.302 ^c (1.73)
USA	2.546 ^b (2.11)	4.825 (0.95)
Countries	11	11
Observations	438	438
Data coverage	1970-2017	1970-2017
Country fixed effects	yes	yes
Time dummies	yes	yes
Time trend	no	no

Notes: ^a, ^b and ^c denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

J.5 Elasticity ϕ of Substitution in Consumption between Traded and Non-Traded goods : Empirical Strategy and Estimates

Derivation of the testable equation. To estimate the elasticity of substitution in consumption, ϕ , between traded and non-traded goods, we derive a testable equation by rearranging the optimal rule for optimal demand for non-traded goods, i.e., $C_t^N = (1 - \phi) \left(\frac{P_t^N}{P_{C,t}} \right)^{-\phi} C_t$, since time series for consumption in non-traded goods are too short. More specifically, we derive an expression for the non-tradable content of consumption expenditure by using the market clearing condition for non-tradables and construct time series for $1 - \alpha_{C,t}$ by using time series for non-traded value added and demand components of GDP while keeping the non-tradable content of investment and government expenditure fixed, in line with the evidence documented by Bems [2008] for the share of non-traded goods in investment and building on our own evidence for the non-tradable content of government spending. After verifying that the (logged) share of non-tradables and the (logged) ratio of non-traded prices to the consumption price index are both integrated of order one and cointegrated, we run the regression by adding country and time fixed effects by using a FMOLS estimator. We consider two variants, one including a country-specific time trend and one without the time trend. We provide more details below.

Multiplying both sides of $C_t^N = (1 - \phi) \left(\frac{P_t^N}{P_{C,t}} \right)^{-\phi} C_t$ by P^N/P_C leads to the non-tradable content of consumption expenditure:

$$1 - \alpha_{C,t} = \frac{P_t^N C_t^N}{P_{C,t} C_t} = (1 - \phi) \left(\frac{P_t^N}{P_{C,t}} \right)^{1-\phi}. \quad (184)$$

Because time series for non-traded consumption display a short time horizon for most of the countries of our sample while data for sectoral value added and GDP demand components are available for all of the countries of our sample over the period running from 1970 to 2017, we construct time series for the share of non-tradables by using the market clearing condition for non-tradables:

$$\frac{P_t^N C_t^N}{P_{C,t} C_t} = \frac{1}{\omega_{C,t}} \left[\frac{P_t^N Y_t^N}{Y_t} - (1 - \alpha_J) \omega_{J,t} - \omega_{G^N} \omega_{G,t} \right]. \quad (185)$$

Since the time horizon is too short at a disaggregated level (for I^j and G^j) for most of the countries, we draw on the evidence documented by Bems [2008] which reveals that $1 - \alpha^J = \frac{P^N J^N}{P^J J}$ is constant

Table 13: Elasticity of Substitution between Tradables and Non-Tradables (ϕ)

	eq. (186)
Whole Sample	0.347 ^a (6.03)
Countries	17
Observations	810
Data coverage	1970-2017
Country fixed effects	yes
Time dummies	yes
Time trend	no

Notes: ^a, ^b and ^c denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

over time; we further assume that $\frac{P^N G^N}{G} = \omega_{GN}$ is constant as well in line with our evidence. We thus recover time series for the share of non-tradables by using time series for the non-traded value added at current prices, $P_t^N Y_t^N$, GDP at current prices, Y_t , consumption expenditure, gross fixed capital formation, I_t , government spending, G_t while keeping the non-tradable content of investment and government expenditure, $1 - \alpha_J$, and ω_{GN} , fixed.

Empirical strategy. Once we have constructed time series for $1 - \alpha_{C,t} = \frac{P_t^N C_t^N}{P_{C,t} C_t}$ by using (184), we take the logarithm of both sides of (184) and run the regression of the logged share of non-tradables on the logged ratio of non-traded prices to the consumption price index:

$$\ln(1 - \alpha_{C,it}) = f_i + f_t + \alpha_i .t + (1 - \phi) \ln(P^N/P_C)_{it} + \mu_{it}, \quad (186)$$

where f_i captures the country fixed effects, f_t are time dummies, and μ_{it} are the i.i.d. error terms. Because parameter φ in (184) may display a trend over time, we add country-specific trends, as captured by $\alpha_i .t$. It is worth mentioning that P^N is the value added deflator of non-tradables.

Data source and construction. Data for non-traded value added at current prices, $P_t^N Y_t^N$ and GDP at current prices, Y_t , are taken from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases (data coverage: 1970-2017 for all countries, except Japan: 1974-2017). To construct time series for consumption, investment and government expenditure as a percentage of nominal GDP, i.e., $\omega_{C,t}$, $\omega_{J,t}$ and $\omega_{G,t}$, respectively, we use data at current prices obtained from the OECD Economic Outlook [2017] Database (data coverage: 1970-2017). Sources, construction and data coverage of time series for the share of non-tradables in investment ($1 - \alpha_J$) and in government spending (ω_{GN}) are described in depth above; P^N is the value added deflator of non-tradables. Data are taken from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases (data coverage: 1970-2017 for all countries, except for Japan: 1974-2017). Finally, data for the consumer price index $P_{C,t}$ are obtained from the OECD Prices and Purchasing Power Parities [2017] database (data coverage: 1970-2017).

Results. Since both sides of (186) display trends, we ran unit root and then cointegration tests. Having verified that these two assumptions are empirically supported, we estimate the cointegrating relationships by using the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000], [2001]. FMOLS estimate of (186) is reported in Table 13. We find a value for the elasticity of substitution between traded and non-traded goods in consumption of 0.35 which is close to the estimated value documented by Stockman and Tesar [1995].

J.6 Estimates of Elasticity of Substitution between Capital and Labor in Production, σ^j : Empirical strategy

To estimate the elasticity of substitution between capital and labor, σ^j , we draw on Antràs [2004]. We let labor- and capital-augmenting technological change grow at a constant rate:

$$A_t^j = A_0^j e^{a^j t}, \quad (187a)$$

$$B_t^j = B_0^j e^{b^j t}, \quad (187b)$$

where a^j and b^j denote the constant growth rate of labor- and capital-augmenting technical progress and A_0^j and B_0^j are initial levels of technology. Inserting first (187a) and (187b) into the demand

for labor and capital, taking logarithm and rearranging gives:

$$\ln(Y_t^j/L_t^j) = \alpha_1 + (1 - \sigma^j) a^j t + \sigma_j \ln(W_t^j/P_t^j), \quad (188a)$$

$$\ln(Y_t^j/K_t^j) = \alpha_2 + (1 - \sigma^j) b^j t + \sigma_j \ln(R_t/P_t^j), \quad (188b)$$

where $\alpha_1 = \left[(1 - \sigma^j) \ln A_0^j - \sigma^j \ln \gamma^j \right]$ and $\alpha_2 = \left[(1 - \sigma^j) \ln B_0^j - \sigma^j \ln(1 - \gamma^j) \right]$ are constants. Above equations describe firms' demand for labor and capital respectively.

We estimate the elasticity of substitution between capital and labor in sector $j = H, N$ from first-order conditions (188a)-(188b) in panel format on annual data. Adding an error term and controlling for country fixed effects, we explore empirically the following equations:

$$\ln(Y_{it}^j/L_{it}^j) = \alpha_{1i} + \lambda_{1i}t + \sigma_i^j \ln(W_{it}^j/P_{it}^j) + u_{it}, \quad (189a)$$

$$\ln(Y_{it}^j/K_{it}^j) = \alpha_{2i} + \lambda_{2i}t + \sigma_i^j \ln(R_{it}/P_{it}^j) + v_{it}, \quad (189b)$$

where i and t index country and time and u_{it} and v_{it} are i.i.d. error terms. Country fixed effects are represented by dummies α_{1i} and α_{2i} , and country-specific trends are captured by λ_{1i} and λ_{2i} . Since all variables display unit root process, we estimate cointegrating relationships by using the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000].

Estimation of (189a) and (189b) requires data for each sector $j = H, N$ on sectoral value added at constant prices Y^j , sectoral hours worked L^j , sectoral capital stock K^j , sectoral value added deflator P^j , sectoral wage rate W^j and capital rental cost R . Data for sectoral value added Y^H and Y^N , hours worked L^H and L^N , value added price deflators P^H and P^N , and, nominal wages W^H and W^N are taken from the EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. To construct the national stock of capital K , we use the perpetual inventory method with a fixed depreciation rate taken from Table 6 and the time series of constant prices investment from the OECD Economic Outlook [2017] Database. Next, following Garofalo and Yamarik [2002], the capital stock is allocated to traded and non-traded industries by using sectoral output shares. Finally, we measure the aggregate rental price of capital R as the ratio of capital income to capital stock. Capital income is derived as nominal value added minus labor compensation. For all aforementioned variables, the sample includes the 17 OECD countries over the period 1970-2017 (except for Japan: 1974-2017).

Employing Monte Carlo experiments, León-Ledesma et al. [2010] compare different approaches for estimating the elasticity of substitution between capital and labor (single equation based on FOCs, system, linear, non-linear and normalization). Their evidence suggests that estimates of both the elasticity of substitution and technical change are close to their true values when the FOC with respect to labor is used. While we take the demand for labor as our baseline model (i.e. eq. (189a)), Table 14 provides FMOLS estimates of σ^j for the demand of both labor and capital. All estimates are positive and statistically significant exception σ^H for Ireland. We replace the inconsistent estimate for σ^j obtained from labor demand with that obtained from the demand of capital. Columns 17-18 of Table 7 report estimates for σ^H and σ^N .

J.7 Estimates of Elasticity of Substitution between Skilled and Unskilled Labor in Production, σ_L^j : Empirical Strategy

To estimate the elasticity of substitution σ_L^j between skilled labor (denoted by S_{it}^j), and unskilled labor (denoted by U_{it}^j), we adapt the approach proposed by Antràs [2004]. We let skilled labor- and unskilled labor-augmenting technological change grow at a constant rate:

$$A_{S,t}^j = A_{S,0}^j e^{a_S^j t}, \quad (190a)$$

$$A_{U,t}^j = A_{U,0}^j e^{a_U^j t}, \quad (190b)$$

where a_S^j and a_U^j denote the constant growth rate of skilled-labor- and unskilled-labor-augmenting technical progress and $A_{S,0}^j$ and $A_{U,0}^j$ are initial levels of technology.

The demand for skilled and unskilled labor read:

$$\frac{\partial L_t^j}{\partial S_t^j} = \gamma_L^j \left(\frac{A_{S,t}^j}{A_t^j} \right)^{\frac{\sigma_L^j - 1}{\sigma_L^j}} (S^j)^{-\frac{1}{\sigma_L^j}} (L^j)^{-\frac{1}{\sigma_L^j}} = \frac{W_t^{S,j}}{W_t}, \quad (191a)$$

$$\frac{\partial L_t^j}{\partial U_t^j} = \gamma_L^j \left(\frac{A_{U,t}^j}{A_t^j} \right)^{\frac{\sigma_L^j - 1}{\sigma_L^j}} (U^j)^{-\frac{1}{\sigma_L^j}} (L^j)^{-\frac{1}{\sigma_L^j}} = \frac{W_t^{U,j}}{W_t}, \quad (191b)$$

Table 14: FMOLS Estimates of the Sectoral Elasticity of Substitution between Capital and Labor (σ^j)

Dependent var. Explanatory var.	Tradables (σ^H)		Non-Tradables (σ^N)	
	$\ln(Y^H/K^H)$ $\ln(R/P^H)$	$\ln(Y^H/L^H)$ $\ln(W^H/P^H)$	$\ln(Y^N/K^N)$ $\ln(R/P^N)$	$\ln(Y^N/L^N)$ $\ln(W^N/P^N)$
AUS	0.214 ^c (1.89)	0.516 ^a (7.29)	0.499 ^a (3.78)	0.825 ^a (12.30)
AUT	0.526 ^b (2.25)	0.954 ^a (10.70)	0.206 (1.39)	1.213 ^a (15.03)
BEL	-0.078 (-0.52)	0.748 ^a (11.77)	0.039 (0.49)	1.145 ^a (11.87)
CAN	0.159 (1.11)	0.888 ^a (4.83)	0.691 ^a (6.28)	0.950 ^a (14.10)
DEU	0.175 ^c (1.79)	0.720 ^a (8.64)	0.549 ^a (9.18)	1.088 ^a (17.95)
DNK	-0.005 (-0.04)	0.555 ^a (5.82)	0.457 ^a (6.41)	0.938 ^a (9.30)
ESP	0.342 ^b (2.49)	0.979 ^a (10.59)	0.179 ^c (1.70)	0.535 ^a (3.11)
FIN	0.222 (1.26)	0.730 ^a (3.29)	0.374 ^a (4.98)	0.837 ^a (12.21)
FRA	0.215 (1.26)	0.867 ^a (8.54)	0.119 ^a (3.21)	1.329 ^a (6.96)
GBR	0.055 (0.28)	0.611 ^a (6.96)	0.097 (0.95)	0.580 ^a (4.77)
IRL	0.652 (13.40)	-0.154 (-0.91)	0.557 ^a (4.27)	0.819 ^a (3.94)
ITA	0.440 ^b (2.30)	0.934 ^a (13.38)	0.321 (1.50)	0.714 ^a (6.37)
JPN	0.765 ^a (10.17)	0.948 ^a (5.92)	0.553 ^a (8.61)	0.400 ^b (2.23)
NLD	0.498 ^a (4.26)	1.136 ^a (9.86)	0.230 ^a (8.29)	0.831 ^a (7.08)
NOR	0.399 ^a (3.15)	0.938 ^a (4.92)	0.547 ^a (8.87)	0.723 ^a (7.80)
SWE	0.260 (0.92)	0.643 ^a (12.91)	0.033 (0.34)	0.801 ^a (5.89)
USA	0.166 (1.32)	0.923 ^a (5.61)	0.324 ^a (5.72)	0.970 ^a (5.91)
Whole sample	0.294 ^a (11.47)	0.761 ^a (31.56)	0.340 ^a (18.42)	0.865 ^a (35.61)
Countries	17	17	17	17
Observations	810	810	810	810
Data coverage	1970-2017	1970-2017	1970-2017	1970-2017
Fixed effects	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes
Time trend	yes	yes	yes	yes

Notes: ^a, ^b and ^c denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

Table 15: FMOLS Estimates of the Sectoral Elasticity of Substitution between Skilled Labor and Unskilled Labor (σ_L^j)

Country	Tradables (σ_L^H)	Non-Tradables (σ_L^N)
AUT	0.249 ^b (2.36)	0.293 (1.36)
BEL	0.901 ^a (3.24)	0.576 ^b (2.36)
CAN	1.074 ^a (17.77)	0.783 ^a (14.54)
DNK	1.531 ^a (19.87)	0.599 ^a (23.15)
ESP	0.986 ^a (23.86)	0.702 ^a (18.94)
FIN	0.860 ^a (11.03)	0.770 ^a (13.66)
GBR	n.a.	0.695 ^a (2.93)
ITA	0.354 ^a (5.21)	0.359 ^a (3.76)
JPN	0.631 ^a (9.53)	0.645 ^a (27.17)
NLD	0.789 ^a (8.08)	1.281 ^a (11.14)
USA	1.110 ^a (11.16)	0.914 ^a (14.18)
Countries	11	11
Observations	449	449
Data coverage	1970-2017	1970-2017
Country fixed effects	yes	yes
Time dummies	yes	yes
Time trend	yes	yes

Notes: ^a, ^b and ^c denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

Inserting first (190a) and (190b) into the demand for labor and capital, taking logarithm and rearranging gives:

$$\ln\left(\frac{S^j}{L_j}\right) = \sigma_L^j \ln \gamma_S^j + (\sigma_L^j - 1) (a_S^j - a^j) t - \sigma_L^j \ln\left(\frac{W_S^j}{W^j}\right), \quad (192a)$$

$$\ln\left(\frac{U^j}{L_j}\right) = \sigma_L^j \ln(1 - \gamma_S^j) + (\sigma_L^j - 1) (a_U^j - a^j) t - \sigma_L^j \ln\left(\frac{W_U^j}{W^j}\right). \quad (192b)$$

Adding an error term, controlling for country fixed effects and year effects, and introducing country-specific time trend to capture the trend caused by skill-biased technological change, we explore empirically the following equations:

$$\ln(S_{it}^j/L_{it}^j) = e_i + e_t + f_i t + \sigma_{L,i}^j \ln(W_{it}^{S,j}/W_{it}^j) + u_{it}, \quad (193a)$$

$$\ln(U_{it}^j/L_{it}^j) = g_i + g_t + h_i t + \sigma_{L,i}^j \ln(W_{it}^{U,j}/W_{it}^j) + v_{it}, \quad (193b)$$

where i and t index country and time and u_{it} and v_{it} are i.i.d. error terms. Country fixed effects are represented by dummies e_i and g_i , year effects by e_t and g_t , and country-specific trends are captured by f_i and h_i . Since all variables display unit root process, we estimate cointegrating relationships by using the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000]. Table 15 provides FMOLS estimates of σ_L^j . All estimates are positive and statistically significant exception σ^H for Denmark for the traded sector and for Great Britain for both sectors. We replace inconsistent estimates with those when we ignore time dummies in the regression for Denmark for the traded and for Great Britain for the non-traded sector only.

J.8 Forecast Error Variance Decomposition

Definition of the FEVD. The IRF is just the VMA representation. The structural form of the VAR system is $A(L)Y_t = B\epsilon_t$. Setting $C(L) = A(L)^{-1}B$, leads to $Y_t = C(L)\epsilon_t$.

The forecast error of a variable at time t is the change in the variable that couldn't have been forecast between $t - 1$ and t . This is due to the realization of the structural shocks in the system, ϵ_t . We can compute the forecast error over many different horizons, h . The forecast error variance at horizon $h = 0$ for one variable x_t of the 2 variable VAR model is:

$$E_t X_t - E_{t-1} x_t = dx_t = C_{1,1}(0)\epsilon_{1,t} + C_{1,2}(0)\epsilon_{2,t}. \quad (194)$$

The forecast error variances are just the squares of the forecast errors (since the mean forecast error is zero). Using the fact that $Var(ax_t) = a^2 Var(x_t)$, we have:

$$\begin{aligned} Var(dx_t) &= (C_{1,1}(0))^2 Var(\epsilon_{1,t}) + (C_{1,2}(0))^2 Var(\epsilon_{2,t}) + 2C_{1,1}(0)C_{1,2}(0)Cov(\epsilon_{1,t}, \epsilon_{2,t}), \\ &= (C_{1,1}(0))^2 Var(\epsilon_{1,t}) + (C_{1,2}(0))^2 Var(\epsilon_{2,t}), \\ \Omega_1 &= (C_{1,1}(0))^2 + (C_{1,2}(0))^2, \end{aligned} \quad (195)$$

where we used the fact that the shocks have unit variance $Var(\epsilon_{1,t}) = 1$ and shocks are uncorrelated so that the covariance of structural shocks is zero.

The fraction of the forecast error variance of variable x due to shock k at horizon h , denoted $\phi_{k,h}$, is then the above divided by the total forecast error variance:

$$\phi_k(h) = \frac{\sum_h (C_k(h))^2 Var(\epsilon_{k,t})}{\sum_k \sum_h (C_k(h))^2 Var(\epsilon_{k,t})}. \quad (196)$$

Therefore, in our case, $\phi_{k,h}$ is the share of the deviation of utilization-adjusted-TFP caused by an symmetric technology shock. As shown below, the deviation of utilization-adjusted TFP collapses to η .

Mapping between η and conditional variance share of symmetric technology shocks. In the model. We define the variance $Var(x_t) = E[x_t - E(x_t)]^2$ or $Var^{\frac{1}{2}} = \sigma_x = E[x_t - E(x_t)]$. In the model, we have:

$$Z_t^A = \left(Z_t^{A,S} \right)^\eta \left(Z_t^{A,D} \right)^{1-\eta}. \quad (197)$$

The expected value is the mean of the variable which collapses to its steady-state. We denote the steady-state (i.e., the mean) value by dropping the time index. Log-linearizing (197) and subtracting the mean leads to:

$$\hat{Z}_t^A - \hat{Z}^A = \eta \left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S} \right) + (1 - \eta) \left(\hat{Z}_t^{A,D} - \hat{Z}^{A,D} \right). \quad (198)$$

Dividing both sides by $\hat{Z}_t^A - \hat{Z}^A$, denoting the standard deviation of aggregate technology shocks by σ^Z , the standard deviation of symmetric technology shocks by $\sigma^{Z,S}$, and the standard deviation of asymmetric technology shocks by $\sigma^{Z,D}$, we get:

$$\begin{aligned} 1 &= \eta \frac{\left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S} \right)}{\left(\hat{Z}_t^A - \hat{Z}^A \right)} + (1 - \eta) \frac{\left(\hat{Z}_t^{A,D} - \hat{Z}^{A,D} \right)}{\left(\hat{Z}_t^A - \hat{Z}^A \right)}, \\ 1 &= \left[\frac{\eta^{1/2} \left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S} \right)}{\left(\hat{Z}_t^A - \hat{Z}^A \right)} \right]^2 \frac{\left(\hat{Z}_t^A - \hat{Z}^A \right)}{\left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S} \right)} + \left[\frac{(1 - \eta)^{1/2} \left(\hat{Z}_t^{A,D} - \hat{Z}^{A,D} \right)}{\left(\hat{Z}_t^A - \hat{Z}^A \right)} \right]^2 \frac{\left(\hat{Z}_t^A - \hat{Z}^A \right)}{\left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S} \right)}, \\ 1 &= \left[\eta^{1/2} \frac{\sigma^{Z,S}}{\sigma^Z} \right]^2 + \left[(1 - \eta)^{1/2} \frac{\sigma^{Z,D}}{\sigma^Z} \right]^2, \\ 1 &= \eta + (1 - \eta), \end{aligned} \quad (199)$$

where the last line is obtained by assuming that the persistence of technology shocks does not vary across technology shocks. More specifically aggregate technology shocks, symmetric and asymmetric technology shocks across sectors are governed by the following dynamic processes

$$\hat{Z}_t^A - \hat{Z}^A = \left[e^{-\xi z t} - (1 - z^A) e^{-\chi z t} \right], \quad (200a)$$

$$\hat{Z}_t^{A,S} - \hat{Z}^{A,S} = \left[e^{-\xi z, st} - (1 - z^{A,S}) e^{-\chi z, st} \right], \quad (200b)$$

$$\hat{Z}_t^{A,D} - \hat{Z}^{A,D} = \left[e^{-\xi z, Dt} - (1 - z^{A,D}) e^{-\chi z, Dt} \right]. \quad (200c)$$

Assuming that the magnitude of the shock (on impact) as captured by $z^{A,S} \simeq z^A$ and $z^{A,D} \simeq z^A$ and its persistence as captured by $\xi_{Z,S} \simeq \xi_Z$, $\chi_{Z,S} \simeq \chi_Z$, and $\xi_{Z,D} \simeq \xi_Z$, $\xi_{Z,D} \simeq \xi_Z$, $\chi_{Z,D} \simeq \chi_Z$, are similar whether technology improvements are symmetric or asymmetric across sectors, then the dynamic processes of symmetric and asymmetric technology shocks are similar to the dynamic process of aggregate TFP shock

$$\frac{(\hat{Z}_t^{A,S} - \hat{Z}^{A,S})}{(\hat{Z}_t^A - \hat{Z}^A)} \simeq 1, \quad \frac{(\hat{Z}_t^{A,D} - \hat{Z}^{A,D})}{(\hat{Z}_t^A - \hat{Z}^A)} \simeq 1. \quad (201)$$

Under the assumption that the underlying dynamic process of technology shocks are similar in first approximation, then η collapses to the share of the variance of aggregate technology improvements on impact (i.e., at time $t = 0$) driven by shocks to symmetric technology shocks across sectors as measured by $\phi_{Z,S}(0)$

$$\begin{aligned} \phi_{Z,S}(0) &= \frac{(C_{Z,S}(0))^2 \text{Var}(\epsilon_{Z,S}(0))}{(C_{Z,S}(0))^2 \text{Var}(\epsilon_{Z,S}(0)) + (C_{Z,D}(0))^2 \text{Var}(\epsilon_{Z,D}(0))}, \\ &= \frac{(C_{S,0})^2}{(C_{S,0})^2 + (C_{Z,D}(0))^2} \\ &= (\eta^{1/2})^2 = \eta. \end{aligned} \quad (202)$$

In the data, we have:

$$\text{VAR}(\epsilon_{it}^Z) = (\eta^{1/2})^2 \text{VAR}(\epsilon_{it}^{Z,S}) + (1 - \eta^{1/2})^2 \text{VAR}(\epsilon_{it}^{Z,D}). \quad (203)$$

Or alternatively:

$$1 = \eta \left(\frac{\sigma^{Z,S}}{\sigma^Z} \right)^2 + (1 - \eta) \left(\frac{\sigma^{Z,D}}{\sigma^Z} \right)^2. \quad (204)$$

To calibrate our model, we compute the share of technology improvements driven by asymmetric technological change by using eq. (22) that we repeat for convenience, i.e., $\hat{Z}^A(t) = \eta \hat{Z}_S^A(t) + (1 - \eta) \hat{Z}_D^A(t)$. More specifically, we calculate the share $1 - \eta$ of asymmetric technology shocks so that response of utilization-adjusted-aggregate-TFP we estimate empirically following a 1% permanent increase in $Z^A(t)$ in the long-run collapses to the weighted average of its symmetric and asymmetric components $\eta \hat{Z}_S^A(t) + (1 - \eta) \hat{Z}_D^A(t)$ where $\hat{Z}_S^A(t)$ and $\hat{Z}_D^A(t)$ are the responses

Estimated share of the conditional FEV of aggregate TFP growth attributable to asymmetric technology shocks vs. inferred share. In Fig. 10(a), we contrast two different measures of the share of aggregate technology improvements driven by asymmetric technology shocks. A standard method to quantify the share of technology shocks driven by the shock to one of its component is to conduct a forecast error variance decomposition (FEVD). We have performed a FEVD for one country of at a time (17 OECD countries) by estimating the VAR model which includes utilization-adjusted-TFP of tradables relative to non-tradables, Z_t^H/Z_t^N , utilization-adjusted-aggregate-TFP, Z_t^A , real GDP, $Y_{R,t}$, total hours worked, L_i , the real consumption wage, $W_{C,t}$. Note that we average the share computed on impact (i.e., at $t = 0$) and in the long-run (i.e., at $t = 10$). We show the share of the variance of aggregate technology improvements driven by asymmetric technology shocks on the vertical axis of Fig. 10(a). We compare these findings with those that we obtain when we infer the share of asymmetric technology shocks in driving aggregate technology improvements by calculating $1 - \eta$ so that the weighted average of technology improvements driven by symmetric and asymmetric technology shocks, $\eta \hat{Z}_S^A(t) + (1 - \eta) \hat{Z}_D^A(t)$, collapses to the endogenous response of $Z^A(t)$ to an aggregate technology shock. We have performed this exercise for one country at a time. Results are shown on the horizontal axis. Overall, both measures are very close and we find a strong cross country relationship. We number only four countries out of 17 countries where the difference (between the inferred and the estimated share) exceeds plus or minus 20% including Austria (+30%), Canada (-23%),

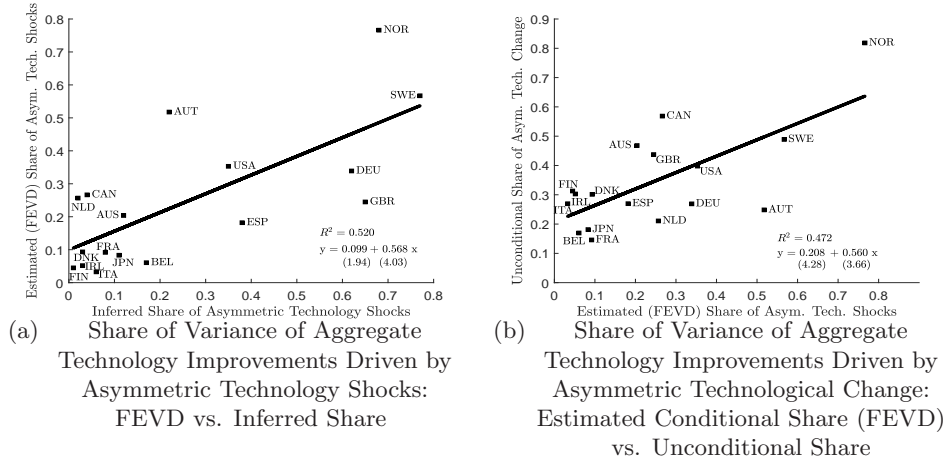


Figure 10: Share of Variance of Technology Improvements Driven by Asymmetric Technological Change: Conditional vs. Inferred vs. Unconditional Variance Decomposition. Notes: In Fig. 10(a), we contrast two different measures of the share of aggregate technology improvements driven by asymmetric technology shocks. A standard method to quantify the share of technology shocks driven by the shock to one of its component is to conduct a forecast error variance decomposition (FEVD). We performed a FEVD for each country of our sample (17 OECD countries) and show results on the vertical axis. We compare these findings with those we obtain by calculating the share of asymmetric technology shocks so that response of utilization-adjusted-aggregate-TFP collapses to the weighted average of its symmetric and asymmetric components, $1 - \eta$, see eq. (22) that we repeat for convenience, i.e., $\hat{Z}^A(t) = \eta \hat{Z}_S^A(t) + (1 - \eta) \hat{Z}_D^A(t)$. In Fig. 10(b), we contrast the share of aggregate technological change driven by asymmetric technology improvements which estimated from conditional shocks to utilization-adjusted-TFP and we contrast the conditional share of asymmetric technology shocks with the unconditional share we estimate directly from time series by using eq. (206). Sample: 17 OECD countries, annual data, 1970-2017.

Table 16: The Share of the FEV of Aggregate TFP Growth Attributable to Asymmetric Technology Shocks: 1970-2017 vs. Sub-Periods

	$t = 0$	$t = 10$
1970 - 2017	0.252	0.232
1970 - 1992	0.074	0.067
1993 - 2017	0.438	0.410

Notes: FEVD: Forecast Error Variance Decomposition. The number in columns denotes the fraction of the total forecast error variance of aggregate TFP growth Z^A attributable to identified asymmetric technology shocks across sectors (Z^H/Z^N). We consider a forecast horizon of 1 and 10 years and compute the FEVs in the five-variable VAR model which includes Z^H/Z^N , Z^A , Y_R , L and W_C , all in growth rate. Sample: 17 OECD countries, 1970-2017, annual data.

Great Britain (+41%), and the Netherlands (-24%). The cross-country average of the inferred share of asymmetric technology shocks stands at 26% while the cross-country average of the estimated share of asymmetric technology shocks amounts to 24%.

Estimated share of the conditional FEV of aggregate TFP growth attributable to asymmetric technology shocks: Whole period vs. sub-periods and whole sample vs. cross-country analysis. The first row of Table 16 reveals that the conditional FEV of aggregate TFP growth attributable to asymmetric technology shocks amounts to 25% on impact and stands at 23% in the long-run. Importantly, as shown in the second and the third row, when we consider two different sub-periods 1970-1992 and 1993-2017, we find that the conditional FEV of aggregate TFP growth attributable to asymmetric technology shocks has increased dramatically from 7% to 42.5%. In Table 17, we perform the same exercise except that we estimate the share of asymmetric technology shocks driving the FEV of aggregate TFP growth for one country a time. Denmark, Italy and to a lesser extent Japan display a low share of asymmetric technology shocks. At the opposite, Austria, Sweden, Norway display a higher share of asymmetric technology shocks.

J.9 Unconditional Variance Decomposition

The deviation of utilization-adjusted-aggregate-TFP relative to the initial steady-state is a weighted average of the deviation of utilization-adjusted-sectoral-TFP, i.e., $\hat{Z}^A(t) = \nu^{Y,H} \hat{Z}^H(t) + (1 - \nu^{Y,H}) \hat{Z}^N(t)$. This equation can be rearranged so that the productivity

Table 17: The Share of the FEV of Aggregate TFP Growth Attributable to Asymmetric Technology Shocks: Cross-Country Analysis

	1970 - 2017		1970 - 1992		1993 - 2017	
	$t = 0$	$t = 10$	$t = 0$	$t = 10$	$t = 0$	$t = 10$
AUS	0.229	0.179	0.020	0.238	0.247	0.194
AUT	0.534	0.501	0.060	0.315	0.454	0.344
BEL	0.050	0.071	0.435	0.173	0.131	0.147
CAN	0.259	0.274	0.255	0.360	0.415	0.356
DEU	0.387	0.291	0.212	0.268	0.220	0.203
DNK	0.098	0.089	0.047	0.070	0.124	0.114
ESP	0.130	0.234	0.274	0.183	0.102	0.129
FIN	0.016	0.074	0.190	0.356	0.028	0.418
FRA	0.059	0.125	0.017	0.216	0.455	0.403
GBR	0.231	0.259	0.206	0.166	0.390	0.423
IRL	0.058	0.045	0.139	0.222	0.282	0.222
ITA	0.000	0.066	0.117	0.264	0.002	0.033
JPN	0.020	0.146	0.097	0.209	0.004	0.393
NLD	0.289	0.224	0.590	0.614	0.230	0.259
NOR	0.814	0.718	0.540	0.350	0.572	0.401
SWE	0.578	0.556	0.128	0.709	0.924	0.833
USA	0.380	0.326	0.735	0.457	0.351	0.402
Panel	0.252	0.232	0.074	0.067	0.438	0.410

Notes: FEVD: Forecast Error Variance Decomposition. The number in columns denotes the fraction of the total forecast error variance of aggregate TFP growth Z^A attributable to identified asymmetric technology shocks across sectors (Z^H/Z^N). We consider a forecast horizon of 1 and 10 years and compute the FEVs in the five-variable VAR model which includes Z^H/Z^N , Z^A , Y_R , L and W_C , all in growth rate. Sample: 17 OECD countries, 1970-2017, annual data.

growth differential shows up, i.e., $\hat{Z}^A(t) = \hat{Z}^N(t) + \nu^{Y,H} (\hat{Z}^H(t) - \hat{Z}^N(t))$. When technology increases by the same amount across sectors, the second term on the RHS vanishes which leads to the following equality $\hat{Z}^A(t) = \hat{Z}^N(t) = \hat{Z}^H(t)$ where utilization-adjusted-TFP collapses to its symmetric component, i.e., $\hat{Z}^A(t) = \hat{Z}_S^A(t)$.

Plugging the latter equality into the sectoral decomposition of aggregate technology improvement, taking the variance leads to the unconditional variance decomposition of technological change:

$$\begin{aligned}
 \text{Var}(\hat{Z}^A(t)) &= \text{Var}(\hat{Z}_S^A(t)) + (\nu^{Y,H})^2 \text{Var}(\hat{Z}^H(t) - \hat{Z}^N(t)) + 2\text{Cov}(\hat{Z}_S^A(t), \hat{Z}_D^A(t)), \\
 \text{Var}'(\hat{Z}^A(t)) &= \text{Var}(\hat{Z}_S^A(t)) + (\nu^{Y,H})^2 \text{Var}(\hat{Z}^H(t) - \hat{Z}^N(t)), \\
 1 &= \frac{\text{Var}(\hat{Z}_S^A(t))}{\text{Var}(\hat{Z}^A(t))} + (\nu^{Y,H})^2 \frac{\text{Var}(\hat{Z}^H(t) - \hat{Z}^N(t))}{\text{Var}'(\hat{Z}^A(t))}, \tag{205}
 \end{aligned}$$

where Var' is the variance of aggregate technological change adjusted with the covariance, i.e.,

$$\text{Var}'(\hat{Z}^A(t)) = \text{Var}(\hat{Z}^A(t)) - 2\text{Cov}(\hat{Z}_S^A(t), \hat{Z}_D^A(t)). \tag{206}$$

Using the fact that $\text{Var}(\hat{X}(t)) = [\hat{X}(t) - \hat{X}]^2$ where $X = Z^A, Z_S^A, Z^j$, the second term on the RHS of eq. (205) says that the contribution of the variance of asymmetric technology shocks to the variance of technological change is increasing in both the value added share of tradables, $\nu^{H,H}$, and the dispersion in technology improvement between the traded and the non-traded sector

By using time series for utilization-adjusted-TFP of tradables and non-tradables, $Z^H(t)$ and $Z^N(t)$, and utilization-adjusted-aggregate-TFP, $Z^A(t)$, we can compute the share of the variance of aggregate technological change (adjusted with the covariance), $\text{Var}'(\hat{Z}^A(t))$,

driven by the the variance asymmetric technological change, $\text{Var}(\hat{Z}^H(t) - \hat{Z}^N(t))$:

$$\text{Unconditional Share of Asym. Tech. Change} = (\nu^{Y,H})^2 \frac{\text{Var}(\hat{Z}^H(t) - \hat{Z}^N(t))}{\text{Var}'(\hat{Z}^A(t))}, \quad (207)$$

where $\nu^{Y,H}$ is the value added share of tradables averaged over 1970-2017.

In Fig. 10(b), we plot the share of asymmetric technological change based on an unconditional decomposition of the variance of the rate of change of utilization-adjusted-aggregate-TFP (vertical axis) against the share of technology improvements driven by asymmetric technology shocks based on the FEVD (horizontal axis). We find a high correlation of the conditional share of asymmetric technology shocks estimated empirically and the unconditional share of asymmetric technological change. Overall, both measures are very close and we find a strong cross country relationship. We quantify some significant differences for seven countries out of 17 countries. More specifically, the difference (between the calculated and the estimated share) exceeds plus or minus 20% for the following countries: Australia (+26%), Austria (-27%), Canada (+30%), Denmark (+21%), Finland (+27%), Ireland (+25%), Great Britain (+41%), and Italy (+24%). The cross-country average of the unconditional share of asymmetric technology shocks stands at 34% while the cross-country average of the estimated share of asymmetric technology shocks amounts to 24%.

J.10 Calibration to the Data

In Table 9, we show the values we choose to set the dynamics of symmetric and asymmetric technology shocks. In this subsection, we contrast the dynamics of technology variables estimated empirically with those computed numerically. The first two rows of Fig. 11 show responses following a symmetric technology shock. Rows 3-4 show responses following an asymmetric technology shock. We attribute a value of 0.6 to the share of symmetric technology shocks and generate the dynamics of technology variables for an aggregate technology improvement which is a combination of symmetric and asymmetric technology shocks, as shown in the last two rows. While the blue line displays responses we estimate empirically, black lines with squares plots theoretical responses we generate by assuming that labor- and capital-augmenting technological change is governed by dynamic equation (45a)-(45b) while the log-linearized version of the technology frontier allows us to recover the law of motion of utilization-adjusted-TFP. The first column shows that the model reproduces well the adjustment of technology improvements in the traded and the non-traded sector.

The second column of Fig. 11 plots empirical responses of the capital utilization rate for the traded and the non-traded sector shown in blue lines. Black lines with squares plots theoretical responses for $u_t^{K,H}$ and $u_t^{K,N}$. The confidence bounds indicate that none of the responses are statistically significant, except for $u^{K,H}(t)$ after an asymmetric technology shock.¹⁹ Inspection of the second column reveals that our model reproduces well the dynamics of the capital utilization rate. First, as shown in the first two rows, the capital utilization rates increase slightly following a symmetric technology shock (but the responses are not statistically significant) because technological change is biased toward capital which increases the return on capital and thus rental rate. By contrast, an asymmetric technology shock leads to a dramatic fall in $u^{K,H}(t)$ because technological change is strongly biased toward labor in the traded sector which drives down the return on capital. As shown in Fig. 11(q), our model reproduces well the adynamic adjustment of the capital utilization rate for non-tradables while Fig. 11(n) indicates that the model tends to somewhat overstate the response of $u^{K,H}$, especially in the short-term.

The last column of Fig. 11 plots empirical responses of FBTC in the traded and the non-traded sector. As mentioned above, symmetric technology shocks are biased toward capital while asymmetric technology shocks are biased toward labor. As shown in the last two rows, our model reproduces well the dynamics of FBTC following an aggregate technology improvement.

¹⁹The reason is that there exists a wide cross-country dispersion in the movement of the capital utilization rates across countries in terms of both direction and magnitude.

Fig. 12 shows utilization-adjusted-TFP for tradables and non-tradables, utilization-adjusted-FBTC for tradables and non-tradables, and SBTC for tradables and non-tradables when we differentiate the labor effects of a permanent technology shock across workers' skills. Across all variables, the model (shown in black lines with squares) reproduces well the adjustment of technology variables we estimate empirically (blue lines).

K More Numerical Results

For reasons of space, we relegate to the online appendix a number of numerical results we refer to in the main text. These results include the effects of symmetric and asymmetric technology shocks across restricted variants of the baseline model.

K.1 Impact Effects across Restricted Versions of the Baseline Model: Symmetric vs. Asymmetric Technology Shocks

For reasons of space, in the main text, we restrict the discussion to the effects of symmetric and asymmetric technology shocks in the baseline model. In this section, we discuss the effects of symmetric and asymmetric technology shocks by considering the restricted versions of the baseline model and show that all variants fail to account for the effects we estimate empirically.

Symmetric technology improvements across sectors. When home- and foreign-produced traded goods are perfect substitutes, as considered in columns 9 and 12, a technology improvement which is evenly spread across sectors leads to a dramatic decline in total hours worked. Intuitively, a technology improvement produces a positive wealth effect which increases consumption in both traded and non-traded goods. Because home- and foreign-produced traded goods are perfect substitutes, households find it optimal to borrow from abroad (see panel E) to consume more foreign goods and increase leisure. As shown in panel B, total hours fall dramatically by -0.88% when we assume perfect mobility of inputs (see column 12) and by -0.67% under the assumption of imperfect mobility of inputs (see column 9). While the technology improvement drives down both traded and non-traded hours worked (see the second and the third row of panel B), the hours worked share of tradables falls (see the last row of panel B) which enters in contradiction with our empirical results which show that labor shifts away from non-traded industries and toward traded industries on impact.

In contrast, when home- and foreign-produced traded goods are assumed to be imperfect substitutes which is the scenario considered in columns 3 and 6, a symmetric technology improvement shifts labor away from non-traded and toward traded industries in accordance with the evidence we document in the empirical section 2. Intuitively, a symmetric technology shock across sectors lowers the marginal cost in both sectors which leads both traded and non-traded firms to cut prices. By increasing exports and mitigating the rise in imports, the terms of trade depreciation reduces considerably the current account deficit as shown in panel E. In addition, because traded and non-traded goods are gross complements (i.e., $\phi < 1$), the excess supply on the non-traded goods market lowers the non-tradable content of expenditure (see the second row of panel D) which leads labor to shift toward the traded sector in line with our evidence. As can be seen in panel E, since households are reluctant to substitute foreign for domestic goods, the current account deficit shrinks from -0.43 ppt of GDP in the restricted model to -0.06 ppt of GDP in the baseline model. To meet higher demand for home-produced traded goods, households must mitigate their appetite for leisure which curbs the fall in hours worked. As shown in columns 3 and 6, a model assuming endogenous terms of trade produces a decline in hours worked ranging from 0.40% to 0.46% which squares well with the decline in hours worked by 0.47% we estimate empirically. The reallocation of labor toward the traded sector and the reduction in the consumption of leisure mitigates substantially the fall in traded hours worked, i.e., from -0.49 ppt of total hours worked (see column 12) to -0.11 ppt (see column 3), and leaves the value added share of tradables at constant prices, $\nu^{Y,H}$ essentially unchanged (see the first row of panel D).

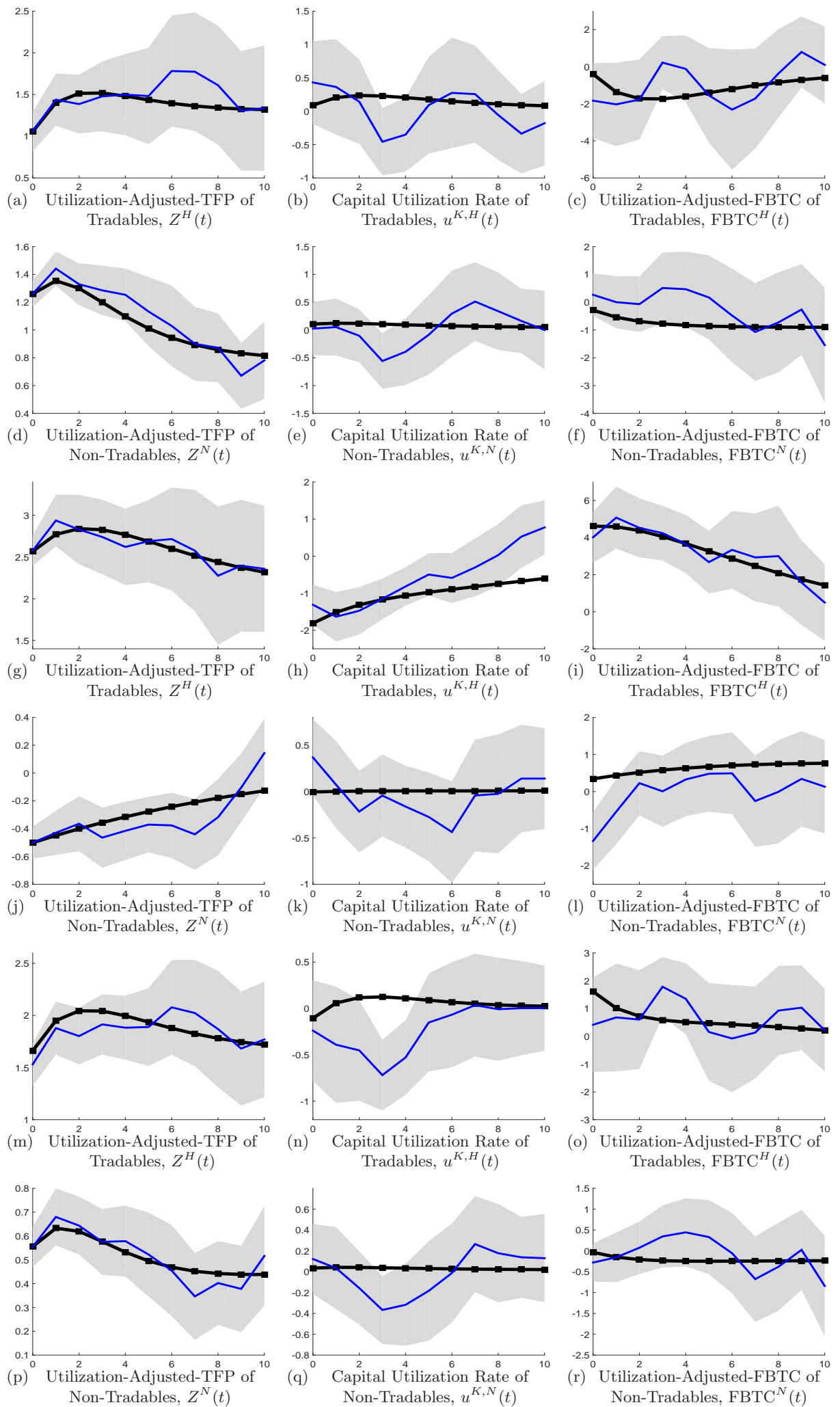


Figure 11: Dynamics of Technology Shocks: Theoretical vs. Empirical Responses. Notes: The solid blue line displays point estimate from local projections with shaded areas indicating 90% confidence bounds. The thick solid black line with squares displays model predictions in the baseline scenario with capital and technology

Table 18: Impact Labor Effects of a Technology Improvement: Baseline vs. Restricted Models

Data	CES: FBTC and uK			CD: IM & TOT			CD: IML& IMK			CD: PM			
	LP (1)	AGG (2)	SYM (3)	ASYM (4)	AGG (5)	SYM (6)	ASYM (7)	AGG (8)	SYM (9)	ASYM (10)	AGG (11)	SYM (12)	ASYM (13)
A. Technology													
Aggregate technology, $dZ^A(t)$	0.93	0.94	1.19	0.58	0.95	1.19	0.58	0.95	1.19	0.58	0.95	1.19	0.58
T technology, $dZ^H(t)$	1.53	1.66	1.06	2.57	1.66	1.06	2.57	1.66	1.06	2.58	1.66	1.06	2.58
NT technology, $dZ^N(t)$	0.55	0.56	1.26	-0.50	0.56	1.26	-0.50	0.56	1.26	-0.50	0.56	1.26	-0.50
T capital utilization, $du^{K,H}(t)$	-0.24	-0.11	0.09	-1.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NT capital utilization, $du^{K,N}(t)$	0.12	0.03	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B. Hours													
Hours, $dL(t)$	-0.15	-0.07	-0.40	0.28	-0.26	-0.47	0.05	-0.42	-0.67	-0.01	-0.70	-0.88	-0.38
Traded Hours, $dL^H(t)$	-0.04	-0.03	-0.11	-0.02	-0.15	-0.11	-0.19	-0.28	-0.29	-0.26	-0.57	-0.49	-0.64
Non-Traded Hours, $dL^N(t)$	-0.11	-0.05	-0.30	0.29	-0.12	-0.35	0.23	-0.14	-0.39	0.25	-0.13	-0.39	0.26
Hours Share of Tradables, $d\nu^{L,H}(t)$	0.01	-0.00	0.03	-0.11	-0.06	0.04	-0.21	-0.14	-0.06	-0.26	-0.33	-0.20	-0.51
C. Relative Prices													
Relative price of NT, $d(P^N/P^H)(t)$	1.05	1.63	-0.43	4.69	1.56	-0.50	4.69	2.11	0.25	4.88	1.15	-0.15	3.12
Terms of trade, $dP^H(t)$	-1.15	-1.09	-0.44	-1.99	-0.93	-0.47	-1.68	0.00	0.00	0.00	0.00	0.00	0.00
D. VA Shares													
VA share of T (constant prices) $d\nu^{Y,H}(t)$	0.18	0.23	-0.02	0.47	0.22	-0.01	0.57	0.14	-0.09	0.50	-0.08	-0.24	0.17
VA share of N (current prices) $d\omega^{Y,N}(t)$	n.a.	0.13	-0.07	0.57	0.13	-0.10	0.47	0.34	0.14	0.59	0.34	0.20	0.53
E. Current Account													
Current Account, $dCA(t)$	n.a.	-0.02	-0.06	0.04	-0.02	-0.04	0.01	-0.18	-0.26	-0.04	-0.38	-0.43	-0.27

Notes: This table shows impact effects of a 1% permanent increase in government consumption in the baseline model (columns 2-4) and in restricted versions of the model (columns 5-13). 'T' refers to traded industries while 'NT' refers to non-tradables. Panel A shows the impact effects for technology variables, panel B displays the impact effects for hours worked, panel C shows the relative price effects while panel D reports the change on impact in the current account (in percentage point of GDP). Across all scenarios, we consider a 1% permanent increase in utilization-adjusted-aggregate-TFP. In column 1, we show impact responses of the corresponding variables. Columns 2, 5, 8, 11 show numerical results following a technology improvement which increases the utilization-adjusted-aggregate-TFP by 1% in the long-run. Columns 3, 6, 9, 12 show numerical results following a symmetric technology shock across sectors which increases the utilization-adjusted-aggregate-TFP by 1% in the long-run. Columns 4, 7, 10, 123 show numerical results following an asymmetric technology shock across sectors which increases the utilization-adjusted-aggregate-TFP by 1% in the long-run. In Columns 11-13 show numerical results for an open economy model with tradables and non-tradables with capital adjustment costs, perfect mobility of labor and capital, perfect substitutability between home- and foreign-produced traded goods. In columns 8-10, we augment the previous model with imperfect mobility of labor and capital. In columns 5-7, we augment the previous model with imperfect substitutability between home- and foreign-produced traded goods so that terms of trade are endogenous. In columns 2-4, we consider the baseline model which allows for endogenous capital utilization rate and assumes that sectoral goods are produced by means of CES production functions and we let technological change to be factor-biased.

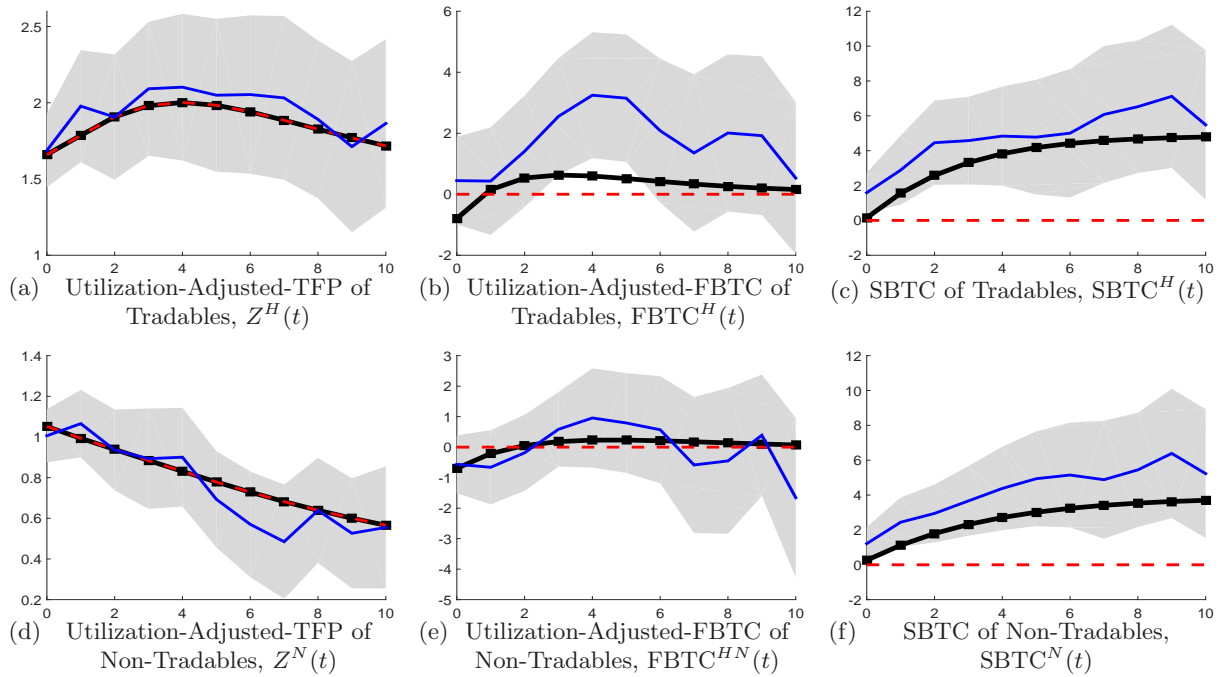


Figure 12: Dynamics of Technology Shocks: Theoretical vs. Empirical Responses. *Notes:* The solid blue line displays point estimate from local projections with shaded areas indicating 90% confidence bounds. The thick solid black line with squares displays model predictions in the baseline scenario with capital and technology utilization together with FBTC. Fig. 12 plots the dynamic effects of a 1% permanent technology improvement on utilization-adjusted-TFP, FBTC, and SBTC for tradables and non-tradables. Note that the dynamic effects are a combination of symmetric and asymmetric technology shocks

Asymmetric technology improvements across sectors. While symmetric technology improvements drive down hours worked in the data, we find empirically that asymmetric technology shocks across sectors do the opposite and increase total hours worked by 0.31%. Importantly, only the baseline model can account for the magnitude of the response of hours worked to a technology improvement. If we consider a restricted version of the model shown in column 13, the model generates a decline in hours worked by 0.38% instead of an increase. Intuitively, when technology improvements are concentrated toward traded industries, non-traded firms set higher prices to compensate for lower productivity gains. Because traded and non-traded goods have low substitutability, the tradable content of expenditure declines (see the second row of panel D). Labor thus shifts away from the traded sector which leads the traded goods-sector share of total hours worked by 0.51 ppt of total hours worked (see the last row of panel B). Because home- and foreign-produced traded goods are perfect substitutes, households import goods from abroad and increase leisure time. While labor supply falls, the rise in the hours worked share of non-tradables is large enough to produce additional units of non-traded goods. As shown in column 10, when we put frictions into the movement of inputs, the reallocation of labor toward the non-traded sector is less and total hours worked is almost unchanged. The reason is that labor mobility costs lead non-traded firms to pay higher wages to encourage workers to shift away from traded industries. Because the non-tradable content of the labor compensation share of non-tradables is two-third, higher non-traded wages push the aggregate wage index up. The higher wage rate produces a substitution effect which almost offsets the positive wealth effect.

While labor mobility costs has a positive impact on hours worked by putting upward pressure on wages, adding imperfect substitutability between home- and foreign-produced traded goods allows the model to produce an increase in hours worked by 0.05% (see the first row of panel B in column 7). Intuitively, when technology improvements are concentrated in traded industries and traded goods are price-elastic, traded firms find it optimal to lower their prices which leads to a current account surplus (see panel E). Because imports increase less than if terms of trade were exogenous, households must increase their labor supply to produce home-produced traded goods units. However, the rise in total hours worked by 0.05% remains significantly below what we estimate. It is only once we allow for FBTC

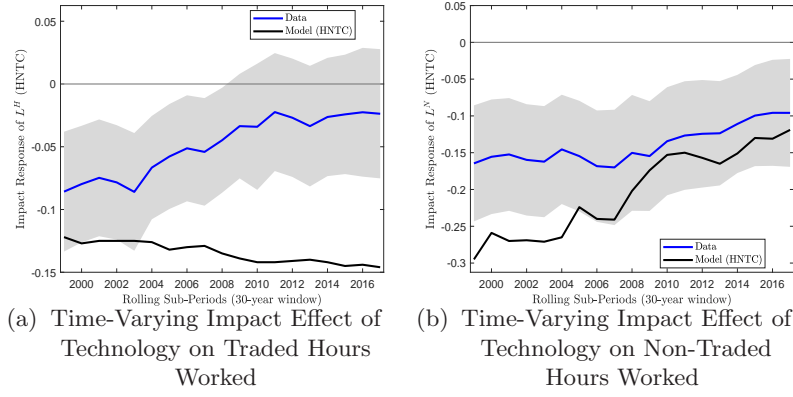


Figure 13: Time-Varying Impact Effects of a Technology Shock on Sectoral Hours Worked.

Notes: The figure shows impact responses of traded and non-traded hours worked to a 1% permanent increase in utilization-adjusted aggregate TFP. The solid blue line shows the impact response we estimate empirically on rolling sub-periods by using Jordà's [2005] single-equation method. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. The solid black line shows the impact response we compute numerically by considering a restricted version of our baseline model where we shut down FBTC by assuming $\sigma^j = 1$ and we abstract from endogenous capital utilization by letting ξ_2^j tend toward infinity. Note that we have normalized the rise in utilization-adjusted aggregate TFP to 1% on impact as we focus on the horizontal axis shows the end year of the period of the sub-sample and the vertical line displays the point estimate of the impact effect of technology on total hours worked.

and endogenous capital utilization at a sectoral level that the open economy model can account for the magnitude of the rise in hours worked we estimate. Intuitively, our empirical evidence reveals that technology improvements in the traded sector are associated with technological change biased toward labor. By making the production in the traded sector more labor intensive, technological change biased toward labor increases wages and further increases labor supply. However, by increasing labor demand in the traded relative to the non-traded sector, the positive FBTC differential between tradables and non-tradables reduces the magnitude of the decline in the hours worked share of tradables. To account for the impact response of hours worked to asymmetric technology shocks and the shift of labor toward the non-traded sector, we have to allow for endogenous capital utilization. Because technological change biased toward labor lowers the demand for capital in the traded sector, it is profitable to reduce in the intensity in the use of physical capital in this sector. The fall in the capital utilization rate of tradables lowers the traded wage rate which amplifies the shift of labor toward the traded sector and generates an increase in labor supply by 0.28% close to what we estimate empirically.

K.2 Time-Varying Effects on Hours Worked in a Model Imposing Hicks-Neutral Technological Change (HNTC)

As highlighted in the main text, one key ingredient of our model is FBTC. Without this ingredient, the model cannot generate an increase in total hours worked which is in line with the evidence after an asymmetric technology shock. In addition, as mentioned in section 4.5, technological change is key to giving rise to a time-increasing impact response of traded and non-traded hours worked. As can be seen in Fig. 13, abstracting from technological change biased toward labor by assuming Cobb-Douglas production functions leads the model to fail to account for the evidence. First, as shown in Fig. 13(a), a model imposing HNTC produces a time-decreasing impact response of traded hours worked (see the black line) while according to the evidence, the contractionary effect of a technology improvement on traded hours shrinks over time. The inability of a model abstracting from FBTC to produce the time-increasing impact response of $L^H(t)$ is that asymmetric technology shocks have a strong expansionary effect on non-traded hours worked at the expense of traded hours worked because such shocks strongly appreciate non-traded goods prices and increase the share of non-tradables. In contrast, by assuming that technological change is significantly biased toward labor in the traded sector in line with the evidence, the baseline model with FBTC can reproduce very well the time-increasing impact responses of $L^H(t)$. Second, when technological change biased toward labor is absent, the model overstates the decline in hours worked.

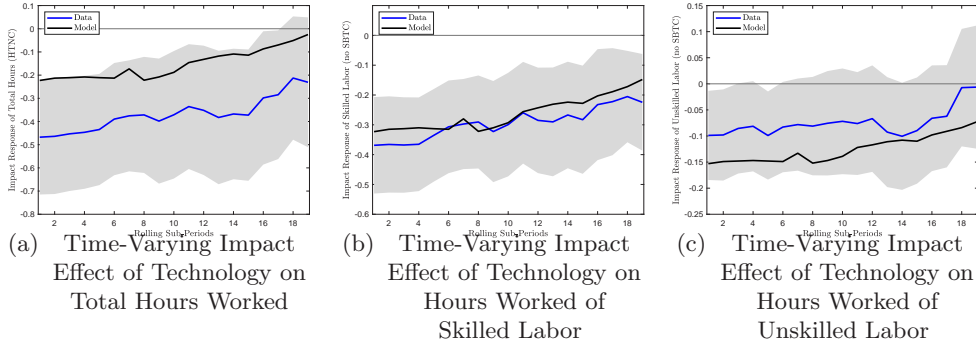


Figure 14: Time-Varying Impact Effects of a Technology Shock. *Notes:* Fig. 8(a)-8(c) show the impact responses on total hours worked together with its skilled vs. unskilled components to a 1% permanent increase in utilization-adjusted aggregate TFP. The solid blue line shows the impact response we estimate empirically on rolling sub-periods by using Jordà's [2005] single-equation method. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. The solid black line in Fig. 14(a) shows the impact response we compute numerically by abstracting from FBTC and SBTC. To isolate and quantify the role of SBTC alone, we allow for FBTC but abstract from SBTC (by setting $\sigma_L^j = 1$) in Fig. 14(b) and Fig. 14(c). Note that we have normalized the rise in utilization-adjusted aggregate TFP to 1% on impact. The horizontal axis shows the end year of the period of the sub-sample and the vertical line displays the impact effect of technology in ppt of total hours worked. Sample: 11 OECD countries, 1970-2017

K.3 Time-Varying Effects on Hours Worked across Workers' Skills in a Model Imposing Hicks-Neutral Technological Change

In the main text, we highlight both FBTC and SBTC as key drivers of the labor market effects of a technology improvement. While Fig. 8 in the main text shows that the baseline model with FBTC and SBTC can reproduce very well the time-increasing impact responses of total hours worked and its skill components of a technology improvement, in Fig. 14 we quantify the role of FBTC and SBTC in driving the results. More specifically, in Fig. 14(a), we shut down both FBTC and SBTC (by setting both $\sigma^j = 1$ and $\sigma_L^j = 1$). Because technological change is significantly biased toward capital and the model imposing HNTC abstracts from this feature, it substantially understates the decline in total hours worked at all horizons. To isolate and quantify the role of SBTC alone, we allow for FBTC but abstract from SBTC (by setting $\sigma_L^j = 1$) in Fig. 14(b) and Fig. 14(c). While the restricted model with FBTC and no SBTC can account for the time-increasing response of skilled labor, it somewhat overstates the negative responses of unskilled labor as the model abstracts from technological change biased toward unskilled labor.

L More Empirical Results: High-, Medium-, and Low-Skilled Workers

In this section, we show empirical results when we consider three types for labor: high-, medium-, and low-skilled workers. Inspection of Fig. 15 and Fig. 16 reveal that adjustments in high- and medium-skilled labor are similar and quite distinct from the dynamics of low-skilled labor. In particular, a permanent increase in utilization-adjusted-aggregate-TFP leads to significant and persistent decline in hours of high- and medium-skilled workers while it gives rise to an increase in hours of low-skilled workers in the medium- and long-run. We also find that adjustments in high- and medium-skilled labor are similar after symmetric and asymmetric technology shocks (available from the authors upon request).

M More Empirical Results and Robustness Checks

In this section, we conduct some robustness checks. Our identification of aggregate technology shocks and their decomposition into symmetric and asymmetric technology shocks is based on the assumption that time series for utilization-adjusted-aggregate-TFP together with the utilization-adjusted-TFP of tradables relative to non-tradables follow a unit root process. Because in the main text, all variables enter the VAR model in growth rate, subsection M.1 shows panel unit tests for all variables considered in the empirical analysis.

Due to data availability, we use annual data for eleven 1-digit ISIC-rev.3 industries that we classify as tradables or non-tradables. At this level of disaggregation, the classification

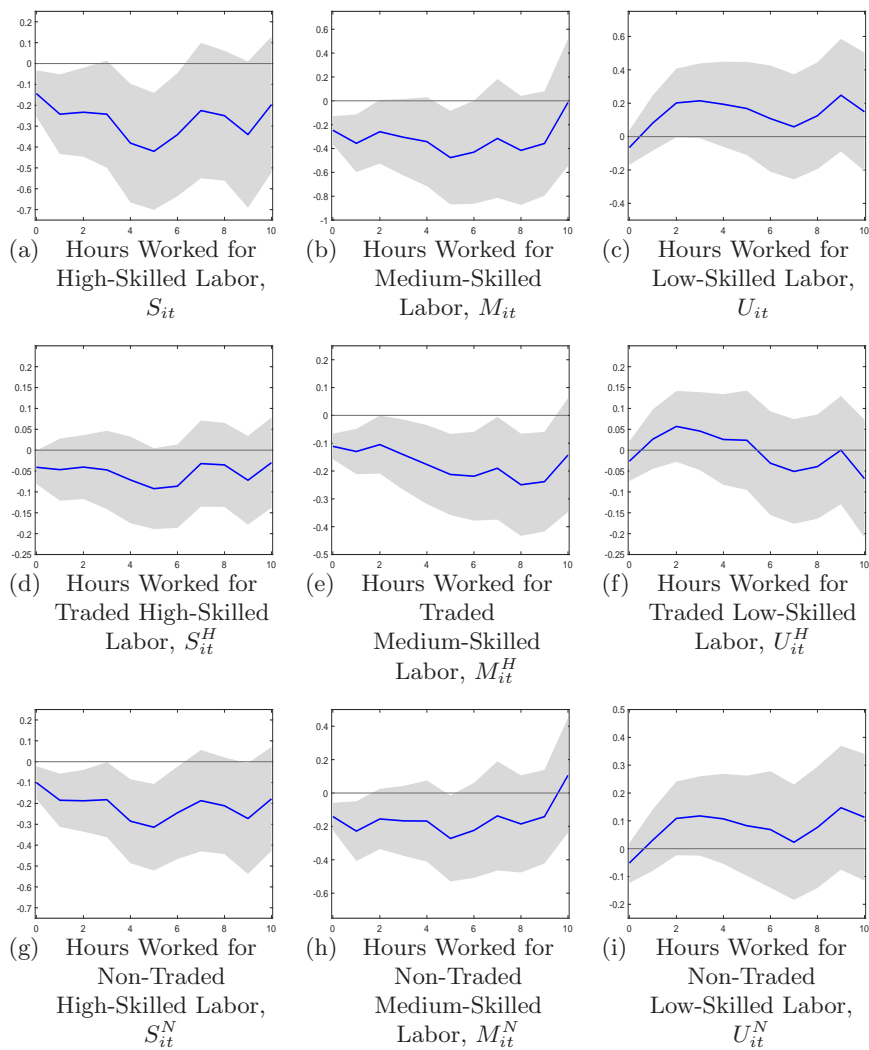


Figure 15: Effects of a Technology Shock across Workers' Skills Notes: The solid blue line shows the response of labor hours across workers' skills to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in total hours worked units (sectoral hours worked). Sample: 11 OECD countries, 1970-2017, annual data.

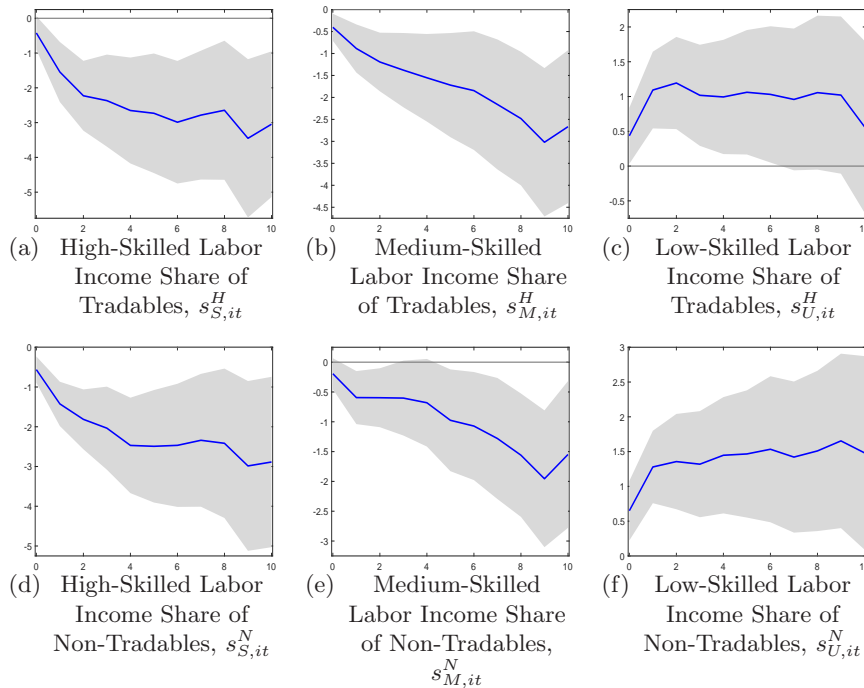


Figure 16: Effects of a Technology Shock on Labor Income Shares across Workers' Skills
Notes: The solid blue line shows the response of labor hours across workers' skills to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in labor compensation units. Sample: 11 OECD countries, 1970-2017, annual data.

is somewhat ambiguous because some broad sectors are made-up of heterogenous sub-industries, a fraction being tradables and the remaining industries being non-tradables. Since we consider a sample of 17 OECD countries over a period running from 1970 to 2017, the classification of some sectors may vary across time and countries. Industries such as 'Transport and Communication', 'Finance Intermediation' classified as tradables, 'Hotels and Restaurants' classified as non-tradables display intermediate levels of tradeness which may vary considerably across countries but also across time. Subsection M.2 deals with this issue and conducts a robustness check to investigate the sensitivity of our empirical results to the classification of industries as tradables or non-tradables.

Since we split the gross capital stock into traded and non-traded industries by using sectoral valued added shares, in subsection M.3, we conduct a robustness check by considering time series for capital stock per industry from KLEMS which are available for a limited number of countries.

Our dataset covers eleven industries which are classified as tradables or non tradables. The traded sector is made up of five industries and the non-traded sector of six industries. In subsection M.4, we conduct our empirical analysis at a more disaggregated level. The objective is twofold. First, we investigate whether all industries classified as tradables or non-tradables behave homogeneously or heterogeneously. Second, we explore empirically which industry drives the responses of broad sectors following a rise in government spending by 1% of GDP.

In subsection M.5, we document evidence about the drivers of asymmetric technology shocks. We find that only asymmetric technology shocks increase significantly the stock of R&D and only in the traded sector. We find that the share of asymmetric technology shocks is larger in countries where the R&D intensity of traded output is higher.

M.1 Panel Unit Root Tests

When estimating alternative VAR specifications, all variables enter in growth rates. In order to support our assumption of $I(1)$ variables, we ran panel unit root tests displayed in Table 19. We consider four panel unit root tests among the most commonly used in the literature:

Levin, Lin and Chu ([2002], hereafter LLC), Breitung [2000], Im, Pesaran and Shin ([2003], hereafter IPS), and Hadri [2000]. All tests, with the exception of Hadri [2000], consider the null hypothesis of a unit root against the alternative that some members of the panel are stationary. Additionally, they are designed for cross sectionally independent panels. LLC and IPS are based on the use of the Augmented Dickey-Fuller test (ADF hereafter) to each individual series of the form $\Delta x_{i,t} = \alpha_i + \rho_i x_{i,t-1} + \sum_{j=1}^{q_i} \theta_{i,j} \Delta x_{i,t-j} + \varepsilon_{i,t}$, where $\varepsilon_{i,t}$ are assumed to be i.i.d. (the lag length q_i is permitted to vary across individual members of the panel). Under the homogenous alternative the coefficient ρ_i in LLC is required to be identical across all units ($\rho_i = \rho, \forall i$). IPS relax this assumption and allow for ρ_i to be individual specific under the alternative hypothesis. We also apply the pooled panel unit root test developed by Breitung [2000] which does not require bias correction factors when individual specific trends are included in the ADF type regression. This is achieved by an appropriate variable transformation. As a sensitivity analysis, we also employ the test developed by Hadri [2000] which proposes a panel extension of the Kwiatkowski et al. [1992] test of the null that the time series for each cross section is stationary against the alternative of a unit root in the panel data. Breitung' and Hadri's tests, like LLC's test, are pooled tests against the homogenous alternative.²⁰

As noted above, IPS test allows for heterogeneity of the autoregressive root, accordingly, we will focus intensively on these tests when testing for unit roots. Across all variables the null hypothesis of a unit root against the alternative of trend stationarity cannot be rejected at conventional significance levels, suggesting that the set of variables of interest are integrated of order one. When considering the Hadri's test for which the null hypothesis implies stationary against the alternative of a unit root in the panel data, we reach the same conclusion and conclude again that all series are nonstationary. Taken together, unit root tests applied to our variables of interest show that non stationarity is pervasive, suggesting that all variables should enter in the VAR models in growth rate.

M.2 Classification of Industries as Tradables vs. Non-Tradables

This section explores the robustness of our findings to the classification of the eleven 1-digit ISIC-rev.3 industries as tradables or non tradables.

Following De Gregorio et al. [1994], we define the tradability of an industry by constructing its openness to international trade given by the ratio of total trade (imports + exports) to gross output. Data for trade and output are provided by the World Input-Output Databases ([2013], [2016]). Table 20 gives the openness ratio (averaged over 1995-2014) for each industry in all countries of our sample. Unsurprisingly, "Agriculture, Hunting, Forestry and Fishing", "Mining and Quarrying", "Total Manufacturing" and "Transport, Storage and Communication" exhibit high openness ratios (0.54 in average if "Mining and Quarrying", due to its relatively low weight in GDP, is not considered). These four sectors are consequently classified as tradables. At the opposite, "Electricity, Gas and Water Supply", "Construction", "Wholesale and Retail Trade" and "Community Social and Personal Services" are considered as non tradables since the openness ratio in this group of industries is low (0.07 on average). For the three remaining industries "Hotels and Restaurants", "Financial Intermediation", "Real Estate, Renting and Business Services" the results are less clearcut since the average openness ratio amounts to 0.18 which is halfway between the two aforementioned averages. In the benchmark classification, we adopt the standard classification of De Gregorio et al. [1994] by treating "Real Estate, Renting and Business Services" and "Hotels and Restaurants" as non traded industries. Given the dramatic increase in financial openness that OECD countries have experienced since the end of the eighties, we allocate "Financial Intermediation" to the traded sector. This choice is also consistent with the classification of Jensen and Kletzer [2006] who categorize "Finance and Insurance" as tradable. They use locational Gini coefficients to measure the geographical concentration of different sectors and classify sectors with a Gini coefficient below 0.1 as non-tradable and all others as tradable (the authors classify activities that are traded domestically as

²⁰In all aforementioned tests and for all variables of interest, we allow for individual deterministic trends and country-fixed effects. Conclusions of unit root tests are robust whether there are individual trends in regressions or not. Appropriate lag length q_i is determined according to the Akaike criterion.

Table 19: Panel Unit Root Tests

	LLC		Breitung		IPS		Hadri	
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
Z_{adjK}^A	2.584	0.995	3.782	1.000	1.368	0.914	49.802	0.000
Z_{adjK}^H/Z_{adjK}^N	5.075	1.000	2.721	0.997	1.677	0.953	38.462	0.000
Z_{adjK}^H	5.512	1.000	3.069	0.999	3.288	0.999	46.085	0.000
Z_{adjK}^N	3.542	1.000	2.105	0.982	-1.784	0.037	40.995	0.000
Z^A	2.770	0.997	2.555	0.995	3.650	1.000	51.528	0.000
Z^H	5.580	1.000	2.626	0.996	5.725	1.000	50.884	0.000
Z^N	3.259	0.999	1.533	0.937	1.180	0.881	43.072	0.000
Z^H/Z^N	3.773	1.000	2.375	0.991	1.237	0.892	38.231	0.000
Y_R	5.999	1.000	4.783	1.000	0.831	0.797	32.188	0.000
I	8.106	1.000	3.977	1.000	-1.657	0.049	27.022	0.000
NX/Y	7.388	1.000	-1.317	0.094	-1.892	0.029	26.619	0.000
L	1.895	0.971	-2.132	0.016	-0.624	0.266	42.163	0.000
W_C	5.027	1.000	3.921	1.000	1.367	0.914	46.474	0.000
Y^H	5.760	1.000	4.343	1.000	1.369	0.915	34.095	0.000
Y^N	4.652	1.000	5.276	1.000	-0.491	0.312	34.677	0.000
Y^H/Y	4.116	1.000	0.950	0.829	0.778	0.782	35.765	0.000
Y^N/Y	4.206	1.000	0.951	0.829	0.854	0.804	36.350	0.000
L^H	3.777	1.000	3.102	0.999	-0.405	0.343	39.294	0.000
L^N	2.652	0.996	3.223	0.999	-1.481	0.069	35.428	0.000
L^H/L	6.378	1.000	3.411	1.000	0.197	0.578	29.488	0.000
L^N/L	3.173	0.999	3.069	0.999	3.110	0.999	49.082	0.000
W_C^H	5.511	1.000	3.957	1.000	2.361	0.991	48.366	0.000
W_C^N	4.372	1.000	4.375	1.000	-0.323	0.373	40.834	0.000
W^H/W	5.655	1.000	1.159	0.877	0.035	0.514	34.592	0.000
W^N/W	5.605	1.000	1.186	0.882	-0.393	0.347	40.573	0.000
W^N/W^H	5.911	1.000	1.195	0.884	0.200	0.579	38.036	0.000
P^N/P^H	4.711	1.000	3.281	0.999	1.036	0.850	37.766	0.000
P^H/P^{H*}	3.697	0.000	-0.015	0.494	-2.845	0.002	49.728	0.000
P^N/P^{H*}	0.930	0.824	0.971	0.834	0.835	0.798	47.444	0.000
s_L^A	7.545	1.000	0.733	0.768	0.479	0.684	29.691	0.000
s_L^H	7.845	1.000	1.280	0.900	-0.778	0.218	28.716	0.000
s_L^N	5.371	1.000	0.302	0.619	0.003	0.501	37.364	0.000
k^A	2.744	0.997	4.505	1.000	-0.965	0.167	36.339	0.000
k^H	4.212	1.000	4.162	1.000	0.200	0.579	34.524	0.000
k^N	3.384	1.000	5.396	1.000	-1.099	0.136	33.419	0.000
$FBTC^H$	7.896	1.000	3.048	0.999	-0.571	0.284	30.124	0.000
$FBTC^N$	4.960	1.000	1.718	0.957	0.661	0.746	37.112	0.000
$FBTC_{adjK}^H$	8.227	1.000	2.862	0.998	-0.610	0.271	28.090	0.000
$FBTC_{adjK}^N$	5.723	1.000	1.612	0.947	0.283	0.612	37.668	0.000

Notes: For LLC, Breitung and IPS, the null of a unit root is not rejected if p-value ≥ 0.05 at a 5% significance level. For Hadri, the null of stationarity is rejected if p-value ≤ 0.05 at a 5% significance level. All tests (with the exception of Breitung) include a linear trend and, for LLC, Breitung and IPS, four lags in the Augmented Dickey-Fuller regressions.

potentially tradable internationally).

Table 20: Openness Ratios per Industry: 1995-2014 Averages

	Agri.	Minig	Manuf.	Elect.	Const.	Trade	Hotels	Trans.	Finance	Real Est.	Public
AUS	0.242	0.721	0.643	0.007	0.005	0.025	0.255	0.247	0.054	0.051	0.054
AUT	0.344	2.070	1.152	0.178	0.075	0.135	0.241	0.491	0.302	0.221	0.043
BEL	1.198	13.374	1.414	0.739	0.067	0.186	0.389	0.536	0.265	0.251	0.042
CAN	0.304	0.821	0.966	0.098	0.002	0.030	0.338	0.211	0.169	0.121	0.038
DEU	0.553	2.594	0.868	0.115	0.037	0.072	0.139	0.266	0.101	0.086	0.017
DNK	0.470	0.786	1.329	0.214	0.014	0.092	0.021	0.832	0.138	0.131	0.027
ESP	0.386	4.699	0.680	0.021	0.003	0.044	0.008	0.206	0.130	0.149	0.022
FIN	0.228	2.899	0.796	0.117	0.006	0.094	0.131	0.280	0.153	0.256	0.021
FRA	0.280	3.632	0.815	0.049	0.004	0.048	0.001	0.224	0.068	0.070	0.014
GBR	0.360	0.853	0.958	0.017	0.010	0.024	0.148	0.209	0.233	0.147	0.041
IRL	0.298	1.384	1.127	0.154	0.013	0.652	0.772	0.285	1.014	0.988	0.049
ITA	0.300	4.130	0.603	0.041	0.013	0.087	0.035	0.150	0.095	0.082	0.012
JPN	0.158	3.923	0.293	0.004	0.000	0.067	0.021	0.159	0.034	0.020	0.005
NLD	0.988	1.496	1.259	0.082	0.076	0.106	0.011	0.562	0.245	0.405	0.114
NOR	0.391	0.837	0.995	0.146	0.024	0.097	0.009	0.354	0.146	0.143	0.058
SWE	0.294	2.263	0.969	0.119	0.020	0.163	0.019	0.392	0.274	0.256	0.026
USA	0.207	0.541	0.428	0.012	0.001	0.055	0.003	0.109	0.066	0.052	0.008
OECD	0.412	2.766	0.900	0.124	0.022	0.116	0.150	0.324	0.205	0.202	0.035
H/N	H	H	H	N	N	N	N	H	H	N	N

Notes: the complete designations for each industry are as follows (EU KLEMS codes are given in parentheses). "Agri.": "Agriculture, Hunting, Forestry and Fishing" (AtB), "Minig": "Mining and Quarrying" (C), "Manuf.": "Total Manufacturing" (D), "Elect.": "Electricity, Gas and Water Supply" (E), "Const.": "Construction" (F), "Trade": "Wholesale and Retail Trade" (G), "Hotels": "Hotels and Restaurants" (H), "Trans.": "Transport, Storage and Communication" (I), "Finance": "Financial Intermediation" (J), "Real Est.": "Real Estate, Renting and Business Services" (K), "Public": "Community Social and Personal Services" (LtQ). The openness ratio is the ratio of total trade (imports + exports) to gross output (source: World Input-Output Databases ([2013], [2016])).

We conduct below a sensitivity analysis with respect to the three industries ("Real Estate, Renting and Business Services", "Hotels and Restaurants" and "Financial Intermediation") which display some ambiguity in terms of tradability to ensure that the benchmark classification does not drive the results. In order to address this issue, we re-estimate the dynamic responses to a permanent technology shock for the main variables of interest using local projections for different classifications in which one of the three above industries initially marked as tradable (non tradable resp.) is classified as non-tradable (tradable resp.), all other industries staying in their original sector. In doing so, the classification of only one industry is altered, allowing us to see if the results are sensitive to the inclusion of a particular industry in the traded or the non-traded sector.

As an additional robustness check, we also exclude the industry "Community Social and Personal Services" from the non-tradable industries' set. This robustness analysis is based on the presumption that among the industries provided by the EU KLEMS and STAN databases, this industry is government-dominated and its removal allows us to assess whether it influences or not our results related to the effects of a permanent technology improvement. The baseline and the four alternative classifications considered in this exercise are shown in Table 21. The last line provides the matching between the color line (when displaying IRFs below) and the classification between tradables and non tradables.

Fig. 17 reports the effects of a permanent technology improvement by 1% in the long-run on selected variables shown in Fig. 2 in the main text. The green line and the red line show results when 'Hotels and restaurants' and 'Real Estate, Renting and Business Services' are treated as tradables, respectively. The black line shows results when 'Financial intermediation' is classified as non-tradables. Finally, the yellow line displays results when Public services ('Community Social and Personal Services') is excluded.

In each panel, the shaded area corresponds to the 90% confidence bounds for the baseline. For aggregate variables shown in the first column, including aggregate utilization-adjusted-aggregate-TFP, total hours worked and real GDP, the responses are remarkably similar across the baseline and alternative classifications. As shown in the yellow line which displays the response for the market sector only, the response of total hours worked is little sensitive to the inclusion or not of the public services. Inspection of the first row reveals that the classification of industries as tradables or non-tradables has an impact on the

Table 21: Robustness check: Classification of Industries as Tradables or Non Tradables

	KLEMS code	Classification				
		Baseline	#1	#2	#3	#4
Agriculture, Hunting, Forestry and Fishing	AtB	H	H	H	H	H
Mining and Quarrying	C	H	H	H	H	H
Total Manufacturing	D	H	H	H	H	H
Electricity, Gas and Water Supply	E	N	N	N	N	N
Construction	F	N	N	N	N	N
Wholesale and Retail Trade	G	N	N	N	N	N
Hotels and Restaurants	H	N	N	N	H	N
Transport, Storage and Communication	I	H	H	H	H	H
Financial Intermediation	J	H	N	H	H	H
Real Estate, Renting and Business Services	K	N	N	H	N	N
Community Social and Personal Services	LtQ	N	N	N	N	neither H or N
Color line in Figure 17		blue	red	black	green	yellow

Notes: H stands for the Traded sector and N for the Non traded sector.

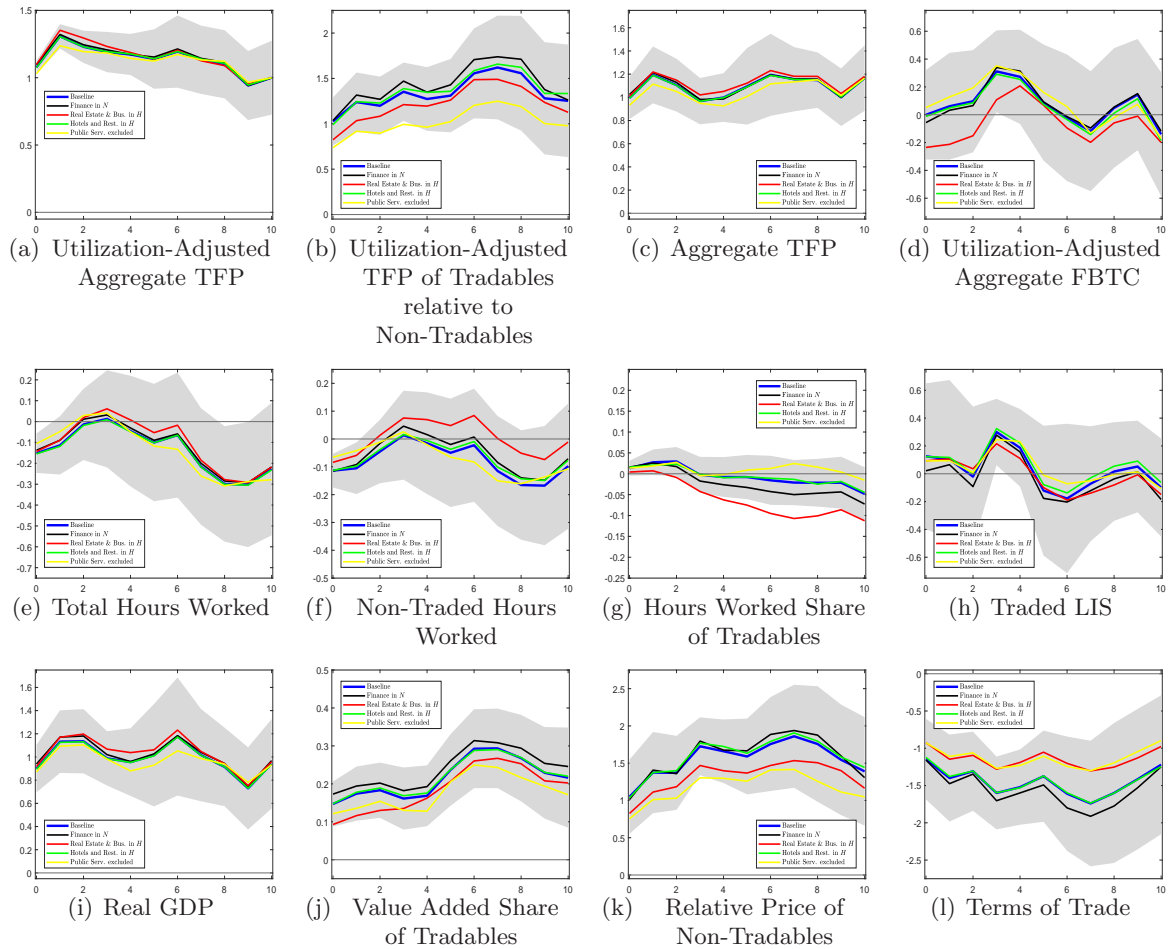


Figure 17: Labor Market Effects of a Technology Shock: Robustness Check w.r.t. the Classification of Industries as Tradable or Non-Tradable. Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. The green line and the red line show results when 'Hotels and restaurants' and 'Real Estate, renting and business services' are treated as tradables, respectively. The black line shows results when 'Financial intermediation' is classified as non-tradables. Finally, the yellow line displays results when Public services ('Community Social and Personal Services') is excluded. Sample: 17 OECD countries, 1970-2017, annual data.

utilization-adjusted-TFP of tradables relative to non-tradables. In particular, the removal of the non-market sector (classification #4 and shown in the yellow line) mitigates the rise in traded relative to non-traded technology. But the shape of the dynamic adjustment is similar to the benchmark classification and the alternative IRF lies within the confidence bounds of the baseline classification. Aggregate TFP and FBTC are not sensitive to the classification.

The second row of Fig. 17 contrasts the responses of total hours worked, non-traded

hours worked (i.e., L^N), the hours worked share of tradables (i.e., $\nu^{L,H}$), and the labor income share of tradables (i.e., s_L^H). Moving 'Real Estate, Renting and Business Services' in the traded sector results in a decline in non-traded hours worked which is less pronounced which in turn amplifies the deindustrialization trend, as displayed by Fig. 17(g). Across all scenarios, the traded LIS exhibits a similar dynamic adjustment following a technology improvement.

The third row of Fig. 17 contrasts the responses of real GDP, the value added share of tradables ($\nu^{Y,H}$), the relative price of non-tradables (P^N/P^H), and the terms of trade ($P^H/P^{H,*}$) for the baseline classification with those obtained for alternative classifications of industries as tradables or non-tradables. Alternative responses are fairly close to those estimated for the baseline classification as they lie within the confidence interval (for the baseline classification) for all the selected horizons. The dynamic adjustment of the relative price of non-tradables displays some differences across the baseline and the four alternative classifications: the appreciation is less pronounced when the public sector is excluded (classification #4 and the yellow line) because Z^H/Z^N increases less which mitigates the excess demand for non-traded goods. We also note some differences for the terms of trade which depreciate more when 'Financial intermediation' is moved to the non-traded sector (classification #2 and the black line) because technology improvements are more pronounced in the traded sector which results in a larger excess supply of traded goods. One can notice that the discrepancy in the estimated effect between the benchmark and the alternative classifications are not statistically significant

In conclusion, our main findings hold and remain insensitive to the classification of one specific industry as tradable or non-tradable. In this regard, the specific treatment of "Hotels and Restaurants", "Real Estate, Renting and Business Services", "Financial Intermediation" or "Community Social and Personal Services" does not drive the results.

M.3 Robustness Check to the Construction of Sectoral Physical Capital Time Series

In the main text, due to data availability, we construct time series for sectoral capital by computing the overall capital stock by adopting the perpetual inventory approach and then by splitting the gross capital stock into traded and non-traded industries by using sectoral valued added shares. In this Appendix, we investigate whether the effects on utilization-adjusted-TFP and utilization-adjusted-FBTC we estimate empirically are driven by our assumption about the construction of time series for sectoral capital stock. To conduct this robustness check, we contrast below empirical responses when sectoral capital stocks are measured by adopting the Garofalo and Yamarik's [2002] methodology (our benchmark) with those obtained by using sectoral data on K^j provided by EU KLEMS [2011], [2017] databases. Due to data availability, our results in the latter case include a sample of thirteen OECD countries which provide time series on sectoral capital of reasonable length. In this regard, Belgium, Germany, Ireland and Sweden are removed from the sample due to a lack of data over a reasonable time length to construct K^H and K^N . To be consistent, our benchmark excludes these four countries and thus focuses on thirteen countries only.

The methodology by Garofalo and Yamarik's [2002] is based on the assumption of perfect mobility of capital across sectors and a small discrepancy in the LIS across sectors, i.e., $s_L^H \simeq s_L^N$. The assumption of perfect capital mobility implies that the marginal revenue product of capital must equalize across sectors:

$$P_t^H (1 - s_L^H) \frac{Y_t^H}{K_t^H} = P_t^N (1 - s_L^N) \frac{Y_t^N}{K_t^N}. \quad (208)$$

Using the resource constraint for capital, $K = K^H + K^N$, dividing the numerator and the denominator in the LHS of (208) by GDP, Y , and denoting by $\omega_t^{Y,j} = \frac{P_t^j Y_t^j}{Y_t}$ the share of value added of sector j in GDP at current prices (at time t), eq. (208) can be solved for the K^H/K :

$$\frac{K_t^H}{K_t} = \frac{\omega_t^{Y,H} (1 - s_L^H)}{(1 - s_L^N) (1 - \omega_t^{Y,H}) + (1 - s_L^H) \omega_t^{Y,H}}. \quad (209)$$

Assuming that $s_L^H \simeq s_L^N$ leads to the rule we apply to split the aggregate stock of capital into tradables and non tradables:

$$\frac{K_t^H}{K_t} = \omega_t^{Y,H}. \quad (210)$$

In the baseline, we adopt the methodology of Garofalo and Yamarik [2002] to split the national gross capital stock into traded and non-traded industries by using sectoral value added shares at current prices. Let $\omega^{Y,j}$ be the share of sector j 's value added (at current prices) $P^j Y^j$ for $j = H, N$ in overall output (at current prices) $Y \equiv P^H Y^H + P^N Y^N$, the allocation of the national capital stock to sector j is given by the rule:

$$K_{GY}^j = \omega^{Y,j} K = \frac{P^j Y^j}{Y} K, \quad (211)$$

where we denote the sectoral stock of capital obtained with the decomposition by Garofalo and Yamarik [2002] by K_{GY}^j . National capital stocks are estimated from the perpetual inventory approach. Following Garofalo and Yamarik [2002], the gross capital stock is then allocated to traded and non-traded industries by using sectoral value added shares according to eq. (211). Once the series for K_{GY}^j are obtained, we can construct the sectoral capital-labor ratios, $k_{GY}^j = K_{GY}^j / L^j$, sectoral capital utilization rates, $u_{GY}^{K,j}$, sectoral utilization-adjusted-TFPs, Z_{GY}^j , and sectoral utilization-adjusted-FBTC (see section E).

Sample. As a robustness check, we alternatively take capital stock series from the EU KLEMS [2011] and [2017] and STAN [2017] and [2017] databases which provide disaggregated capital stock data (at constant prices) at the 1-digit ISIC-rev.3 level for up to 11 industries, but only for thirteen countries of our sample which include Australia (1970-2007), Austria (1976-2017), Canada (1970-2016), Denmark (1970-2017), Spain (1970-2016), Finland (1970-2017), France (1978-2017), the United Kingdom (1970-2015), Italy (1970-2017), Japan (1973-2015), the Netherlands (1970-2017), Norway (1970-2017) and the United States (1970-2016). In efforts to have time series of a reasonable length, we exclude Belgium (1995-2017), Germany (1991-2017), Ireland (1985-2017) and Sweden (1993-2016) because the period is too short.

Results. In Fig. 18, we compare the responses of selected variables displayed by Fig. 2 in the main text. Note that because we consider new time series for K^j , we have reconstructed time series for sectoral TFPs and the capital utilization rates. The blue line shows the dynamic effects of a 1% permanent increase in utilization-adjusted-aggregate-TFP when the sectoral capital stock is measured by adopting the methodology by Garofalo and Yamarik [2002] while the black line shows the dynamic effects when the capital stock is obtained directly from KLEMS (black line). For comparison purposes and to ensure consistency, we compare the results by considering the same sample, i.e. the restricted sample that includes 13 OECD countries over the period 1970-2017. As it stands out, the construction of capital stocks does not affect the results as we cannot detect any difference, even for the utilization-adjusted-TFP, TFP, or FBTC. In conclusion, our main findings are robust and insensitive to the way the sectoral capital stocks are constructed in the data. While the responses of capital-labor ratios are not reproduced, one can observe that a discrepancy in the results in the short-run only. To conclude, the dynamic effects of a technology improvement are similar across the two methods as they are both qualitatively and quantitatively similar since the solid black line lies within the original confidence bounds of those obtained when K^j is constructed with the use of the methodology of Garofalo and Yamarik [2002]. In particular, one can observe that the discrepancy in the results is small and not statistically significant at conventional level.

M.4 How Technology at Industry Level Responds to Aggregate Technology Improvements: A Disaggregated Approach

Empirical analysis at a disaggregate sectoral level. Our dataset covers eleven industries which are classified as tradables or non-tradables. The traded sector is made up of five industries and the non-traded sector of six industries. To conduct a decomposition of the sectoral effects at a sub-sector level, we estimate the responses of sub-sectors to the same identified government spending shock by adopting the two-step approach detailed in

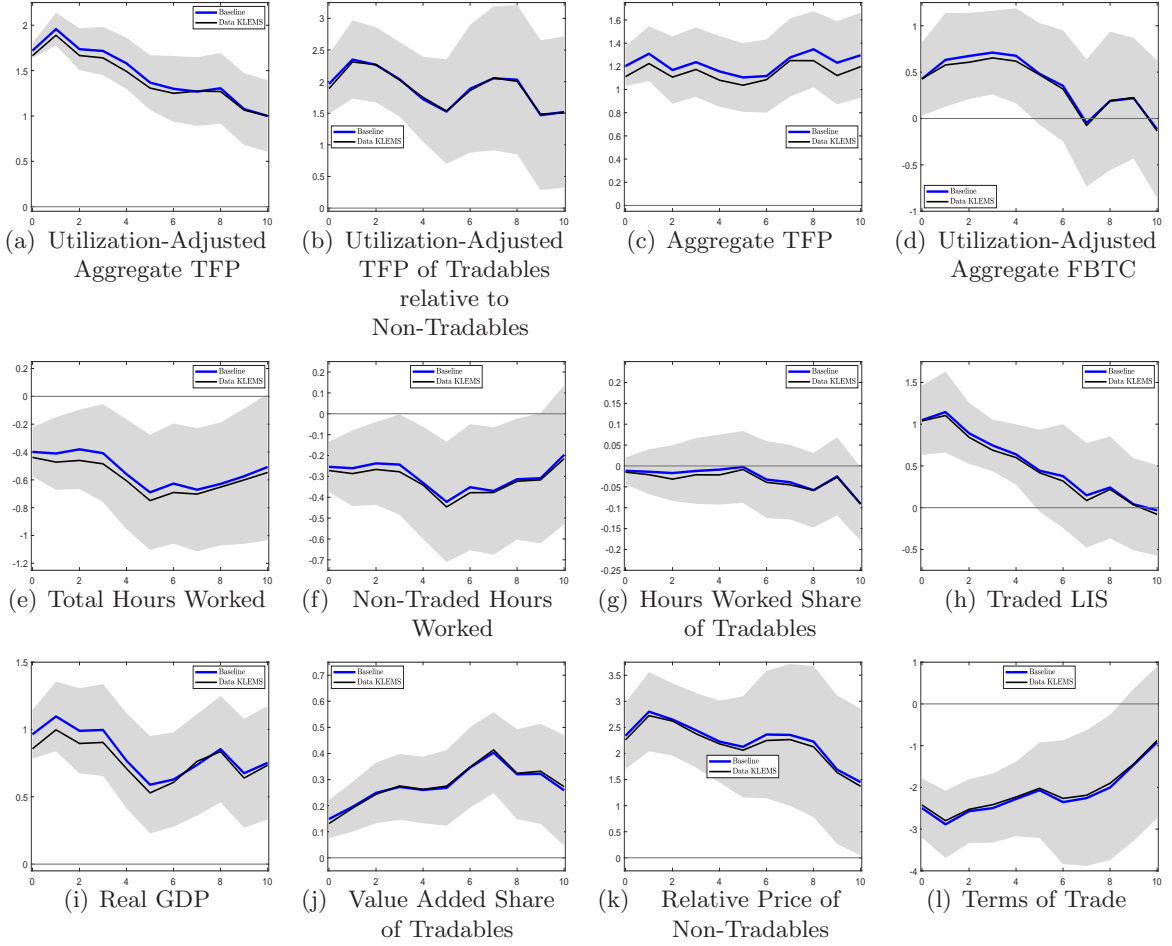


Figure 18: Labor Market Effects of a Technology Shock: Robustness Check w.r.t. the Construction of Sectoral Capital Stocks Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. The black line reports responses when we use the EU KLEMS [2011] and [2017] databases to construct sectoral capital stocks series K^j . Sample: 13 OECD countries, 1970-2017, annual data.

the main text. More specifically, indexing countries with i , time with t , sectors with j , and sub-sectors with k , we first identify the permanent technology shock, by estimating a VAR model which includes utilization-adjusted-aggregate-TFP, Z_{it}^A , real GDP, total hours worked, the real consumption wage (all quantities are divided by the working age population and all variables are in rate of growth) and next we estimate the dynamic effects by using the Jordà's [2005] single-equation method. The local projection method amounts to running a series of regression of each variable of interest on the structural identified shock for each horizon $h = 0, 1, 2, \dots$:

$$x_{i,t+h}^{k,j} = \alpha_{i,h}^{k,j} + \alpha_{t,h}^{k,j} + \psi_h^{k,j}(L) z_{i,t-1} + \gamma_h^{k,j} \cdot \epsilon_{i,t}^{ZA} + \eta_{i,t+h}^{k,j}, \quad (212)$$

where $x = \text{TFP}_{i,t}^{k,j}, L_{i,t}^{k,j}$. To express the results in meaningful units, i.e., we multiply the responses of TFP of sub-sector k by the share of industry k in the value added of the broad sector j (at current prices), i.e., $\omega^{Y,k,j} = \frac{P^{k,j} Y^{k,j}}{P^j Y^j}$. We multiply the responses of hours worked within the broad sector j by its labor compensation share, i.e., $\alpha^{L,k,j} = \frac{W^{k,j} L^{k,j}}{W^j L^j}$. We detail below the mapping between the responses of broad sector's variables and responses of variables in sub-sector k of one broad sector j .

The response of $L^{k,j}$ to a technology shock is the percentage deviation of hours worked in sub-sector $k \in j$ relative to initial steady-state: $\ln L_t^{k,j} - \ln L^{k,j} \simeq \frac{dL_t^{k,j}}{L^{k,j}} = \hat{L}_t^{k,H}$ where $L^{k,j}$ is the initial steady-state. We assume that hours worked of the broad sector is an aggregate of sub-sector hours worked which are imperfect substitutes. Therefore, the response of hours worked in the broad sector \hat{L}_t^j is a weighted average of the responses of hours worked

$\frac{W^{k,j}L^{k,j}}{W^jL^j}\hat{L}_t^{k,j}$ where $\frac{W^{k,j}L^{k,j}}{W^jL^j}$ is the share of labor compensation of sub-sector k in labor compensation of the broad sector j :

$$\begin{aligned}\hat{L}_t^j &= \sum_{k \in j} \frac{W^{k,j}L^{k,j}}{W^jL^j} \hat{L}_t^{k,j}, \\ \frac{W^jL^j}{WL} \hat{L}_t^j &= \sum_{k \in j} \frac{W^{k,j}L^{k,j}}{WL} \hat{L}_t^{k,j}, \\ \alpha^{L,j} \hat{L}_t^j &= \sum_{k \in j} \alpha^{L,k} \hat{L}_t^{k,j},\end{aligned}\tag{213}$$

where $\sum_j \sum_k \alpha^{L,k} = 1$. Above equation breaks down the response of hours worked in broad sector j into the responses of hours worked in sub-sectors $k \in j$ weighted by their labor compensation share $\alpha^{L,k} = \frac{W^{k,j}L^{k,j}}{W^jL^j}$ averaged over 1970-2017. In multiplying $\hat{L}_t^{k,j}$ by $\alpha^{L,k}$, we express the response of hours worked in sub-sector $k \in j$ in percentage point of hours worked in the broad sector $j = H, N$.

The response of TFP in the broad sector j is a weighted average of responses $\text{TFP}_t^{k,j}$ of TFP in sub-sector $k \in j$ where the weight collapses to the value added share of sub-sector k :

$$\begin{aligned}\text{TFP}_t^{k,j} &= \sum_{k \in j} \frac{P^{k,j}Y^{k,j}}{P^jY^j} \hat{\text{TFP}}_t^{k,j}, \\ \text{TFP}_t^j &= \sum_{k \in j} \frac{P^{k,j}Y^{k,j}}{P^jY^j} \hat{\text{TFP}}_t^{k,j}, \\ \text{TFP}_t^j &= \sum_{k \in j} \omega^{Y,k,j} \hat{\text{TFP}}_t^{k,j},\end{aligned}\tag{214}$$

where $\omega^{Y,k,j} = \frac{P^{k,j}Y^{k,j}}{P^jY^j}$ averaged over 1970-2017 is the value added share at current prices of sub-sector $k \in j$ which collapses (at the initial steady-state) to the value added share at constant prices as prices at the base year are prices at the initial steady-state. Note that $\sum_k \sum_{k \in j} \omega^{Y,k,j} = 1$.

Aggregate technology shock. The first column of Fig. 19 shows responses of TFP and hours worked of sub-sectors classified in the traded sector and the non-traded sector to a permanent technology improvement of 1% in the long-run. When we consider an aggregate technology shock, all industries behave as the broad sector as they all experience a permanent technology improvement, except 'Mining' shown in the black line for which the rise in TFP vanishes in the long-run. More interestingly, the rise in traded TFP is driven by technology improvement in 'Manufacturing' because this sector accounts for the greatest value added share of the traded sector and also experiences significant increases in TFP. With regard to non-traded industries, 'Real Estate, Renting, and Business Services' drives the rise in non-traded TFP followed by 'Wholesale and Retail Trade' and 'Community Social and Personal Services' (i.e., the public sector which also includes health and education services). When we focus on traded and non-traded hours worked, we find that all industries experience a decline in hours worked except 'Construction'. One explanation to this lies in the shift of labor away from traded and toward non-traded industries. As we shall see, this sector experiences a dramatic increase in its hours worked following an asymmetric technology shock.

Symmetric technology shock. The second column of Fig. 19 shows responses of TFP and hours worked of sub-sectors classified in the traded sector and the non-traded sector to a permanent technology improvement of 1% which is evenly spread between the traded and non-traded sectors. Like for an aggregate technology shock, the rise in traded TFP is driven by technology improvement in 'Manufacturing' while 'Real Estate, Renting, and Business Services' drives the rise in non-traded TFP. All traded industries experience a decline in hours worked on impact while only 'Agriculture' and 'Manufacturing' experience a fall in the long-run. All non-traded industries experience a decline in hours worked on

impact while only 'Real Estate, Renting, and Business Services' experiences a persistent decline in its hours worked below trend.

Asymmetric technology shock. The third column of Fig. 19 shows responses of TFP and hours worked of sub-sectors classified in the traded sector and the non-traded sector to a permanent technology improvement of 1% which is concentrated toward traded industries. As it stands out, the rise in traded TFP is driven by a technology improvement in 'Manufacturing' and the gap with other sectors is even more pronounced than after an aggregate technology shock. We can notice that the contribution of 'Mining' is substantial given its small weight in the traded sector. When we turn to the non-traded TFP, we find that 'Real Estate, Renting, and Business Services' together with 'Community Social and Personal Services' (i.e., the public sector which also includes health and education services) drive the fall in non-traded TFP. Traded industries such as 'Manufacturing', 'Financial Intermediation', 'Transport and Communication' drive the rise in traded hours worked following an asymmetric technology shock. All non-traded industries experience an increase in hours worked. The rise in non-traded hours worked is driven by the rise in labor in 'Construction' and 'Community Social and Personal Services' followed by 'Real Estate, Renting, and Business Services' and 'Wholesale and Retail Trade'. The diversity of industries which experience a rise in labor can explain why both skilled and unskilled labor shift away from traded industries and toward non-traded industries following an asymmetric technology shock.

M.5 Do both Symmetric and Asymmetric Technology Shocks Stimulate Innovation

In this subsection, we further investigate the drivers behind symmetric and asymmetric technology shocks and if these two shocks are different. We must acknowledge that the literature on technology shocks is silent about the factors driving technology improvements except Shea [1999] and Alexopoulos [2011]. Shea [1999] employs direct measures of technological change based on research and R&D expenditure and patent activities in a VAR to identify technology shocks. Using annual panel data for 19 U.S. manufacturing industries from 1959 to 1991, the author estimates VARs to determine the dynamic impact of shocks to two observable indicators of technological change: R&D spending (measures the amount of input devoted to innovative activity), and patent applications (measure innovation). The author finds that favorable technology shocks tend to increase input use, especially labor, in the short run, but to reduce inputs in the long run. Alexopoulos [2011] presents new measures of technical change based on new book titles in the field of technology from 1955-1997. Results show that technology shocks driven by book publications in the area of technology increases R&D and employment.

Effects of symmetric and asymmetric technology shocks on R&D. First, we identify asymmetric and symmetric technology shocks by estimating a VAR model which includes the ratio of traded to non-traded technology measure, aggregate technology measure, real GDP, total hours worked and real consumption wage and then we estimate the dynamics effects of aggregate, symmetric and asymmetric technology improvements on the stock of R&D of tradables and non-tradables at constant prices. Table 22 and Table 23 present the point estimate at horizons $t = 0...8$ which measures the increase in percentage in the stock of R&D in the traded and the non-traded sectors after an aggregate, asymmetric and symmetric technology shocks, respectively. Our sample includes 13 OECD countries over 1995-2017. The evidence reveals that only asymmetric technology shocks has a positive and a statistically significant impact in the stock of R&D and only in the traded sector.

Do asymmetric technology shocks increase innovation? Asymmetric technology shocks are technology improvements which are concentrated toward traded industries. As discussed above, only these shocks give rise to a significant and positive increase in the stock of R&D which reflects cumulated investment devoted to innovative activity. As shown in section R.4, the stock of R&D has a significant impact on utilization-adjusted-TFP of tradables while it has virtually no impact on non-traded technology. Therefore, accumulation of R&D investment can generate innovation since according to our FMOLS estimates, an increase in the stock of R&D in the traded sector by 1% improves technology of tradables

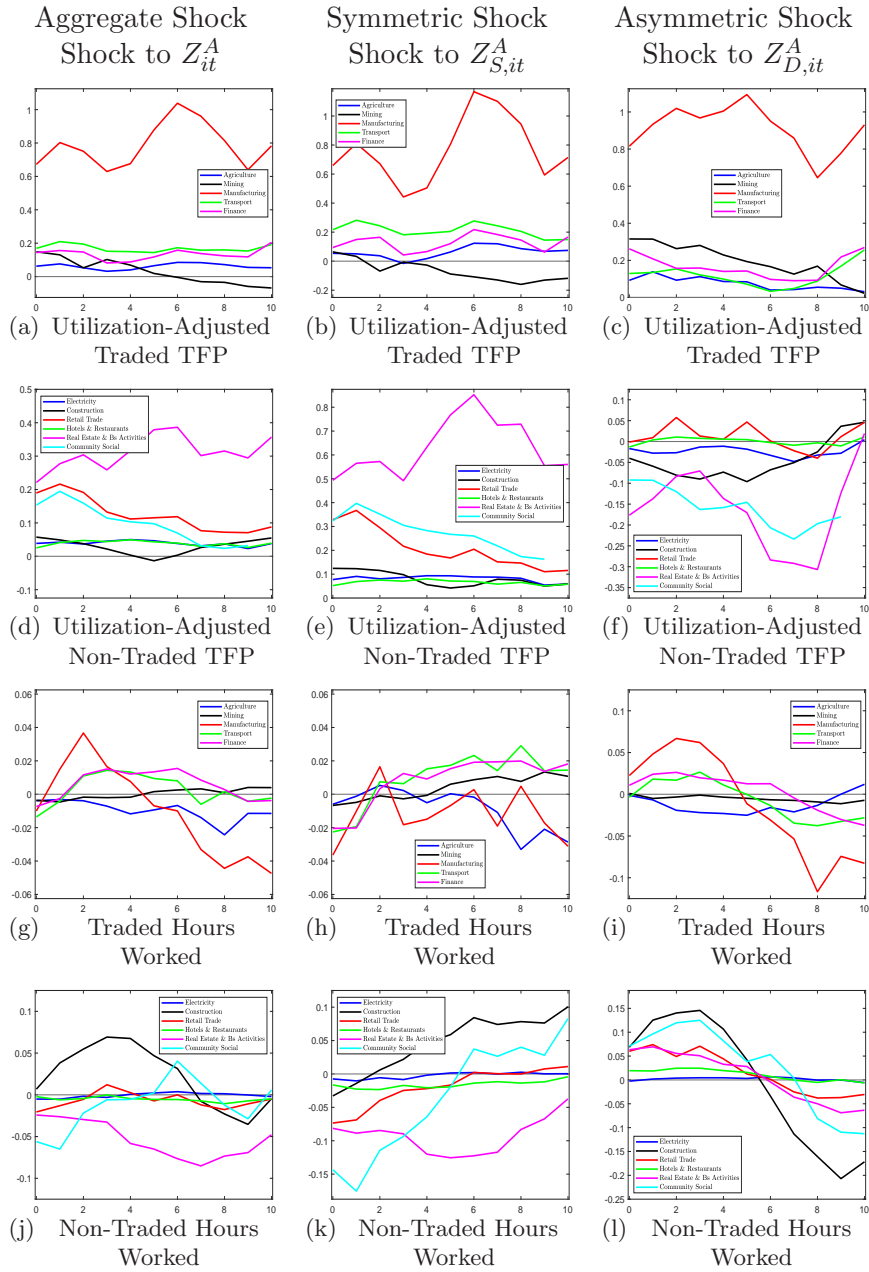


Figure 19: Effects Technology Shocks on Eleven Sub-Sectors. Notes: Because the traded and non-traded sector are made up of industries, we conduct a decomposition of the sectoral effects at a sub-sector level following an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. To express the results in meaningful units, i.e., total hours worked units, we multiply the responses of hours worked sub-sector k by its labor compensation share (in the traded sector of traded industries or in the non-traded sector for non-traded industries), i.e., $\frac{W^k \cdot j \cdot L^j \cdot j}{W^j \cdot L^j}$. Column 1-3 display the responses of technology and hours in traded and non-traded industries to aggregate, symmetric and asymmetric technology shocks across sectors, respectively. For tradable industries: the blue line shows results for 'Agriculture', the black line for 'Mining and Quarrying', the red line for 'Manufacturing', the green line for 'Transport and Communication', and the purple line for 'Financial Intermediation'. The second/fourth columns show results for sub-sectors classified in the non-traded sector. For non-tradable industries: the blue line shows results for 'Electricity, Gas and Water Supply', the black line for 'Construction', the red line for 'Wholesale and Retail Trade', the green line for 'Hotels and Restaurants', and the cyan line for 'Community Social and Personal Services'. Sample: 17 OECD countries, 11 industries, 1970-2017, annual data.

by 0.23%. This evidence thus underlines that technology improvements concentrated in traded industries, i.e., asymmetric technology shocks, are shocks which increase innovation. In contrast, symmetric technology shocks do not increase the stock of R&D significantly and may capture improvements in work organization within the firm and/or better management practices.

Table 22: IRF of the Stock of R&D in the Traded Sector After Technology Shocks

Horizon	AGG	ASYM	SYM
0	-0.025	0.148	-0.163
2	0.381	0.511 ^b	0.187
4	0.328	0.639 ^b	0.009
6	-0.015	0.461	-0.416
8	0.332	1.213 ^a	-0.349

Notes: ^a, ^b and ^c denote significance at 1%, 5% and 10% levels. The number in columns denotes the impulse response function (estimated with local projections) of the stock of R&D in the traded sector after an aggregate technology shock (column AGG), an asymmetric technology shock (column ASYM) and an symmetric technology shock (column SYM). Sample: 12 OECD countries, 1995-2017, annual data.

Table 23: IRF of the Stock of R&D in the Non Traded Sector After Technology Shocks

Horizon	AGG	ASYM	SYM
0	0.086	0.134	0.029
2	0.310	0.388	0.173
4	0.224	0.109	0.273
6	-0.103	-0.006	-0.161
8	0.085	0.291	-0.120

Notes: ^a, ^b and ^c denote significance at 1%, 5% and 10% levels. The number in columns denotes the impulse response function (estimated with local projections) of the stock of R&D in the non traded sector after an aggregate technology shock (column AGG), an asymmetric technology shock (column ASYM) and an symmetric technology shock (column SYM). Sample: 12 OECD countries, 1995-2017, annual data.

Effects of technology shocks on labor: shocks to the stock of R&D vs. shocks to utilization-adjusted-TFP. Shea [1999] and Alexopoulos [2011] find that technology shocks driven by innovation increase employment. In this paper, we show that symmetric technology shocks lower dramatically hours worked while asymmetric technology shocks increase significantly labor. Since asymmetric technology shocks are driven by innovation, our work can reconcile the labor effects of technology shocks reported by the literature and the evidence documented by Shea [1999] and Alexopoulos [2011] who focus on shocks to innovation and find that innovation-driven technology shocks increase employment.

To further investigate the discrepancy in the effects on hours caused by shocks to innovation or driven by technology shocks reflecting mainly technology adoption of better worker organizations, we estimate a SVAR which includes the aggregate stock of R&D at constant prices, utilization-adjusted-aggregate-TFP, real GDP, total hours worked and the real consumption wage, all variables entering the VAR model in growth rates. Our identification strategy lies in long-run restrictions. We identify innovation shocks as shocks which increase permanently the stock of R&D while we identify technology improvements not driven by innovative activities as technology shocks which increase permanently the utilization-adjusted-aggregate-TFP. We find that innovation shocks does not drive down hours on impact and instead increase labor in the long-run. In contrast, technology shocks which are not driven by innovative industries lower persistently hours worked.

N Addressing the SVAR Critique

The SVAR methodology allows researchers to estimate the adjustment of macroeconomic variables conditional on a shock. We run VARs on the actual data and impose identification assumptions to identify a specific shock and trace out the dynamic responses of variables to this shock. Then we calibrate the macroeconomic model and compare the theoretical responses with empirical responses in order to determine which model is more suited to

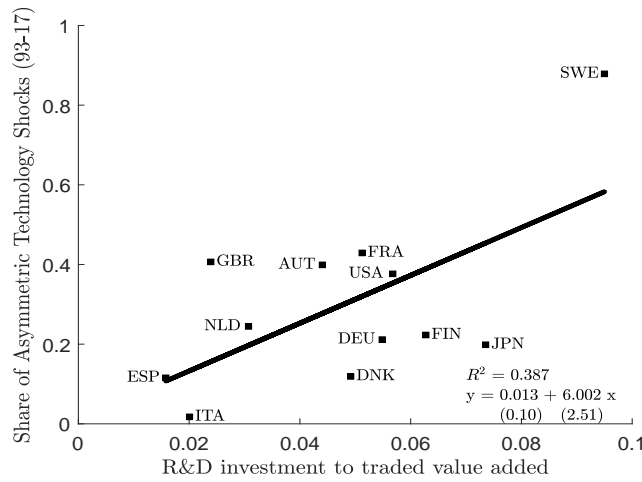


Figure 20: Cross-Country Relationship between Investment in R&D (% of Value Added in the Traded Sector) and the Share of FEV of Technological Change Driven by Asymmetric Technology Improvements. *Notes:* The horizontal axis shows the R&D investment to value added ratio for the traded sector. To measure the intensity of the traded sector in investment in R&D, we take data from EU KLEMS, Stehrer et al. [2019], see Table 28 for data coverage in section R.4. Sample: 12 OECD countries, 1995-2017. On the vertical axis, we show the FEV of technological change attributed to asymmetric technology shocks over the period 1993-2017 to fit the period over which data on R&D is available. The share of asymmetric technology shocks is an average of the share at time $t = 0$ and $t = 10$. Sample: 12 OECD countries, 1993-2017.

rationalize the SVAR evidence.

The identification of technology shocks by adopting the SVAR methodology has been subject to criticism. As summarized by Dupaigne, Fève, and Matheron [2007], the distortions in a DSVAR may originate from several sources: (i) hours are over-differenced (Erceg, Gust and Guerrieri [2005]) (ii) average labor productivity is a poor proxy for total factor productivity at business cycle frequencies (Chang and Hong [2006]); (iii) the estimation of DSVARs is subject to small-sample biases, especially with long-run restrictions (see Faust and Leeper [1997]); (iv) a structural VAR with a finite number of lags may poorly approximate the dynamics of DSGE models (Chari, Kehoe and McGrattan [2008]). Whilst SVAR models might be subject to potential biases, nevertheless, the information they produce can effectively complement analyses conducted with dynamic macroeconomic models, help to point out the dimensions where these models fail, and provide stylized facts and predictions which can improve the realism of macroeconomic models.

In this section, we address the SVAR critique. In section N.2, we investigate if our identification of asymmetric technology shocks across sectors is contaminated by non-technology shocks. In section N.3, we conduct a robustness check w.r.t. to the number of lags. In section N.4, we adjust sectoral TFPS with sectoral capital utilization rates and identify shocks to traded relative to non-traded utilization-adjusted-TFP. In section N.5, we replace the country-level traded relative to non-traded TFP with its world counterpart. In section N.6, we employ the Max Share approach. In section N.7, we use a two-step procedure proposed by Fève and Guay [2010] to identify technology shocks so that a VAR model with a finite number of lags can more easily approximate the true underlying dynamics of the data.

N.1 Short Review of the Issues about SVAR Identification of Technology Shocks

Small sample bias. Faust and Leeper [1997] argue that structural VARs with long-run restriction do not enable precise inference due to small sample bias. Erceg, Gust and Guerrieri [2005] find that most of the small-sample bias is attributable to the difficulty in precisely estimating the long-run response of variables to the structural shocks in the VAR model. Such a difficulty is caused by the slow adjustment of capital which complicates the estimation of the long-run impact of the technology shock on labor productivity and also makes it hard to disentangle technology shocks from highly persistent non-technology shocks. By using utilization-adjusted-TFP, we overcome this difficulty. Chari, Kehoe and McGrattan [2008] have shown that the small sample bias remains limited and that the lag truncation bias might cause a more significant bias. Our Panel SVAR estimates very accurately the responses of variables as it circumvents the small sample bias at a country level by con-

sidering 17 countries. The confidence bands are tight enough to allow us to discriminate between competing flexible price models. Christiano, Eichenbaum, and Vigfusson [2006] make the case that even if the VAR point estimates of the structural impulse responses are inaccurate in small samples, after accounting for sampling uncertainty, researchers would rarely reject a DSGE model incorrectly. Although the confidence bands may be wide, they are not so wide as to be consistent with any possible DSGE model.

Finite number of lags: lag-truncation bias. Whilst estimation of VAR models necessitates only a small number of lags (commonly 4 lags on quarterly data and 2 lags on annual data), the VAR representation of many theoretical models includes an infinite number of lags. Chari, Kehoe and McGrattan [2008], Erceg, Guerrieri and Gust [2005]) and Dupaigne, Fève and Matheron [2007] show that persistent non-technology shocks disturb the identification of permanent technology shocks. When non-technology shocks are persistent and they account for a large share of GDP fluctuations, the SVAR estimations are biased. Conversely, when demand shocks are not too persistent or if they account for a trivial fraction of output fluctuations, the means of the SVAR impulse responses are close to the model's theoretical impulse responses.

Their common intuition is that, under decreasing returns to labor input, every shock with long-lasting negative effects on labor input stimulates average labor productivity, even in the medium-run. Such shocks contaminate the estimated response of labor input to permanent productivity shocks. CKM argue that the need for a large number of lags when running the VAR stems from the presence of capital. As shown by Chaudourne, Fève and Guay [2014], the use of average labor productivity as a proxy for technology is responsible for the lag-truncation bias as persistent non-technology shocks have long-lasting effects on the capital stock which contaminates the identification of true technology shocks. In addition, shocks to labor tax or capital tax have permanent effects on labor productivity.

TFP is a better proxy of technological change than labor productivity. Most of the literature investigating the effects of technology shocks uses labor productivity to approximate technological change. The use of average labor productivity (i.e., $y^j = \text{tfp}^j + s_L^j k^j$) as a proxy for technology imposes a long-run identification which implies that any shock which has a persistent effect on the capital-labor ratio might contaminate the estimated responses to technology shocks which explains why Chari, Kehoe and McGrattan [2008] find that an economy without capital will not be subject to the bias identified by the authors. On the contrary, the use of TFP is less prone to be influenced by persistent non-technology shocks.

Chang and Hong [2006] have shown that labor productivity is not the correct measure from which to identify technology shocks. The reason to this is that labor productivity reflects both improved efficiency and changes in the input mix (i.e., in the capital-labor ratio). In support of their argument, the authors show that labor productivity and TFP are not cointegrated, therefore the long-run component of labor productivity does not truly identify technology shocks. Chaudourne, Fève and Guay [2014] estimate the short-run responses of hours worked in various (bivariate) SVARs estimated on (actual) U.S. data by using three different measures of productivity (used for long-run identification): labor productivity, TFP, adjusted-TFP. When the Solow residual and the adjusted measure of TFP are considered, the specification of hours (in level or in first difference) does not matter. On impact, the authors find that hours worked decrease and after two years the response becomes persistently positive. This finding means that when technological change is properly measured, i.e., by using TFP or adjusted-TFP, consistent VAR estimates are obtained. In contrast, VAR estimates are significantly biased when labor productivity is used to approximate technological change. The reason why labor productivity might lead the SVAR identification to be subject to biases is that as claimed by Erceg, Gust and Guerrieri [2005], the slow adjustment of capital makes it hard to gauge the long-run impact of a technology shock on labor productivity, contributing to downward bias in the estimated impulse responses.

N.2 Are Utilization-Adjusted Technology Shocks Contaminated by Non-Technology Shocks?

In the lines of Francis and Ramey [2005], we assess below the validity of the technology shocks identified using long-run restrictions by subjecting the model to exogeneity tests.

Mertens and Ravn [2011] find that permanent changes in income tax rates induce permanent changes in hours worked as well as in labor productivity which leads to a violation of the standard long-run identification strategy for technology shocks. The importance of controlling for tax changes was raised earlier by Uhlig [2004] who points out that changes in capital income tax rates may give rise to long-lasting changes in labor productivity, thus leading to a violation of the identifying assumption for technology shocks. Because Gali [1999] uses labor productivity, the shocks identified could include capital income tax rate shocks. As stressed by Francis and Ramey [2005], permanent shifts in government spending have permanent effects on wages, and hours, but not on labor productivity (because the capital-labor ratio remains unaffected). However, as shown by Chaudourne, Fève and Guay [2014], permanent or long-lasting non-technology shocks can contaminate the SVAR identification of technology shocks as they impinge on hours worked and thus on labor productivity.

Because our measure of productivity is utilization-adjusted-TFP, the technology shocks we identified in the main text should not be contaminated by non-technology shocks. The reason is twofold. One advantage of using TFP is that labor productivity is presumably affected in more important ways by business cycle fluctuations than TFP. More specifically, total factor productivity is a measure of technological change purified from changes in the capital labor-ratio. Second, we consider a 'purified' measure of technology as recommended by BKF [2006] and Chaudourne, Fève and Guay [2014] which ensures that technology shocks are less likely to be contaminated by non-technology shocks, such as shocks to taxation, monetary policy and government spending. To confirm this assumption, we closely follow Francis and Ramey [2005].

Exogeneity tests. The identified technology shock should not in principle be correlated with other exogenous non-technology shifts nor with lagged endogenous variables. To investigate whether the identified shows are really technology shocks is to test whether non-technology variables are correlated with the shocks. We consider three types of non-technology shocks: unanticipated temporary changes in taxation, in government spending, and in monetary policy. We identify three types of shocks by considering two different VAR models. Our identification of government spending shocks follows Blanchard and Perotti [2002] and our identification of monetary policy shocks follows from Christiano et al. [2005]. We estimate a Vector Autoregression (VAR) which includes government consumption, real GDP, total hours worked, the real consumption wage, utilization-adjusted aggregate total factor productivity, and the short-term interest rate. For consistency reasons, we adjust the nominal interest rate with foreign prices as foreign goods and services are the numeraire in our model. All quantities are divided by the working age population. All variables enter the VAR model in log level except the interest rate which is in level. Like Blanchard and Perotti [2002], we base the identification scheme on the assumption that there are some delays inherent to the legislative system which prevents government spending from responding endogenously to contemporaneous output developments. We thus order government consumption before the other variables which amounts to adopting the standard Cholesky decomposition pioneered by Blanchard and Perotti [2002]. Like Christiano et al. [2005], we identify monetary policy shocks as the innovation to the federal funds rate under a recursive ordering, with the policy rate ordered last. The ordering of the variables embodies the key identifying assumptions according to which the variables do not respond contemporaneously to a monetary policy shock.

Source: Government final consumption expenditure (CGV), OECD Economic Outlook Database [2017]. The short-term interest rate based on three-month money market rates taken from OECD Economic Outlook Database. The nominal interest rate deflated by the price of foreign goods which is the numeraire in our model and thus we subtract the rate of change of the weighted average of the traded value added deflators of trade partners of the country i from the nominal interest rate denoted by R_{it} .

To identify shocks to tax rates, denoted by ϵ_{it}^T , we estimate a VAR model which includes net taxes defined as taxes minus security social benefits paid by general government (deflated using the GDP deflator), real GDP, total hours worked, the real consumption wage, and utilization-adjusted aggregate TFP. Following Blanchard and Perotti [2002], we identify shocks to taxation by assuming that net taxes do not respond within the year to the other variables included in the VAR model.

Empirical strategy and results. As in the main text, we identify technology shocks by estimating a VAR which includes utilization-adjusted-aggregate-TFP, real GDP, total hours worked, the real consumption wage and identify technology shocks as shocks which increase permanently utilization-adjusted aggregate TFP. We run the regression, in panel format on annual data, of identified technology shocks, ϵ_{it}^{ZA} , on three different structural shocks:

$$\epsilon_{it}^Z = d_i + d_t + \beta_G \epsilon_{it}^G + \beta_R \epsilon_{it}^R + \beta_T \epsilon_{it}^T + \nu_{it}. \quad (215)$$

where ν_{it} is an i.i.d. error term; country fixed effects are captured by country dummies, d_i , and common macroeconomic shocks by year dummies, d_t . Note that in estimating eq. (215), we add lagged values (we consider four lags) on non-technology shocks which allow us to take into account for the persistence of non-technology shocks. As detailed in the next section, we consider a 'purified' measure of technology as recommended by BKF [2006] and Chaudourne, Fève and Guay [2014] which ensures that technology shocks are less likely to be contaminated by non-technology shocks. To show this point, we re-estimate the VAR model by replacing utilization-adjusted aggregate TFP with the Solow residual and identify technology shocks as shocks which increase permanent aggregate TFP. As pointed out above, TFP is a better measure than labor productivity to identify technology shocks. To test this statement, we estimate a VAR model which includes labor productivity (calculated as the ratio of real GDP to total hours worked), total hours worked, and the real consumption wage. We omit real GDP which collapses to the product of labor productivity with total hours worked.

If our identification is correct, we should observe that non-technology shocks are correlated with demand shocks or tax shocks. To test this assumption, we run the regression of non-technology shocks which are shocks to real GDP denoted by ϵ_{it}^{YR} on the set of three shocks shown on the RHS of eq. (215) and thus replace ϵ_{it}^Z with ϵ_{it}^{YR} .

Panel data estimations are shown in Table 24. We test the null hypothesis that all of the coefficients on explanatory variables are jointly equal to zero. If $p\text{-value} \geq 0.05$ at a 5% significance level, the variables are not significant in explaining the identified technology shock ϵ_{it}^Z or the identified non-technology shock ϵ_{it}^{YR} . The first row of Table 24 runs the regression (215) by considering our baseline measure of technology shocks and two alternative measures based on the Solow residual and labor productivity on the three sets of shocks. The p -value of 0.136 for the F -test show that none of the variables is significant in explaining our identified technology shocks. By contrast, the p -value is lower than 0.05 for both technology shocks identified on the basis of the Solow residual and labor productivity.

In contrast, we expect non-technology shocks we identify by estimating the VAR model with long-run restrictions to be correlated with the set of non-technology variables. To test this assumption, we run the same regression as above, i.e., eq. (215) where ϵ_{it}^Z is replaced with the shock denoted by ϵ_{it}^{YR} which increases permanently real GDP but have no permanent effect on utilization-adjusted TFP. As shown in the second row of Table 24, the p -value is lower than 0.05 which thus reveals that non-technology shocks are correlated with demand shocks and tax shocks.

N.3 Robustness Check w.r.t. lags

Erceg, Gust and Guerrieri [2005] find that a four-variable SVAR with four lags (as the authors use quarterly data) performs well in recovering the true responses from DGP. More specifically, the SVAR predicts correctly the sign and the pattern of responses but some empirical IRFs are biased as the SVAR tends to understate the rise in labor productivity and real GDP. The source of bias, called the lag-truncation bias arises because the VAR allows for a limited number of lags which provides an approximation of the true dynamics

Table 24: Identified Shocks: Exogeneity Tests

p-value for Exogeneity Test	TFP variable used in the VAR		
	adjusted TFP	Solow residual	Labor productivity
Identified Aggregate Technology Shocks (ϵ_{it}^Z)	0.136	0.009	0.023
Identified Non-Technology Shocks (ϵ_{it}^{YR})	0.000	0.000	-

Notes: The exogeneity F-test is based on a regression of the identified aggregate technology shock ϵ_{it}^Z (shown in the first row) or non-technology shocks ϵ_{it}^{YR} shown in the second row, on fixed effects, time dummies and current and four lags of government spending shocks (ϵ_{it}^G), monetary shocks (ϵ_{it}^R) and tax shocks (ϵ_{it}^T). The null hypothesis is that all of the coefficients on explanatory variables are jointly equal to zero. If p-value ≥ 0.05 at a 5% significance level, the variables are not significant in explaining the identified technology shock ϵ_{it}^Z or the identified non-technology shock ϵ_{it}^{YR} .

implied by the model which considers an infinite number of lags. Erceg, Gust and Guerrieri [2005] find that the truncation bias appears negligible for each variable considered by the authors. Thus a short-ordered VAR provides a good approximation of the true dynamics.

In the baseline VAR model, we consider 2 lags. Because Chari et al. [2008] find that increasing the number of lags implies that empirical IRF is a good approximation of theoretical IRF, as a robustness check, we increase the number of lags from 2 to 8 to estimate all VAR models.²¹ Chaudourne, Fève and Gay [2014] also indicate that the bias can be reduced by increasing the number of lags in the DSVAR. De Graeve and Westermarck [2013] perform Monte Carlo experiments and find that raising the number of lags may be a viable strategy to reduce the severity of the problem. We document below that the results are robust with respect to using a smaller number of lags.

In Fig. 21, we re-estimate the VAR model of the main text and generate impulse response functions by increasing the number of lags (for both the SVAR and local projections). Note that the SVAR critique focuses on the identification of technology shocks and thus only the number of lags in the VAR model should affect estimation of the response of hours worked. For consistency purposes, we set the same number of lags to estimate local projections.

The baseline VAR model which allows for two lags as we use annual data is displayed by the solid blue line. Whilst in the red line we allow for one lag, in the green line, we allow for three lags; in the cyan line, we allow for four lags, in the magenta line, we allow for five lags and in the yellow line, we allow for six lags; in the solid black line, we allow for seven lags and in the dashed black line, we allow for eight lags. Overall, all responses lie within the 90% confidence bounds of the original VAR model. We may notice some quantitative differences. First, as we increase the number of lags, the rise in the relative productivity of tradables is softened in the short-run but quantitatively, the difference with the baseline is small. Second, with regard to aggregate variables, whilst the decline in hours worked is somewhat amplified, the rise in GDP demand components are strongly mitigated, including investment, consumption, and net exports. Most importantly, the dynamic adjustment of sectoral variables remains little sensitive to the increase in the number of lags.

N.4 Utilization-Adjusted TFP: Basu [1996], BKF [2006], HLPN [2023] vs. Imbs [1999]

'Purified' TFP eliminates biases in estimating the effects of technology shocks. Chaudourne, Fève and Guay [2014] analyze the properties of estimators and IRF to a permanent technology shock when technological change is measured by means of labor productivity, TFP, 'purified' TFP. The authors show that the estimated responses from the DSVAR model are biased in a finite sample if technological change is measured by labor productivity. This bias comes from the fact that both the technology and the non-technology shocks have a permanent effect on labor productivity when hours worked follow a persistent process. The authors also demonstrate that the bias is considerably reduced

²¹The simulations in Chari et al. [2008] (see Figure 3), which represent the least favorable DSGE model example discussed in this literature, show that with four autoregressive lags, the approximation to the true impulse response is poor, but with 40 lags the bias appears reasonably small.

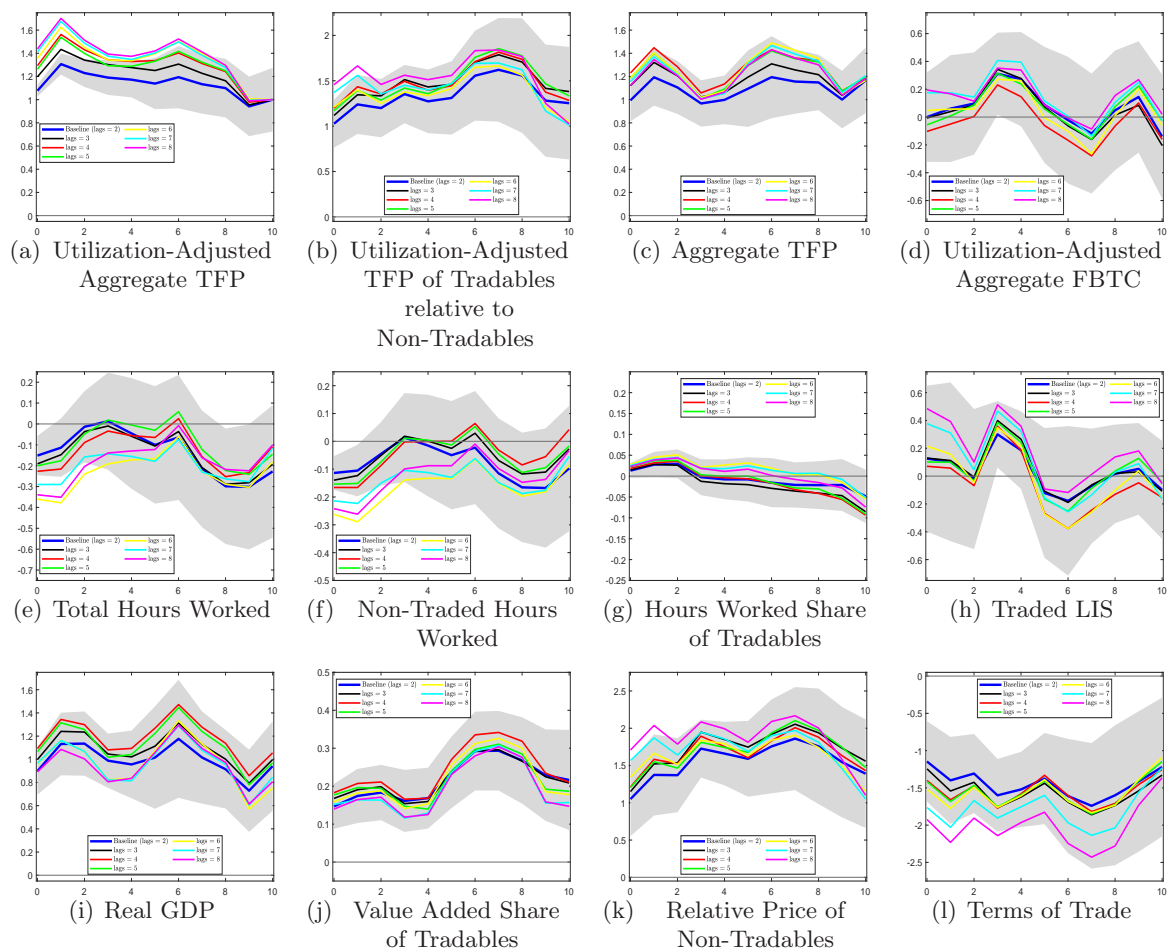


Figure 21: Labor Market Effects of a Technology Shock: Robustness Check w.r.t. Lags Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. The baseline VAR model which allows for two lags is displayed by the solid blue line. Whilst in the red line we allow for one lag, in the green line we allow for three lags; in the cyan line, we allow for four lags; in the magenta line, we allow for five lags and in the yellow line, we allow for six lags; in the solid black line, we allow for seven lags and in the dashed black line, we allow for eight lags. Sample. Sample: 17 OECD countries, 1970-2017, annual data.

when the econometrician uses the TFP to measure technological change and the bias is completely eliminated when TFP is purified, i.e., adjusted with factor utilization rate. In addition to eliminating the potential bias in empirical IRFs, Basu, Fernald and Kimball [2006] show that correcting for unobserved input utilization can avoid understating TFP changes when technology improves because utilization falls.

To measure technology, in line with the recommendation of Basu, Fernald and Kimball (BFK henceforth) [2006], we adjust aggregate and sectoral TFPs with the utilization rate. Because time series for utilization-adjusted TFP are only available for the United States at an aggregate level, we have constructed time series for the capital utilization rate for the 17 OECD countries of our sample and at a sectoral level by adopting the methodology proposed by Imbs [1999].

To check whether our purified measure of efficiency reflects technology, we conduct below a robustness check where we use alternative measures to ours and we also propose a set of factors that can rationalize our findings. Note that in contrast to existing methods which 'purify' TFP measure from variations in the utilization rate, our method has two advantages over others: first, we are able to construct time series at a sectoral level in line with our classification T/N for our sample of seventeen OECD countries over 1970-2017 and second we adapt the existing methodology to CES production functions where the labor income share is variable over time.

We conduct a robust check by considering three different approaches. The first approach by BFK [2006] is thinner than ours because the authors construct a measure of aggregate technology change, controlling for varying utilization of capital and labor, non-constant returns to scale, and imperfect competition. HLPN [2023] construct time series for utilization-adjusted TFP for a sample of 29 OECD countries, 30 sectors and up to 37 years (1970-2007). The authors control for the capital utilization rate, the labor utilization rate (or worker's efforts), hours per worker, by adapting the approach initiated by BFK 2006. While the authors allow for non-constant returns to scale, their estimations indicate that returns to scale are close to constant. They show that hours per worker are not always an ideal proxy for unobserved utilization. The third approach by Basu [1996] has the advantage of controlling for unobserved changes in both capital utilization and intensity of worker effort while we control for the intensity in the use of capital only by adapting Imbs's [1999] method. Basu's [1996] approach is based on the ingenious idea that intermediate inputs do not have an extra effort or intensity dimension and thus variations in the use of intermediate inputs relative to measured capital and labor are an index of unmeasured capital and labor input.

Because time series for utilization-adjusted TFP at a sectoral level are not available for the countries in our sample over 1970-2017, we conduct a third robustness check where we construct time series of utilization-adjusted TFP measure at a sectoral level for all OECD countries by adopting the methodology developed by Basu [1996] and we compare the responses of utilization-adjusted TFP based on Basu [1996] methodology with the responses of utilization-adjusted TFP based on Imbs [1999] approach.

Detailed steps of derivation of the utilization rate in Basu [1996] approach

It is useful to detail the steps of derivation of the capacity utilization rate by Basu [1996] as it shows that the methodology is completely different from ours. The advantage of Basu [1996] over Imbs [1999] approach is that we control for unobserved changes in both capital utilization and in the intensity of work effort by using an ingenious and simple assumption based on the fact that intermediate inputs is a convenient indicator of cyclical factor utilization because its input does not have an extra effort or intensity dimension. Therefore, we can infer increasing extraction from capital and labor services by firms from materials use as firms need more material to produce more. Variations in the use of intermediate inputs relative to measured capital and labor are an index of unmeasured capital and labor input.

Both the traded and non-traded sectors use physical capital inclusive of capital utilization, $\tilde{K}^j(t) = u^{K,j}(t)K^j(t)$, and labor inclusive of workers' efforts, $\tilde{L}^j(t) = u^{L,j}(t)L^j(t)$, according to constant returns to scale production functions which are assumed to take a

CES form:

$$Y_t^j = \left[\gamma^j \left(u_t^{L,j} L_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} + (1-\gamma^j) \left(u_t^{K,j} K_t^j \right)^{\frac{\sigma^j-1}{\sigma^j}} \right]^{\frac{\sigma^j}{\sigma^j-1}}, \quad (216)$$

where γ^j and $1-\gamma^j$ are the weight of labor and capital in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$. Firms lease the capital from households and hire workers. They face two cost components: a capital rental cost equal to $R(t)$, and a labor cost equal to the wage rate $W^j(t)$.

Aggregate output denoted by Q_t^j is an aggregate of value added Y_t^j and intermediate inputs M_t^j :

$$Q_t^j = Z_t^j \left[\xi^j \left(Y_t^j \right)^{\frac{\sigma_M^j-1}{\sigma_M^j}} + (1-\xi^j) \left(M_t^j \right)^{\frac{\sigma_M^j-1}{\sigma_M^j}} \right]^{\frac{\sigma_M^j}{\sigma_M^j-1}}, \quad (217)$$

where σ_M^j is the elasticity of substitution between value added and intermediate inputs. We denote the unit cost for value added by $c_t^j = P_{Y,t}^j$ where P^Y is the value added deflator since the goods market is perfectly competitive and we denote the aggregate price index of intermediate inputs by $P_{M,t}^j$. Both sectors are perfectly competitive and maximize profits by taking prices as given. Denoting the gross output deflator by P_Q^j , firms choose value added and intermediate inputs so as to maximize:

$$\max_{Y^j, M^j} \Pi_Q^j = \max_{Y^j, M^j} \left\{ P_Q^j Q^j - P_Y^j Y^j - P_M^j M^j \right\}. \quad (218)$$

First-order conditions lead to optimal demand for value added and intermediate inputs:

$$P_Q^j \xi^j (Y^j)^{-\frac{1}{\sigma_M^j}} (Q^j)^{\frac{1}{\sigma_M^j}} \equiv P_Y^j, \quad (219a)$$

$$P_Q^j (1-\xi^j) (M^j)^{-\frac{1}{\sigma_M^j}} (Q^j)^{\frac{1}{\sigma_M^j}} \equiv P_M^j. \quad (219b)$$

Dividing the demand for value added by the demand for intermediate inputs leads to:

$$\frac{Y^j}{M^j} = \left(\frac{\xi^j}{1-\xi^j} \right)^{\sigma_M^j} \left(\frac{P_Y^j}{P_M^j} \right)^{-\sigma_M^j}. \quad (220)$$

Log-linearizing (220) gives:

$$\hat{Y}^j - \hat{M}^j = -\sigma_M^j \left(\hat{P}_Y^j - \hat{P}_M^j \right). \quad (221)$$

Log-linearizing the production function for gross output (217) leads to:

$$\begin{aligned} \hat{Q}^j &= \hat{Z}^j + \alpha_Y^j \hat{Y}^j + (1-\alpha_Y^j) \hat{M}^j, \\ &= \hat{M}^j + \alpha_Y^j \left(\hat{Y}^j - \hat{M}^j \right), \\ &= \hat{Z}^j + \hat{M}^j - \alpha_Y^j \sigma_M^j \left(\hat{P}_Y^j - \hat{P}_M^j \right), \end{aligned} \quad (222)$$

where $\alpha_Y^j = \frac{P_Y^j Y^j}{P_Q^j Q^j}$.

Log-linearizing the production function for value added (216) leads to:

$$\hat{Y}^j = s_L^j \left(\hat{u}^{L,j} + \hat{L}^j \right) + \left(1 - s_L^j \right) \left(\hat{u}^{K,j} + \hat{K}^j \right), \quad (223)$$

where $s_L^j = \frac{W^j L^j}{P^j Y^j}$.

Plugging (223) into the first line of (222) leads to:

$$\hat{Q}^j = \hat{Z}^j + \alpha_Y^j \left\{ s_L^j \left(\hat{u}^{L,j} + \hat{L}^j \right) + \left(1 - s_L^j \right) \left(\hat{u}^{K,j} + \hat{K}^j \right) \right\} + \left(1 - \alpha_Y^j \right) \hat{M}^j. \quad (224)$$

Equating (224) to the last line of (222) allows us to derive an expression for the capacity utilization rate:

$$\begin{aligned}\hat{u}_Y^j &= s_L^j \hat{u}^{L,j} + (1 - s_L^j) \hat{u}^{K,j}, \\ &= \hat{M}^j - s_L^j \hat{L}^j - (1 - s_L^j) \hat{K}^j - \sigma_M^j (\hat{P}_Y^j - \hat{P}_M^j).\end{aligned}\quad (225)$$

Assuming that $\sigma_M^j = 0$ implies that the capacity utilization rate can be calculated as follows:

$$\hat{u}_Y^j = \hat{M}^j - s_L^j \hat{L}^j - (1 - s_L^j) \hat{K}^j, \quad (226)$$

where M^j are intermediate inputs (i.e., intermediate consumption) at constant prices, L^j hours worked, K^j the capital stock at constant prices, s_L^j is the LIS.

We use (226) to measure the intensity in the use of capital and labor at a sectoral level (i.e., for each industry) and adjust the Solow residual with this measure to construct time series for the utilization-adjusted TFP in sector $j = H, N$:

$$\hat{Z}^j = \text{TFP}^j - \hat{u}_Y^j. \quad (227)$$

Source: Time series for intermediate inputs at constant prices are taken from EU KLEMS. Data coverage: 1970-2017 for 17 OECD countries except for JPN (1973-2017). Table 25 provides the information about data availability for our four measures of utilization-adjusted-TFP.

Table 25: Alternative Measures of Technology: Data Availability

	Imbs [1999]	Basu [1996]	HLPN [2023]	BFK [2006]
AUS	1970-2017	1970-2007	1970-2007	1970-2007
AUT	1970-2017	1970-2017	1976-2007	1976-2007
BEL	1970-2017	1970-2017	1970-2006	1970-2006
CAN	1970-2017	1970-2007	1970-2007	1970-2007
DEU	1970-2017	1970-2017	1970-2007	1970-2007
DNK	1970-2017	1970-2017	1970-2007	1970-2007
ESP	1970-2017	1970-2007	1970-2007	1970-2007
FIN	1970-2017	1970-2017	1970-2007	1970-2007
FRA	1970-2017	1970-2017	1970-2007	1970-2007
GBR	1970-2016	1970-2007	1970-2007	1970-2007
IRL	1970-2017	1970-2007	1988-2007	1988-2007
ITA	1970-2017	1970-2017	1970-2007	1970-2007
JPN	1973-2015	1973-2015	1973-2006	1973-2006
NLD	1970-2017	1970-2017	1970-2007	1970-2007
NOR	1970-2017	1970-2017	no data	no data
SWE	1970-2017	1970-2017	1993-2007	1993-2007
USA	1970-2017	1970-2017	1977-2007	1977-2007

Results. Fig. 22 contrasts the effects of a technology shock by considering our baseline measure of technology shown in the blue line where we adjust the TFP with the capital utilization rate constructed by adapting the method proposed by Imbs [1999] and three alternative measures. We have constructed an alternative measure of technology where we adjust the Solow residual with the capacity utilization rate constructed by following the approach proposed by Basu [1996] shown in the yellow line. To further test our approach, we also consider two different time series, i.e., the utilization-adjusted-TFP constructed by Levchenko et al. [2023] shown in the green line, and that constructed by Basu et al. [2006] which is displayed by the brown line. While in the baseline case, we estimate the VAR model with two lags, we alternatively allow for four lags, as displayed by the black line, and eight lags, as displayed by the red line.

The first column shows the dynamic effects of a technology shock on utilization-adjusted-aggregate-TFP, total hours worked, traded hours worked, non-traded hours worked, and the hours worked share of tradables. Overall, a technology improvement produces similar

effects across measures of technology. Importantly, the adjustment of utilization-adjusted-aggregate TFP is very close whether we adjust the Solow residual with the capital utilization rate or with alternative methods. We may notice some quantitative differences as alternative measures of technology tend to produce a larger decline in total hours worked and in non-traded hours worked. The second and the third columns show the effects following an asymmetric and a symmetric technology shock. While our measure of technology controls for the intensity in the use of capital only, columns 2 and 3 reveal that the controlling for the both capital and labor utilization rate does not modify the results, as can be seen in the yellow line where we consider the Basu’s [1996] approach. Increasing the lags tend to produce a larger decline in hours worked following symmetric technology shocks and a smaller increase in hours worked after asymmetric technology shocks. In conclusion, our results are robust to the measure of technology.

N.5 Shock to World TFP

Motivation. In this subsection, we conduct a third empirical test of the robustness of our SVAR results. Because labor productivity growth depends on adjustment of the capital stock which adjusts sluggishly and through this channel non-technology shocks can contaminate the ‘true’ identification of technology shocks, Dupaigne and Fève [2009] find that each country’s average productivity of labor reflects all the shocks in the model, including those which materialize in the other countries.

Because SVARs on country-level data fail to properly disentangle the permanent technology shock common to all countries from the country-specific stationary shocks, Dupaigne and Fève propose to replace the country-level measure of productivity with an aggregate measure of country-level productivity. Because world permanent productivity shocks are not affected by country-specific persistent non-technology shocks, identifying technology shocks by using productivity growth common to all countries can eliminate the problem of identification raised by Erceg, Gust and Guerrieri [2005], Chari, Kehoe and McGrattan [2008]. Dupaigne and Fève [2009] find empirically that when they use the G7 labor productivity instead of country-level labor productivities, there is almost no discrepancy between the responses of employment evaluated at the country and G7 level.

Construction of the world utilization-adjusted-TFP growth. Building on the ingenious idea of Dupaigne and Fève [2009], we replace the country-level utilization-adjusted TFP with the ‘world’ stock of knowledge. The first measure we consider has the advantage to reflect the common component of the stock ideas across countries. To ensure that our measure of world sectoral TFP reflects the common component of each sectoral TFP to the seventeen OECD countries, we run the regression of the growth rate of utilization-adjusted-TFP in sector j at time t in country i on country and year effects:

$$\hat{Z}_{it}^j = d_i + d_t + \eta_{it}, \quad (228)$$

where d_i captures the country fixed effects, d_t are time dummies, and η_{it} are the i.i.d. error terms. We interpret estimates of time dummies as the growth rate of TFP which is common to the seventeen OECD countries. We denote the world component of sectoral utilization-adjusted-TFP in sector j by $Z_{it}^{W,j}$ and the world component of utilization-adjusted-aggregate-TFP by Z_{it}^W . Fig. 23 plots in the black line with triangles the rate of growth of the world productivity growth. In the blue line with circles, we plot the growth rate of the utilization-adjusted-aggregate-TFP which is constructed as a cross-country average of country-level TFP growth. Because the blue and the black line are hardly distinguishable, we can conclude that estimating the world component of productivity gives very similar results to averaging utilization-adjusted-TFP.

Contribution of world TFP component to rate of growth of domestic TFP. One interesting question to ask is to what extent the world component of utilization-adjusted-TFP contributes to the rate of growth of the country-level utilization-adjusted-TFP. Column 1 of Table 26 shows the variance of the growth rate of utilization-adjusted-TFP. We consider four measures: utilization-adjusted-aggregate-TFP, utilization-adjusted-traded-TFP, utilization-adjusted-non-traded-TFP and the ratio of traded to non-traded utilization-adjusted-TFP. Column 2 of Table 26 shows the variance of the rate of growth of

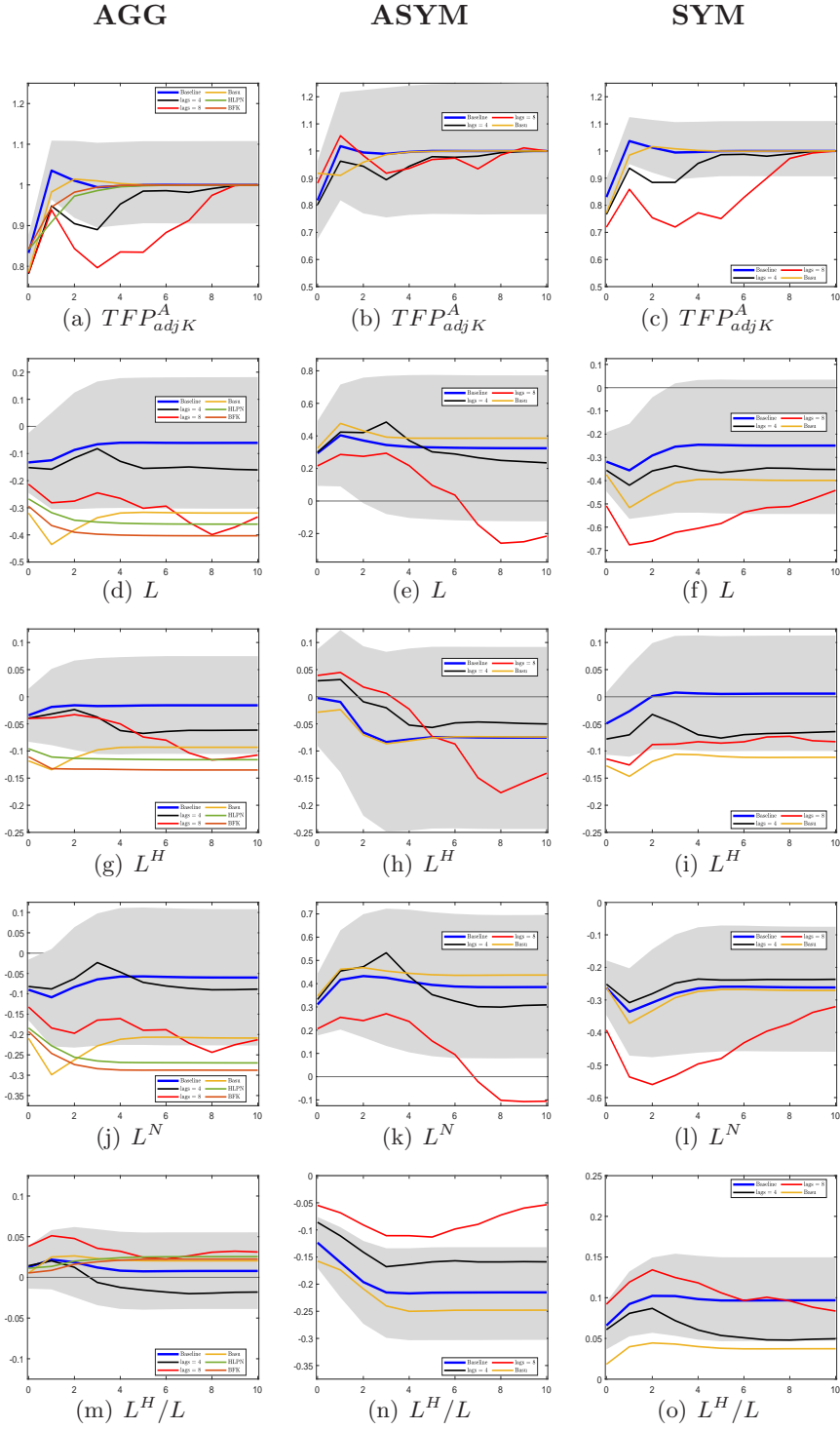


Figure 22: Labor Market Effects of a Technology Shock: Country-Level vs. World Technology Shock **Notes:** Robustness Check w.r.t. the Measure of Technology **Notes:** The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in the country level utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. We estimate a VAR model which includes the country-level utilization-adjusted-aggregate-TFP, total hours worked, traded hours worked, non-traded hours worked, the hours worked share of tradables, all variables entering the VAR model in rate of growth. While in the baseline case, we estimate the VAR model with two lags, we alternatively allow for four lags, as displayed by the black line, and eight lags, as displayed by the red line. Because in our measure of technology, we adjust the Solow residual with the capital utilization rate constructed by adapting the methodology proposed by Imbs [1999], we alternatively adopt the approach of Basu [1996]. The yellow line shows the response of TFP based on the Solow residual adjusted with the time series for the capacity utilization rate by using Basu's [1996] method. To further test our approach, we also consider two different time series, i.e., the utilization-adjusted-TFP constructed by Levchenko et al. [2023] shown in the green line, and that constructed by Basu et al. [2006] which is displayed by the brown line. Sample: 17 OECD countries, 1970-2017, annual data.

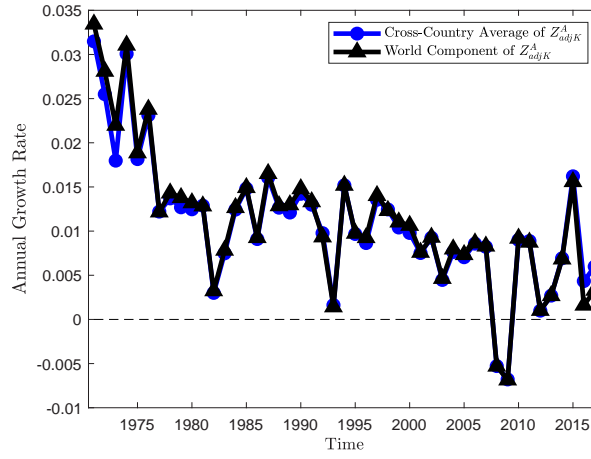


Figure 23: Rate of Growth of the Ratio of World TFP of Tradables Relative to Non-Tradable Notes: We run the regression of the growth rate of TFP in sector j at time t in country i on country and year effects, see eq. (228), and interpret estimated coefficients for time dummies as the rate of growth of sectoral TFP which is common to the seventeen OECD countries of our sample. The solid blue line with circles plots the world productivity growth against time. Alternatively, we calculate a world productivity growth by averaging logged sectoral TFP across countries which is displayed by the black line with triangles. The two measures give similar results. Sample: 17 OECD countries, 1970-2017, annual data.

world utilization-adjusted-TFP. Column 3 gives the contribution of the world component to the rate of growth of the country-level of utilization-adjusted-TFP. The first row reveals that over the period 1970-2017, the common component to the seventeen OECD countries of the rate of growth of aggregate TFP contributes 32% to the rate of growth of the country-level aggregate TFP. As can be seen in the second and third row, as expected, the world component of utilization-adjusted-traded-TFP is larger than the world component of non-traded utilization-adjusted-non-traded-TFP since traded firms are more prone to benefit from international innovations as they are more open to trade and investment more in R&D. Importantly, the analysis over sub-periods reveals that the intensity of traded technology in the world component has increased from 36% to 49%.

Table 26: The Share of Variance of TFP Growth Attributable to World TFP Growth (in %)

	Total	Variance	Contribution in %		Sub-periods	
	Variance	World	World	Country-level	1970-1992	1993-2017
	(1)	(2)	(3)	(4)	(5)	(6)
Agg. Technology	0.0043	0.0014	32.2	67.8	0.0015 (35.7%)	0.0013 (37.9%)
H -Technology	0.0125	0.0046	36.9	63.1	0.0041 (36.6%)	0.0060 (49.0%)
N -Technology	0.0032	0.0010	30.5	69.5	0.0015 (34.5%)	0.0006 (32.7%)
H/N Technology	0.0138	0.0052	37.7	62.3	0.0044 (34.7%)	0.0069 (48.6%)

Notes: We run a principal component analysis to extract the common component to all country-level-adjusted-aggregate-TFP growth that we interpret as the world component. In columns 1 and 2, we show the variance of the rate of growth of country-level-adjusted-TFP and its common component, respectively. The figure in columns 3-4 denotes the fraction of the variance of country-level TFP growth attributable to the world component and country-specific component, respectively. In columns 5 and 6, we show the variance of the rate of growth of world adjusted-TFP. Numbers in parentheses denote shares of the country-level-adjusted-TFP. Sample: 17 OECD countries, 1970-2017, annual data.

Empirical strategy and results. Fig. 24 contrasts the effects of a technology improvement in the baseline scenario where we estimate a VAR model which includes the country-level utilization-adjusted-aggregate-TFP, total hours worked, traded hours worked, non-traded hours worked, the hours worked share of tradables, all variables entering the VAR model in rate of growth. The black line shows the dynamic effects of hours worked when the country-level utilization-adjusted-aggregate-TFP is replaced with the world component of TFP. The world stock of knowledge or world technology is constructed as an import-share-geometric-weighted-average of TFP of trade partners of country i , i.e., $Z_{i,t}^W = \prod_{k=1}^{16} \left(Z_{k,t}^A \right)^{\alpha_M^k}$ where $Z_{k,t}$ is the utilization-adjusted-TFP of country i 's trade partner. We use this index in running our estimates in order to use the panel SVAR methodology which

leads to higher accuracy of estimated values. We may notice a discrepancy in the adjustment of utilization-adjusted-aggregate-TFP. When we use the international stock of knowledge, we find that technology improves gradually. Our interpretation is that taking advantage of existing technologies from abroad might generate adoption technology costs which result in a gradual increase in Z_{it}^A .

Overall, world technology shocks do not lower labor on impact. Our interpretation is that world technology shocks are mostly driven by asymmetric technology shocks and symmetric technology shocks play a minor role. As shown in column 2, world technology shocks produce very similar effects to those following country-level technology shocks once we consider asymmetric technology shocks. More specifically, we find that a technology improvement which is concentrated within traded industries generates an increase in non-traded hours worked while traded hours worked are unresponsive, thus leading to a gradual decline in the hours worked share of tradables. As can be seen in the second row of column 2, the response of total hours worked following an asymmetric world technology shock is very similar to that following an asymmetric country-level technology shock. In contrast, the effects of symmetric technology shocks are somewhat different from our baseline when we approximate the stock of knowledge with the international stock of ideas. The reason is that while we impose in the long-run that the ratio of traded to non-traded utilization-adjusted-TFP is fixed, in the short-run, technology improves in the traded relative to the non-traded sector which appreciates the relative price of non-tradables and thus has an expansionary effect non non-traded hours worked on impact. However, when we consider an aggregate technology shock, overall, the discrepancy in the labor market effects are not statistically different when we consider the baseline measure of technology or the international stock of knowledge.

N.6 Max Share Identification

Advantages of Max share over LR identification of technology shocks. One key difference between the empirical and the theoretical model is that the former imposes a small number of lags whilst the latter allows for an infinite number of lags. Erceg, Gust and Guerrieri [2005], Chari et al. [2008] argue that it causes a lag-truncation bias which lead estimated IRFs to be biased, in magnitude for the former and in sign for the latter. Francis et al. [2014] offer an alternative approach to identification with the intent of addressing the aforementioned shortcoming associated with long-run restriction in small-sample estimation. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. This method has two major advantages over the standard long-run identification which assumes that the technology shock is the sole contributor of long-run productivity shifts, all other structural innovations having transitory effects on productivity. First, in place of the restriction that the unit root in productivity is driven exclusively by technology, their approach imposes a weaker restriction that the forecast-error variance in productivity at long horizons is dominated by the technology shock. This allows other shocks to influence productivity at finite horizon. Second, the max share approach considers a finite horizon which is more suited to estimate $B_k A_0$ (see section F, eq. (100)). Intuitively, as shown by Uhlig [2004], there is no horizon, at which technology shocks alone explain productivity. Thus, neither short-run, medium-run, nor long-run identification will exactly identify the technology shock. He finds however that medium-run identification works better than the other two.

Using data simulated from a RBC model and a standard medium-scale DSGE model with sticky prices, Francis et al. [2014] find that the Max Share approach exhibits less bias (measured by the deviation between the median response and the theoretical response) and less uncertainty (measured by the width of the 68 percent error bands) than the LR approach. In addition to the responses to the shocks, when the authors compare the model-generated and the estimated technology shocks, they find a high correlation (of 0.81) for the Max share shocks with the true shocks generated by RBC and NK models whilst the correlation is lower for technology shocks from the LR model.

Advantages of max share identification. As mentioned in section F where we

detail formally the long-run identification of asymmetric technology shocks across sectors, we consider a specification where all variables enter the VAR model in growth rate, we order utilization-adjusted-aggregate-TFP first, and identify asymmetric technology shocks across sectors as shocks that increase permanently utilization-adjusted-aggregate-TFP (at an infinite horizon). We consider below two VAR specifications to estimate the labor labor effects of a permanent technology improvement. In addition to utilization-adjusted-aggregate-TFP, the baseline VAR model includes real GDP, total hours worked, the real consumption wage, while the alternative VAR model includes traded and non-traded hours worked (all variables in rate of growth).

Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including labor productivity enter the VAR in log levels. As mentioned above, instead of estimating the long-run cumulative matrix $B(1)A_0$, the max share approach amounts to estimating $B_k A_0$ at a finite horizon. The Maximum Forecast Error Variance approach extracts the shock that best explains the FEV at a long but finite horizon of utilization-adjusted-TFP.

LR model vs. Max share: One country at a time. In Fig. 25-28, we generate the empirical responses from the VAR model estimated for one country at a time. We have estimated the same VAR model for the seventeen OECD countries of our sample. The blue line shows responses obtained by imposing LR restrictions to identify asymmetric technology shocks across sectors. The black line shows results when we estimate the aforementioned VAR model and use the max share identification developed by Francis et al. [2014] to estimate the effects of a permanent increase in traded TFP relative to non-traded TFP by 1% in the long-run. As it stands out, for all countries and all variables, the LR model generates empirical responses which lie within the confidence bounds associated with the baseline VAR model estimated with long-run restrictions.

Overall, the responses of hours worked generated by applying the Max share (black line) identification lie within the confidence bounds associated with the LR model (blue line) except for three countries (Austria, Belgium, Germany) out of seventeen in our sample. We may notice some quantitative differences however. The LR model generates a gradual increase in utilization-adjusted-TFP while the Max share produces a larger technology improvement on impact. This overshooting may produce a larger increase in traded relative to non-traded technology that would explain why in Austria, Belgium, Germany, non-traded hours worked increases instead of falling or being muted.

LR model vs. Max share: Median estimates. So far, we have compared the responses to technology shocks across countries by considering the Max share (black line) approach and the LR model (blue line). To ease the comparison between the two approaches, it is convenient to compare one single IRF of one variable between the LR model and the Max share identification by considering the median of estimates for both methods. Fig. 29 shows the responses for the VAR model which includes aggregate technology, Z_{it}^A , real GDP, hours worked and the real consumption wage. Overall the responses to the Max share lie within the confidence bounds of the baseline LR model although the Max share predicts a smaller decline in hours on impact and a greater increase in real GDP.

N.7 Two-Step SVARs-Based Procedure to Identify Technology Shocks

Why should hours be removed from the SVAR? Evidence documented by Christiano et al. [2006] from their simulation experiments suggests using other variables than hours worked which are less sensitive to the volatility of non-technology shocks and/or contain a sizeable part of technology shocks. The reason is that they show that when the model is more properly estimated, the standard error of the non-technology shocks is half the standard error of the technology shock. In such a case, the bias in SVARs with labour productivity and hours is strongly reduced. In light of the above findings, Fève and Guay [2010] argue that SVARs can deliver accurate results if more efforts are made over the choice of the stationary variables. More precisely, hours (or other highly persistent variables subject to empirical controversies about their stationarity) must be excluded from SVARs and replaced by any variable which presents better stochastic properties. The introduction

of a highly persistent variable as hours worked in the SVARs confounds the identification of the permanent and transitory shocks and thus contaminates the corresponding Impulse Response Functions (IRFs). Following the previously mentioned contributions, the selected variable must satisfy the following stochastic properties. First, the variable must display less controversy over its stationarity. Second, the variable must behave more as a capital (or state) variable than hours worked do, so that a VAR model with a finite number of lags can more easily approximate the true underlying dynamics of the data. Third, the variable must contain a sizeable technology component and present less sensitivity to highly persistent non-technology shocks. According to Fève and Guay [2010], the consumption to output ratio (in logs) is a promising candidate for fulfilling these three requirements as it is stationary and consequently displays less persistence than hours worked, it represents a better approximation of the state variables than hours worked and appears less sensitive to transitory shocks.

Two-step approach. The proposed approach by Fève and Guay [2010] consists in two steps. In the first step, a SVAR model which includes utilization adjusted aggregate TFP Z_{it}^A and the consumption to GDP ratio $\omega_{C,it}$ is considered to consistently estimate technology shocks using a long-run restriction. Note that consumption includes both private and government consumption. Because we consider an open economy model, for the purposes of consistency, we augment the broad measure of consumption with net exports which has the advantage to isolate the demand for domestic goods. In the second step, the IRFs of hours (or any other aggregate variable under interest) at different horizons are obtained by a simple (univariate or multivariate) regression of hours on the estimated technology shock. The VAR we estimate, i.e., $[\hat{Z}_{it}^A, \log \omega_{C,it}]$, includes utilization adjusted aggregate TFP is in growth rate and ω_C is in log as in Blanchard and Quah where they consider a VAR model which includes the rate of change in real GDP and the unemployment rate (which is in level). In Fève and Guay ω_C enters the VAR model in log level (and not in level). In the second step, we estimate the dynamic effects on total hours worked by using local projection methods.

Fig. 30 reveals that the two-step approach (black line) leads to empirical results which are very close to our baseline estimates shown in the blue line. Because the two-step approach should considerably mitigate the likelihood for technology shocks to be contaminated by long-lasting demand shocks, these results corroborate the robustness of our approach.

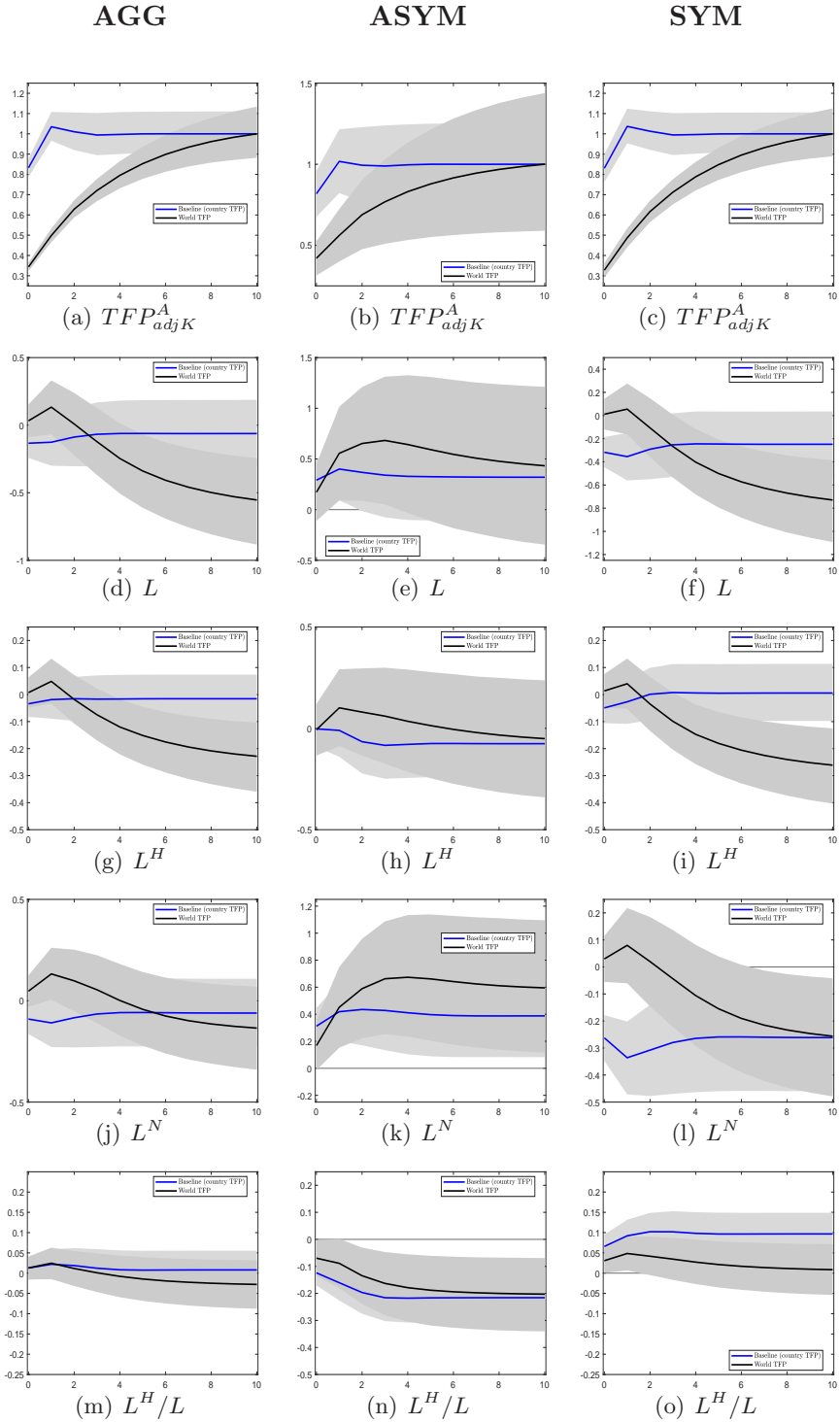


Figure 24: Labor Market Effects of a Technology Shock: Country-Level vs. World Technology Shock

Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in the country level utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. We estimate a VAR model which includes the country-level utilization-adjusted-aggregate-TFP, total hours worked, traded hours worked, non-traded hours worked, the hours worked share of tradables, all variables entering the VAR model in rate of growth. The black line shows the dynamic effects of hours worked when the country-level utilization-adjusted-aggregate-TFP is replaced with the world component of TFP. The world stock of knowledge or world technology is constructed as an import-share-geometric-weighted-average of TFP of trade partners of country i , i.e., $Z_{i,t}^W = \prod_{k=1}^{16} (Z_{k,t}^A)^{\alpha_k^M}$ where $Z_{k,t}$ is the utilization-adjusted-TFP of country i 's trade partner (i.e., country k). Sample: 17 OECD countries, 1970-2017, annual data.

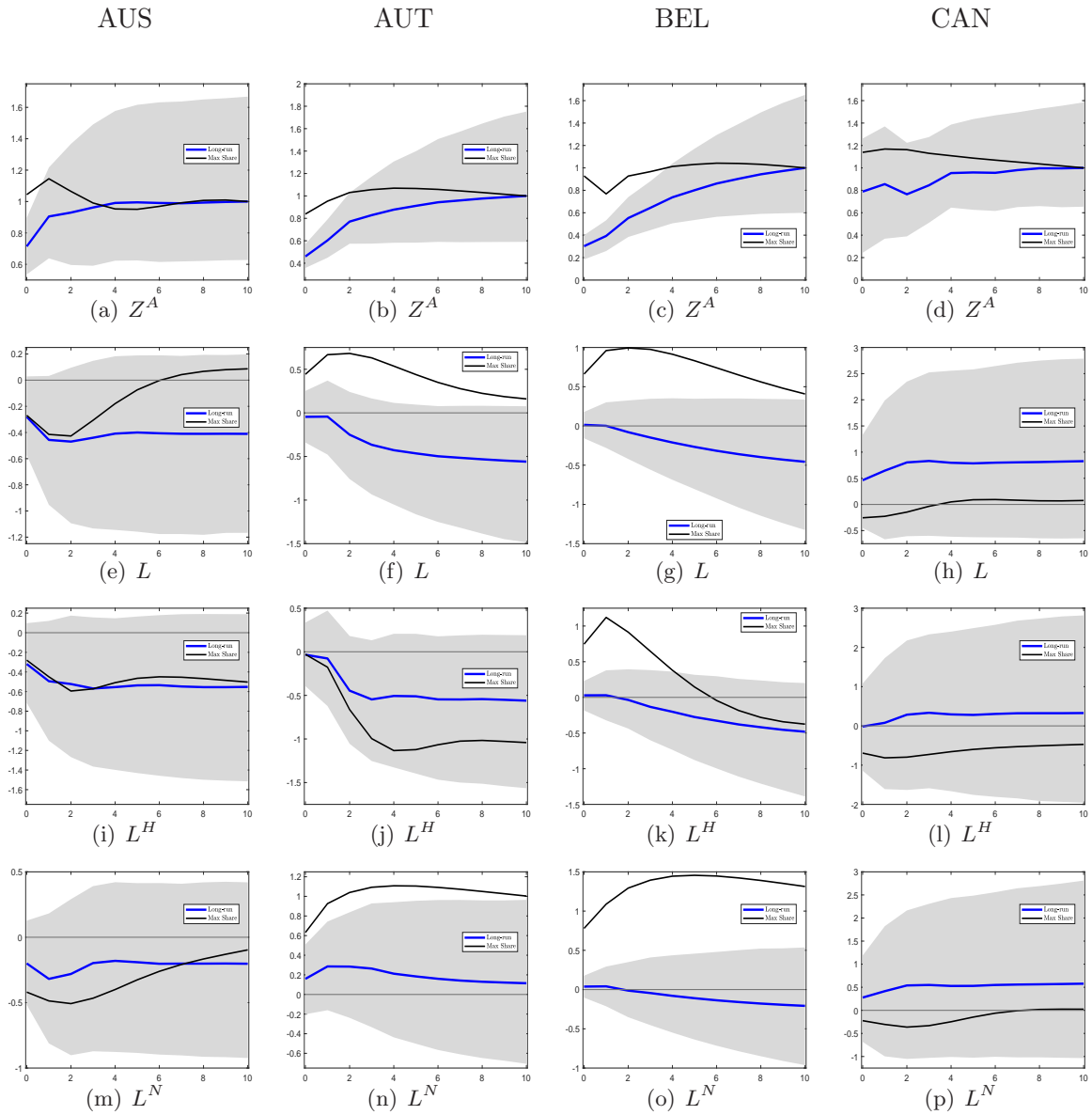


Figure 25: Responses of Hours to a Technology Shock: Max Share (solid black line) vs. Long-Run Restriction (solid blue line) Identification for Australia, Austria, Belgium, Canada. *Notes:* The solid lines show the responses of aggregate variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. We compare the dynamic effects of two identification methods. In both cases, we estimate a VAR model which includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage. In the baseline shown in the blue line, the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the alternative identification method, we employ the Max Share approach. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted aggregate TFP enter the VAR in log levels. The black line shows the median of the responses. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: Australia, Austria, Belgium, Canada, 1970-2017, annual data.

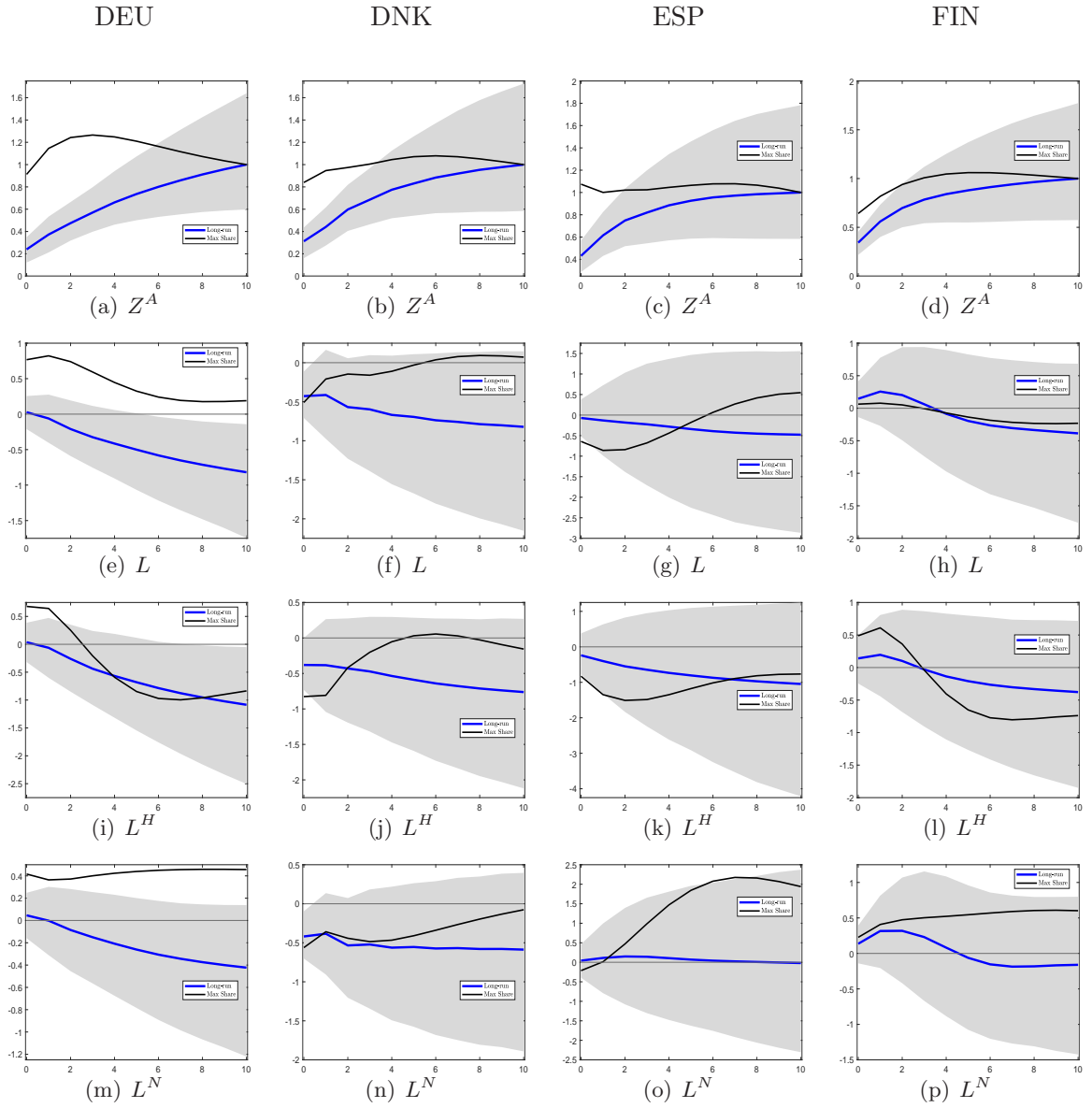


Figure 26: Responses of Hours to a Technology Shock: Max Share (solid black line) vs. Long-Run Restriction (solid blue line) Identification for Germany, Denmark, Spain, Finland.

Notes: The solid lines show the responses of aggregate variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. We compare the dynamic effects of two identification methods. In both cases, we estimate a VAR model which includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage. In the baseline shown in the blue line, the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the alternative identification method, we employ the Max Share approach. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted aggregate TFP enter the VAR in log levels. The black line shows the median of the responses. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: Germany, Denmark, Spain, Finland, 1970-2013, annual data.

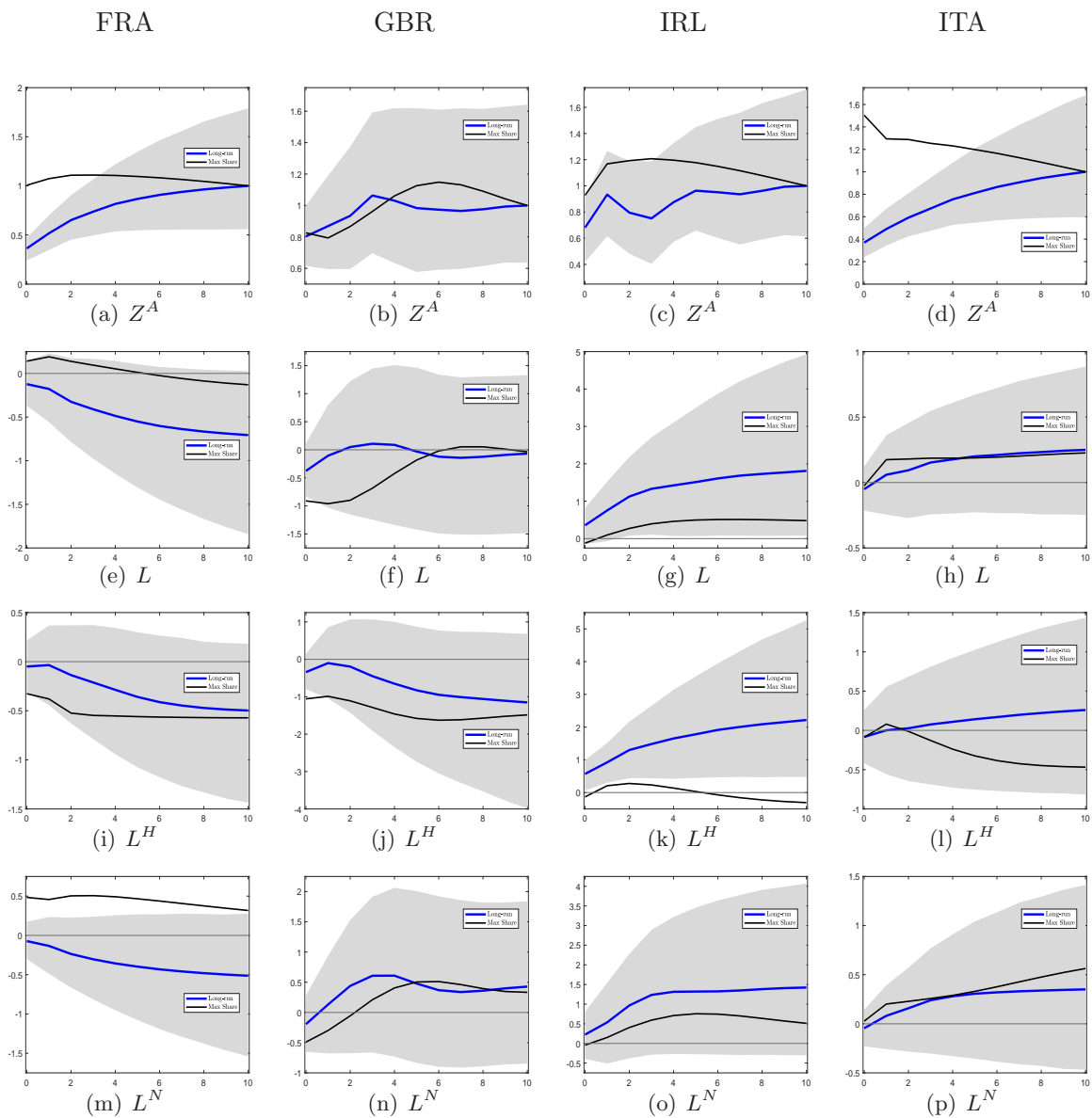


Figure 27: Responses of Hours to a Technology Shock: Max Share (solid black line) vs. Long-Run Restriction (solid blue line) Identification for France, the United Kingdom, Ireland, Italy. *Notes:* The solid lines show the responses of aggregate variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. We compare the dynamic effects of two identification methods. In both cases, we estimate a VAR model which includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage. In the baseline shown in the blue line, the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the alternative identification method, we employ the Max Share approach. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted aggregate TFP enter the VAR in log levels. The black line shows the median of the responses. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: France, the United Kingdom, Ireland, Italy, 1970-2013, annual data.

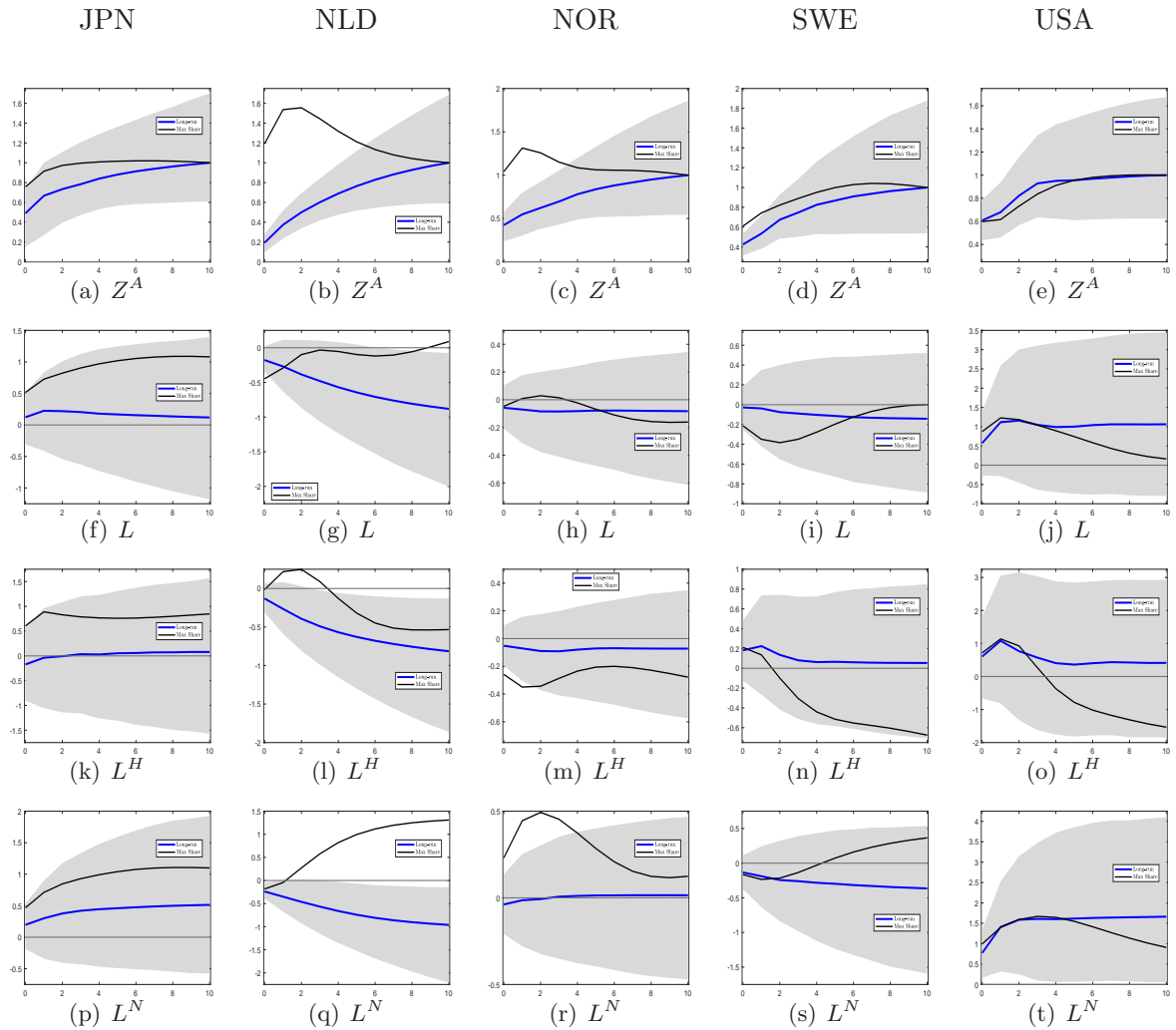


Figure 28: Responses of Hours to a Technology Shock: Max Share (solid black line) vs. Long-Run Restriction (solid blue line) Identification for Japan, the Netherlands, Norway, Sweden, the United States. *Notes:* The solid lines show the responses of aggregate variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. We compare the dynamic effects of two identification methods. In both cases, we estimate a VAR model which includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage. In the baseline shown in the blue line, the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the alternative identification method, we employ the Max Share approach. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted aggregate TFP enter the VAR in log levels. The black line shows the median of the responses. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: Japan, the Netherlands, Norway, Sweden, the United States, 1970-2017, annual data.

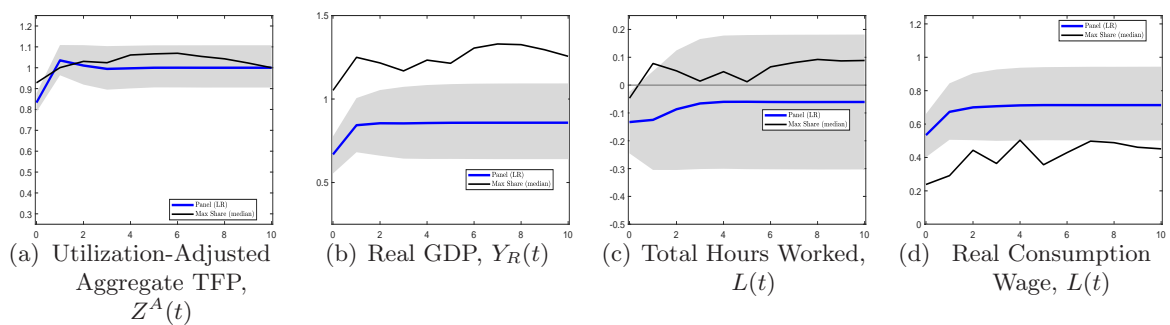


Figure 29: Labor Market Effects of a Technology Shock: Robustness Check w.r.t. Lags *Notes:* The solid lines show the responses of aggregate variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds obtained by bootstrap sampling. We compare the dynamic effects of two identification methods. In both cases, we estimate a VAR model which includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage. In the baseline shown in the blue line, the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the alternative identification method, we employ the Max Share approach. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted aggregate TFP enter the VAR in log levels. The black line shows the median of the responses. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: Sample: 17 OECD countries, 1970-2017, annual data.

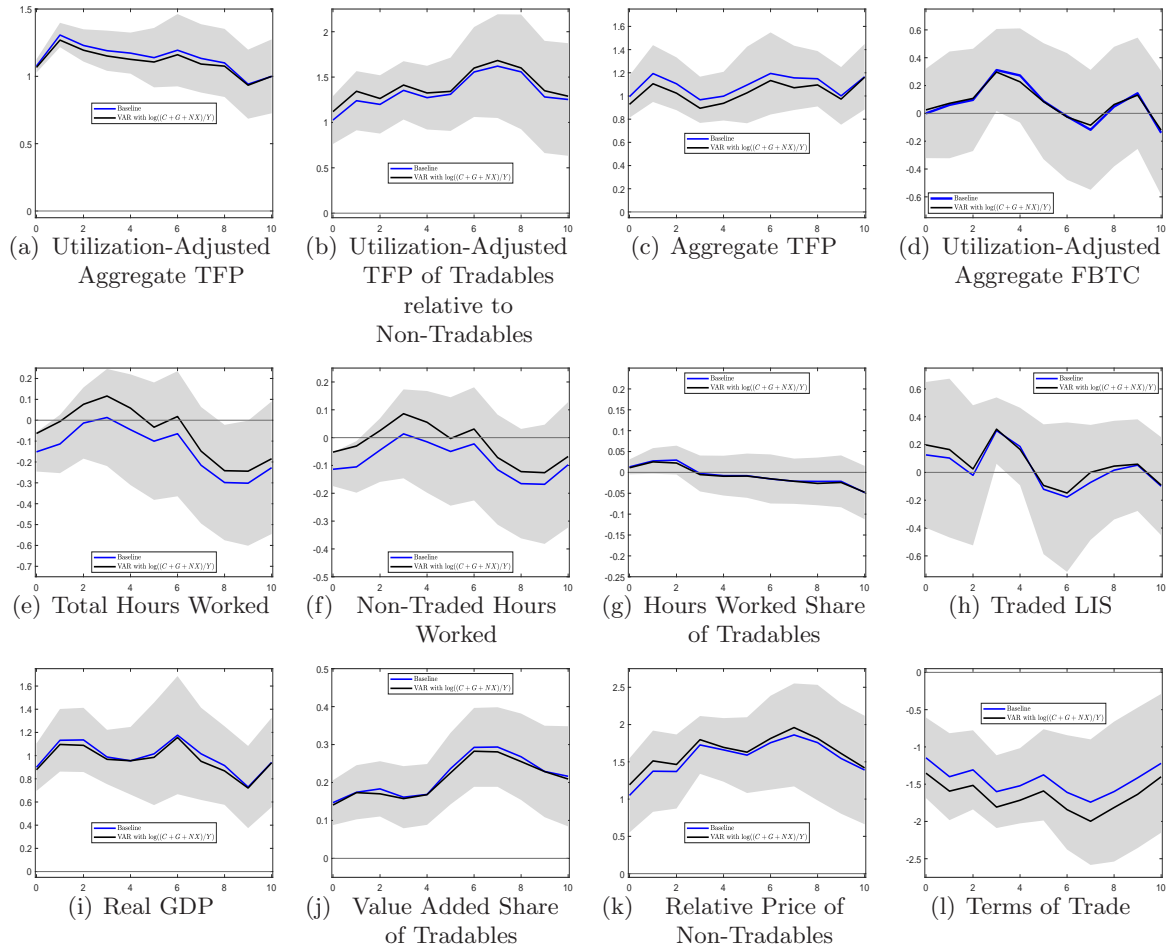


Figure 30: Labor Market Effects of a Technology Shock: Robustness Check w.r.t. Lags Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run in the baseline case. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. In the lines of Fève and Guay [2010], we estimate in the first step a VAR model which includes the measure of technology, i.e., utilization-adjusted aggregate TFP, and real GDP both in log differences and the ratio of the sum of consumption, government spending and net exports to GDP in log level. Results are shown in the black line. Vertical axes measure percentage deviation from trend. Sample: 17 OECD countries, 1970-2017, annual data.

O Semi-Small Open Economy Model

This Appendix puts forward an open economy version of the neoclassical model with tradables and non-tradables, imperfect mobility of labor and capital across sectors, capital adjustment costs and endogenous terms of trade. This section illustrates in detail the steps we follow in solving this model. We assume that production functions take a Cobb-Douglas form since this economy is the reference model for our calibration as we normalize CES productions by assuming that the initial steady state of the Cobb-Douglas economy is the normalization point.

Households supply labor, L , and must decide on the allocation of total hours worked between the traded sector, L^H , and the non-traded sector, L^N . They consume both traded, C^T , and non-traded goods, C^N . Traded goods are a composite of home-produced traded goods, C^H , and foreign-produced foreign (i.e., imported) goods, C^F . Households also choose investment which is produced using inputs of the traded, J^T , and the non-traded good, J^N . As for consumption, input of the traded good is a composite of home-produced traded goods, J^H , and foreign imported goods, J^F . The numeraire is the foreign good whose price, P^F , is thus normalized to one.

O.1 Households

At each instant of time, the representative household consumes traded and non-traded goods denoted by C^T and C^N , respectively, which are aggregated by means of a CES function:

$$C(t) = \left[\varphi^{\frac{1}{\phi}} (C^T(t))^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}} (C^N(t))^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}, \quad (229)$$

where $0 < \varphi < 1$ is the weight of the traded good in the overall consumption bundle and ϕ corresponds to the elasticity of substitution between traded goods and non-traded goods. The index C^T is defined as a CES aggregator of home-produced traded goods, C^H , and foreign-produced traded goods, C^F :

$$C^T(t) = \left[(\varphi^H)^{\frac{1}{\rho}} (C^H(t))^{\frac{\rho-1}{\rho}} + (1-\varphi^H)^{\frac{1}{\rho}} (C^F(t))^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \quad (230)$$

where $0 < \varphi^H < 1$ is the weight of the home-produced traded good in the overall traded consumption bundle and ρ corresponds to the elasticity of substitution between home-produced traded goods and foreign-produced traded goods.

As in De Cordoba and Kehoe [2000], the investment good is produced using inputs of the traded good and the non-traded good according to a constant-returns-to-scale function which is assumed to take a CES form:

$$J(t) = \left[\iota^{\frac{1}{\phi_J}} (J^T(t))^{\frac{\phi_J-1}{\phi_J}} + (1-\iota)^{\frac{1}{\phi_J}} (J^N(t))^{\frac{\phi_J-1}{\phi_J}} \right]^{\frac{\phi_J}{\phi_J-1}}, \quad (231)$$

where ι is the weight of the investment traded input ($0 < \iota < 1$) and ϕ_J corresponds to the elasticity of substitution in investment between traded and non-traded inputs. The index J^T is defined as a CES aggregator of home-produced traded inputs, J^H , and foreign-produced traded inputs, J^F :

$$J^T(t) = \left[(\iota_H)^{\frac{1}{\rho_J}} (J^H(t))^{\frac{\rho_J-1}{\rho_J}} + (1-\iota_H)^{\frac{1}{\rho_J}} (J^F(t))^{\frac{\rho_J-1}{\rho_J}} \right]^{\frac{\rho_J}{\rho_J-1}}, \quad (232)$$

where $0 < \iota_H < 1$ is the weight of the home-produced traded input in the overall traded investment bundle and ρ_J corresponds to the elasticity of substitution between home- and foreign-produced traded inputs.

Following Horvath [2000], we assume that hours worked in the traded and the non-traded sectors are aggregated by means of a CES function:

$$L(t) = \left[\vartheta_L^{-1/\epsilon_L} (L^H(t))^{\frac{\epsilon_L+1}{\epsilon_L}} + (1-\vartheta_L)^{-1/\epsilon_L} (L^N(t))^{\frac{\epsilon_L+1}{\epsilon_L}} \right]^{\frac{\epsilon_L}{\epsilon_L+1}}, \quad (233)$$

where $0 < \vartheta_L < 1$ is the weight of labor supply to the traded sector in the labor index $L(\cdot)$ and ϵ_L measures the ease with which hours worked can be substituted for each other and thereby captures the degree of labor mobility across sectors.

Like labor, we generate imperfect capital mobility by assuming that traded $K^H(t)$ and non-traded $K^N(t)$ capital stock are imperfect substitutes:

$$K(t) = \left[\vartheta_K^{-1/\epsilon_K} (K^H(t))^{\frac{\epsilon_K+1}{\epsilon_K}} + (1 - \vartheta_K)^{-1/\epsilon_K} (K^N(t))^{\frac{\epsilon_K+1}{\epsilon_K}} \right]^{\frac{\epsilon_K}{\epsilon_K+1}}, \quad (234)$$

where $0 < \vartheta_K < 1$ is the weight of capital supply to the traded sector in the aggregate capital index $K(\cdot)$ and ϵ_K measures the ease with which sectoral capital can be substituted for each other and thereby captures the degree of capital mobility across sectors.

Households choose the level of capital utilization in sector j , denoted by $u^{K,j}(t)$. The capital utilization rate collapses to one at the steady-state. Capital utilization adjustment costs are assumed to be an increasing and convex function of the capital utilization rate:

$$C^{K,j}(t) = \xi_1^j (u^{K,j}(t) - 1) + \frac{\xi_2^j}{2} (u^{K,j}(t) - 1)^2. \quad (235)$$

The representative agent is endowed with one unit of time, supplies a fraction $L(t)$ as labor, and consumes the remainder $1 - L(t)$ as leisure. At any instant of time, households derive utility from their consumption and experience disutility from working and maximizes the following objective function:

$$\mathcal{U} = \int_0^\infty \Lambda(C(t), L(t)) e^{-\beta t} dt, \quad (236)$$

where $\beta > 0$ is the discount rate and we consider the utility specification proposed by Shimer [2009]:

$$\Lambda(C, L) \equiv \frac{C^{1-\sigma} V(L)^\sigma - 1}{1 - \sigma}, \quad \text{if } \sigma \neq 1, \quad V(L) \equiv \left(1 + (\sigma - 1) \gamma \frac{\sigma_L}{1 + \sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}} \right), \quad (237)$$

subject to the flow budget constraint:²²

$$\begin{aligned} \dot{N}(t) &+ P_C(t)C(t) + P_J(t)J(t) + \sum_{j=H,N} P^j(t)C^{K,j}(t)\nu^{K,j}(t)K(t) \\ &= r^*N(t) + W(t)L(t) + R^K(t)K(t) - \sum_{j=H,N} \alpha_K^j(t)u^{K,j}(t) - T(t), \end{aligned} \quad (238)$$

and capital accumulation which evolves as follows:

$$\dot{K}(t) = I(t) - \delta_K K(t), \quad (239)$$

where I is investment and $0 \leq \delta_K < 1$ is a fixed depreciation rate. We assume that capital accumulation is subject to increasing and convex cost of net investment, $I(t) - \delta_K K(t)$:

$$J(t) = I(t) + \frac{\kappa}{2} \left(\frac{I(t)}{K(t)} - \delta_K \right)^2 K(t), \quad (240)$$

Partial derivatives of total investment expenditure are:

$$\frac{\partial J(t)}{\partial I(t)} = 1 + \kappa \left(\frac{I(t)}{K(t)} - \delta_K \right), \quad (241a)$$

$$\frac{\partial J(t)}{\partial K(t)} = -\frac{\kappa}{2} \left(\frac{I(t)}{K(t)} - \delta_K \right) \left(\frac{I(t)}{K(t)} + \delta_K \right). \quad (241b)$$

²²we denote the share of sectoral capital in the aggregate capital stock by $\nu^{K,j}(t) = K^j(t)/K(t)$ and the capital and labor compensation share in sector $j = H, N$ by $\alpha_K^j(t) = \frac{R^j(t)K^j(t)}{R^K(t)K(t)}$ and $\alpha_L^j(t) = \frac{W^j(t)L^j(t)}{W(t)L(t)}$.

Denoting the co-state variables associated with (238) and (239) by λ and Q' , respectively, the first-order conditions characterizing the representative household's optimal plans are:

$$C(t)^{-\sigma}V(t)^\sigma = P_C(t)\lambda(t), \quad (242a)$$

$$C(t)^{1-\sigma}V(t)^\sigma \gamma L(t)^{\frac{1}{\sigma_L}} = \lambda(t)W(t), \quad (242b)$$

$$Q(t) = P_J(t) \left[1 + \kappa \left(\frac{I(t)}{K(t)} - \delta_K \right) \right], \quad (242c)$$

$$\dot{\lambda}(t) = \lambda(\beta - r^*), \quad (242d)$$

$$\begin{aligned} \dot{Q}(t) = & (r^* + \delta_K) Q(t) - \left\{ \sum_{j=H,N} \alpha_K^j(t) u^{K,j}(t) R^K(t) \right. \\ & \left. - \sum_{j=H,N} P^j(t) C^{K,j}(t) \nu^{K,j}(t) - P_J(t) \frac{\partial J(t)}{\partial K(t)} \right\}, \end{aligned} \quad (242e)$$

$$\frac{R^j(t)}{P^j(t)} = \xi_1^j + \xi_2^j (u^{K,j}(t) - 1), \quad j = H, N, \quad (242f)$$

and the transversality conditions $\lim_{t \rightarrow \infty} \bar{\lambda}N(t)e^{-\beta t} = 0$ and $\lim_{t \rightarrow \infty} Q(t)K(t)e^{-\beta t} = 0$; to derive (242c) and (242e), we used the fact that $Q(t) = Q'(t)/\lambda(t)$. We drop the time index below when it does not cause confusion.

Given the above consumption indices, we can derive appropriate price indices. With respect to the general consumption index, we obtain the consumption-based price index P_C :

$$P_C = \left[\varphi (P^T)^{1-\phi} + (1-\varphi) (P^N)^{1-\phi} \right]^{\frac{1}{1-\phi}}, \quad (243)$$

where the price index for traded goods is:

$$P^T = \left[\varphi_H (P^H)^{1-\rho} + (1-\varphi_H) \right]^{\frac{1}{1-\rho}}. \quad (244)$$

Given the consumption-based price index (243), the representative household has the following demand of traded and non-traded goods:

$$C^T = \varphi \left(\frac{P^T}{P_C} \right)^{-\phi} C, \quad (245a)$$

$$C^N = (1-\varphi) \left(\frac{P^N}{P_C} \right)^{-\phi} C. \quad (245b)$$

Given the price indices (243) and (244), the representative household has the following demand of home-produced traded goods and foreign-produced traded goods:

$$C^H = \varphi \left(\frac{P^T}{P_C} \right)^{-\phi} \varphi_H \left(\frac{P^H}{P^T} \right)^{-\rho} C, \quad (246a)$$

$$C^F = \varphi \left(\frac{P^T}{P_C} \right)^{-\phi} (1-\varphi_H) \left(\frac{1}{P^T} \right)^{-\rho} C. \quad (246b)$$

As will be useful later, the percentage change in the consumption price index is a weighted average of percentage changes in the price of traded and non-traded goods in terms of foreign goods:

$$\hat{P}_C = \alpha_C \hat{P}^T + (1-\alpha_C) \hat{P}^N, \quad (247a)$$

$$\hat{P}^T = \alpha_H \hat{P}^H, \quad (247b)$$

where α_C is the tradable content of overall consumption expenditure and α^H is the home-

produced goods content of consumption expenditure on traded goods:

$$\alpha_C = \varphi \left(\frac{P^T}{P_C} \right)^{1-\phi}, \quad (248a)$$

$$1 - \alpha_C = (1 - \varphi) \left(\frac{P^N}{P_C} \right)^{1-\phi}, \quad (248b)$$

$$\alpha^H = \varphi_H \left(\frac{P^H}{P^T} \right)^{1-\rho}, \quad (248c)$$

$$1 - \alpha^H = (1 - \varphi_H) \left(\frac{1}{P^T} \right)^{1-\rho}. \quad (248d)$$

Given the CES aggregator functions above, we can derive the appropriate price indices for investment. With respect to the general investment index, we obtain the investment-based price index P_J :

$$P_J = \left[\iota (P_J^T)^{1-\phi_J} + (1 - \iota) (P^N)^{1-\phi_J} \right]^{\frac{1}{1-\phi_J}}, \quad (249)$$

where the price index for traded goods is:

$$P_J^T = \left[\iota^H (P^H)^{1-\rho_J} + (1 - \iota^H) \right]^{\frac{1}{1-\rho_J}}. \quad (250)$$

Given the investment-based price index (249), we can derive the demand for inputs of the traded good and the non-traded good:

$$J^T = \iota \left(\frac{P_J^T}{P_J} \right)^{-\phi_J} J, \quad (251a)$$

$$J^N = (1 - \iota) \left(\frac{P^N}{P_J} \right)^{-\phi_J} J. \quad (251b)$$

Given the price indices (249) and (250), we can derive the demand for inputs of home-produced traded goods and foreign-produced traded goods:

$$J^H = \iota \left(\frac{P_J^T}{P_J} \right)^{-\phi_J} \iota^H \left(\frac{P^H}{P_J^T} \right)^{-\rho_J} J, \quad (252a)$$

$$J^F = \iota \left(\frac{P_J^T}{P_J} \right)^{-\phi_J} (1 - \iota^H) \left(\frac{1}{P_J^T} \right)^{-\rho_J} J. \quad (252b)$$

As will be useful later, the percentage change in the investment price index is a weighted average of percentage changes in the price of traded and non-traded inputs in terms of foreign inputs:

$$\hat{P}_J = \alpha_J \hat{P}_J^T + (1 - \alpha_J) \hat{P}^N, \quad (253a)$$

$$\hat{P}_J^T = \alpha_J^H \hat{P}^H, \quad (253b)$$

where α_J is the tradable content of overall investment expenditure and α_J^H is the home-produced goods content of investment expenditure on traded goods:

$$\alpha_J = \iota \left(\frac{P_J^T}{P_J} \right)^{1-\phi_J}, \quad (254a)$$

$$1 - \alpha_J = (1 - \iota) \left(\frac{P^N}{P_J} \right)^{1-\phi_J}, \quad (254b)$$

$$\alpha_J^H = \iota^H \left(\frac{P^H}{P_J^T} \right)^{1-\rho_J}, \quad (254c)$$

$$1 - \alpha_J^H = (1 - \iota^H) \left(\frac{1}{P_J^T} \right)^{1-\rho_J}. \quad (254d)$$

The aggregate wage index, W , associated with the labor index defined above (233) is:

$$W = \left[\vartheta_L (W^H)^{\epsilon_L+1} + (1 - \vartheta_L) (W^N)^{\epsilon_L+1} \right]^{\frac{1}{\epsilon_L+1}}, \quad (255)$$

where W^H and W^N are wages paid in the traded and the non-traded sectors, respectively. The aggregate capital rental rate, R^K , associated with the aggregate capital index defined above (234) is:

$$R^K = \left[\vartheta_K (R^H)^{\epsilon_K+1} + (1 - \vartheta_K) (R^N)^{\epsilon_K+1} \right]^{\frac{1}{\epsilon_K+1}}, \quad (256)$$

where R^H and R^N are capital rental rates paid in the traded and the non-traded sectors, respectively.

Given the aggregate wage index and the aggregate capital rental rate, the allocation of aggregate labor supply and the aggregate capital stock to the traded and the non-traded sector reads:

$$L^H = \vartheta_L \left(\frac{W^H}{W} \right)^{\epsilon_L} L, \quad L^N = (1 - \vartheta_L) \left(\frac{W^N}{W} \right)^{\epsilon_L} L, \quad (257a)$$

$$K^H = \vartheta_K \left(\frac{R^H}{R} \right)^{\epsilon_K} K, \quad K^N = (1 - \vartheta_K) \left(\frac{R^N}{R} \right)^{\epsilon_K} K, \quad (257b)$$

As will be useful later, the percentage change in the aggregate return index on labor and capital is a weighted average of percentage changes in sectoral wages and sectoral capital rental rates:

$$\hat{W} = \alpha_L \hat{W}^H + (1 - \alpha_L) \hat{W}^N, \quad \hat{R} = \alpha_K \hat{R}^H + (1 - \alpha_K) \hat{R}^N, \quad (258)$$

where α_L and α_K are the tradable content of aggregate labor and capital compensation:

$$\alpha_L = \vartheta_L \left(\frac{W^H}{W} \right)^{1+\epsilon_L}, \quad 1 - \alpha_L = (1 - \vartheta_L) \left(\frac{W^N}{W} \right)^{1+\epsilon_L}, \quad (259a)$$

$$\alpha_K = \vartheta_K \left(\frac{R^H}{R} \right)^{1+\epsilon_K}, \quad 1 - \alpha_K = (1 - \vartheta_K) \left(\frac{R^N}{R} \right)^{1+\epsilon_K}. \quad (259b)$$

O.2 Firms

Both the traded and non-traded sectors use physical capital, $\tilde{K}^j = u^{K,j} K^j$, and labor, L^j , according to constant returns to scale production functions $Y^j = Z^j F^j(\tilde{K}^j, L^j)$ which are assumed to take a Cobb-Douglas form:

$$Y^j = Z^j (L^j)^{\theta^j} (\tilde{K}^j)^{1-\theta^j}, \quad j = H, N \quad (260)$$

where θ^j is the labor income share in sector j and Z^j corresponds to the total factor productivity. Both sectors face two cost components: a capital rental cost equal to R^j , and a labor cost equal to the wage rate, i.e., W^j .

Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given:

$$\max_{\tilde{K}^j, L^j} \Pi^j = \max_{\tilde{K}^j, L^j} \left\{ P^j Y^j - W^j L^j - R^j \tilde{K}^j \right\}. \quad (261)$$

Since capital can move freely between the two sectors, the value of marginal products in the traded and non-traded sectors equalizes while costly labor mobility implies a wage differential across sectors:

$$P^j Z^j (1 - \theta^j) (L^j)^{\theta^j} (\tilde{K}^j)^{-\theta^j} = R^j, \quad (262a)$$

$$P^j Z^j \theta^j (L^j)^{1-\theta^j} (\tilde{K}^j)^{1-\theta^j} = W^j. \quad (262b)$$

O.3 Short-Run Solutions

Consumption and Labor

Before linearizing, we have to determine short-run solutions. First-order conditions (242a) and (242b) can be solved for consumption and aggregate labor supply which of course must hold at any point of time:

$$C = C(\bar{\lambda}, P^N, P^H), \quad L = L(\bar{\lambda}, W^H, W^N), \quad (263)$$

with partial derivatives given by

$$\hat{C} = -\sigma_C \hat{\lambda} - \sigma_C \alpha_C \alpha^H \hat{P}^H - \sigma_C (1 - \alpha_C) \hat{P}^N, \quad (264a)$$

$$\hat{L} = \sigma_L \hat{\lambda} + \sigma_L (1 - \alpha_L) \hat{W}^N + \sigma_L \alpha_L \hat{W}^H, \quad (264b)$$

where we used (258) and (247).

Inserting first the solution for consumption (263) into (245a)-(246b) allows us to solve for C^N , C^H , and C^F :

$$C^N = C^N(\bar{\lambda}, P^N, P^H), \quad C^H = C^H(\bar{\lambda}, P^N, P^H), \quad C^F = C^F(\bar{\lambda}, P^N, P^H), \quad (265)$$

with partial derivatives given by

$$\begin{aligned} \hat{C}^N &= -\phi \hat{P}^N + (\phi - \sigma_C) \hat{P}^C - \sigma_C \hat{\lambda}, \\ &= -[\alpha_C \phi + (1 - \alpha_C) \sigma_C] \hat{P}^N + (\phi - \sigma_C) \alpha_C \alpha^H \hat{P}^H - \sigma_C \hat{\lambda}, \end{aligned} \quad (266a)$$

$$\hat{C}^H = -[\rho(1 - \alpha^H) + \phi(1 - \alpha_C) \alpha^H + \sigma_C \alpha_C \alpha^H] \hat{P}^H + (1 - \alpha_C) (\phi - \sigma_C) \hat{P}^N - \sigma_C \hat{\lambda}, \quad (266b)$$

$$\hat{C}^F = \alpha^H [\rho - \phi(1 - \alpha_C) - \sigma_C \alpha_C] \hat{P}^H + (1 - \alpha_C) (\phi - \sigma_C) \hat{P}^N - \sigma_C \hat{\lambda}. \quad (266c)$$

Inserting first the solution for labor (263) into (257a) allows us to solve for L^H and L^N :

$$L^H = L^H(\bar{\lambda}, W^H, W^N), \quad L^N = L^N(\bar{\lambda}, W^H, W^N), \quad (267)$$

with partial derivatives given by:

$$\hat{L}^H = [\epsilon_L (1 - \alpha_L) + \sigma_L \alpha_L] \hat{W}^H - (1 - \alpha_L) (\epsilon_L - \sigma_L) \hat{W}^N + \sigma_L \hat{\lambda}, \quad (268a)$$

$$\hat{L}^N = [\epsilon_L \alpha_L + \sigma_L (1 - \alpha_L)] \hat{W}^N - \alpha_L (\epsilon_L - \sigma_L) \hat{W}^H + \sigma_L \hat{\lambda}. \quad (268b)$$

The decision to allocate capital between to the traded and the non-traded sectors (257b) allows us to solve for K^H and K^N :

$$K^H = K^H(K, R^H, R^N), \quad K^N = K^N(K, R^H, R^N), \quad (269)$$

with partial derivatives given by:

$$\hat{K}^H = \epsilon_K (1 - \alpha_K) \hat{R}^H - (1 - \alpha_K) \epsilon_K \hat{R}^N + \hat{K}, \quad (270a)$$

$$\hat{K}^N = \epsilon_K \alpha_K \hat{R}^N - \alpha_K \epsilon_K \hat{R}^H + \hat{K}. \quad (270b)$$

Sectoral Wages and Sectoral Capital Rental Rates

Plugging the short-run solutions for L^H , L^N , K^H , K^N , given by (267)-(269) into the demand for capital and labor (262a)-(262b), the system of four equations can be solved for sectoral wages W^j and sectoral capital rental rates R^j . Log-differentiating (262a)-(262b)

yields in matrix form:

$$\begin{aligned}
& \begin{pmatrix} - \left[(1 - \theta^H) \frac{L_{WH}^H}{L^H} + \frac{1}{W^H} \right] & - (1 - \theta^H) \frac{L_{WN}^H}{L^H} & (1 - \theta^H) \frac{K_{RH}^H}{K^H} & (1 - \theta^H) \frac{K_{RN}^H}{K^H} \\ - (1 - \theta^N) \frac{L_{WN}^N}{L^N} & - \left[(1 - \theta^N) \frac{L_{WN}^N}{L^N} + \frac{1}{W^N} \right] & (1 - \theta^N) \frac{K_{RH}^N}{K^N} & (1 - \theta^N) \frac{K_{RN}^N}{K^N} \\ \theta^H \frac{L_{WH}^H}{L^H} & \theta^H \frac{L_{WN}^H}{L^H} & - \left[\theta^H \frac{K_{RH}^H}{K^H} + \frac{1}{R^H} \right] & \theta^H \frac{K_{RN}^H}{K^H} \\ \theta^N \frac{L_{WH}^N}{L^N} & \theta^N \frac{L_{WN}^N}{L^N} & \theta^N \frac{K_{RH}^N}{K^N} & - \left[\theta^N \frac{K_{RN}^N}{K^N} + \frac{1}{R^N} \right] \end{pmatrix} \\
& \times \begin{pmatrix} dW^H \\ dW^N \\ dR^H \\ dR^N \end{pmatrix} \\
& = \begin{pmatrix} (1 - \theta^H) \frac{L_{PN}^H}{L^H} dP^N + \left[(1 - \theta^H) \frac{L_{PH}^H}{L^H} - \frac{1}{P^H} \right] dP^H - (1 - \theta^H) \frac{K_K^H}{K^H} dK - \hat{Z}^H - (1 - \theta^H) du^{K,H} \\ \left[(1 - \theta^N) \frac{L_{PN}^N}{L^N} - \frac{1}{P^N} \right] dP^N + (1 - \theta^N) \frac{L_{PH}^N}{L^N} dP^H - (1 - \theta^N) \frac{K_K^N}{K^N} dK - \hat{Z}^N - (1 - \theta^N) du^{K,N} \\ - \theta^H \frac{L_{PH}^H}{L^H} dP^N - \left[\theta^H \frac{L_{PH}^H}{L^H} + \frac{1}{P^H} \right] dP^H + \theta^H \frac{K_K^H}{K^H} dK - \hat{Z}^H + \theta^H du^{K,H} \\ - \left[\theta^N \frac{L_{PN}^N}{L^N} + \frac{1}{P^N} \right] dP^N - \theta^N \frac{L_{PH}^N}{L^N} dP^H + \theta^N \frac{K_K^N}{K^N} dK - \hat{Z}^N + \theta^N du^{K,N} \end{pmatrix} \quad (271)
\end{aligned}$$

The short-run solutions for sectoral wages and the capital rental rates are:

$$W^j = W^j(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N, u^{K,H}, u^{K,N}), \quad R^j = R^j(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N, u^{K,H}, u^{K,N}). \quad (272)$$

Inserting first sectoral wages and capital rental rates (272) into intermediate solutions for sectoral hours worked (267) and sector capital capital (269), these equations can be solved as functions of the aggregate capital stock, the price of non-traded goods in terms of foreign goods, P^N , the terms of trade, and the capital utilization rates:

$$L^j = L^j(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N, u^{K,H}, u^{K,N}), \quad K^j = K^j(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N, u^{K,H}, u^{K,N}), \quad (273)$$

Finally, plugging solutions for sectoral labor (273) and sector capital-labor ratios (272), production functions (260) can be solved for sectoral value added:

$$Y^j = Y^j(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N, u^{K,H}, u^{K,N}). \quad (274)$$

Capital Utilization Rates, $u^{K,j}(t)$

Inserting firm's optimal decision for capital (262a) in sector j in the optimal intensity in the use of physical capital (242f) leads to:

$$\frac{R^j(t)}{P^j(t)} = \xi_1^j + \xi_2^j (u^{K,j}(t) - 1) = Z^j(t) (1 - \theta^j) (L^j(t))^{\theta^j} (\tilde{K}^j(t))^{-\theta^j}. \quad (275)$$

Inserting intermediate solutions (273) for sectoral hours worked and sectoral capital into (275) and log-differentiating leads to in a matrix form:

$$\begin{aligned}
& \begin{pmatrix} \left[\frac{\xi_2^H}{\xi_1^H} + \theta^H + \theta^H \frac{K_{u^{K,H}}^H}{K^H} \right] - \theta^H \frac{L_{u^{K,H}}^H}{L^H} & \theta^H \frac{K_{u^{K,N}}^H}{K^H} - \theta^H \frac{L_{u^{K,N}}^H}{L^H} \\ \theta^N \frac{K_{u^{K,H}}^N}{K^N} - \theta^N \frac{L_{u^{K,H}}^N}{L^N} & \left[\frac{\xi_2^N}{\xi_1^N} + \theta^N + \theta^N \frac{K_{u^{K,N}}^N}{K^N} \right] - \theta^N \frac{L_{u^{K,N}}^N}{L^N} \end{pmatrix} \begin{pmatrix} \hat{u}^{K,H} \\ \hat{u}^{K,N} \end{pmatrix} \\
& = \begin{pmatrix} \left[\theta^H \frac{L_X^H}{L^H} - \theta^H \frac{K_X^H}{K^H} \right] dX + \hat{Z}^H \\ \left[\theta^N \frac{L_X^N}{L^N} - \theta^N \frac{K_X^N}{K^N} \right] dX + \hat{Z}^N \end{pmatrix}, \quad (276)
\end{aligned}$$

where $X = K, P^H, P^N, Z^H, Z^N$

The short-run solutions for capital and technology utilization rates are:

$$u^{K,j} = u^{K,j}(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N). \quad (277)$$

Intermediate Solutions for R^j, W^j, K^j, L^j, Y^j

Plugging back solutions for the capital utilization rates (277) into the intermediate solutions for the sectoral wage rates and the capital rental rates (272), for sectoral hours worked and sectoral capital stocks (273), and for sectoral value added (274) leads to intermediate solutions for sectoral wages, sectoral capital rental rates, sectoral hours worked, sectoral capital stocks, sectoral value added:

$$W^j, R^j, L^j, K^j, Y^j(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N). \quad (278)$$

Optimal Investment Decision, I/K

Eq. (242c) can be solved for the investment rate:

$$\frac{I}{K} = v\left(\frac{Q}{P_I(P^T, P^N)}\right) + \delta_K, \quad (279)$$

where

$$v(\cdot) = \frac{1}{\kappa} \left(\frac{Q}{P_J} - 1 \right), \quad (280)$$

with

$$v_Q = \frac{\partial v(\cdot)}{\partial Q} = \frac{1}{\kappa} \frac{1}{P_J} > 0, \quad (281a)$$

$$v_{P^H} = \frac{\partial v(\cdot)}{\partial P^H} = -\frac{1}{\kappa} \frac{Q}{P_J} \frac{\alpha_J \alpha_J^H}{P^H} < 0, \quad (281b)$$

$$v_{P^N} = \frac{\partial v(\cdot)}{\partial P^N} = -\frac{1}{\kappa} \frac{Q}{P_J} \frac{(1 - \alpha_J)}{P^N} < 0. \quad (281c)$$

Inserting (279) into (240), investment including capital installation costs can be rewritten as follows:

$$\begin{aligned} J &= K \left[\frac{I}{K} + \frac{\kappa}{2} \left(\frac{I}{K} - \delta_K \right)^2 \right], \\ &= K \left[v(\cdot) + \delta_K + \frac{\kappa}{2} (v(\cdot))^2 \right]. \end{aligned} \quad (282)$$

Eq. (282) can be solved for investment including capital installation costs:

$$J = J(K, Q, P^N, P^H), \quad (283)$$

where

$$J_K = \frac{\partial J}{\partial K} = \frac{J}{K}, \quad (284a)$$

$$J_X = \frac{\partial J}{\partial X} = \kappa v_X (1 + \kappa v(\cdot)) > 0, \quad (284b)$$

with $X = Q, P^H, P^N$.

Substituting (284) into (251b), (252a), and (252b) allows us to solve for the demand of non-traded, home-produced traded, and foreign inputs:

$$J^N = J^N(K, Q, P^N, P^H), \quad J^H = J^H(K, Q, P^N, P^H), \quad J^F = J^F(K, Q, P^N, P^H), \quad (285)$$

with partial derivatives given by

$$\begin{aligned}
\hat{J}^N &= -\alpha_J \phi_J \hat{P}^N + \phi_J \alpha_J \alpha_J^H \hat{P}^H + \hat{J}, \\
&= \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} \hat{Q} - \left[\alpha_J \phi_J + \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} (1 - \alpha_J) \right] \hat{P}^N \\
&+ \alpha_J \alpha_J^H \left[\phi_J - \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} \right] \hat{P}^H + \hat{K}, \tag{286a}
\end{aligned}$$

$$\begin{aligned}
\hat{J}^H &= -[\rho_J (1 - \alpha_J^H) + \alpha_J^H \phi_J (1 - \alpha_J)] \hat{P}^H + \phi_J (1 - \alpha_J) \hat{P}^N + \hat{J}, \\
&= -\left\{ [\rho_J (1 - \alpha_J^H) + \alpha_J^H \phi_J (1 - \alpha_J)] + \alpha_J \alpha_J^H \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} \right\} \hat{P}^H \\
&+ (1 - \alpha_J) \left[\phi_J - \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} \right] \hat{P}^N + \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} \hat{Q} + \hat{K}, \tag{286b}
\end{aligned}$$

$$\begin{aligned}
\hat{J}^F &= \alpha_J^H [\rho_J - \phi_J (1 - \alpha_J)] \hat{P}^H + \phi_J (1 - \alpha_J) \hat{P}^N + \hat{J}, \\
&= \alpha_J^H \left\{ [\rho_J - \phi_J (1 - \alpha_J)] - \alpha_J \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} \right\} \hat{P}^H \\
&+ (1 - \alpha_J) \left[\phi_J - \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} \right] \hat{P}^N + \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} \hat{Q} + \hat{K}, \tag{286c}
\end{aligned}$$

where use has been made of (284), i.e.,

$$\begin{aligned}
\hat{J} &= \hat{K} + \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} \hat{Q} - \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} (1 - \alpha_J) \hat{P}^N \\
&- \alpha_J \alpha_J^H \frac{Q}{P_J} \frac{(1 + \kappa v(\cdot))}{J} \hat{P}^H.
\end{aligned}$$

O.4 Market Clearing Conditions

Finally, we have to solve for non-traded good prices and the terms of trade. The role of the price of non-traded goods in terms of foreign goods is to clear the non-traded goods market:

$$Y^N = C^N + G^N + J^N + C^{K,N} K^N. \tag{287}$$

The role of the price of home-produced goods in terms of foreign-produced goods or the terms of trade is to clear the home-produced traded goods market:

$$Y^H = C^H + G^H + J^H + X^H + C^{K,H} K^H, \tag{288}$$

where X^H stands for exports which are negatively related to the terms of trade:

$$X^H = \varphi_X (P^H)^{-\phi_X}, \tag{289}$$

with ϕ_X is the elasticity of exports with respect to the terms of trade. The rationale behind (289) comes from the fact that exports are the sum of foreign demand for the domestically produced tradable consumption goods and investment inputs denoted by $C^{F,\star}$ and $J^{F,\star}$, respectively:

$$\begin{aligned}
X^H(t) &= C^{F,\star}(t) + J^{F,\star}(t), \\
&= \varphi \left(\frac{P^{T,\star}}{P_C^\star} \right)^{-\phi} (1 - \varphi_H^\star) \left(\frac{P^H(t)}{P_T^\star} \right)^{-\rho^\star} C^\star + \iota \left(\frac{P_J^{T,\star}}{P_J^\star} \right)^{-\phi_J} (1 - \iota_H^\star) \left(\frac{P^H(t)}{P_J^{T,\star}} \right)^{-\rho_J^\star} J^\star,
\end{aligned}$$

where we assume that the rest of the world have similar preferences with potentially different elasticities (i.e., $\rho^\star \neq \rho$ and $\rho_J^\star \neq \rho_J$) between foreign and domestic tradable goods. To keep things simple, we assume that technology is fixed abroad. Therefore foreign prices denoted with a star remain constant and thus domestic exports are decreasing in the terms of trade, $P^H(t)$.

As shall be useful to write formal expressions in a compact form, we wet

$$\Delta_{PH}^H = Y_{PH}^H - C_{PH}^H - J_{PH}^H - X_{PH}^H - \xi_1^H u_{PH}^{K,H}, \quad (290a)$$

$$\Delta_{PN}^H = Y_{PN}^H - C_{PN}^H - J_{PN}^H - \xi_1^H u_{PN}^{K,H}, \quad (290b)$$

$$\Delta_K^H = Y_K^H - C_K^H - J_K^H - \xi_1^H u_K^{K,H}, \quad (290c)$$

$$\Delta_{Z^j}^H = Y_{Z^j}^H - C_{Z^j}^H - \xi_1^H u_{Z^j}^{K,H}, \quad (290d)$$

$$\Delta_{PH}^N = Y_{PH}^N - C_{PH}^N - J_{PH}^N - \xi_1^N u_{PH}^{K,N} > 0, \quad (290e)$$

$$\Delta_{PN}^N = Y_{PN}^N - C_{PN}^N - J_{PN}^N - \xi_1^N u_{PN}^{K,N}, \quad (290f)$$

$$\Delta_K^N = Y_K^N - C_K^N - J_K^N - \xi_1^N u_K^{K,N}, \quad (290g)$$

$$\Delta_{Z^j}^N = Y_{Z^j}^N - C_{Z^j}^N - \xi_1^N u_{Z^j}^{K,N}, \quad (290h)$$

where $X_{PH}^H = \frac{\partial X^H}{\partial P^H} < 0$.

Totally differentiating the market clearing conditions (287)-(288) leads to in a matrix form:

$$\begin{pmatrix} \Delta_{PH}^H & \Delta_{PN}^H \\ \Delta_{PH}^N & \Delta_{PN}^N \end{pmatrix} \begin{pmatrix} dP^H \\ dP^N \end{pmatrix} = \begin{pmatrix} -\Delta_K^H dK + J_Q^H dQ - \sum_j \Delta_{Z^j}^H dZ^j \\ -\Delta_K^N dK + J_Q^N dQ - \sum_j \Delta_{Z^j}^N dZ^j \end{pmatrix}. \quad (291)$$

Applying the implicit functions theorem leads to the short-run solutions for the terms of trade and non-traded good prices:

$$P^H, P^N (\bar{\lambda}, K, Q, Z^H, Z^N). \quad (292)$$

Plugging back the solutions for sectoral prices into (277) and (278) allow us to find the final versions of solutions of the capital utilization rate, sectoral wages, sectoral capital rental rates, sectoral hours worked, sectoral capital stocks, sectoral value added:

$$u^{K,j}, W^j, R^j, L^j, K^j, Y^j (\bar{\lambda}, K, Q, Z^H, Z^N). \quad (293)$$

Inserting the solutions for prices into the intermediate solutions for consumption (265) and investment (285) leads to:

$$C^g, J^g (K, Q, Z^H, Z^N, \bar{\lambda}), \quad (294)$$

where $g = H, N, F$.

O.5 Solving the Model

Remembering that the non-traded input J^N used to produce the capital good is equal to $(1 - \iota) \left(\frac{P^N}{P^J} \right)^{-\phi_J} J$ (see eq. (251b)) with $J = I + \frac{\kappa}{2} \left(\frac{I}{K} - \delta_K \right)^2 K$, using the fact that $J^N = Y^N - C^N - G^N - C^{K,N} K^N$ and inserting $I = \dot{K} + \delta_K K$, the capital accumulation equation reads as follows:

$$\dot{K} = \frac{Y^N - C^N - G^N - C^{K,N} K^N}{(1 - \iota) \left(\frac{P^N}{P^J} \right)^{-\phi_J}} - \delta_K K - \frac{\kappa}{2} \left(\frac{I}{K} - \delta_K \right)^2 K. \quad (295)$$

Inserting short-run solutions for the capital utilization rate and value added, i.e., (293), investment and consumption in non-tradables (294), into the physical capital accumulation equation (295), and plugging the short-run solution for the return on domestic capital (293) into the dynamic equation for the shadow value of capital stock (242e), the dynamic system reads as follows:²³

$$\dot{K} \equiv \Upsilon (K, Q, Z^H, Z^N) = \frac{E^N (K, Q, Z^H, Z^N)}{(1 - \iota) \left\{ \frac{P^N(\cdot)}{P^J[P^H(\cdot), P^N(\cdot)]} \right\}^{-\phi_J}} - \delta_K K - \frac{K}{2\kappa} \left\{ \frac{Q}{P^J [P^H(\cdot), P^N(\cdot)]} - 1 \right\}^2, \quad (296a)$$

$$\begin{aligned} \dot{Q} \equiv \Sigma (K, Q, Z^H, Z^N) &= (r^* + \delta_K) Q - \left[\frac{\sum_j R^j (K, Q, Z^H, Z^N) \tilde{K}^j (K, Q, Z^H, Z^N)}{K} \right. \\ &\quad \left. - \sum_j C^{K,j} (u^{K,j} (K, Q, Z^H, Z^N)) \frac{K^j (K, Q, Z^H, Z^N)}{K} + P^J \frac{\kappa}{2} v(\cdot) (v(\cdot) + 2) \right] \end{aligned} \quad (296b)$$

²³We omit the shadow value of wealth from short-run solutions for clarity purposes as λ remains constant over time.

where $E^N = Y^N - C^N - G^N - C^{K,N}K^N$

To facilitate the linearization, it is useful to break down the capital accumulation into two components:

$$\hat{K} = J - \delta_K K - \frac{\kappa}{2} \left(\frac{I}{K} - \delta_K \right)^2 K. \quad (297)$$

The first component is J . Using the fact that $J = \frac{J^N}{(1-\iota)\left(\frac{P^N}{P^J}\right)^{-\phi_J}}$ and log-linearizing gives:

$$\hat{J} = \hat{J}^N + \phi_J \alpha_J \hat{P}^N - \phi_J \alpha_J \alpha_J^H \hat{P}^H \quad (298)$$

where we used the fact that $\hat{P}_J = \alpha_J \alpha_J^H \hat{P}^H + (1 - \alpha_J) \hat{P}^N$. Using (297) and the fact that $J^N = Y^N - C^N - G^N - C^{K,N}u^{K,N}$, linearizing (297) in the neighborhood of the steady-state gives:

$$\begin{aligned} \dot{K} &= \frac{J}{J^N} [dY^N(t) - dC^N(t) - \xi_1^N du^{K,N}(t)] + \phi_J \frac{J}{P^N} \alpha_J dP^N(t) \\ &\quad - \phi_J \frac{J}{P^H} \alpha_J \alpha_J^H dP^H(t) - \delta_K dK(t), \end{aligned} \quad (299)$$

where $J = I = \delta_K K$ in the long-run.

As will be useful, let us denote by Υ_K , Υ_Q , and Υ_{Z^j} the partial derivatives evaluated at the steady-state of the capital accumulation equation w.r.t. K , Q , and Z^j , respectively. Using (299), these elements of the Jacobian matrix are given by:

$$\Upsilon_K \equiv \frac{\partial \dot{K}}{\partial K} = \frac{J}{J^N} E_K^N + \alpha_J \phi_J J \left(\frac{P_K^N}{P^N} - \alpha_J^H \frac{P_K^H}{P^H} \right) - \delta_K \geq 0, \quad (300a)$$

$$\Upsilon_Q \equiv \frac{\partial \dot{K}}{\partial Q} = \frac{J}{J^N} E_Q^N + \alpha_J \phi_J J \left(\frac{P_Q^N}{P^N} - \alpha_J^H \frac{P_Q^H}{P^H} \right) > 0, \quad (300b)$$

$$\Upsilon_{Z^j} \equiv \frac{\partial \dot{K}}{\partial Z^j} = \frac{J}{J^N} E_{Z^j}^N + \alpha_J \phi_J J \left(\frac{P_{Z^j}^N}{P^N} - \alpha_J^H \frac{P_{Z^j}^H}{P^H} \right), \quad (300c)$$

where $J = \delta_K K$ in the long run and $E_X^N = Y_X^N - C_X^N - \xi_1^N u_X^{K,N}$ with $X = K, Q, Z^j$,

Let us denote by Σ_K , Σ_Q , and Σ_{Z^j} the partial derivatives evaluated at the steady-state of the dynamic equation for the marginal value of an additional unit of capital w.r.t. K , Q , and Z^j , respectively:

$$\Sigma_K \equiv \frac{\partial \dot{Q}}{\partial K} = - \left[-\frac{R}{K} + \frac{\Delta_K}{K} + P_J \kappa v_K \delta_K \right] > 0, \quad (301a)$$

$$\Sigma_Q \equiv \frac{\partial \dot{Q}}{\partial Q} = (r^* + \delta_K) - \left[\frac{\Delta_Q}{K} + P_J \kappa v_Q \delta_K \right] > 0, \quad (301b)$$

$$\Sigma_{Z^j} \equiv \frac{\partial \dot{Q}}{\partial Z^j} = - \left[\frac{\Delta_{Z^j}}{K} + P_J \kappa v_{Z^j} \delta_K \right]. \quad (301c)$$

where $\Delta_K = \sum_j K^j R_K^j + R^j K_K^j + R^j K^j u_{K^j}^{K,j}$, $\Delta_Q = \sum_j K^j R_Q^j + R^j K_Q^j + R^j K^j u_{Q^j}^{K,j}$, $\Delta_{Z^j} = \sum_j K^j R_{Z^j}^j + R^j K_{Z^j}^j + R^j K^j u_{Z^j}^{K,j}$.

Assuming that the saddle-path stability condition is fulfilled, and denoting the negative eigenvalue by ν_1 and the positive eigenvalue by ν_2 , the general solutions for K and Q are:

$$K(t) - \tilde{K} = D_1 e^{\nu_1 t} + D_2 e^{\nu_2 t}, \quad Q(t) - \tilde{Q} = \omega_2^1 D_1 e^{\nu_1 t} + \omega_2^2 D_2 e^{\nu_2 t}, \quad (302)$$

where K_0 is the initial capital stock and $(1, \omega_2^i)'$ is the eigenvector associated with eigenvalue ν_i :

$$\omega_2^i = \frac{\nu_i - \Upsilon_K}{\Upsilon_Q}. \quad (303)$$

Because $\nu_1 < 0$, $\Upsilon_K > 0$ and $\Upsilon_Q > 0$, we have $\omega_2^1 < 0$, regardless of sectoral capital intensities, which implies that the shadow value of investment and the stock physical capital move in opposite direction along a stable path (i.e., $D_2 = 0$).

O.6 Current Account Equation and Intertemporal Solvency Condition

To determine the current account equation, we use the following identities and properties:

$$P_C C = P^H C^H + C^F + P^N C^N, \quad (304a)$$

$$P_J J = P^H J^H + J^F + P^N J^N, \quad (304b)$$

$$T = G = P^H G^H + G^F + P^N G^N, \quad (304c)$$

$$WL + R\tilde{K} = \left(W^H L^H + R^H \tilde{K}^H \right) + \left(W^N L^N + R^N \tilde{K}^N \right) = P^H Y^H + P^N Y^N, \quad (304d)$$

where (304d) follows from Euler theorem. Using (304a)-(304c) into (238) and invoking market clearing conditions for non-traded goods (287) and home-produced traded goods (288) yields:

$$\begin{aligned} \dot{N} &= r^* N + P^H (Y^H - C^H - G^H - J^H - C^{K,H} K^H) - (C^F + J^F + G^F), \\ &= r^* N + P^H X^H - M^F, \end{aligned} \quad (305)$$

where $X^H = Y^H - C^H - G^H - J^H$ stands for exports of home goods and we denote by M^F imports of foreign consumption and investment goods:

$$M^F = C^F + G^F + J^F. \quad (306)$$

Inserting appropriate solutions, the current account equation reads:

$$\begin{aligned} \dot{N} &\equiv r^* N + \Xi(K, Q, Z^H, Z^N), \\ &= r^* N + P^H(K, Q, Z^H, Z^N) X^H(K, Q, Z^H, Z^N) - M^F(K, Q, Z^H, Z^N). \end{aligned} \quad (307)$$

Let us denote by Ξ_K , Ξ_Q , and Ξ_{Z^j} the partial derivatives evaluated at the steady-state of the dynamic equation for the current account w.r.t. K , Q , and Z^j , respectively:

$$\Xi_K \equiv \frac{\partial \dot{N}}{\partial K} = (1 - \phi_X) X^H P_K^H - M_K^F, \quad (308a)$$

$$\Xi_Q \equiv \frac{\partial \dot{N}}{\partial Q} = (1 - \phi_X) X^H P_Q^H - M_Q^F, \quad (308b)$$

$$\Xi_{Z^j} \equiv \frac{\partial \dot{N}}{\partial Z^j} = (1 - \phi_X) X^H P_{Z^j}^H - M_{Z^j}^F. \quad (308c)$$

where we used the fact that $P^H X^H = \varphi_X (P^H)^{1-\phi_X}$ (see eq. (289)).

Linearizing (307) in the neighborhood of the steady-state, making use of (308a) and (308b), inserting solutions for $K(t)$ and $Q(t)$ given by (302) and solving yields the general solution for the net foreign asset position:

$$N(t) = N + [(N_0 - N) - \Psi_1 D_1 - \Psi_2 D_2] e^{r^* t} + \Psi_1 D_1 e^{\nu_1 t} + \Psi_2 D_2 e^{\nu_2 t}, \quad (309)$$

where N_0 is the initial stock of traded bonds and we set

$$E_i = \Xi_K + \Xi_Q \omega_2^i, \quad (310a)$$

$$\Psi_i = \frac{E_i}{\nu_i - r^*}. \quad (310b)$$

Invoking the transversality condition leads to the linearized version of the nations's intertemporal solvency condition:

$$N - N_0 = \Psi_1 (K - K_0), \quad (311)$$

where K_0 is the initial stock of physical capital.

O.7 Derivation of the Accumulation Equation of Non Human Wealth

Remembering that the stock of financial wealth $A(t)$ is equal to $N(t) + Q(t)K(t)$, differentiating w.r.t. time, i.e., $\dot{A}(t) = \dot{N}(t) + \dot{Q}(t)K(t) + Q(t)\dot{K}(t)$, plugging the dynamic equation for the marginal value of capital (242e), inserting the accumulation equations for physical capital (239) and traded bonds (238), yields the accumulation equation for the stock of financial wealth or the dynamic equation for private savings:

$$\dot{A}(t) = r^*A(t) + W(t)L(t) - T(t) - P_C(t)C(t). \quad (312)$$

where we assume that the government levies lump-sum taxes, T , to finance purchases of foreign-produced, home-produced and non-traded goods, i.e., $T = G = (G^F + P^H(\cdot)G^H + P^N(\cdot)G^N)$.

Solving for $C = C(K, Q, Z^H, Z^N)$ by inserting the solutions for sectoral prices (292) into the optimal decision for consumption (242a), inserting solutions for W^j, L^j , into (278) allows us to write the financial wealth accumulation equation as follows:

$$\begin{aligned} \dot{A} &\equiv r^*A + \Lambda(K, Q, Z^H, Z^N), \\ &= r^*A + \sum_j W^j(K, Q, Z^H, Z^N) L^j(K, Q, Z^H, Z^N) - G(K, Q, Z^H, Z^N) \\ &\quad - P_C[P^H(\cdot), P^N(\cdot)]C(K, Q, Z^H, Z^N), \end{aligned} \quad (313)$$

where P^N and P^H are given by (292).

Let us denote by Λ_K, Λ_Q , and Λ_{Z^j} the partial derivatives evaluated at the steady-state of the dynamic equation for the non human wealth w.r.t. K, Q , and Z^j , respectively:

$$\Lambda_K \equiv \frac{\partial \dot{A}}{\partial K} = (W_K L + W L_K) - G_K - \left(\frac{\partial P_C}{\partial K} C + P_C C_K \right), \quad (314a)$$

$$\Lambda_Q \equiv \frac{\partial \dot{A}}{\partial Q} = (W_Q L + W L_Q) - G_Q - \left(\frac{\partial P_C}{\partial Q} C + P_C C_Q \right), \quad (314b)$$

$$\Lambda_{Z^j} \equiv \frac{\partial \dot{A}}{\partial Z^j} = (W_{Z^j} L + W L_{Z^j}) - G_{Z^j} - \left(\frac{\partial P_C}{\partial Z^j} C + P_C C_{Z^j} \right). \quad (314c)$$

Linearizing (313) in the neighborhood of the steady-state, making use of (314a) and (314b), inserting solutions for $K(t)$ and $Q(t)$ given by (302) and solving yields the general solution for the stock of non human wealth:

$$A(t) = A + [(A_0 - A) - \Delta_1 D_1 - \Delta_2 D_2] e^{r^* t} + \Delta_1 D_1 e^{\nu_1 t} + \Delta_2 D_2 e^{\nu_2 t}, \quad (315)$$

where A_0 is the initial stock of financial wealth and we set

$$M_i = A_K + A_Q \omega_2^i, \quad (316a)$$

$$\Delta_i = \frac{M_i}{\nu_i - r^*}. \quad (316b)$$

The linearized version of the representative household's intertemporal solvency condition is:

$$A - A_0 = \Delta_1 (K - K_0), \quad (317)$$

where A_0 is the initial stock of non human wealth.

P Semi-Small Open Economy Model with CES Production Functions

In section O, we have laid out a model with Cobb-Douglas production functions. The steady-state of this model is used to normalize CES production functions. This section extends the model with Cobb-Douglas production functions in two directions. First, in the baseline model we allow for CES production functions and factor-biased technological change (FBTC henceforth). Second, we assume that factor-augmenting efficiency has both a symmetric and an asymmetric component. The first order conditions from households' maximization problem detailed in subsection O.1 remain almost identical and we emphasize only the main changes.

P.1 Households

Households choose the level of capital utilization in sector j , which includes both a symmetric and an asymmetric component, denoted by $u_S^{K,j}(t)$ and $u_D^{K,j}(t)$:

$$u^{K,j}(t) = \left(u_S^{K,j}(t)\right)^\eta \left(u_D^{K,j}(t)\right)^{1-\eta}. \quad (318)$$

Both components of the capital utilization rate collapse to one at the steady-state. The capital utilization adjustment costs are assumed to be an increasing and convex function of the capital utilization rate:

$$C_S^{K,j}(t) = \xi_{1,S}^j \left(u_S^{K,j}(t) - 1\right) + \frac{\xi_{2,S}^j}{2} \left(u_S^{K,j}(t) - 1\right)^2, \quad (319a)$$

$$C_D^{K,j}(t) = \xi_{1,D}^j \left(u_D^{K,j}(t) - 1\right) + \frac{\xi_{2,D}^j}{2} \left(u_D^{K,j}(t) - 1\right)^2, \quad (319b)$$

where $\xi_{2,S}^j > 0$, $\xi_{2,D}^j > 0$, are free parameters which indicate the extent of the cost of adjusting the intensity in the use of capital. When we let $\xi_{2,c}^j \rightarrow \infty$ ($c = S, D$), capital utilization is fixed at unity and TFP growth collapses to technological change.

The dynamic equation of the shadow price of capital (242e) and the optimal decision about the capital utilization rate (242f) are modified as follows:

$$\begin{aligned} \dot{Q}(t) = & (r^* + \delta_K) Q(t) - \left\{ \sum_{j=H,N} \alpha_K^j(t) u^{K,j}(t) R^K(t) \right. \\ & \left. - \sum_{j=H,N} P^j(t) \left(C_S^{K,j}(t) + C_D^{K,j}(t) \right) \nu^{K,j}(t) - P_J(t) \frac{\partial J(t)}{\partial K(t)} \right\}, \end{aligned} \quad (320a)$$

$$\frac{R^j(t)}{P^j(t)} \eta \frac{u^{K,j}(t)}{u_S^{K,j}(t)} = \xi_{1,S}^j + \xi_{2,S}^j \left(u_S^{K,j}(t) - 1\right), \quad j = H, N, \quad (320b)$$

$$\frac{R^j(t)}{P^j(t)} (1 - \eta) \frac{u^{K,j}(t)}{u_D^{K,j}(t)} = \xi_{1,D}^j + \xi_{2,D}^j \left(u_D^{K,j}(t) - 1\right), \quad j = H, N, \quad (320c)$$

where η is the share of aggregate technology shocks driven by symmetric technology improvements.

P.2 Firms

Both the traded and non-traded sectors use physical capital, \tilde{K}^j , and labor, L^j , according to constant returns to scale production functions which are assumed to take a CES form:

$$Y^j(t) = \left[\gamma^j \left(A^j(t) L^j(t) \right)^{\frac{\sigma^j - 1}{\sigma^j}} + (1 - \gamma^j) \left(B^j(t) \tilde{K}^j(t) \right)^{\frac{\sigma^j - 1}{\sigma^j}} \right]^{\frac{\sigma^j}{\sigma^j - 1}}, \quad (321)$$

where γ^j and $1 - \gamma^j$ are the weight of labor and capital in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, A^j and B^j are labor- and capital-augmenting efficiency. Both sectors face two cost components: a capital rental cost equal to R^j , and a labor cost equal to the wage rate W^j .

Factor-augmenting productivity is made up of a symmetric component (across sectors) denoted by the subscript S and an asymmetric component denoted by the subscript D :

$$A^j(t) = \left(A_S^j(t) \right)^\eta \left(A_D^j(t) \right)^{1-\eta}, \quad B^j(t) = \left(B_S^j(t) \right)^\eta \left(B_D^j(t) \right)^{1-\eta}, \quad (322)$$

where the elasticity of factor-augmenting productivity w.r.t. to its symmetric component is denoted by η which is assumed to be symmetric across sectors. As we shall see below, this parameter determines the share of technology improvements which are symmetric across sectors.

Firms rent capital $\tilde{K}^j(t)$ and labor $L^j(t)$ services from households. We assume that the movements in capital and labor across sectors are subject to frictions which imply that the capital rental cost equal to $R^j(t)$, and the wage rate $W^j(t)$, are sector-specific. Both sectors are assumed to be perfectly competitive and thus choose capital services and labor by taking prices P^j as given:

$$\max_{\tilde{K}^j(t), L^j(t)} \Pi^j(t) = \max_{\tilde{K}^j(t), L^j(t)} \left\{ P^j(t)Y^j(t) - W^j(t)L^j(t) - R^j(t)\tilde{K}^j(t) \right\}. \quad (323)$$

We drop the time index when it does not cause confusion. Costly labor and capital mobility implies a labor and capital cost differential across sectors:

$$P^j(t)\gamma^j (A^j(t))^{\frac{\sigma^j-1}{\sigma^j}} (L^j(t))^{-\frac{1}{\sigma^j}} (Y^j(t))^{\frac{1}{\sigma^j}} \equiv W^j(t), \quad (324a)$$

$$P^j(t) (1 - \gamma^j) (B^j(t))^{\frac{\sigma^j-1}{\sigma^j}} (u^{K,j}(t)K^j(t))^{-\frac{1}{\sigma^j}} (Y^j(t))^{\frac{1}{\sigma^j}} = R^j(t). \quad (324b)$$

Some Useful Results

Multiplying both sides of (324a)-(324b) by L^j and \tilde{K}^j , respectively, and dividing by sectoral value added leads to the labor and capital income share:

$$s_L^j = \gamma^j \left(\frac{A^j}{y^j} \right)^{\frac{\sigma^j-1}{\sigma^j}}, \quad 1 - s_L^j = \gamma^j \left(\frac{B^j u^{K,j} k^j}{y^j} \right)^{\frac{\sigma^j-1}{\sigma^j}}, \quad (325)$$

where

$$y^j = \left[\gamma^j (A^j)^{\frac{\sigma^j-1}{\sigma^j}} + (1 - \gamma^j) (B^j u^{K,j} k^j)^{\frac{\sigma^j-1}{\sigma^j}} \right]^{\frac{\sigma^j}{\sigma^j-1}}. \quad (326)$$

Dividing eq. (325) by eq. (326), the ratio of the labor to the capital income share denoted by $S^j = \frac{s_L^j}{1-s_L^j}$ reads as follows:

$$S^j = \frac{\gamma^j}{1 - \gamma^j} \left(\frac{B^j u^{K,j} K^j}{A^j L^j} \right)^{\frac{1-\sigma^j}{\sigma^j}}. \quad (327)$$

Dividing (324a) by (324b) leads to a positive relationship between the relative cost of labor and the capital-labor ratio in sector j :

$$\frac{W^j}{R^j} = \frac{\gamma^j}{1 - \gamma^j} \left(\frac{B^j}{A^j} \right)^{\frac{1-\sigma^j}{\sigma^j}} \left(\frac{\tilde{K}^j}{L^j} \right)^{\frac{1}{\sigma^j}}. \quad (328)$$

To determine the conditional demands for both inputs, we make use of (328) which leads to:

$$L^j = \tilde{K}^j \left(\frac{\gamma^j}{1 - \gamma^j} \right)^{\sigma^j} \left(\frac{B^j}{A^j} \right)^{1-\sigma^j} \left(\frac{W^j}{R^j} \right)^{-\sigma^j}, \quad (329a)$$

$$\tilde{K}^j = L^j \left(\frac{1 - \gamma^j}{\gamma^j} \right)^{\sigma^j} \left(\frac{B^j}{A^j} \right)^{\sigma^j-1} \left(\frac{W^j}{R^j} \right)^{\sigma^j}. \quad (329b)$$

Inserting eq. (329b) (eq. (329a) resp.) in the CES production function and solving for L^j (\tilde{K}^j resp.) leads to the conditional demand for labor (capital resp.):

$$L^j = Y^j (A^j)^{\sigma^j-1} \left(\frac{\gamma^j}{W^j} \right)^{\sigma} (X^j)^{\frac{\sigma^j}{1-\sigma^j}}, \quad \tilde{K}^j = Y^j (B^j)^{\sigma^j-1} \left(\frac{1 - \gamma^j}{R^j} \right)^{\sigma^j} (X^j)^{\frac{\sigma^j}{1-\sigma^j}}, \quad (330)$$

where X^j is given by:

$$X^j = (\gamma^j)^{\sigma^j} (A^j)^{\sigma^j-1} (W^j)^{1-\sigma^j} + (1 - \gamma^j)^{\sigma^j} (B^j)^{\sigma^j-1} (R^j)^{1-\sigma^j}. \quad (331)$$

Total cost is equal to the sum of the labor and capital cost:

$$C^j = W^j L^j + R^j K^j. \quad (332)$$

Inserting conditional demand for inputs (329) into total cost (332), we find C^j is homogeneous of degree one with respect to the level of production

$$C^j = c^j Y^j, \quad \text{with} \quad c^j = (X^j)^{\frac{1}{1-\sigma^j}}. \quad (333)$$

Using the fact that $(c^j)^{1-\sigma^j} = X^j$, conditional demand for labor (329a) can be rewritten as $L^j = Y^j (A^j)^{\sigma^j-1} \left(\frac{\gamma^j}{W^j}\right) (c^j)^{\sigma^j}$ which gives the labor income share denoted by s_L^j :

$$s_L^j = \frac{W^j L^j}{P^j Y^j} = (\gamma^j)^{\sigma^j} \left(\frac{W^j}{A^j}\right)^{1-\sigma^j} (c^j)^{\sigma^j-1}, \quad (334a)$$

$$1 - s_L^j = \frac{R^j \tilde{K}^j}{P^j Y^j} = (1 - \gamma^j)^{\sigma^j} \left(\frac{R^j}{B^j}\right)^{1-\sigma^j} (c^j)^{\sigma^j-1}. \quad (334b)$$

P.3 Short-Run Solutions

Sectoral Wages and Capital-Labor Ratios

Plugging the short-run solutions for L^H, L^N, K^H, K^N , given by (267)-(269) into the demand for capital and labor (324a)-(324b), the system of four equations can be solved for sectoral wages W^j and sectoral capital rental rates R^j . Log-differentiating (324a)-(324b) yields in matrix form:

$$\begin{pmatrix} -\left[\left(\frac{1-s_L^H}{\sigma^H L^H}\right) \frac{L^H W^H}{L^H} + \frac{1}{W^H}\right] & -\left(\frac{1-s_L^H}{\sigma^H L^H}\right) \frac{L^H W^N}{L^H} & \left(\frac{1-s_L^H}{\sigma^H L^H}\right) \frac{K^H R^H}{K^H} & \left(\frac{1-s_L^H}{\sigma^H L^H}\right) \frac{K^H R^N}{K^H} \\ -\left(\frac{1-s_L^N}{\sigma^N L^N}\right) \frac{L^N W^H}{L^N} & -\left[\left(\frac{1-s_L^N}{\sigma^N L^N}\right) \frac{L^N W^N}{L^N} + \frac{1}{W^N}\right] & \left(\frac{1-s_L^N}{\sigma^N L^N}\right) \frac{K^N R^H}{K^N} & \left(\frac{1-s_L^N}{\sigma^N L^N}\right) \frac{K^N R^N}{K^N} \\ \frac{s_L^H}{\sigma^H} \frac{L^H W^H}{L^H} & \frac{s_L^H}{\sigma^H} \frac{L^H W^N}{L^H} & -\left[\frac{s_L^H}{\sigma^H} \frac{K^H R^H}{K^H} + \frac{1}{R^H}\right] & \frac{s_L^H}{\sigma^H} \frac{K^H R^N}{K^H} \\ \frac{s_L^N}{\sigma^N} \frac{L^N W^H}{L^N} & \frac{s_L^N}{\sigma^N} \frac{L^N W^N}{L^N} & \frac{s_L^N}{\sigma^N} \frac{K^N R^H}{K^N} & -\left[\frac{s_L^N}{\sigma^N} \frac{K^N R^N}{K^N} + \frac{1}{R^N}\right] \end{pmatrix} \times \begin{pmatrix} dW^H \\ dW^N \\ dR^H \\ dR^N \end{pmatrix} = \begin{pmatrix} \left(\frac{1-s_L^H}{\sigma^H L^H}\right) \frac{L^H P^N}{L^H} dP^N + \left[\left(\frac{1-s_L^H}{\sigma^H L^H}\right) \frac{L^H P^H}{L^H} - \frac{1}{P^H}\right] dP^H - \left(\frac{1-s_L^H}{\sigma^H L^H}\right) \frac{K^H}{K^H} dK - \left(\frac{1-s_L^H}{\sigma^H L^H}\right) du^{K,H} - \left[\frac{\sigma^H-1}{\sigma^H} + \frac{s_L^H}{\sigma^H}\right] \hat{A}^H - \left(\frac{1-s_L^H}{\sigma^H L^H}\right) \hat{B}^H \\ \left[\left(\frac{1-s_L^N}{\sigma^N L^N}\right) \frac{L^N P^N}{L^N} - \frac{1}{P^N}\right] dP^N + \left(\frac{1-s_L^N}{\sigma^N L^N}\right) \frac{L^N P^H}{L^N} dP^H - \left(\frac{1-s_L^N}{\sigma^N L^N}\right) \frac{K^N}{K^N} dK - \left(\frac{1-s_L^N}{\sigma^N L^N}\right) du^{K,N} - \left[\frac{\sigma^N-1}{\sigma^N} + \frac{s_L^N}{\sigma^N}\right] \hat{A}^N - \left(\frac{1-s_L^N}{\sigma^N L^N}\right) \hat{B}^N \\ -\frac{s_L^H}{\sigma^H} \frac{L^H P^H}{L^H} dP^H - \left[\frac{s_L^H}{\sigma^H} \frac{L^H P^H}{L^H} + \frac{1}{P^H}\right] dP^H + \frac{s_L^H}{\sigma^H} \frac{K^H}{K^H} dK + \frac{s_L^H}{\sigma^H} du^{K,H} - \left(\frac{\sigma^H-s_L^H}{\sigma^H L^H}\right) \hat{B}^H - \left(\frac{s_L^H}{\sigma^H}\right) \hat{A}^H \\ -\left[\frac{s_L^N}{\sigma^N} \frac{L^N P^N}{L^N} + \frac{1}{P^N}\right] dP^N - \frac{s_L^N}{\sigma^N} \frac{L^N P^H}{L^N} dP^H + \frac{s_L^N}{\sigma^N} \frac{K^N}{K^N} dK + \frac{s_L^N}{\sigma^N} du^{K,N} - \left(\frac{\sigma^N-s_L^N}{\sigma^N L^N}\right) \hat{B}^N - \left(\frac{s_L^N}{\sigma^N}\right) \hat{A}^N \end{pmatrix} \quad (335)$$

From eq. (318), i.e., $u^{K,j}(t) = \left(u_S^{K,j}\right)^\eta \left(u_D^{K,j}\right)^{1-\eta}$, the capital utilization rate is a function of its symmetric and asymmetric components:

$$u^{K,j} = u^{K,j} \left(u_S^{K,j}, u_D^{K,j}\right), \quad (336)$$

where

$$\frac{\partial u^{K,j}}{\partial u_S^{K,j}} = \eta, \quad \frac{\partial u^{K,j}}{\partial u_D^{K,j}} = 1 - \eta. \quad (337)$$

By using the implicit function theorem, eq. (335) together with eq. (336) leads to the short-run solutions for sectoral wages

$$W^j = W^j \left(\bar{\lambda}, K, P^j, A^j, B^j, u_S^{K,j}, u_D^{K,j}\right), \quad j = H, N, \quad (338)$$

and capital rental rates

$$R^j = R^j \left(\bar{\lambda}, K, P^j, A^j, B^j, u_S^{K,j}, u_D^{K,j}\right), \quad j = H, N. \quad (339)$$

Inserting sectoral wages (338) into (267), sectoral hours worked can be solved as functions of the shadow value of wealth, the capital stock, the price of non-traded goods in terms of foreign goods, P^N , the terms of trade, factor-augmenting productivity and capital utilization rates:

$$L^j = L^j \left(\bar{\lambda}, K, P^j, A^j, B^j, u_S^{K,j}, u_D^{K,j} \right), \quad j = H, N. \quad (340)$$

Inserting capital rental rates (339) into (269), sectoral capital stock can be solved as functions of the shadow value of wealth, the aggregate capital stock, the price of non-traded goods in terms of foreign goods, P^N , the terms of trade, factor-augmenting productivity and capital utilization rates:

$$K^j = K^j \left(\bar{\lambda}, K, P^N, P^H, A^H, A^j, B^j, u_S^{K,j}, u_D^{K,j} \right). \quad (341)$$

Finally, plugging solutions for sectoral hours worked (340) and sectoral capital stock (341), and using (318), production functions (321) can be solved for sectoral value added:

$$Y^j = Y^j \left(\bar{\lambda}, K, P^j, A^j, B^j, u_S^{K,j}, u_D^{K,j} \right), \quad j = H, N. \quad (342)$$

Symmetric and Asymmetric Components of Capital Utilization Rates, $u_S^{K,j}(t)$ and $u_D^{K,j}(t)$

Inserting firm's optimal decision for capital (324b) in sector j in the optimal intensity in the use of physical capital (320b) leads to:

$$\eta \frac{u^{K,j}(t)}{u_S^{K,j}(t)} = \xi_{1,S}^j + \xi_{2,S}^j \left(u_S^{K,j}(t) - 1 \right) = (1 - \gamma^j) (B^j(t))^{\frac{\sigma^j - 1}{\sigma^j}} \left(u^{K,j}(t) K^j(t) \right)^{-\frac{1}{\sigma^j}} \left(Y^j(t) \right)^{\frac{1}{\sigma^j}}. \quad (343)$$

Inserting intermediate solutions (340) for sectoral hours worked and (341) for sectoral capital into (343) and log-differentiating leads to in a matrix form:

$$\begin{pmatrix} a_{11} & a_{12} & -\frac{s_L^H}{\sigma^H} \frac{L^H u_S^{K,N}}{L^H} + \frac{s_L^H}{\sigma^H} \frac{K^H u_S^{K,N}}{K^H} & -\frac{s_L^H}{\sigma^H} \frac{L^H u_D^{K,N}}{L^H} + \frac{s_L^H}{\sigma^H} \frac{K^H u_D^{K,N}}{K^H} \\ a_{21} & a_{22} & -\frac{s_L^H}{\sigma^H} \frac{L^H u_S^{K,N}}{L^H} + \frac{s_L^H}{\sigma^H} \frac{K^H u_S^{K,N}}{K^H} & -\frac{s_L^H}{\sigma^H} \frac{L^H u_D^{K,N}}{L^H} + \frac{s_L^H}{\sigma^H} \frac{K^H u_D^{K,N}}{K^H} \\ -\frac{s_L^N}{\sigma^N} \frac{L^N u_S^{K,H}}{L^N} + \frac{s_L^N}{\sigma^N} \frac{K^N u_S^{K,H}}{K^N} & -\frac{s_L^N}{\sigma^N} \frac{L^N u_D^{K,H}}{L^N} + \frac{s_L^N}{\sigma^N} \frac{K^N u_D^{K,H}}{K^N} & a_{33} & a_{34} \\ -\frac{s_L^N}{\sigma^N} \frac{L^N u_S^{K,H}}{L^N} + \frac{s_L^N}{\sigma^N} \frac{K^N u_S^{K,H}}{K^N} & -\frac{s_L^N}{\sigma^N} \frac{L^N u_D^{K,H}}{L^N} + \frac{s_L^N}{\sigma^N} \frac{K^N u_D^{K,H}}{K^N} & a_{43} & a_{44} \end{pmatrix} \times \begin{pmatrix} \hat{u}_{K,H}^{K,H} \\ \hat{u}_{K,H}^{K,N} \\ \hat{u}_{K,N}^{K,N} \\ \hat{u}_{D,N}^{K,N} \end{pmatrix} = \begin{pmatrix} \sum_{X^j=A^j, B^j, P^j, j=H, N} \left(\frac{s_L^H}{\sigma^H} \frac{L^H X^j}{L^H} - \frac{s_L^H}{\sigma^H} \frac{K^H X^j}{K^H} \right) dX^j + \left(\frac{s_L^H}{\sigma^H} \frac{L^H}{L^H} - \frac{s_L^H}{\sigma^H} \frac{K^H}{K^H} \right) dK + \frac{s_L^H}{\sigma^H} \hat{A}^H - \left(\frac{\sigma^H - s_L^H}{\sigma^H} \right) \hat{B}^H \\ \sum_{X^j=A^j, B^j, P^j, j=H, N} \left(\frac{s_L^H}{\sigma^H} \frac{L^H X^j}{L^H} - \frac{s_L^H}{\sigma^H} \frac{K^H X^j}{K^H} \right) dX^j + \left(\frac{s_L^H}{\sigma^H} \frac{L^H}{L^H} - \frac{s_L^H}{\sigma^H} \frac{K^H}{K^H} \right) dK + \frac{s_L^H}{\sigma^H} \hat{A}^H - \left(\frac{\sigma^H - s_L^H}{\sigma^H} \right) \hat{B}^H \\ \sum_{X^j=A^j, B^j, P^j, j=H, N} \left(\frac{s_L^N}{\sigma^N} \frac{L^N X^j}{L^N} - \frac{s_L^N}{\sigma^N} \frac{K^N X^j}{K^N} \right) dX^j + \left(\frac{s_L^N}{\sigma^N} \frac{L^N}{L^N} - \frac{s_L^N}{\sigma^N} \frac{K^N}{K^N} \right) dK + \frac{s_L^N}{\sigma^N} \hat{A}^N - \left(\frac{\sigma^N - s_L^N}{\sigma^N} \right) \hat{B}^N \\ \sum_{X^j=A^j, B^j, P^j, j=H, N} \left(\frac{s_L^N}{\sigma^N} \frac{L^N X^j}{L^N} - \frac{s_L^N}{\sigma^N} \frac{K^N X^j}{K^N} \right) dX^j + \left(\frac{s_L^N}{\sigma^N} \frac{L^N}{L^N} - \frac{s_L^N}{\sigma^N} \frac{K^N}{K^N} \right) dK + \frac{s_L^N}{\sigma^N} \hat{A}^N - \left(\frac{\sigma^N - s_L^N}{\sigma^N} \right) \hat{B}^N \end{pmatrix}, \quad (344)$$

where $X^j =, P^H, P^N, Z^H, Z^N$ and

$$a_{11} = \left[\frac{\xi_{2,S}^H}{\xi_{1,S}^H} + \eta \frac{s_L^H}{\sigma^H} + (1 - \eta) \right] - \frac{s_L^H}{\sigma^H} \frac{L_{u_S}^H}{L^H} + \frac{s_L^H}{\sigma^H} \frac{K_{u_S}^H}{K^H}, \quad (345a)$$

$$a_{12} = - \left(\frac{\sigma^H - s_L^H}{\sigma^H} \right) (1 - \eta) - \frac{s_L^H}{\sigma^H} \frac{L_{u_D}^H}{L^H} + \frac{s_L^H}{\sigma^H} \frac{K_{u_D}^H}{K^H}, \quad (345b)$$

$$a_{21} = - \left(\frac{\sigma^H - s_L^H}{\sigma^H} \right) \eta - \frac{s_L^H}{\sigma^H} \frac{L_{u_S}^H}{L^H} + \frac{s_L^H}{\sigma^H} \frac{K_{u_S}^H}{K^H}, \quad (345c)$$

$$a_{22} = \left[\frac{\xi_{2,D}^H}{\xi_{1,D}^H} + (1 - \eta) \frac{s_L^H}{\sigma^H} + \eta \right] - \frac{s_L^H}{\sigma^H} \frac{L_{u_D}^H}{L^H} + \frac{s_L^H}{\sigma^H} \frac{K_{u_D}^H}{K^H}, \quad (345d)$$

$$a_{33} = \left[\frac{\xi_{2,S}^N}{\xi_{1,S}^N} + \eta \frac{s_L^N}{\sigma^N} + (1 - \eta) \right] - \frac{s_L^N}{\sigma^N} \frac{L_{u_S}^N}{L^N} + \frac{s_L^N}{\sigma^N} \frac{K_{u_S}^N}{K^N}, \quad (345e)$$

$$a_{34} = - \left(\frac{\sigma^N - s_L^N}{\sigma^N} \right) (1 - \eta) - \frac{s_L^N}{\sigma^N} \frac{L_{u_D}^N}{L^N} + \frac{s_L^N}{\sigma^N} \frac{K_{u_D}^N}{K^N}, \quad (345f)$$

$$a_{43} = - \left(\frac{\sigma^N - s_L^N}{\sigma^N} \right) \eta - \frac{s_L^N}{\sigma^N} \frac{L_{u_S}^N}{L^N} + \frac{s_L^N}{\sigma^N} \frac{K_{u_S}^N}{K^N}, \quad (345g)$$

$$a_{44} = \left[\frac{\xi_{2,D}^N}{\xi_{1,D}^N} + \eta \frac{s_L^N}{\sigma^N} + (1 - \eta) \right] - \frac{s_L^N}{\sigma^N} \frac{L_{u_D}^N}{L^N} + \frac{s_L^N}{\sigma^N} \frac{K_{u_D}^N}{K^N}. \quad (345h)$$

The short-run solutions for capital and technology utilization rates are:

$$u_c^{K,j} = u_c^{K,j} (\bar{\lambda}, K, P^j, A^j, B^j), \quad c = S, D, \quad j = H, N. \quad (346)$$

Intermediate Solutions for R^j, W^j, K^j, L^j, Y^j

Plugging back solutions for the capital utilization rates (346) into the intermediate solutions for the sectoral wage rates (338) and the capital rental rates (339), for sectoral hours worked (340) and sectoral capital stocks (341), and for sectoral value added (342) leads to intermediate solutions for sectoral wages, sectoral capital rental rates, sectoral hours worked, sectoral capital stocks, sectoral value added:

$$W^j, R^j, L^j, K^j, Y^j (\bar{\lambda}, K, P^N, P^H, A^H, B^H, A^N, B^N). \quad (347)$$

P.4 Market Clearing Conditions

Finally, we have to solve for non-traded good prices and the terms of trade. The role of the price of non-traded goods in terms of foreign goods is to clear the non-traded goods market:

$$Y^N = C^N + G^N + J^N + \left(C_S^{K,N} + C_D^{K,N} \right) K^N. \quad (348)$$

The role of the price of home-produced goods in terms of foreign-produced goods or the terms of trade is to clear the home-produced traded goods market:

$$Y^H = C^H + G^H + J^H + X^H + \left(C_S^{K,H} + C_D^{K,H} \right) K^H. \quad (349)$$

As shall be useful to write formal expressions in a compact form, we wet

$$\Delta_{PH}^H = Y_{PH}^H - C_{PH}^H - J_{PH}^H - X_{PH}^H - \xi_{1,S}^H \frac{\partial u_S^{K,H}}{\partial PH} - \xi_{1,D}^H \frac{\partial u_D^{K,H}}{\partial PH}, \quad (350a)$$

$$\Delta_{PN}^H = Y_{PN}^H - C_{PN}^H - J_{PN}^H - \xi_{1,S}^H \frac{\partial u_S^{K,H}}{\partial PN} - \xi_{1,D}^H \frac{\partial u_D^{K,H}}{\partial PH}, \quad (350b)$$

$$\Delta_K^H = Y_K^H - C_K^H - J_K^H - \xi_{1,S}^H \frac{\partial u_S^{K,H}}{\partial K} - \xi_{1,D}^H \frac{\partial u_D^{K,H}}{\partial K}, \quad (350c)$$

$$\Delta_{Aj}^H = Y_{Aj}^H - C_{Aj}^H - \xi_{1,S}^H \frac{\partial u_S^{K,H}}{\partial Aj} - \xi_{1,D}^H \frac{\partial u_D^{K,H}}{\partial Aj}, \quad j = H, N, \quad (350d)$$

$$\Delta_{Bj}^H = Y_{Bj}^H - C_{Bj}^H - \xi_{1,S}^H \frac{\partial u_S^{K,H}}{\partial Bj} - \xi_{1,D}^H \frac{\partial u_D^{K,H}}{\partial Bj}, \quad j = H, N, \quad (350e)$$

$$\Delta_{Pj}^N = Y_{Pj}^N - C_{Pj}^N - J_{Pj}^N - \xi_{1,S}^N \frac{\partial u_S^{K,N}}{\partial Pj} - \xi_{1,D}^N \frac{\partial u_D^{K,N}}{\partial Pj}, \quad j = H, N, \quad (350f)$$

$$\Delta_K^N = Y_K^N - C_K^N - J_K^N - \xi_{1,S}^N \frac{\partial u_S^{K,N}}{\partial K} - \xi_{1,D}^N \frac{\partial u_D^{K,N}}{\partial K}, \quad (350g)$$

$$\Delta_{Aj}^N = Y_{Aj}^N - C_{Aj}^N - J_{Aj}^N - \xi_{1,S}^N \frac{\partial u_S^{A^j,N}}{\partial Aj} - \xi_{1,D}^N \frac{\partial u_D^{A^j,N}}{\partial Aj}, \quad j = H, N, \quad (350h)$$

$$\Delta_{Bj}^N = Y_{Bj}^N - C_{Bj}^N - J_{Bj}^N - \xi_{1,S}^N \frac{\partial u_S^{B^j,N}}{\partial Bj} - \xi_{1,D}^N \frac{\partial u_D^{B^j,N}}{\partial Bj}, \quad j = H, N. \quad (350i)$$

Totally differentiating the market clearing conditions (348)-(349) leads to in a matrix form:

$$\begin{pmatrix} \Delta_{PH}^H & \Delta_{PN}^H \\ \Delta_{PH}^N & \Delta_{PN}^N \end{pmatrix} \begin{pmatrix} dP^H \\ dP^N \end{pmatrix} = \begin{pmatrix} -\Delta_K^H dK + J_Q^H dQ - \sum_{j=H,N} \Delta_{Aj}^H dA^j - \sum_{j=H,N} \Delta_{Bj}^H dB^j \\ -\Delta_K^N dK + J_Q^N dQ - \sum_{j=H,N} \Delta_{Aj}^N dA^j - \sum_{j=H,N} \Delta_{Bj}^N dB^j \end{pmatrix}. \quad (351)$$

Applying the implicit functions theorem leads to the short-run solutions for the terms of trade and non-traded good prices:

$$P^H, P^N (\bar{\lambda}, K, Q, A^H, B^H, A^N, B^N). \quad (352)$$

Plugging back the solutions (352) for sectoral prices into (346) and (347) allow us to find the final versions of solutions of capital utilization rates, sectoral wages, sectoral capital rental rates, sectoral hours worked, sectoral capital stocks, sectoral value added:

$$u_S^{K,j}, u_D^{K,j}, W^j, R^j, L^j, K^j, Y^j (\bar{\lambda}, K, Q, A^H, B^H, A^N, B^N). \quad (353)$$

Inserting the solutions for prices into the intermediate solutions for consumption (265) and investment (285)

$$C^g, Q^g (\bar{\lambda}, K, Q, A^H, B^H, A^N, B^N). \quad (354)$$

where $g = H, N, F$.

Using the fact that factor-augmenting efficiency X^j (with $X = A, B, j = H, N$) has both a symmetric S and an asymmetric D component across sectors,

$$X^j = X^j \left(X_S^j, X_D^j \right). \quad (355)$$

where

$$X_{X_S^j}^j = \frac{\partial X^j}{\partial X_S^j} = \eta \frac{X^j}{X_S^j}, \quad X_{X_D^j}^j = \frac{\partial X^j}{\partial X_D^j} = (1 - \eta) \frac{X^j}{X_D^j}, \quad (356)$$

and inserting (355) into (352), (353) and (354) leads to the following solutions for capital utilization rate, sectoral wages, sectoral capital rental rates, sectoral hours worked, sectoral capital stocks, sectoral value added:

$$P^j, u_S^{K,j}, u_D^{K,j}, W^j, R^j, L^j, K^j, Y^j (\bar{\lambda}, K, Q, X_c^j), \quad j = H, N, \quad (357)$$

and for consumption and investment in good $g = H, N, F$:

$$C^g, Q^g (\bar{\lambda}, K, Q, X_c^j), \quad (358)$$

where $X = A, B, j = H, N, c = S, D$.

P.5 Solving the Model

In our model, there are nine state variables, namely K , X_c^j where $X = A$, $j = H, N$, $c = S, D$, and one control variable, Q . The capital accumulation equation reads as follows:

$$\dot{K} = \frac{Y^N - C^N - G^N - \left(C_S^{K,N} + C_D^{K,N}\right) K^N}{(1 - \iota) \left(\frac{P^N}{P_J}\right)^{-\phi_J}} - \delta_K K - \frac{\kappa}{2} \left(\frac{I}{K} - \delta_K\right)^2 K. \quad (359)$$

Inserting short-run solutions for value added and the capital utilization rate (357), investment and consumption in non-tradables (358), into the physical capital accumulation equation (359), and plugging the short-run solution for the return on domestic capital (357) into the dynamic equation for the shadow value of capital stock (320a), the dynamic system reads as follows:²⁴

$$\dot{K} \equiv \Upsilon(K, Q, X_c^j) = \frac{E^N(K, Q, X_c^j)}{(1 - \iota) \left\{ \frac{P^N(\cdot)}{P_J [P^H(\cdot), P^N(\cdot)]} \right\}^{-\phi_J}} - \delta_K K - \frac{K}{2\kappa} \left\{ \frac{Q}{P_J [P^H(\cdot), P^N(\cdot)]} - 1 \right\}^2, \quad (360a)$$

$$\begin{aligned} \dot{Q} \equiv \Sigma(K, Q, X_c^j) &= (r^* + \delta_K) Q - \left[\frac{\sum_j R^j(K, Q, X_c^j) K^j(K, Q, X_c^j) (u_S^{K,j}(K, Q, X_c^j))^\eta (u_D^{K,j}(K, Q, X_c^j))^{1-\eta}}{K} \right. \\ &\quad - \sum_j [C_S^{K,j} u_S^{K,j}(K, Q, X_c^j) + C_D^{K,j} u_D^{K,j}(K, Q, X_c^j)] \frac{K^j(K, Q, X_c^j)}{K} \\ &\quad \left. + P_J [P^H(\cdot), P^N(\cdot)] \frac{\kappa}{2} v(\cdot) (v(\cdot) + 2\delta_K) \right], \end{aligned} \quad (360b)$$

where $E^N = Y^N - C^N - G^N - \left(C_S^{K,N} + C_D^{K,N}\right) K^N$

P.6 Current Account Equation and Intertemporal Solvency Condition

Following the same steps as in subsection O.6, the current account reads as:

$$\dot{N} = r^* N + P^H X^H - M^F, \quad (361)$$

where $X^H = Y^H - C^H - G^H - J^H$ stands for exports of home goods and we denote by M^F imports of foreign consumption and investment goods:

$$M^F = C^F + G^F + J^F. \quad (362)$$

Substituting first solutions for sectoral prices P^j given by (357) into export function (289) and substituting solutions for consumption and investment (358) into (362) allows us to write the current account equation as follows:

$$\begin{aligned} \dot{N} &\equiv r^* N + \Xi(\bar{\lambda}, K, Q, X_c^j), \\ &= r^* N + P^H(\bar{\lambda}, K, Q, X_c^j) X^H(\bar{\lambda}, K, Q, X_c^j) \\ &\quad - M^F(\bar{\lambda}, K, Q, X_c^j). \end{aligned} \quad (363)$$

P.7 CES Technology Frontier

We assume that firms in sector j choose labor and capital efficiency along the technology frontier which is assumed to take a CES form:

$$\left[\gamma_Z^j (A^j(t))^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} + (1 - \gamma_Z^j) (B^j(t))^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} \right]^{\frac{\sigma_Z^j}{\sigma_Z^j - 1}} \leq Z^j(t), \quad (364)$$

where $Z^j > 0$ is the height of the technology frontier, $0 < \gamma_Z^j < 1$ is the weight of labor efficiency in technology and $\sigma_Z^j > 0$ corresponds to the elasticity of substitution between

²⁴We omit the shadow value of wealth from short-run solutions for clarity purposes as λ remains constant over time.

labor and capital efficiency. Performing the minimization of the unit cost for producing (69) subject to the technology frontier (364) leads to:

$$\frac{\gamma_Z^j}{1 - \gamma_Z^j} \left(\frac{A^j}{B^j} \right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} = \frac{s_L^j}{1 - s_L^j}, \quad (365)$$

where we used the fact that $(\gamma^j)^{\sigma^j} \left(\frac{W^j(t)}{A^j(t)} \right)^{1 - \sigma^j} (c^j(t))^{\sigma^j - 1} = s_L^j(t)$, see eq. (334a), and $(1 - \gamma^j)^{\sigma^j} \left(\frac{R^j(t)}{B^j(t)} \right)^{1 - \sigma^j} (c^j(t))^{\sigma^j - 1} = 1 - s_L^j(t)$, see eq. (334b). As shall be useful later, we solve eq. (365) for s_L^j :

$$\begin{aligned} s_L^j &= \frac{\gamma_Z^j (A^j)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}}}{\gamma_Z^j (A^j)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} + (1 - \gamma_Z^j) (B^j)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}}}, \\ &= \gamma_Z^j \left(\frac{A^j}{Z^j} \right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}}, \end{aligned} \quad (366)$$

where we made use of (364) to obtain the last line.

Log-linearizing (364) in the neighborhood of the initial steady-state and making use of eq. (366) leads to:

$$\begin{aligned} \hat{Z}^j(t) &= \gamma_Z^j \left(\frac{A^j}{Z^j} \right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} \hat{A}^j(t) + (1 - \gamma_Z^j) \left(\frac{B^j}{Z^j} \right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} \hat{B}^j(t), \\ &= s_L^j \hat{A}^j(t) + (1 - s_L^j) \hat{B}^j(t). \end{aligned} \quad (367)$$

Solving eq. (367) and the log-linearized version of the demand for factors of production (327) leads to the solutions for $\hat{A}^j(t)$ and $\hat{B}^j(t)$. By using the fact that factor-augmenting productivity has a symmetric and an asymmetric component across sectors, i.e., $X^j = X^j(X_S^j, X_D^j)$ (see eq. (355)), **leads to the solutions for $\hat{A}_c^j(t)$ and $\hat{B}_c^j(t)$ described by (47a)-(47b) in the main text.**

Q Solving for Permanent Technology Shocks Shocks

In this section, we detail the steps to solve the model for permanent technology shocks which have a symmetric and an asymmetric component.

The percentage deviation of factor-augmenting efficiency $X_c^j = A_c^j, B_c^j$ relative to its long-run value X_c^j ($c = S, D, j = H, N$) is described by:

$$\hat{X}_S^j(t) = e^{-\xi_X^j t} - (1 - x_S^j) e^{-\chi_X^j t}, \quad (368a)$$

$$\hat{X}_D^j(t) = e^{-\xi_X^j t} - (1 - x_D^j) e^{-\chi_X^j t}, \quad (368b)$$

where $\hat{X}_c^j(t) = \frac{X_c^j(t) - X_c^j}{X_c^j}$, x_c^j ($c = S, D, j = H, N$) parameterizes the impact response of factor-augmenting technological change; $\xi_X^j > 0$ and $\chi_X^j > 0$ are (positive) parameters which are set in order to reproduce the dynamic adjustment of factor-augmenting technological change.

Linearizing the dynamic equations of physical capital and its shadow price in the neighborhood of the steady-state, we get in a matrix form:

$$\begin{pmatrix} \dot{K}(t) \\ \dot{Q}(t) \end{pmatrix} = \begin{pmatrix} \Upsilon_K & \Upsilon_Q \\ \Sigma_K & \Sigma_Q \end{pmatrix} \begin{pmatrix} dK(t) \\ dQ(t) \end{pmatrix} + \begin{pmatrix} \sum_{c=S,D} \sum_{j=H}^N \Upsilon_{A_c^j} dA_c^j(t) + \sum_{c=S,D} \sum_{j=H}^N \Upsilon_{B_c^j} dB_c^j(t) \\ \sum_{c=S,D} \sum_{j=H}^N \Sigma_{A_c^j} dA_c^j(t) + \sum_{c=S,D} \sum_{j=H}^N \Sigma_{B_c^j} dB_c^j(t) \end{pmatrix}, \quad (369)$$

where the coefficients of the Jacobian matrix are partial derivatives evaluated at the steady-state, e.g., $\Upsilon_X = \frac{\partial \Upsilon}{\partial Y}$ with $Y = K, Q$, and the direct effects of an exogenous change in factor-augmenting productivity on K and Q are described by $\Upsilon_X = \frac{\partial \Upsilon}{\partial X}$ and $\Sigma_X = \frac{\partial \Sigma}{\partial X}$, also evaluated at the steady-state.

Now define the auxiliary vector $\hat{X}(t) = \begin{pmatrix} \hat{X}_1(t) \\ \hat{X}_2(t) \end{pmatrix}$ as follows:

$$\hat{X}(t) = \mathbf{V}^{-1} \hat{Y}(t) \quad (370)$$

Given this renaming, we can write the system as:

$$\dot{\hat{X}}(t) = \Lambda \hat{X}(t) + \mathbf{V}^{-1} \Sigma \hat{S}(t)$$

where $\Lambda = \begin{pmatrix} \nu_1 & 0 \\ 0 & \nu_2 \end{pmatrix}$, \mathbf{V}^{-1} is the inverse of the matrix of eigenvectors; let us write out the product $\mathbf{V}^{-1} \Sigma$

$$\begin{pmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \end{pmatrix} \times \begin{pmatrix} \Upsilon_{A_S^H} & \Upsilon_{B_S^H} & \Upsilon_{A_S^N} & \Upsilon_{B_S^N} & \Upsilon_{A_D^H} & \Upsilon_{B_D^H} & \Upsilon_{A_D^N} & \Upsilon_{B_D^N} \\ \Sigma_{A_S^H} & \Sigma_{B_S^H} & \Sigma_{A_S^N} & \Sigma_{B_S^N} & \Sigma_{A_D^H} & \Sigma_{B_D^H} & \Sigma_{A_D^N} & \Sigma_{B_D^N} \end{pmatrix}.$$

The product leads to a matrix of the same size as the matrix of shocks, i.e., with two rows and eight columns with elements denoted by $s_{1k} = u_{11} \Upsilon_{X_c^j} + u_{12} \Sigma_{X_c^j}$ and $s_{2k} = u_{21} \Upsilon_{X_c^j} + u_{22} \Sigma_{X_c^j}$ (l the row, k is the column).

The differential equation for $X_1(t)$ reads:

$$\dot{X}_1(t) = \nu_1 X_1(t) + \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} s_{1k} X_c^j \left[e^{-\xi_{X,c}^j} - (1 - x_c^j) e^{-\chi_{X,c}^j} \right], \quad (371a)$$

$$\dot{X}_2(t) = \nu_2 X_2(t) + \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} s_{2k} X_c^j \left[e^{-\xi_{X,c}^j} - (1 - x_c^j) e^{-\chi_{X,c}^j} \right]. \quad (371b)$$

Solving (371a)-(371b) for $X_1(t)$ and $X_2(t)$ leads to:

$$dX_1(t) = dX_1(0) + \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{s_{1k} X_c^j}{\nu_1 + \xi_{X,c}^j} \left[\left(e^{\nu_1 t} - e^{-\xi_{X,c}^j} \right) - (1 - x_c^j) \left(\frac{\nu_1 + \xi_{X,c}^j}{\nu_1 + \chi_{X,c}^j} \right) \left(e^{\nu_1 t} - e^{-\chi_{X,c}^j} \right) \right], \quad (372a)$$

$$dX_2(t) = dX_2(0) + \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{s_{2k} X_c^j}{\nu_2 + \xi_{X,c}^j} \left[\left(e^{\nu_2 t} - e^{-\xi_{X,c}^j} \right) - (1 - x_c^j) \left(\frac{\nu_2 + \xi_{X,c}^j}{\nu_2 + \chi_{X,c}^j} \right) \left(e^{\nu_2 t} - e^{-\chi_{X,c}^j} \right) \right]. \quad (372b)$$

As shall be useful to write the solutions in a compact form, we set

$$\Delta_1^{X_c^j} = \frac{s_{1k} X_c^j}{\nu_1 + \xi_{X,c}^j}, \quad (373a)$$

$$\Delta_2^{X_c^j} = \frac{s_{2k} X_c^j}{\nu_2 + \xi_{X,c}^j}. \quad (373b)$$

$$\Theta_1^{X_c^j} = (1 - x_c^j) \frac{\nu_1 + \xi_{X,c}^j}{\nu_1 + \chi_{X,c}^j}, \quad (373c)$$

$$\Theta_2^{X_c^j} = (1 - x_c^j) \frac{\nu_2 + \xi_{X,c}^j}{\nu_2 + \chi_{X,c}^j}, \quad (373d)$$

The solution for $X_1(t)$ and the 'stable' solution for $X_2(t)$, i.e., consistent with convergence toward the steady-state when t tends toward infinity, is thus given by:

$$dX_1(t) = X_{11} e^{\nu_1 t} + \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \Delta_1^{X_c^j} \left[e^{-\xi_{X,c}^j} - (1 - x_c^j) e^{-\chi_{X,c}^j} \right], \quad (374a)$$

$$dX_2(t) = - \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \Delta_2^{X_c^j} \left[e^{-\xi_{X,c}^j} - (1 - x_c^j) e^{-\chi_{X,c}^j} \right], \quad (374b)$$

where

$$X_{11} = dX_1(0) - \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \Delta_1^{X_c^j} \left(1 - \Theta_1^{X_c^j}\right). \quad (375)$$

Using the definition of $X_i(t)$ (with $i = 1, 2$) given by (370), we can recover the solutions for $K(t)$ and $Q(t)$:

$$K(t) - \tilde{K} = X_1(t) + X_2(t), \quad (376a)$$

$$Q(t) - \tilde{Q} = \omega_2^1 X_1(t) + \omega_2^2 X_2(t). \quad (376b)$$

Linearizing the current account equation around the steady-state:

$$\begin{aligned} \dot{N}(t) &= r^* dN(t) + \Xi_K dK(t) + \Xi_Q dQ(t) + \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \Xi_{X_c^j} dX_c^j(t), \\ &= (\Xi_K + \Xi_Q \omega_2^1) X_1(t) + (\Xi_K + \Xi_Q \omega_2^2) X_2(t) \\ &+ \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} X_c^j \left[e^{-\xi_{X,c}^j t} - (1 - x_c^j) e^{-\chi_{X,c}^j t} \right]. \end{aligned} \quad (377)$$

Setting $N_1 = \Xi_K + \Xi_Q \omega_2^1$, $N_2 = \Xi_K + \Xi_Q \omega_2^2$, inserting solutions for $K(t)$ and $Q(t)$ given by (376), solving yields the solution for traded bonds:

$$\begin{aligned} dN(t) &= e^{r^* t} \left[(N_0 - N) - \frac{\omega_N^1}{\nu_1 - r^*} + \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Xi_{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left(1 - \Theta^{X_c^j, \prime}\right) \right. \\ &+ N_1 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_1^{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left(1 - \Theta_1^{X_c^j, \prime}\right) - N_2 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_2^{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left(1 - \Theta_2^{X_c^j, \prime}\right) \left. \right] \\ &+ \frac{\omega_N^1}{\nu_1 - r^*} e^{\nu_1 t} - \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Xi_{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left[e^{-\xi_{X,c}^j t} - \Theta^{X_c^j, \prime} e^{-\chi_{X,c}^j t} \right], \\ &- N_1 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_1^{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left[e^{-\xi_{X,c}^j t} - \Theta_1^{X_c^j, \prime} e^{-\chi_{X,c}^j t} \right], \\ &+ N_2 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_2^{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left[e^{-\xi_{X,c}^j t} - \Theta_2^{X_c^j, \prime} e^{-\chi_{X,c}^j t} \right], \end{aligned} \quad (378)$$

where $\omega_N^1 = N_1 X_{11}$ and we set

$$\Theta^{X_c^j, \prime} = (1 - x_c^j) \frac{\xi_{X,c}^j + r^*}{\chi_{X,c}^j + r^*}, \quad (379a)$$

$$\Theta_1^{X_c^j, \prime} = \Theta_1^{X_c^j} \frac{\xi_{X,c}^j + r^*}{\chi_{X,c}^j + r^*}, \quad (379b)$$

$$\Theta_2^{X_c^j, \prime} = \Theta_2^{X_c^j} \frac{\xi_{X,c}^j + r^*}{\chi_{X,c}^j + r^*}. \quad (379c)$$

Inserting the transversality condition into (378) leads to the 'stable' solution for the stock of foreign assets:

$$\begin{aligned} dN(t) &= \frac{\omega_N^1}{\nu_1 - r^*} e^{\nu_1 t} - \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Xi_{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left[e^{-\xi_{X,c}^j t} - \Theta^{X_c^j, \prime} e^{-\chi_{X,c}^j t} \right], \\ &- N_1 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_1^{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left[e^{-\xi_{X,c}^j t} - \Theta_1^{X_c^j, \prime} e^{-\chi_{X,c}^j t} \right], \\ &+ N_2 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_2^{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left[e^{-\xi_{X,c}^j t} - \Theta_2^{X_c^j, \prime} e^{-\chi_{X,c}^j t} \right], \end{aligned} \quad (380)$$

which is consistent with the intertemporal solvency condition

$$\begin{aligned}
dN = & -\frac{\omega_N^1}{\nu_1 - r^*} + \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Xi_{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left(1 - \Theta_{X_c^j}'\right) \\
& + N_1 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_1^{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left(1 - \Theta_1^{X_c^j}\right) - N_2 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_2^{X_c^j} X_c^j}{\xi_{X,c}^j + r^*} \left(1 - \Theta_2^{X_c^j}\right)
\end{aligned} \tag{381}$$

where $dN = N - N_0$. Eq. (381) determines the change in the equilibrium value of the marginal utility of wealth which adjusts once for all once the permanent shock hits the economy so that the open economy remains solvent.

R Semi-Small Open Economy Model with Endogenous Technology Decisions

This Appendix puts forward an open economy version of the neoclassical model with tradables and non-tradables, imperfect mobility of inputs across sectors, adjustment costs and endogenous terms of trade. We assume that production functions take a Cobb-Douglas form and importantly, firms must decide about the optimal amount of tangible and intangible assets to rent.

Households accumulate both physical and intangible capital stocks in the economy and rent them out to firms in the production sector. Households supply labor, L , and must decide on the allocation of total hours worked between the traded sector, L^H , and the non-traded sector, L^N . They consume both traded, C^T , and non-traded goods, C^N . Traded goods are a composite of home-produced traded goods, C^H , and foreign-produced foreign (i.e., imported) goods, C^F . Households also choose investment in physical which is produced using inputs of the traded, J^T , and the non-traded good, J^N . As for consumption, input of the traded good to produce tangible investment goods is a composite of home-produced traded goods, J^H , and foreign imported goods, J^F . Households also choose investment in intangible capital which is produced by using domestic inputs only, i.e., J^Z is a composite of home-produced traded goods, $J^{Z,H}$, and non-traded goods, $J^{Z,N}$. The numeraire is the foreign good whose price, P^F , is thus normalized to one. We assume that services from labor, tangible and intangible assets are imperfect substitutes across sectors. While households choose the intensity in the use of the stock of physical capital, the optimal allocation of labor, tangible and intangible assets is determined by optimal conditions from firms' profit maximization.

R.1 Households

Like labor and tangible assets, we allow for imperfect mobility of intangible assets by assuming that traded $Z^H(t)$ and non-traded $Z^N(t)$ stock of ideas are imperfect substitutes:

$$Z^A(t) = \left[\vartheta_Z^{-1/\epsilon_Z} (Z^H(t))^{\frac{\epsilon_Z+1}{\epsilon_Z}} + (1 - \vartheta_Z)^{-1/\epsilon_Z} (Z^N(t))^{\frac{\epsilon_Z+1}{\epsilon_Z}} \right]^{\frac{\epsilon_Z}{\epsilon_Z+1}}, \tag{382}$$

where $0 < \vartheta_Z < 1$ is the weight of traded intangible assets and ϵ_Z measures the ease with which sectoral intangible assets can be substituted for each other and thereby captures the degree of mobility of ideas across sectors.

We assume that the households own tangible $K^j(t)$ and intangible assets $Z^j(t)$ and lease both services from tangible and intangible assets to firms in sector j at rental rate $R^{K,j}(t)$ and $R^{Z,j}(t)$, respectively. Thus income from leasing activity received by households reads $\sum_j (R^{K,j}(t)u^{K,j}(t)K^j(t) + R^{Z,j}(t)Z^j(t))$ where we assume that households also choose the intensity $u^{K,j}(t)$ in the use of the physical capital stock. Households supply labor services to firms in sector j at a wage rate $W^j(t)$. Thus labor income received by households reads $\sum_j W^j(t)L^j(t)$.

In addition, households accumulate internationally traded bonds, $N(t)$, that yield net interest rate earnings of $r^*N(t)$. Denoting lump-sum taxes by $T(t)$, households' flow budget

constraint states that real disposable income can be saved by accumulating traded bonds, consumed, $P_C(t)C(t)$, invested in tangible assets, $P_J(t)J^K(t)$, invested in intangible assets, $P_Z(t)J^Z(t)$, and covers capital utilization costs:

$$\begin{aligned} & \dot{N}(t) + P_C(t)C(t) + P_J(t)J^K(t) + P_Z(t)J^Z(t) + \sum_j P^j(t)C^{K,j}(t)\nu^{K,j}(t)K(t) \\ &= r^*N(t) + [\alpha_K(t)u^{K,H}(t) + (1 - \alpha_K(t))u^{K,N}(t)]R^K(t)K(t) + R^Z(t)Z^A(t) + W(t)L(t) - \end{aligned} \quad (B88)$$

where we denote the share of sectoral tangible assets in the aggregate capital stock by $\nu^{K,j}(t) = K^j(t)/K(t)$, and the share of income on tangible and intangible assets in sector j in total income from tangible and intangible assets, by capital compensation share of sector $j = H, N$ by $\alpha_K^j(t) = \frac{R^{K,j}(t)K^j(t)}{R^K(t)K(t)}$ and $\alpha_Z(t) = \frac{R^{Z,j}(t)Z^j(t)}{R^Z(t)Z^A(t)}$, respectively. As shall be useful, we denote the labor compensation share by $\alpha_L^j(t) = \frac{W^j(t)L^j(t)}{W(t)L(t)}$.

The intangible good is produced using inputs of the home-produced traded good and the non-traded good according to a constant-returns-to-scale function which is assumed to take a CES form:

$$J^Z(t) = \left[\nu_Z^{\frac{1}{\phi_Z}} (J^{Z,H}(t))^{\frac{\phi_Z-1}{\phi_Z}} + (1 - \nu_Z)^{\frac{1}{\phi_Z}} (J^{Z,N}(t))^{\frac{\phi_Z-1}{\phi_Z}} \right]^{\frac{\phi_Z}{\phi_Z-1}}, \quad (384)$$

where ν_Z is the weight of the intangible traded input ($0 < \nu_Z < 1$) and ϕ_Z corresponds to the elasticity of substitution in investment between traded and non-traded intangible inputs. The price index associated with the aggregator function (384) is:

$$P_Z = \left[\nu_Z (P^H)^{1-\phi_Z} + (1 - \nu_Z) (P^N)^{1-\phi_Z} \right]^{\frac{1}{1-\phi_Z}}. \quad (385)$$

Accumulation of intangible assets is governed by the following law of motion:

$$\dot{Z}^A(t) = I^Z(t) - \delta_Z Z^A(t), \quad (386)$$

where I^Z is investment in intangible assets and $0 \leq \delta_Z < 1$ is a fixed depreciation rate. We assume that capital accumulation is subject to increasing and convex cost of net investment:

$$J^Z(t) = I^Z(t) + \Psi(I^Z(t), Z^A(t))Z^A(t), \quad (387)$$

with partial derivatives

$$\frac{\partial J^Z(t)}{\partial I^Z(t)} = 1 + \zeta \left(\frac{I^Z(t)}{Z^A(t)} - \delta_Z \right), \quad (388a)$$

$$\frac{\partial J^Z(t)}{\partial Z^A(t)} = -\frac{\zeta}{2} \left(\frac{I^Z(t)}{Z^A(t)} - \delta_Z \right) \left(\frac{I^Z(t)}{Z^A(t)} + \delta_Z \right). \quad (388b)$$

Households choose consumption, worked hours, capital and technology utilization rates, investment in tangible and intangible assets by maximizing lifetime utility (236) subject to (383), (239) and (386). Denoting the co-state variables associated with (383), (239) (i.e., $\dot{K}(t) = I(t) - \delta_K K(t)$), and (386) by λ , $Q^{K,'}$, and $Q^{Z,'}$ respectively, the first-order conditions characterizing the representative household's optimal plans are described by (242a)-(242f) and

$$Q^Z(t) = P_Z(t) \left[1 + \zeta \left(\frac{I^Z(t)}{Z^A(t)} - \delta_Z \right) \right], \quad (389a)$$

$$\dot{Q}^Z(t) = (r^* + \delta_Z) Q^Z(t) - \left[R^Z(t) - P_Z(t) \frac{\partial J^Z(t)}{\partial Z^A(t)} \right], \quad (389b)$$

and the transversality conditions $\lim_{t \rightarrow \infty} \bar{\lambda} N(t) e^{-\beta t} = 0$, $\lim_{t \rightarrow \infty} Q^K(t) K(t) e^{-\beta t} = 0$, and $\lim_{t \rightarrow \infty} Q^Z(t) Z^A(t) e^{-\beta t} = 0$; to derive (389a) and (389b), we used the fact that $Q^Z(t) = Q^{Z,'}(t)/\lambda(t)$.

Given the knowledge investment-based price index (385), we can derive the demand for inputs of the traded good and the non-traded good:

$$J^{Z,H} = \iota_Z \left(\frac{P^H}{P_Z} \right)^{-\phi_Z} J^Z, \quad (390a)$$

$$J^{Z,N} = (1 - \iota_Z) \left(\frac{P^N}{P_Z} \right)^{-\phi_Z} J^Z. \quad (390b)$$

As will be useful later, the percentage change in the R&D investment price index is a weighted average of percentage changes in the price of traded and non-traded inputs:

$$\hat{P}_Z = \alpha_Z \hat{P}^H + (1 - \alpha_Z) \hat{P}^N, \quad (391)$$

where

$$\alpha_J^Z = \frac{P^H J^{Z,H}}{P_Z J^Z} = \iota_Z \left(\frac{P^H}{P_Z} \right)^{1-\phi_Z}. \quad (392)$$

The aggregate rental rate for intangible assets, $R^Z(t)$, associated with the aggregate stock of knowledge defined above (382) is:

$$R^Z = \left[\vartheta_Z (R^{Z,H})^{\epsilon_Z+1} + (1 - \vartheta_Z) (R^{Z,N})^{\epsilon_Z+1} \right]^{\frac{1}{\epsilon_Z+1}}, \quad (393)$$

where $R^{Z,H}$ and $R^{Z,N}$ are rental rates for intangible assets paid in the traded and the non-traded sectors, respectively.

Given the aggregate rental rate for intangible assets, R^Z , the allocation of the stock of knowledge to the traded and the non-traded sector reads:

$$Z^H = \vartheta_Z \left(\frac{R^{Z,H}}{R^Z} \right)^{\epsilon_Z} Z^A, \quad Z^N = (1 - \vartheta_Z) \left(\frac{R^{Z,N}}{R^Z} \right)^{\epsilon_Z} Z^A. \quad (394)$$

As will be useful later, the percentage change in the aggregate rental rate of intangible assets is a weighted average of percentage changes in sectoral rental rates:

$$\hat{R}^Z = \alpha_Z \hat{R}^{Z,H} + (1 - \alpha_Z) \hat{R}^{Z,N}, \quad (395)$$

where α_Z is the tradable content of the aggregate income from intangible assets

$$\alpha_Z = \vartheta_Z \left(\frac{R^{Z,H}}{R^Z} \right)^{1+\epsilon_Z}, \quad 1 - \alpha_Z = (1 - \vartheta_Z) \left(\frac{R^{Z,N}}{R^Z} \right)^{1+\epsilon_Z}. \quad (396)$$

The decision to allocate intangible assets between the traded and the non-traded sectors (257b) allows us to solve for Z^H and Z^N :

$$Z^H = Z^H(Z^A, R^{Z,H}, R^{Z,N}), \quad Z^N = Z^N(Z^A, R^{Z,H}, R^{Z,N}), \quad (397)$$

with partial derivatives given by:

$$\hat{Z}^H = \epsilon_Z (1 - \alpha_Z) \hat{R}^{Z,H} - (1 - \alpha_Z) \epsilon_Z \hat{R}^{Z,N} + \hat{Z}^A, \quad (398a)$$

$$\hat{Z}^N = \epsilon_Z \alpha_Z \hat{R}^{Z,N} - \alpha_Z \epsilon_Z \hat{R}^{Z,H} + \hat{Z}^A. \quad (398b)$$

R.2 Final and Intermediate Good Producers

We assume that within each sector, there are a large number of intermediate good producers which produce differentiated varieties and thus are imperfectly competitive. They choose to rent labor services from households along with services from tangible and intangible assets.

Final Goods Firms

The final non-traded output, Y^j , is produced in a competitive retail sector using a constant-returns-to-scale production function which aggregates a continuum measure one of sectoral goods:

$$Y^j = \left[\int_0^1 \left(X_i^j \right)^{\frac{\omega^j-1}{\omega^j}} di \right]^{\frac{\omega^j}{\omega^j-1}}, \quad (399)$$

where $\omega^j > 0$ represents the elasticity of substitution between any two different sectoral goods and X_i^j stands for intermediate consumption of sector j variety (with $i \in (0, 1)$). The final good producers behave competitively, and the households use the final good for both consumption and investment. While the output of non-traded final good, Y^N , is for domestic absorption only, the output of home-produced traded good can be consumed domestically, invested or exported.

Denoting by P^j and P_i^j the price of the final good in sector j and the price of the i th variety of the intermediate good, respectively, the profit the final good producer reads:

$$\Pi_F^j = P^j \left[\int_0^1 \left(X_i^j \right)^{\frac{\omega^j - 1}{\omega^j}} di \right]^{\frac{\omega^j}{\omega^j}} - \int_0^1 P_i^j X_i^j di. \quad (400)$$

Total cost minimization for a given level of final output gives the (intratemporal) demand function for each input:

$$X_i^j = \left(\frac{P_i^j}{P^j} \right)^{-\omega^j} Y^j, \quad (401)$$

and the price of the final output is given by:

$$P^j = \left(\int_0^1 \left(P_i^j \right)^{1 - \omega^j} di \right)^{\frac{1}{1 - \omega^j}}, \quad (402)$$

where P_i^j is the price of variety i in sector j and P^j is the price of the final good in sector $j = H, N$. Making use of eq. (401), the price-elasticity of the demand for output of the i th variety within sector j is:

$$-\frac{\partial X_i^j}{\partial P_i^j} \frac{P_i^j}{X_i^j} = \omega^j. \quad (403)$$

Intermediate Goods Firms

Within each sector j , there are firms producing differentiated goods. Each intermediate good producer uses labor services, $L^j(t)$, services from tangible assets (inclusive of the intensity in the use of tangible assets) $\tilde{K}^j(t)$, and services from intangible assets $Z^j(t)$, to produce a final good according to a technology of production which displays increasing returns to scale:

$$X^j(t) = \left(Z^j(t) \right)^{\nu^j} \left(L^j(t) \right)^{\theta^j} \left(\tilde{K}^j(t) \right)^{1 - \theta^j}, \quad (404)$$

where the stock of knowledge Z^j is a stock of ideas used by domestic firms in sector $j = H, N$. this stock of ideas gives rise to the utilization-adjusted-TFP, i.e., $(Z^j(t))^{\nu^j} = \text{TFP}_{adj}^j(t)$. The stock of ideas is made up of a domestic $Z^j(t)$ and an international stock of knowledge $Z^W(t)$:

$$Z^j(t) = \left(Z_i^j(t) \right)^{\zeta^j} \left(Z^W(t) \right)^{1 - \zeta^j}. \quad (405)$$

Note that because the firm must pay (time-invariant) fixed costs F^j , we require the markup denoted by μ^j to be larger than the degree of increasing returns to scale, i.e., $1 + \nu^j \zeta^j < \mu^j$, so that the excess of value added over the payment of factors of production is large enough to cover fixed costs.

Firms face three cost components: a labor cost equal to the wage rate $W^j(t)$, and a sector-specific rental cost for tangible and intangible assets equal to $R^{K,j}(t)$ and $R^{Z,j}(t)$, respectively. Both sectors are assumed to be imperfectly competitive and thus choose capital services and labor by taking prices as given:

$$\begin{aligned} & \max_{L_i^j(t), \tilde{K}_i^j(t), Z_i^j(t)} \Pi_i^j(t) \\ \equiv & \max_{L_i^j(t), \tilde{K}_i^j(t), Z_i^j(t)} P_i^j(t) X_i^j(t) - W^j(t) L_i^j(t) - R^{K,j}(t) \tilde{K}_i^j(t) - R^{Z,j}(t) Z_i^j(t) - P^j F^j, \end{aligned} \quad (406)$$

where F^j is a fixed cost which is symmetric across all intermediate good producers but varies across sectors.

From (404), we have $X_i^j = F(L_i^j, \tilde{K}_i^j, Z_i^j)$. the Lagrangian for the i -th firm's optimization problem in the sector j is:

$$\begin{aligned} \mathcal{L}_i^j &= P_i^j F^j(L_i^j, \tilde{K}_i^j, Z_i^j) - W^j(t) L_i^j(t) - R^{K,j}(t) \tilde{K}_i^j(t) - R^{Z,j}(t) Z_i^j(t) - P^j F^j \\ &\quad + \eta_i^j \left[F(L_i^j, \tilde{K}_i^j, Z_i^j) - (P_i^j)^{-\omega^j} (P^j)^{\omega^j} Y^j \right], \end{aligned} \quad (407)$$

where $(\frac{P_i^j}{P^j})^{-\omega^j} Y^j = X_i^j$ stands for the demand for variety j ; firm j chooses its price P_i^j to maximize profits treating the factor prices as given. The corresponding first-order necessary conditions (for labor, physical capital, intangible capital, and variety- i price) are:

$$(P_i^j + \eta_i^j) \frac{\partial F^j(\cdot)}{\partial L_i^j} = W^j, \quad (408a)$$

$$(P_i^j + \eta_i^j) \frac{\partial F^j(\cdot)}{\partial \tilde{K}_i^j} = R^{K,j}, \quad (408b)$$

$$(P_i^j + \eta_i^j) \frac{\partial F^j(\cdot)}{\partial Z_i^j} = R^{Z,j}, \quad (408c)$$

$$X_i^j = -\eta_i^j \omega^j (P_i^j)^{-\omega^j - 1} (P^j)^{\omega^j} Y^j, \quad (408d)$$

where $F^j(\cdot) = X_i^j$. Using (401), i.e., $X_i^j = (\frac{P_i^j}{P^j})^{-\omega^j} Y^j$, eq. (408d) can be rewritten as follows:

$$\eta_i^j = -\frac{P_i^j}{\omega^j}. \quad (409)$$

Denoting the markup charged by intermediate good producers by $\mu^j = \frac{\omega^j}{\omega^j - 1} > 1$, and inserting (409) into (408a)-(408c), first-order conditions can be rewritten as follows:

$$P_i^j \theta^j \frac{X_i^j}{L_i^j} = \mu^j W^j, \quad (410a)$$

$$P_i^j (1 - \theta^j) \frac{X_i^j}{\tilde{K}_i^j} = \mu^j R^{K,j}, \quad (410b)$$

$$P_i^j \nu^j \zeta^j \frac{X_i^j}{Z_i^j} = \mu^j R^{Z,j}, \quad (410c)$$

where we used the fact that $\frac{\partial X_i^j}{\partial L_i^j} = \theta^j \frac{X_i^j}{L_i^j}$, $\frac{\partial X_i^j}{\partial \tilde{K}_i^j} = (1 - \theta^j) \frac{X_i^j}{\tilde{K}_i^j}$, and $\frac{\partial X_i^j}{\partial Z_i^j} = \nu^j \zeta^j \frac{X_i^j}{Z_i^j}$.

Free entry Condition

We assume free entry in the goods markets so that the movement of firms in and out of the goods market drives profits to zero at each instant of time, i.e., $\Pi_i^j(t) = P_i^j(t) X_i^j(t) - W^j(t) L_i^j(t) - R^{K,j}(t) \tilde{K}_i^j(t) - R^{Z,j}(t) Z_i^j(t) - P^j F^j = 0$. Inserting first-order conditions (410a)-(410c) into (406) leads to:

$$\begin{aligned} &P_i^j(t) X_i^j(t) - W^j(t) L_i^j(t) - R^{K,j}(t) \tilde{K}_i^j(t) - R^{Z,j}(t) Z_i^j(t) - P^j F^j = 0, \\ &= P_i^j X_i^j - \frac{P_i^j}{\mu^j} \theta^j X_i^j - \frac{P_i^j}{\mu^j} (1 - \theta^j) X_i^j - \frac{P_i^j}{\mu^j} \nu^j \zeta^j X_i^j - P^j F^j = 0, \\ &P_i^j X_i^j \left[1 - \frac{\theta^j + (1 - \theta^j) + \nu^j \zeta^j}{\mu^j} \right] - P_i^j F^j = 0, \\ &P_i^j X_i^j \left[1 - \frac{1 + \nu^j \zeta^j}{\mu^j} \right] - P_i^j F^j = 0. \end{aligned} \quad (411)$$

To ensure that profits cannot be negative, we assume that the contribution of the stock of intangible assets to the production of the i -th variety of the intermediate good is lower than the markup:

$$\mu^j > 1 + \nu^j \zeta^j. \quad (412)$$

Because intermediate good producers are symmetric, they face the same costs of factors and the same price elasticity of demand. Therefore, they set same prices which collapse to final good prices, i.e., $P_i^j = P^j$ and they produce the same quantity, i.e., $X_i^j = X^j = Y^j$. Eq. (411) implies that value added covers the payment of labor services, $W^j L^j$, rental payments of services from tangible and intangible assets to households, i.e., $R^{K,j} \tilde{K}^j$ and $R^{Z,j} Z^j$, and also covers the payment of the fixed cost:

$$P^j Y^j = W^j L^j + R^{K,j} \tilde{K}^j + R^{Z,j} Z^j + P^j F^j. \quad (413)$$

Output Net of Fixed Costs

We denote output net of fixed costs by $Q^j = Y^j - F^j$. By using the free entry condition (411), i.e., $P^j F^j = P^j Y^j \left[1 - \frac{1+\nu^j \zeta^j}{\mu^j}\right]$, output net of fixed costs is thus equal to:

$$Q^j = Y^j - F^j = Y^j \left(\frac{1 + \nu^j \zeta^j}{\mu^j} \right). \quad (414)$$

Unit Cost for Producing

As shall be useful, we derive the unit cost for producing in sector j . Dividing the demand for labor (410a) by the demand for capital (410b), and next dividing the demand for demand for tangible assets (410b) by the demand for intangible assets (410c), and finally the demand for labor (410a) by the demand for intangible assets (410c), we get:

$$\frac{1 - \theta^j}{\theta^j} \frac{L^j}{\tilde{K}^j} = \frac{R^{K,j}}{W^j}, \quad (415a)$$

$$\frac{1 - \theta^j}{\nu^j \zeta^j} \frac{Z^j}{\tilde{K}^j} = \frac{R^{K,j}}{R^{Z,j}}, \quad (415b)$$

$$\frac{\nu^j \zeta^j}{\theta^j} \frac{L^j}{Z^j} = \frac{R^{Z,j}}{W^j}. \quad (415c)$$

Making use of eq. (415a) and (415b) to eliminate L^j and Z^j from the Cobb-Douglas production function (404)-(405) and solving for \tilde{K}^j , and next making use of eq. (415a) and (415c) to eliminate \tilde{K}^j and Z^j from the Cobb-Douglas production function (404)-(405) and solving for L^j , and finally making use of eq. (415b) and (415c) to eliminate \tilde{K}^j and L^j from the Cobb-Douglas production function (404)-(405) and solving for Z^j leads to the conditional demand for capital stock, for labor, and for intangible assets:

$$\left(\tilde{K}^j\right)^{1+\nu^j \zeta^j} = \frac{Y^j}{(ZW)^{(1-\zeta^j)\nu^j}} \left(\frac{1-\theta^j}{\theta^j}\right)^{\theta^j} \left(\frac{1-\theta^j}{\nu^j \zeta^j}\right)^{\nu^j \zeta^j} \frac{(R^{Z,j})^{\nu^j \zeta^j} (W^j)^{\theta^j}}{(R^{K,j})^{\theta^j + \nu^j \zeta^j}}, \quad (416a)$$

$$\left(L^j\right)^{1+\nu^j \zeta^j} = \frac{Y^j}{(ZW)^{(1-\zeta^j)\nu^j}} \left(\frac{\theta^j}{1-\theta^j}\right)^{1-\theta^j} \left(\frac{\theta^j}{\nu^j \zeta^j}\right)^{\nu^j \zeta^j} \frac{(R^{Z,j})^{\nu^j \zeta^j} (R^{K,j})^{1-\theta^j}}{(W^j)^{(1-\theta^j) + \nu^j \zeta^j}}, \quad (416b)$$

$$\left(Z^j\right)^{1+\nu^j \zeta^j} = \frac{Y^j}{(ZW)^{(1-\zeta^j)\nu^j}} \frac{\nu^j \zeta^j}{(1-\theta^j)^{1-\theta^j} (\theta^j)^{\theta^j}} \frac{(W^j)^{\theta^j} (R^{K,j})^{1-\theta^j}}{R^{Z,j}}. \quad (416c)$$

Total (variable) cost is equal to the sum of labor compensation, rental cost of tangible and intangible assets:

$$C^j = W^j L^j + R^{K,j} \tilde{K}^j + R^{Z,j} Z^j. \quad (417)$$

Inserting conditional demand for inputs (416a)-(416c) into total cost (417), we find that C^j is homogenous of a degree smaller than one with respect to value added due to the fact that the production function displays increasing returns to scale:

$$C^j = \left[\frac{Y^j}{(ZW)^{(1-\zeta^j)\nu^j}} \right]^{\frac{1}{1+\nu^j \zeta^j}} (M^j)^{\frac{1}{1+\nu^j \zeta^j}} (1 + \nu^j \zeta^j) \quad (418)$$

where we set

$$M^j = (\Psi^j)^{-1} [W^j]^{\theta^j} (R^{K,j})^{1-\theta^j} (R^{Z,j})^{\nu^j \zeta^j}, \quad (419)$$

where

$$\Psi^j = (\theta^j)^{\theta^j} (1 - \theta^j)^{1-\theta^j} (\nu^j \zeta^j)^{\nu^j \zeta^j}. \quad (420)$$

By using (413) and the definition of total costs (417) which implies that $P^j Y^j - P^j F^j = C^j$ and by using the fact that $P^j Y^j - P^j F^j = P^j Y^j \left(\frac{1+\nu^j \zeta^j}{\mu^j} \right) = P^j Q^j$ (see eq. (414)), we have $P^j Q^j = C^j$. The unit cost for producing denoted by c^j is obtained by dividing C^j by $Q^j = Y^j \left(\frac{1+\nu^j \zeta^j}{\mu^j} \right)$ which leads to

$$c^j = \mu^j (Y^j)^{-\frac{\nu^j \zeta^j}{1+\nu^j \zeta^j}} \left[\frac{M^j}{(ZW)^{(1-\zeta^j)\nu^j}} \right]^{\frac{1}{1+\nu^j \zeta^j}}. \quad (421)$$

The price over the markup P^j/μ^j thus equalizes with c^j/μ^j .

R.3 Solving the Model

First-order conditions from firm's profit maximization are for sector $j = H, N$:

$$\frac{P^j}{\mu^j} \theta^j (Z^j)^{\nu^j \zeta^j} (ZW)^{(1-\nu^j)\zeta^j} (L^j)^{\theta^j-1} (u^{K,j} K^j)^{1-\theta^j} = W^j, \quad (422a)$$

$$\frac{P^j}{\mu^j} (1 - \theta^j) (Z^j)^{\nu^j \zeta^j} (ZW)^{(1-\nu^j)\zeta^j} (L^j)^{\theta^j} (u^{K,j} K^j)^{-\theta^j} = R^{K,j}, \quad (422b)$$

$$\frac{P^j}{\mu^j} \nu^j \zeta^j (Z^j)^{(\nu^j \zeta^j-1)} (ZW)^{(1-\nu^j)\zeta^j} (L^j)^{\theta^j} (u^{K,j} K^j)^{1-\theta^j} = R^{Z,j}. \quad (422c)$$

Totally differentiating first-order conditions from firm's profit maximization leads to:

$$- \left[(1 - \theta^j) \hat{L}^j + \hat{W}^j \right] + (1 - \theta^j) \left(\hat{u}^{K,j} + \hat{K}^j \right) + \nu^j \zeta^j \hat{Z}^j = -\hat{P}^j - (1 - \nu^j) \zeta^j \hat{Z}^W, \quad (423a)$$

$$\theta^j \hat{L}^j - \left[\theta^j \left(\hat{u}^{K,j} + \hat{K}^j \right) + \hat{R}^{K,j} \right] + \nu^j \zeta^j \hat{Z}^j = -\hat{P}^j - (1 - \nu^j) \zeta^j \hat{Z}^W, \quad (423b)$$

$$\theta^j \hat{L}^j + (1 - \theta^j) \left(\hat{u}^{K,j} + \hat{K}^j \right) - \left[(1 - \nu^j \zeta^j) \hat{Z}^j + \hat{R}^{Z,j} \right] = -\hat{P}^j - (1 - \zeta^j) \nu^j \hat{Z}^W. \quad (423c)$$

Inserting intermediate solutions for L^j and K^j described by (267) and (269), respectively, and inserting the intermediate solution for Z^j described by eq. (397) into (423a)-(423c) and invoking the theorem of implicit functions leads to

$$W^j, R^{K,j}, R^{Z,j} (P^N, P^H, K, Z^A, u^{K,H}, u^{K,N}, Z^W). \quad (424)$$

Plugging back (424) into (267) and (269) together with (397) leads to solutions for L^j, K^j, Z^j and then for Y^j by inserting these solutions onto the production function (404)-(405), i.e.,

$$L^j, K^j, Y^j (P^N, P^H, K, Z^A, u^{K,H}, u^{K,N}, Z^W). \quad (425)$$

Inserting first the marginal revenue product of capital(422b) into the optimal decision for the capital utilization rate

$$\frac{R^{K,j}(t)}{P^j(t)} = \xi_1^j + \xi_2^j (u^{K,j}(t) - 1) = \frac{(1 - \theta^j)}{\mu^j} (Z^j)^{\nu^j \zeta^j} (ZW)^{\nu^j(1-\zeta^j)} (L^j)^{\theta^j} (u^{K,j} K^j)^{-\theta^j}. \quad (426)$$

Totally differentiating (426) leads to:

$$\left[\begin{array}{c} \xi_2^j \\ \xi_1^j \end{array} + \theta^j \right] \hat{u}^{K,j} - \theta^j \hat{L}^j + \theta^j \hat{K}^j - \nu^j \zeta^j \hat{Z}^j = \nu^j (1 - \zeta^j) \hat{Z}^W. \quad (427)$$

Inserting (425) into (427) and invoking the implicit function theorem leads to:

$$u^{K,j} (P^N, P^H, K, Z^A, Z^W). \quad (428)$$

Plugging (428) into (424) and (425) leads to

$$W^j, R^{K,j}, R^{Z,j}, L^j, K^j, Y^j (P^N, P^H, K, Z^A, Z^W). \quad (429)$$

From eq. (389a), we have $\frac{I^Z(t)}{Z^A(t)}$ which is a positive function of $\frac{1}{\zeta} \left(\frac{Q^Z(t)}{P_Z(t)} - 1 \right) + \delta_Z$.
Setting

$$v^Z(\cdot) = \frac{1}{\zeta} \left(\frac{Q^Z}{P_Z} - 1 \right) \quad (430)$$

we have $J^Z = Z^A \left[\frac{I^Z}{Z^A} + \frac{\zeta}{2} \left(\frac{I^Z}{Z^A} - \delta_Z \right)^2 \right]$ which can be solved for R&D investment including installation costs:

$$J^Z = J^Z(Z^A, Q^Z, P^N, P^H). \quad (431)$$

Inserting first (431) into (390a)-(390b), we can solve for investment in traded and non-traded R&D:

$$J^{Z,H}, J^{Z,N}(Z^A, Q^Z, P^N, P^H). \quad (432)$$

The market clearing conditions for traded and non-traded goods read:

$$Q^H = C^H + G^H + J^{K,H} + J^{Z,H} + X^H + C^{K,H} K^H, \quad (433a)$$

$$Q^N = C^N + G^N + J^{K,N} + J^{Z,N} + C^{K,N} K^N. \quad (433b)$$

Inserting first appropriate intermediate solutions and differentiating enables to solve for home-produced traded good and non-traded good prices:

$$P^H, P^N(K, Q^K, Z^A, Q^Z, Z^W). \quad (434)$$

Plugging back these solutions (434) into (428), (429) leads to:

$$u^{K,j}, W^j, R^{K,j}, R^{Z,j}, L^j, K^j, Y^j(K, Q^K, Z^A, Q^Z, Z^W). \quad (435)$$

Inserting solutions for sectoral prices (434) into intermediate solutions for investment in tangible (285) and intangible assets (432) and consumption (265) leads to:

$$C^g, J^{K,g}, J^{Z,g}(K, Q^K, Z^A, Q^Z, Z^W). \quad (436)$$

The adjustment of the open economy toward the steady state is described by a dynamic system which comprises five equations

$$\begin{aligned} \dot{K}(t) = & \frac{Q^N(t) - C^N(t) - G^N(t) - J^{Z,N}(t) - C^{K,N}(t)K^N(t)}{(1 - \iota) \left(\frac{P^N(t)}{P_J(t)} \right)^{-\phi_J}} \\ & - \delta_K K(t) - \frac{\kappa}{2} \left(\frac{I(t)}{K(t)} - \delta_K \right)^2 K(t), \end{aligned} \quad (437a)$$

$$\begin{aligned} \dot{Q}^K(t) = & (r^* + \delta_K) Q(t) - \left\{ \sum_{j=H,N} \alpha_K^j(t) u^{K,j}(t) R^K(t) \right. \\ & \left. - \sum_{j=H,N} P^j(t) C^{K,j}(t) \nu^{K,j}(t) - P_J(t) \frac{\partial J(t)}{\partial K(t)} \right\}, \end{aligned} \quad (437b)$$

$$\dot{Z}^A(t) = v^Z(K(t), Q^K(t), Z^A(t), Q^Z(t), Z^W(t)) Z^A(t), \quad (437c)$$

$$\dot{Q}^Z(t) = (r^* + \delta_Z) Q^Z(t) - \left[R^Z(t) - P_Z(t) \frac{\partial J^Z(t)}{\partial Z^A(t)} \right], \quad (437d)$$

$$\dot{Z}^W(t) = \hat{Z}^W + z^W e^{-\xi_Z t} \quad (437e)$$

where we have used the fact that $v^Z = \frac{I^Z}{Z^A} - \delta_Z$ with $v^Z(Q^Z(t), P^N(t), P^H(t))$, \hat{Z}^W is the long-run rate of change in the international stock of knowledge, z^W and ξ_Z are parameters which capture the magnitude of the change in Z^W on impact and its persistence.

The dynamic system can be written in a compact form:

$$\dot{K}(t) = \Upsilon(K(t), Q^K(t), Z^A(t), Q^Z(t), Z^W(t)), \quad (438a)$$

$$\dot{Q}^K(t) = \Sigma(K(t), Q^K(t), Z^A(t), Q^Z(t), Z^W(t)), \quad (438b)$$

$$\dot{Z}^A(t) = \Pi(K(t), Q^K(t), Z^A(t), Q^Z(t), Z^W(t)), \quad (438c)$$

$$\dot{Q}^Z(t) = \Gamma(K(t), Q^K(t), Z^A(t), Q^Z(t), Z^W(t)), \quad (438d)$$

$$\dot{Z}^W(t) = -\xi_Z (Z^W(t) - Z^W), \quad (438e)$$

where $j = H, N$.

We linearize (438a)-(438e) around the steady-state:

$$\begin{pmatrix} \dot{K}(t) \\ \dot{Q}^K(t) \\ \dot{Z}^A(t) \\ \dot{Q}^Z(t) \\ \dot{Z}^W(t) \end{pmatrix} = \begin{pmatrix} \Upsilon_K & \Upsilon_{QK} & \Upsilon_{ZA} & \Upsilon_{QZ} & \Upsilon_{ZW} \\ \Sigma_K & \Sigma_{QK} & \Sigma_{ZA} & \Sigma_{QZ} & \Sigma_{ZW} \\ \Pi_K & \Pi_{QK} & \Pi_{ZA} & \Pi_{QZ} & \Pi_{ZW} \\ \Gamma_K & \Gamma_{QK} & \Gamma_{ZA} & \Gamma_{QZ} & \Gamma_{ZW} \\ 0 & 0 & 0 & 0 & -\xi_Z \end{pmatrix} \begin{pmatrix} dK(t) \\ dQ^K(t) \\ dZ^A(t) \\ dQ^Z(t) \\ dZ^W(t) \end{pmatrix}. \quad (439)$$

Denoting by ω_k^i the k th element of eigenvector ω^i related to eigenvalue ν_i , the general solution that characterizes the adjustment toward the new steady-state can be written as follows: $V(t) - V = \sum_{i=1}^5 \omega^i D_i e^{\nu_i t}$ where V is the vector of state and control variables. Denoting the positive eigenvalue by $\nu_3, \nu_4 > 0$, we set $D_3 = D_4 = 0$ to eliminate explosive paths and determine the five arbitrary constants D_i (with $i = 1, \dots, 5, i \neq 3, 4$) by using the three initial conditions, i.e., $K(0) = K_0$, $Z^A(0) = Z_0^A$, $Z^W(0) = Z_0^W$. Convergent solutions toward the stable manifold read:

$$dK(t) = D_1 e^{\nu_1 t} + D_2 e^{\nu_2 t} + \omega_1^5 D_5 e^{\nu_5 t}, \quad (440a)$$

$$dQ^K(t) = \omega_2^1 D_1 e^{\nu_1 t} + \omega_2^2 D_2 e^{\nu_2 t} + \omega_2^5 D_5 e^{\nu_5 t}, \quad (440b)$$

$$dZ^A(t) = \omega_3^1 D_1 e^{\nu_1 t} + \omega_3^2 D_2 e^{\nu_2 t} + \omega_3^5 D_5 e^{\nu_5 t}, \quad (440c)$$

$$dQ^Z(t) = \omega_4^1 D_1 e^{\nu_1 t} + \omega_4^2 D_2 e^{\nu_2 t} + \omega_4^5 D_5 e^{\nu_5 t}, \quad (440d)$$

$$dZ^W(t) = D_5 e^{\nu_5 t}, \quad (440e)$$

where $dX(t) = X(t) - X$ with X corresponding to the steady-state value in the next steady-state, and $\nu_5 = -\xi_Z < 0$.

Setting $t = 0$ into the solutions for the stock of capital and the stock of knowledge, i.e., $K_0 - K - \omega_1^5 D_5 = D_1 + D_2$ and $Z_0^A - Z^A - \omega_3^5 D_5 = \omega_3^1 D_1 + \omega_3^2 D_2$, and solving for arbitrary constants:

$$D_1 = \frac{(K_0 - K) \omega_3^2 - (Z_0^A - Z^A) - D_5 (\omega_1^5 \omega_3^2 - \omega_3^5)}{\omega_3^2 - \omega_3^1}, \quad (441a)$$

$$D_2 = \frac{(Z_0^A - Z^A) - (K_0 - K) \omega_3^1 - D_5 (\omega_3^5 - \omega_3^1 \omega_1^5)}{\omega_3^2 - \omega_3^1}. \quad (441b)$$

The current account reads $\dot{N}(t) = r^* N(t) + P^H(t) X^H(t) - M^F(t)$ where $M^F = C^F + G^F + J^{K,F}$. Linearizing the current account equation, inserting solutions (440a)-(440e), integrating over $(0, t)$, solving, invoking the transversality condition leads to the stable convergent path for the stock of net foreign assets:

$$dN(t) = \frac{E_1 D_1}{\nu_1 - r^*} e^{\nu_1 t} + \frac{E_2 D_2}{\nu_2 - r^*} e^{\nu_2 t} + \frac{E_5 D_5}{\nu_5 - r^*} e^{\nu_5 t}, \quad (442)$$

and the intertemporal solvency condition

$$dN + \frac{E_1 D_1}{\nu_1 - r^*} + \frac{E_2 D_2}{\nu_2 - r^*} + \frac{E_5 D_5}{\nu_5 - r^*}, \quad (443)$$

where $\nu_1, \nu_2, \nu_5 < 0$, $E_i = \Xi_K + \Xi_{QK} \omega_2^i + \Xi_{ZA} \omega_3^i + \Xi_{QZ} \omega_4^i$ for $i = 1, 2$, and $E_5 = \Xi_K \omega_1^5 + \Xi_{QK} \omega_2^5 + \Xi_{ZA} \omega_3^5 + \Xi_{QZ} \omega_4^5 + \Xi_{ZW}$.

R.4 Numerical Strategy to Compute the Share of the Asymmetric Technological Change Driven by the Increase in the Stock of Knowledge

Panel A of Table 27 shows the variance of asymmetric technological change, the variance of the growth rate of aggregate utilization-adjusted-TFP (adjusted with the covariance), the ratio of the former to the latter, and the contribution of asymmetric technological change to the variance of the growth rate of aggregate utilization-adjusted-TFP. The share of asymmetric technological change has increased from 18.7% to 38.9%. Our objective is

to quantify the contribution of the growing stock of knowledge together with the greater exposition of traded industries than the non-traded sector to innovation abroad to rationalize the growing contribution of asymmetric technological change to aggregate technological change.

We denote utilization-adjusted-TFP in sector j by Z^j and utilization-adjusted-aggregate-TFP by Z^A . As demonstrated in section J.9, the variance of aggregate technological change (adjusted with the covariance), $\text{Var}'\left(\hat{Z}^A(t)\right)$, driven by the the variance asymmetric technological change, $\text{Var}\left(\hat{Z}^H(t) - \hat{Z}^N(t)\right)$ can be measured by means of the following formula:

$$\text{Unconditional Share of Asym. Tech. Change} = (\nu^{Y,H})^2 \frac{\text{Var}\left(\hat{Z}^H(t) - \hat{Z}^N(t)\right)}{\text{Var}'\left(\hat{Z}^A(t)\right)}, \quad (444)$$

where $\nu^{Y,H}$ is the value added share of tradables averaged over 1970-2017. Eq. (444) shows that the variance of aggregate technological change driven by asymmetric technology improvements is driven by the dispersion between traded and non-traded technology improvements and also by the value added share of tradables.

First step. In the first step, we calibrate the semi-small open economy with endogenous technology decisions and estimate the effects on utilization-adjusted-TFP of tradables and non-tradables of a 1% permanent increase in the world utilization-adjusted-TFP (driven by the permanent increase in the international stock of knowledge $Z^W(t)$).

As detailed in section R.1, households decide about the investment in R&D which gives rise to an aggregate stock of knowledge $Z^A(t)$. Households stand ready to supply the stock of knowledge to firms in the traded and the non-traded sectors. Because intangible assets are imperfect substitutes, they pay different returns. Given sector-specific rental rates on intangible assets denoted by $R_Z^j(t)$, traded and non-traded firms choose the amount of intangible assets $Z^H(t)$ and $Z^N(t)$ according to the following optimal rules:

$$\frac{P^j(t)}{\mu^j} \zeta^j \nu^j (Z^j(t))^{\zeta^j \nu^j - 1} (Z^W(t))^{(1-\zeta^j)\nu^j} (L^j(t))^{\theta^j} (\tilde{K}^j(t))^{1-\theta^j} = R_Z^j(t),$$

where P^j is the price of the final good in sector $j = H, N$. This equation shows that an increase in international stock of knowledge $Z^W(t)$ raises the marginal revenue product of investing in intangible assets and thus has a positive impact on $Z^j(t)$. Higher levels in both international Z^W and domestic $Z^j(t)$ stock of knowledge have a positive impact on utilization-adjusted-TFP.

In this regard, one key parameter is ν^j which measures the impact of 1% increase in the stock of R&D in sector j on utilization-adjusted-TFP in sector j . Using data from Stehrer et al. [2019] (EU KLEMS database) we construct time series for both gross fixed capital formation and capital stock in R&D in the traded and non-traded sectors. Data are available for thirteen countries over 1995-2017, see Table 28. We have run the regression of the logged utilization-adjusted-TFP in sector j on the logged stock of R&D at constant prices by using cointegration techniques. As shown in Table 29, we find a FMOLS estimated value of the long-term elasticity of utilization-adjusted-TFP w.r.t. the stock of R&D of 0.1499 for the traded sector and 0.0007 for the non-traded sector. Once we have estimated the elasticity γ^j of utilization-adjusted-TFP in sector j w.r.t the stock of knowledge in sector j , we have to recover the parameter ν^H and ν^N by using values of parameters ζ^H and ζ^N . By adopting a principal component analysis, we have estimated the common component of utilization-adjusted-TFP which stands at $1 - \zeta^H = 0.369$ for tradables and $1 - \zeta^N = 0.305$ for non-tradables. These values lead to $\nu^H = \gamma^H / \zeta^H = 0.238$ and $\nu^N = \gamma^N / \zeta^N = 0.001$. These values suggest that increasing the domestic or the international stock of knowledge have little impact on utilization-adjusted TFP of non-tradables and instead have a significant impact on utilization-adjusted TFP of tradables. These values fit the data which indicates that utilization-adjusted-TFP has increased by 0.2% per year while technology improves by 1.6% on average per year in the traded sector over 1995-2017.

First step. In the quantitative analysis, we consider two scenarios. First, in line with the principal component analysis we have conducted in section N.5 to extract the

Table 27: Contribution of the International Stock of R&D to the Increasing Share of Asymmetric Technological Change

Period	Variance		$\frac{\text{Var}(\hat{Z}^H(t) - \hat{Z}^N(t))}{\text{Var}(\hat{Z}^A(t))}$	Share Asymmetric
	$\hat{Z}^H(t) - \hat{Z}^N(t)$ (1)	$\hat{Z}^A(t)$ (2)	(1)/(2) (3)	Tech. Change (in %) (4)
A.Total				
1970-1992	0.000096	0.000077	1.25	18.7%
1993-2017	0.000072	0.000028	2.60	38.9%
B.International				
1970-1992	0.000040	0.000050	0.52	7.7%
1993-2017	0.000041	0.000023	1.48	22.1%

Notes: In columns 1 and 2, we show the variance of the rate of the growth of the utilization-adjusted-TFP differential between tradables and non-tradables, i.e., and the rate of the growth of the utilization-adjusted-aggregate-TFP. Column 3 shows the ratio of $\text{Var}(\hat{Z}^H(t) - \hat{Z}^N(t))$ to $\text{Var}(\hat{Z}^A(t))$. Column 4 displays the share of the variance of asymmetric technological change to the variance of technological change, i.e., compute the second term on the RHS of eq. (49). In panel A, we consider the seventeen OECD countries average. In panel B, we have created artificial data by i) estimating numerically the effect of a 1% permanent increase in the world utilization-adjusted-TFP on the utilization-adjusted TFP of tradables and non-tradables by considering two sub-periods 70-92 and 93-17 by setting the world component of sectoral utilization-adjusted-TFP to their estimates by means of PCA, 2) calculating the growth rate of $Z^j(t)$ by multiplying the growth rate of $Z^W(t)$ with the long-run effect of a 1% permanent increase in $Z^W(t)$ on $Z^H(t)$ and $Z^N(t)$ which stand at 0.92 and 1.23 for tradables over 70-92 and 93-17, respectively, and 0.004 for non-tradables over the two sub-periods, 3) calculating the contribution of variance of the productivity growth differential between tradables and non-tradables as if the differential was only driven by the increase in $Z^W(t)$. Sample: 17 OECD countries, 1970-2017, annual data.

Table 28: Stocks of Capital from KLEMS and sectoral R&D series: Data Availability

	data on K from KLEMS	data on R&D
AUS	1970-2007	no data
AUT	1976-2017	1995-2017
BEL	1995-2017	1995-2017
CAN	1970-2016	no data
DEU	1991-2017	1995-2017
DNK	1970-2017	1995-2017
ESP	1970-2016	1995-2016
FIN	1970-2017	1995-2017
FRA	1978-2017	1995-2017
GBR	1970-2017	1995-2017
IRL	1985-2017	no data
ITA	1970-2017	1995-2017
JPN	1973-2015	1995-2015
NLD	1970-2017	1995-2017
NOR	1970-2017	no data
SWE	1993-2016	1995-2016
USA	1970-2016	1995-2017

international component of traded and non-traded technology, see Table 26, we set the world components of utilization-adjusted-TFP of tradables and non-tradables to 37% and 35% respectively over 1970-1992 and to 49% and 33% respectively over 1993-2017. In Fig. 9(a), we consider a shock to the international stock of knowledge $Z^W(t)$ which generates a 1% permanent increase in the world utilization-adjusted-TFP. In Fig. 9(b), we plot the endogenous responses of utilization-adjusted-TFP of tradables and non-tradables, i.e., $\text{TFPadj}^H(t) = Z^H(t) = (Z^H(t))^{\zeta^H \nu^H} (Z^W(t))^{(1-\zeta^H)\nu^H}$ and $\text{TFPadj}^N(t) = Z^N(t) = (Z^N(t))^{\zeta^N \nu^N} (Z^W(t))^{(1-\zeta^N)\nu^N}$, in the blue line and the red line, respectively. We find that a 1% permanent increase in $\text{TFPadj}^W(t)$ generates an increase in $Z^H(t)$ by 0.92 and 1.24 for tradables over 70-92 and 93-17, respectively, and an increase in $Z^N(t)$ by 0.004 for non-tradables over the two sub-periods. These findings suggest that the greater asymmetry of technology improvements between sectors is driven by the increasing exposition of tradable

Table 29: Elasticity of Utilization-Adjusted-TFP w.r.t. the Stock of R&D

	Z^H	Z^N	Z^W
	(1)	(2)	(3)
Z^H	0.1499 ^a (5.88)	n.a.	0.0777 ^a (4.71)
Z^N	n.a.	0.0007 ^b (1.66)	-0.002 ^b (-2.13)
Z^A			0.019 (0.42)

Notes: ^a, ^b and ^c denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. Denoting utilization-adjusted-TFP in sector j by Z_{it}^j is We run the regression of utilization adjusted TFP on the stock of R&D at constant prices in sector j in panel format on annual data:

$$\ln Z_{it}^j = \alpha_i + \alpha_t + \beta_{it} + \gamma^j \ln Z_t^j + \eta_{it},$$

where we include country fixed effects, time dummies, country-specific linear time trend and we estimate $\gamma^j = \nu^j \zeta^j$. Because ζ^j is the domestic component of country-level-utilization-adjusted-TFP we obtain from the principal component analysis, we can infer $\nu^j = \frac{\gamma^j}{\zeta^j}$. Since our estimates for 17 countries by adopting an ACP reveals that $\zeta^H = 0.631$ and $\zeta^N = 0.695$, and our FMOLS estimates show that $\gamma^H = 0.1499$ and $\gamma^N = 0.0007$, we can recover $\nu^H = 0.238$ and $\nu^N = 0.001$. In column 3, we construct the international stock of knowledge as a geometric weighted average of trade partners' aggregate stock of R&D at constant prices for country i , i.e., $Z_{it}^W = \prod_{k=1}^{12} (Z_{kt})^{\alpha_k^M}$ where α_k^M is the share of imports of home country i from the trade partner k . Sample: 13 OECD countries, 1970-2017, annual data.

industries to innovation from abroad together with the higher elasticity of technological change in traded industries w.r.t. the stock of intangible assets.

Second step. Once we have computed the elasticity of utilization-adjusted-TFP in sector j w.r.t. the world utilization-adjusted-TFP, we calculate the growth rate of $\text{TFPAdj}^j(t)$ predicted by the progression in the international stock of knowledge by using the 'real' (i.e., taken from the data) growth rate of the (import share) weighted averaged of utilization-adjusted TFP $Z^W(t)$ of all trade partners and multiply this growth rate by the numerically computed elasticity of $Z^j(t)$ w.r.t. $Z^W(t)$ which allows us to generate artificial time series for $\text{TFPAdj}^j(t)$ only driven by the change in $\text{TFPAdj}^W(t)$. We need now to decompose the share of the variance of aggregate technological change driven by asymmetric technology improvements into a country-specific- and a world-driven component.

We denote by $Z^{W,j}(t)$ the sectoral utilization-adjusted-TFP only driven by the progression in $Z^W(t)$. We need to quantify the share of the FEV of aggregate technological change driven by asymmetric technology improvements when asymmetric technological change is only driven by the increase in the international stock of knowledge conditional on the exposition of industries to the world stock of innovation. To conduct this analysis, we must use the fact that utilization-adjusted-TFP has a world (indexed by the superscript W) and a country-specific component (indexed by the superscript C), i.e., $\hat{Z}^j(t) = \hat{Z}^{W,j}(t) + \hat{Z}^{C,j}(t)$. The share of the FEV of aggregate technological change driven by asymmetric technology

improvements described by eq. (444) can be rewritten as follows:

$$\begin{aligned}
& \text{Share of asm. tech. change} \\
&= (\nu^{Y,H})^2 \frac{\text{Var} \left(\hat{Z}^H(t) - \hat{Z}^N(t) \right)}{\text{Var}' \left(\hat{Z}^A(t) \right)}, \\
&= (\nu^{Y,H})^2 \frac{\text{Var} \left[\left(\hat{Z}^{C,H}(t) - \hat{Z}^{C,N}(t) \right) + \left(\hat{Z}^{W,H}(t) - \hat{Z}^{W,N}(t) \right) \right]}{\text{Var}' \left(\hat{Z}^A(t) \right)}, \\
&= (\nu^{Y,H})^2 \frac{\text{Var}' \left(\hat{Z}^{C,H}(t) - \hat{Z}^{C,N}(t) \right)}{\text{Var}' \left(\hat{Z}^A(t) \right)} + (\nu^{Y,H})^2 \frac{\text{Var} \left(\hat{Z}^{W,H}(t) - \hat{Z}^{W,N}(t) \right)}{\text{Var}' \left(\hat{Z}^A(t) \right)}, \quad (445)
\end{aligned}$$

where Var' is the variance of asymmetric country-specific technological change adjusted with the covariance, i.e.,

$$\begin{aligned}
\text{Var}' \left(\hat{Z}^{C,H}(t) - \hat{Z}^{C,N}(t) \right) &= \text{Var} \left(\hat{Z}^{C,H}(t) - \hat{Z}^{C,N}(t) \right) \\
&\quad - 2\text{Cov} \left[\left(\hat{Z}^{C,H}(t) - \hat{Z}^{C,N}(t) \right), \left(\hat{Z}^{W,H}(t) - \hat{Z}^{W,N}(t) \right) \right] \quad (446)
\end{aligned}$$

By using the decomposition shown in (446), panel B of Table 27 shows the variance of asymmetric technological change caused by the international stock of ideas only, the variance of the growth rate of aggregate utilization-adjusted-TFP (adjusted with the covariance), the ratio of the former to the latter, and the contribution of asymmetric technological change caused by the international stock of knowledge to the variance of the growth rate of aggregate utilization-adjusted-TFP. The share of the variance of technological change driven by asymmetric technological change when shutting down the country-specific component has almost tripled, passing from 7.7% to 22.1%. More specifically, the international stock of ideas accounts for $7.7\%/18.7\% = 41\%$ of the variance of technological change attributed to asymmetric technological change over 1970-1992 and this contribution has increased to $22.1\%/38.9\% = 57\%$ over 1993-2017 due to the increased exposition of traded industries to the world stock of innovation.

S Skilled vs. Unskilled Labor: Model

This Appendix puts forward an open economy version of the neoclassical model with tradables and non-tradables, imperfect mobility of labor and capital across sectors, capital adjustment costs, endogenous terms of trade. This section illustrates in detail the steps we follow in solving this model. We assume that production functions take a CES form and we allow for factor-biased technological change. We also make the distinction between skilled and unskilled labor and allow for skill-biased technological change.

S.1 Households

At each instant of time, the representative household consumes traded and non-traded goods denoted by C^T and C^N , respectively, which are aggregated by means of a CES function:

$$C = \left[\varphi^{\frac{1}{\phi}} (C^T)^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}} (C^N)^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}, \quad (447)$$

where $0 < \varphi < 1$ is the weight of the traded good in the overall consumption bundle and ϕ corresponds to the elasticity of substitution between traded goods and non-traded goods. The index C^T is defined as a CES aggregator of home-produced traded goods, C^H , and foreign-produced traded goods, C^F :

$$C^T = \left[(\varphi^H)^{\frac{1}{\rho}} (C^H)^{\frac{\rho-1}{\rho}} + (1-\varphi_H)^{\frac{1}{\rho}} (C^F)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \quad (448)$$

where $0 < \varphi_H < 1$ is the weight of the home-produced traded good in the overall traded consumption bundle and ρ corresponds to the elasticity of substitution between home-produced traded goods and foreign-produced traded goods.

As in De Cordoba and Kehoe [2000], the investment good is produced using inputs of the traded good and the non-traded good according to a constant-returns-to-scale function which is assumed to take a CES form:

$$J^K = \left[\iota^{\frac{1}{\phi_J}} (J^T)^{\frac{\phi_J-1}{\phi_J}} + (1 - \iota)^{\frac{1}{\phi_J}} (J^N)^{\frac{\phi_J-1}{\phi_J}} \right]^{\frac{\phi_J}{\phi_J-1}}, \quad (449)$$

where ι is the weight of the investment traded input ($0 < \iota < 1$) and ϕ_J corresponds to the elasticity of substitution in investment between traded and non-traded inputs. The index J^T is defined as a CES aggregator of home-produced traded inputs, J^H , and foreign-produced traded inputs, J^F :

$$J^T = \left[(\iota_H)^{\frac{1}{\rho_J}} (J^H)^{\frac{\rho_J-1}{\rho_J}} + (1 - \iota_H)^{\frac{1}{\rho_J}} (J^F)^{\frac{\rho_J-1}{\rho_J}} \right]^{\frac{\rho_J}{\rho_J-1}}, \quad (450)$$

where $0 < \iota_H < 1$ is the weight of the home-produced traded in input in the overall traded investment bundle and ρ_J corresponds to the elasticity of substitution between home- and

We allow for imperfect mobility of capital across sectors by assuming that the capital stock in the traded and the non-traded sectors are aggregated by means of a CES function:

$$K = \left[\vartheta_K^{-1/\epsilon_K} (K^H)^{\frac{\epsilon_K+1}{\epsilon_K}} + (1 - \vartheta_K)^{-1/\epsilon_K} (K^N)^{\frac{\epsilon_K+1}{\epsilon_K}} \right]^{\frac{\epsilon_K}{\epsilon_K+1}}, \quad (451)$$

where $0 < \vartheta_K < 1$ is the weight of capital supply to the traded sector in the aggregate capital index $K(\cdot)$ and ϵ_K measures the ease with which tangible assets can be substituted for each other and thereby captures the degree of capital mobility across sectors.

The aggregate capital rental index $R^K(\cdot)$ associated with the above defined capital index (451) is:

$$R^K(t) = \left[\vartheta_K (R^H(t))^{\epsilon_K+1} + (1 - \vartheta_K) (R^N(t))^{\epsilon_K+1} \right]^{\frac{1}{\epsilon_K+1}}, \quad (452)$$

where $R^H(t)$ and $R^N(t)$ are capital rental rates paid in the traded and the non-traded sectors.

The representative agent is endowed with one unit of time, supplies a fraction $L(t)$ as labor, and consumes the remainder $1 - L(t)$ as leisure. At any instant of time, households derive utility from their consumption and experience disutility from working. The representative household maximizes the following objective function:

$$\mathcal{U} = \int_0^{\infty} \Lambda(C(t), L(t)) e^{-\beta t} dt, \quad (453)$$

where $\beta > 0$ is the discount rate. We allow for non-separability in consumption and leisure in preferences. The household's period utility function is increasing in his/her consumption C and decreasing in his/her labor supply L , with functional form (see Shimer [2009]):

$$\Lambda(C, L) \equiv \frac{C^{1-\sigma} V(L)^\sigma - 1}{1 - \sigma}, \quad \text{if } \sigma \neq 1, \quad V(L) \equiv \left(1 + (\sigma - 1) \zeta \frac{\sigma_L}{1 + \sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}} \right) \quad (454)$$

and

$$U(C, L) \equiv \log C - \zeta \frac{\sigma_L}{1 + \sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}}, \quad \text{if } \sigma = 1. \quad (455)$$

These preferences are characterized by two crucial parameters: σ_L is the Frisch elasticity of labor supply, and $\sigma > 0$ determines the substitutability between consumption and leisure; it is worthwhile noticing that if $\sigma > 1$, the marginal utility of consumption is increasing in hours worked. Importantly, such preferences imply that the Frisch elasticity of labor supply is constant.

Each household supplies skilled and unskilled labor denoted by $S(t)$ and $U(t)$, respectively. We keep the labor-supply side of our model simple and do not model flows between occupations in order to focus on the role of skills in driving both the labor reallocation and wage effects of technology shocks. We thus assume that the desutility from aggregate labor supply is split into the desutility from the supply of skilled labor and the supply of unskilled labor:

$$\zeta \frac{\sigma_L}{1 + \sigma_L} L^{\frac{1 + \sigma_L}{\sigma_L}} = \left[\zeta_S \frac{\sigma_L}{1 + \sigma_L} (S)^{\frac{\sigma_L + 1}{\sigma_L}} + \zeta_U \frac{\sigma_L}{1 + \sigma_L} (U)^{\frac{\sigma_L + 1}{\sigma_L}} \right], \quad (456)$$

where $0 < \zeta_s < 1$ ($s = S, U$) is the weight of skilled (unskilled) labor supply to the labor index $L(\cdot)$.

As shall be useful below, we write down the partial derivatives of (455):

$$\Lambda_C = C^{-\sigma} V(L)^\sigma, \quad (457a)$$

$$\Lambda_{CC} = -\sigma \frac{\Lambda_C}{C}, \quad (457b)$$

$$\Lambda_S = \frac{C^{1-\sigma} \sigma V_S V^{\sigma-1}}{1 - \sigma}, \quad (457c)$$

$$\Lambda_{SS} = \Lambda_S \left[\frac{V_{SS}}{V_S} + (\sigma - 1) \frac{V_S}{V} \right], \quad (457d)$$

$$\Lambda_U = \frac{C^{1-\sigma} \sigma V_U V^{\sigma-1}}{1 - \sigma}, \quad (457e)$$

$$\Lambda_{UU} = \Lambda_U \left[\frac{V_{UU}}{V_U} + (\sigma - 1) \frac{V_U}{V} \right], \quad (457f)$$

$$\Lambda_{CS} = \sigma C^{-\sigma} V_S V^{\sigma-1}, \quad (457g)$$

$$\Lambda_{CU} = \sigma C^{-\sigma} V_U V^{\sigma-1}, \quad (457h)$$

$$\Lambda_{SU} = \Lambda_S (\sigma - 1) \frac{V_U}{V}, \quad (457i)$$

where $\Lambda_C = \frac{\partial \Lambda}{\partial C}$. According to eq. (457g) and (457h), the marginal utility of consumption is increasing in labor supply as long as $\sigma > 1$, i.e., if consumption and leisure are gross substitutes. To get (457i), we have used the fact that $V_{SU} = 0$ which comes from our assumption that skills are immobile across occupations although they are mobile (to a certain extent) across sectors. To see it formally, we write out the partial derivatives of the desutility from labor supply:

$$V_S = (\sigma - 1) \zeta_S (S)^{\frac{1}{\sigma_L}}, \quad (458a)$$

$$V_{SS} = (\sigma - 1) \frac{\zeta_S}{\sigma_L} (S)^{\frac{1}{\sigma_L} - 1}, \quad (458b)$$

$$V_{SU} = 0, \quad (458c)$$

$$V_U = (\sigma - 1) \zeta_U (U)^{\frac{1}{\sigma_L}}, \quad (458d)$$

$$V_{UU} = (\sigma - 1) \frac{\zeta_U}{\sigma_L} (U)^{\frac{1}{\sigma_L} - 1}. \quad (458e)$$

Following Horvath [2000], we assume that hours worked in the traded and the non-traded sectors are aggregated by means of a CES function:

$$S(t) = \left[\vartheta_S^{-1/\epsilon_S} (S^H)^{\frac{\epsilon_S + 1}{\epsilon_S}} + (1 - \vartheta_S)^{-1/\epsilon_S} (S^N)^{\frac{\epsilon_S + 1}{\epsilon_S}} \right]^{\frac{\epsilon_S}{\epsilon_S + 1}}, \quad (459a)$$

$$U(t) = \left[\vartheta_U^{-1/\epsilon_U} (U^H)^{\frac{\epsilon_U + 1}{\epsilon_U}} + (1 - \vartheta_U)^{-1/\epsilon_U} (U^N)^{\frac{\epsilon_U + 1}{\epsilon_U}} \right]^{\frac{\epsilon_U}{\epsilon_U + 1}}, \quad (459b)$$

where $0 < \vartheta_s < 1$ (ϑ_U) is the weight of skilled (unskilled) labor supply to the traded sector in the skilled (unskilled) labor index $S(\cdot)$ ($U(\cdot)$) and ϵ_S (ϵ_U) measures the ease with which

skilled (unskilled) hours worked can be substituted for each other and thereby captures the degree of skilled (unskilled) labor mobility across sectors.

The aggregate wage index $W(\cdot)$ associated with the above defined labor index for skilled (459a) and unskilled (459b) labor supply is:

$$W^S(t) = \left[\vartheta_S (W^{S,H}(t))^{\epsilon_{S+1}} + (1 - \vartheta_S) (W^{S,N}(t))^{\epsilon_{S+1}} \right]^{\frac{1}{\epsilon_{S+1}}}, \quad (460a)$$

$$W^U(t) = \left[\vartheta_U (W^{U,H}(t))^{\epsilon_{U+1}} + (1 - \vartheta_U) (W^{U,N}(t))^{\epsilon_{U+1}} \right]^{\frac{1}{\epsilon_{U+1}}}, \quad (460b)$$

where $W^{S,H}(t)$ ($W^{U,H}(t)$) and $W^{S,N}(t)$ ($W^{U,N}(t)$) are wages paid in the traded and the non-traded sectors for skilled (unskilled) labor.

We assume that the households own the physical capital stock and choose the level of capital utilization $u^{K,j}(t)$. Households lease capital services (the product of utilization and physical capital) to firms in sector j at rental rate $R^j(t)$. Thus capital income received by households reads $\sum_j R^j(t)u^{K,j}(t)K^j(t)$. Households supply labor services to firms in sector j at a wage rate $W^j(t)$. Thus labor income received by households reads $\sum_j W^j(t)L^j(t)$. In addition, households accumulate internationally traded bonds, $N(t)$, that yield net interest rate earnings of $r^*N(t)$. Denoting lump-sum taxes by $T(t)$, households' flow budget constraint states that real disposable income can be saved by accumulating traded bonds, consumed, $P_C(t)C(t)$, invested in tangible assets, $P_J(t)J^K(t)$, and covers the capital utilization cost:

$$\begin{aligned} \dot{N}(t) = & r^*N(t) + [\alpha_K(t)u^{K,H}(t) + (1 - \alpha_K(t))u^{K,N}(t)] R^K(t)K(t) + W^S(t)S(t) + W^U(t)U(t) \\ & - T(t) - P_C(t)C(t) - P_J(t)J^K(t) - \sum_j P^j(t)C^{K,j}(t)\nu^{K,j}K(t) \end{aligned} \quad (461)$$

where we denote the capital return share of tradables by $\alpha_K = \frac{R^H K^H}{R^K K}$ and the share of sectoral capital in the aggregate capital stock by $\nu^{K,j}(t) = K^j(t)/K(t)$.

The role of the capital utilization rate is to mitigate the effect of a rise in the capital cost. We let the function $C^{K,j}(t)$ denote the adjustment costs associated with the choice of capital and technology utilization rates which are increasing and convex functions of utilization rates $u^{K,j}(t)$:

$$C^{K,j}(t) = \xi_1^j (u^{K,j}(t) - 1) + \frac{\xi_2^j}{2} (u^{K,j}(t) - 1)^2, \quad (462)$$

where $\xi_2^j > 0$ is a free parameter; as $\xi_2^j \rightarrow \infty$, utilization is fixed at unity; ξ_1^j must be restricted so that the optimality conditions are consistent with the normalization of steady state utilization of 1.

The accumulation of tangible assets is governed by the following law of motions:

$$\dot{K}(t) = I^K(t) - \delta_K K(t), \quad (463)$$

where I^K is investment and $0 \leq \delta_K < 1$ is a fixed depreciation rate. We assume that capital accumulation is subject to increasing and convex cost of net investment:

$$J^K(t) = I^K(t) + \Psi(I^K(t), K(t))K(t), \quad (464)$$

where $\Psi(\cdot)$ is increasing (i.e., $\Psi'(\cdot) > 0$), convex (i.e., $\Psi''(\cdot) > 0$), is equal to zero at δ_K (i.e., $\Psi(\delta_K) = 0$), and has first partial derivative equal to zero as well at δ_K (i.e., $\Psi'(\delta_K) = 0$). We suppose the following functional form for the adjustment cost function:

$$\Psi^K(I^K(t), K(t)) = \frac{\kappa}{2} \left(\frac{I^K(t)}{K(t)} - \delta_K \right)^2. \quad (465)$$

Using (458), partial derivatives of total investment expenditure are:

$$\frac{\partial J^K(t)}{\partial I^K(t)} = 1 + \kappa \left(\frac{I^K(t)}{K(t)} - \delta_K \right), \quad (466a)$$

$$\frac{\partial J^K(t)}{\partial K(t)} = -\frac{\kappa}{2} \left(\frac{I^K(t)}{K(t)} - \delta_K \right) \left(\frac{I^K(t)}{K(t)} + \delta_K \right). \quad (466b)$$

To solve the representative household's optimization problem, we set up current-value Hamiltonian:

$$\mathcal{H}^H(t) = \Lambda(C(t), S(t), U(t)) + \lambda(t)\dot{B}(t) + Q'_K \dot{K}(t), \quad (467)$$

where we denote the co-state variables associated with the flow budget constraint (461), investment in tangible assets (463) by λ , Q'_K , respectively,

The representative household chooses $C(t)$, $L(t)$, $J^K(t)$, $J^Z(t)$, $u^{K,j}(t)$, $u^{Z,j}(t)$, which are control variables, $B(t)$, $K(t)$, $Z^A(t)$, which are state variables. Denoting $Q_K(t) = Q'_K(t)/\lambda(t)$ and $Q_Z(t) = Q'_Z(t)/\lambda(t)$, the first-order conditions characterizing the representative household's optimal plans are:

$$\Lambda_C(t) = P_C(t)\lambda(t), \quad (468a)$$

$$-\Lambda_S(t) = \lambda(t)W^S(t), \quad (468b)$$

$$-\Lambda_U(t) = \lambda(t)W^U(t), \quad (468c)$$

$$Q_K(t) = P_J(t) \left[1 + \kappa \left(\frac{I^K(t)}{K(t)} - \delta_K \right) \right], \quad (468d)$$

$$R^H(t) = P^H(t) [\xi_1^H + \xi_2^H (u^{K,H}(t) - 1)], \quad (468e)$$

$$R^N(t) = P^N(t) [\xi_1^N + \xi_2^N (u^{K,N}(t) - 1)], \quad (468f)$$

$$\dot{\lambda}(t) = \lambda(\beta - r^*), \quad (468g)$$

$$\begin{aligned} \dot{Q}_K(t) = (r^* + \delta_K) Q_K(t) - \left\{ [\alpha_K(t)u^{K,H}(t) + (1 - \alpha_K(t))u^{K,N}(t)] R^K(t) \right. \\ \left. - P^H(t)C^{K,H}(t)\alpha_K(t) - P^N(t)C^{K,N}(t)(1 - \alpha_K(t)) - P_J(t)\frac{\partial J^K(t)}{\partial K(t)} \right\}, \end{aligned} \quad (468h)$$

and the transversality conditions $\lim_{t \rightarrow \infty} \bar{\lambda}B(t)e^{-\beta t} = 0$, $\lim_{t \rightarrow \infty} Q_K(t)K(t)e^{-\beta t} = 0$. We used the fact that $\dot{Q}_K(t) = \frac{\dot{Q}'_K(t)}{\lambda(t)} - \frac{\dot{\lambda}(t)Q'_K(t)}{\lambda(t)^2}$.

Given the above consumption indices, we can derive appropriate price indices. With respect to the general consumption index, we obtain the consumption-based price index P_C :

$$P_C = \left[\varphi (P^T)^{1-\phi} + (1 - \varphi) (P^N)^{1-\phi} \right]^{\frac{1}{1-\phi}}, \quad (469)$$

where the price index for traded goods is:

$$P^T = \left[\varphi_H (P^H)^{1-\rho} + (1 - \varphi_H) \right]^{\frac{1}{1-\rho}}. \quad (470)$$

Given the consumption-based price index (469), the representative household has the following demand of traded and non-traded goods:

$$C^T = \varphi \left(\frac{P^T}{P_C} \right)^{-\phi} C, \quad (471a)$$

$$C^N = (1 - \varphi) \left(\frac{P^N}{P_C} \right)^{-\phi} C. \quad (471b)$$

Given the price indices (469) and (470), the representative household has the following demand of home-produced traded goods and foreign-produced traded goods:

$$C^H = \varphi \left(\frac{P^T}{P_C} \right)^{-\phi} \varphi_H \left(\frac{P^H}{P^T} \right)^{-\rho} C, \quad (472a)$$

$$C^F = \varphi \left(\frac{P^T}{P_C} \right)^{-\phi} (1 - \varphi_H) \left(\frac{1}{P^T} \right)^{-\rho} C. \quad (472b)$$

As will be useful later, the percentage change in the consumption price index is a weighted average of percentage changes in the price of traded and non-traded goods in terms of foreign goods:

$$\hat{P}_C = \alpha_C \hat{P}^T + (1 - \alpha_C) \hat{P}^N, \quad (473a)$$

$$\hat{P}^T = \alpha_H \hat{P}^H, \quad (473b)$$

where α_C is the tradable content of overall consumption expenditure and α^H is the home-produced goods content of consumption expenditure on traded goods:

$$\alpha_C = \varphi \left(\frac{P^T}{P_C} \right)^{1-\phi}, \quad (474a)$$

$$1 - \alpha_C = (1 - \varphi) \left(\frac{P^N}{P_C} \right)^{1-\phi}, \quad (474b)$$

$$\alpha^H = \varphi_H \left(\frac{P^H}{P^T} \right)^{1-\rho}, \quad (474c)$$

$$1 - \alpha^H = (1 - \varphi_H) \left(\frac{1}{P^T} \right)^{1-\rho}. \quad (474d)$$

Given the CES aggregator functions above, we can derive the appropriate price indices for investment. With respect to the general investment index, we obtain the investment-based price index P_J :

$$P_J = \left[\iota (P_J^T)^{1-\phi_J} + (1 - \iota) (P^N)^{1-\phi_J} \right]^{\frac{1}{1-\phi_J}}, \quad (475)$$

where the price index for traded goods is:

$$P_J^T = \left[\iota^H (P^H)^{1-\rho_J} + (1 - \iota^H) \right]^{\frac{1}{1-\rho_J}}. \quad (476)$$

Given the physical investment-based price index (475), we can derive the demand for inputs of the traded good and the non-traded good:

$$J^T = \iota \left(\frac{P_J^T}{P_J} \right)^{-\phi_J} J, \quad (477a)$$

$$J^N = (1 - \iota) \left(\frac{P^N}{P_J} \right)^{-\phi_J} J. \quad (477b)$$

Given the price indices (475) and (476), we can derive the demand for inputs of home-produced traded goods and foreign-produced traded goods:

$$J^H = \iota \left(\frac{P_J^T}{P_J} \right)^{-\phi_J} \iota^H \left(\frac{P^H}{P^T} \right)^{-\rho_J} J, \quad (478a)$$

$$J^F = \iota \left(\frac{P_J^T}{P_J} \right)^{-\phi_J} (1 - \iota^H) \left(\frac{1}{P^T} \right)^{-\rho_J} J. \quad (478b)$$

As will be useful later, the percentage change in the investment price index is a weighted average of percentage changes in the price of traded and non-traded inputs in terms of foreign inputs:

$$\hat{P}_J = \alpha_J \hat{P}_J^T + (1 - \alpha_J) \hat{P}^N, \quad (479a)$$

$$\hat{P}_J^T = \alpha_J^H \hat{P}^H, \quad (479b)$$

where α_J is the tradable content of overall investment expenditure and α_J^H is the home-produced goods content of investment expenditure on traded goods:

$$\alpha_J = \iota \left(\frac{P_J^T}{P_J} \right)^{1-\phi_J}, \quad (480a)$$

$$1 - \alpha_J = (1 - \iota) \left(\frac{P^N}{P_J} \right)^{1-\phi_J}, \quad (480b)$$

$$\alpha_J^H = \iota^H \left(\frac{P^H}{P^T} \right)^{1-\rho_J}, \quad (480c)$$

$$1 - \alpha_J^H = (1 - \iota^H) \left(\frac{1}{P^T} \right)^{1-\rho_J}. \quad (480d)$$

Given the aggregate wage index for skilled labor (460a) and unskilled labor (460b), we can derive the allocation of labor supply to the traded and the non-traded sector for each type of skill:

$$S^H(t) = \vartheta_S \left(\frac{W^{S,H}(t)}{W^S(t)} \right)^{\epsilon_S} S(t), \quad S^N(t) = (1 - \vartheta_S) \left(\frac{W^{S,N}(t)}{W^S(t)} \right)^{\epsilon_S} S(t). \quad (481a)$$

$$U^H(t) = \vartheta_U \left(\frac{W^{U,H}(t)}{W^U(t)} \right)^{\epsilon_U} U(t), \quad S^N(t) = (1 - \vartheta_U) \left(\frac{W^{U,N}(t)}{W^U(t)} \right)^{\epsilon_U} U(t). \quad (481b)$$

Aggregating labor compensation across sectors and skills leads to:

$$W^{S,H} S^H + W^{S,N} S^N = W^S S, \quad (482a)$$

$$W^{U,H} U^H + W^{U,N} U^N = W^U U, \quad (482b)$$

$$W^S S + W^U U = WL, \quad (482c)$$

where W is the aggregate wage and L is aggregate labor supply.

As will be useful later, log-linearizing the wage index in the neighborhood of the initial steady-state leads to:

$$\hat{W}^S(t) = \alpha_S^H \hat{W}^{S,H}(t) + (1 - \alpha_S^H) \hat{W}^{S,N}(t), \quad (483a)$$

$$\hat{W}^U(t) = \alpha_U^H \hat{W}^{U,H}(t) + (1 - \alpha_U^H) \hat{W}^{U,N}(t), \quad (483b)$$

where $\alpha_S^H = \frac{W^{S,H} S^H}{W^S S}$ and $\alpha_U^H = \frac{W^{U,H} U^H}{W^U U}$ tradable content of aggregate labor compensation:

$$\alpha_S^H = \vartheta_S \left(\frac{W^{S,H}}{W^S} \right)^{1+\epsilon_S}, \quad 1 - \alpha_S^H = (1 - \vartheta_S) \left(\frac{W^{S,N}}{W^S} \right)^{1+\epsilon_S}, \quad (484a)$$

$$\alpha_U^H = \vartheta_U \left(\frac{W^{U,H}}{W^U} \right)^{1+\epsilon_U}, \quad 1 - \alpha_U^H = (1 - \vartheta_U) \left(\frac{W^{U,N}}{W^U} \right)^{1+\epsilon_U}, \quad (484b)$$

Given the aggregate capital rental index, we can derive the allocation of aggregate capital supply to the traded and the non-traded sector:

$$K^H = \vartheta_K \left(\frac{R^H}{R^K} \right)^{\epsilon_K} K, \quad K^N = (1 - \vartheta_K) \left(\frac{R^N}{R^K} \right)^{\epsilon_K} K, \quad (485)$$

where the elasticity of capital supply across sectors ϵ captures the degree of capital mobility. As will be useful later, log-linearizing the capital rental index in the neighborhood of the initial steady-state leads to:

$$\hat{R}^K(t) = \alpha_K \hat{R}^H(t) + (1 - \alpha_K) \hat{R}^N(t), \quad (486)$$

where $\alpha_K = \frac{R^H K^H}{R^K K}$ is the tradable content of aggregate capital return which reads as follows:

$$\alpha_K = \vartheta_K \left(\frac{R^H}{R^K} \right)^{1+\epsilon_K}, \quad 1 - \alpha_K = (1 - \vartheta_K) \left(\frac{R^N}{R^K} \right)^{1+\epsilon_K}. \quad (487)$$

S.2 Firms

Each sector consists of a large number of identical firms which use labor, L^j , and physical capital (inclusive of capital utilization), \tilde{K}^j , according to a technology described by a CES production function:

$$Y^j(t) = \left[\gamma^j (A^j(t) L^j(t))^{\frac{\sigma^j-1}{\sigma^j}} + (1 - \gamma^j) (B^j(t) \tilde{K}^j(t))^{\frac{\sigma^j-1}{\sigma^j}} \right]^{\frac{\sigma^j}{\sigma^j-1}}, \quad (488)$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, and $A^j(t)$ and $B^j(t)$ are labor- and capital-augmenting efficiency.

We assume that efficient labor is a CES aggregator of skilled and unskilled labor:

$$A^j L^j(t) = \left[\gamma_L^j \left(A_S^j(t) S^j(t) \right)^{\frac{\sigma_L^j - 1}{\sigma_L^j}} + \left(1 - \gamma_L^j \right) \left(A_U^j(t) U^j(t) \right)^{\frac{\sigma_L^j - 1}{\sigma_L^j}} \right]^{\frac{\sigma_L^j}{\sigma_L^j - 1}}, \quad (489)$$

where $0 < \gamma_L^j < 1$ is the weight of skilled labor in the efficient labor index, σ_L^j is the elasticity of substitution between skilled and unskilled labor in sector $j = H, N$, and $A_S^j(t)$ and $A_U^j(t)$ are skilled labor- and unskilled labor-augmenting efficiency. While capital-augmenting productivity has a symmetric and an asymmetric component across sectors, see eq. (15), both skilled- and unskilled-labor augmenting productivity are made up of a symmetric component across sectors denoted by the subscript S and an asymmetric component denoted by the subscript D :

$$A^{S,j}(t) = \left(A_S^{S,j}(t) \right)^\eta \left(A_D^{S,j}(t) \right)^{1-\eta}, \quad A^{U,j}(t) = \left(A_S^{U,j}(t) \right)^\eta \left(A_D^{U,j}(t) \right)^{1-\eta}, \quad (490)$$

where η is assumed to be symmetric across sectors.

Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given:

$$\max_{S^j, U^j, \tilde{K}^j} \Pi^j = \max_{S^j, U^j, \tilde{K}^j} \left\{ P^j Y^j - W^{S,j} S^j - W^{U,j} U^j - R^j \tilde{K}^j \right\}. \quad (491)$$

Since skilled, unskilled and capital cannot move freely between the two sectors, the value of marginal revenue products in the traded and non-traded sectors do not equalize while costly labor and capital mobility implies a wage and a capital rental rate differential across sectors. The demand for skilled and unskilled labor together with the demand for capital by traded firms are described by:

$$\begin{aligned} P^H \frac{\partial Y^H}{\partial L^H} \frac{\partial L^H}{\partial S^H} &= \gamma^H (A^H)^{\frac{\sigma^H - 1}{\sigma^H}} (L^H)^{-\frac{1}{\sigma^H}} (Y^H)^{\frac{1}{\sigma^H}} \gamma_S^H \left(\frac{A_S^H}{A^H} \right)^{\frac{\sigma_L^H - 1}{\sigma_L^H}} (S^H)^{-\frac{1}{\sigma_L^H}} (L^H)^{\frac{1}{\sigma_L^H}} \\ &= W^{S,H}, \end{aligned} \quad (492a)$$

$$\begin{aligned} P^H \frac{\partial Y^H}{\partial L^H} \frac{\partial L^H}{\partial U^H} &= \gamma^H (A^H)^{\frac{\sigma^H - 1}{\sigma^H}} (L^H)^{-\frac{1}{\sigma^H}} (Y^H)^{\frac{1}{\sigma^H}} (1 - \gamma_S^H) \left(\frac{A_U^H}{A^H} \right)^{\frac{\sigma_L^H - 1}{\sigma_L^H}} (U^H)^{-\frac{1}{\sigma_L^H}} (L^H)^{\frac{1}{\sigma_L^H}} \\ &= W^{U,H}, \end{aligned} \quad (492b)$$

$$P^H \frac{\partial Y^H}{\partial \tilde{K}^H} = P^H (1 - \gamma^H) (B^H)^{\frac{\sigma^H - 1}{\sigma^H}} \left(\tilde{K}^H \right)^{-\frac{1}{\sigma^H}} (Y^H)^{\frac{1}{\sigma^H}} = R^H. \quad (492c)$$

The demand for skilled and unskilled labor together with the demand for capital by traded firms are described by:

$$\begin{aligned} P^N \frac{\partial Y^N}{\partial L^N} \frac{\partial L^N}{\partial S^N} &= \gamma^N (A^N)^{\frac{\sigma^N - 1}{\sigma^N}} (L^N)^{-\frac{1}{\sigma^N}} (Y^N)^{\frac{1}{\sigma^N}} \gamma_S^N \left(\frac{A_S^N}{A^N} \right)^{\frac{\sigma_L^N - 1}{\sigma_L^N}} (S^N)^{-\frac{1}{\sigma_L^N}} (L^N)^{\frac{1}{\sigma_L^N}} \\ &= W^{S,N}, \end{aligned} \quad (493a)$$

$$\begin{aligned} P^N \frac{\partial Y^N}{\partial L^N} \frac{\partial L^N}{\partial U^N} &= \gamma^N (A^N)^{\frac{\sigma^N - 1}{\sigma^N}} (L^N)^{-\frac{1}{\sigma^N}} (Y^N)^{\frac{1}{\sigma^N}} (1 - \gamma_S^N) \left(\frac{A_U^N}{A^N} \right)^{\frac{\sigma_L^N - 1}{\sigma_L^N}} (U^N)^{-\frac{1}{\sigma_L^N}} (L^N)^{\frac{1}{\sigma_L^N}} \\ &= W^{U,N}, \end{aligned} \quad (493b)$$

$$P^N \frac{\partial Y^N}{\partial \tilde{K}^N} = P^N (1 - \gamma^N) (B^N)^{\frac{\sigma^N - 1}{\sigma^N}} \left(\tilde{K}^N \right)^{-\frac{1}{\sigma^N}} (Y^N)^{\frac{1}{\sigma^N}} = R^N. \quad (493c)$$

Pre-multiplying the equality between the marginal revenue product of skilled labor by S^j/L^j , i.e., $P^j \frac{\partial Y^j}{\partial L^j} \frac{\partial L^j}{\partial S^j} \frac{S^j}{L^j} = \frac{W^{S,j} S^j}{L^j}$ and using the fact that $P^j \frac{\partial Y^j}{\partial L^j} = W^j$, leads to the

equality between the elasticity of labor w.r.t. skilled labor and the skilled labor income share denoted by s_S^j . Applying the same logic to unskilled labor leads to:

$$\frac{\partial L^j S^j}{\partial S^j L^j} = \frac{W^{S,j} S^j}{W^j L^j} \equiv s_S^j, \quad (494a)$$

$$\frac{\partial L^j S^j}{\partial U^j L^j} = \frac{W^{U,j} U^j}{W^j L^j} \equiv s_U^j = 1 - s_S^j. \quad (494b)$$

Dividing the skilled labor income share by the unskilled labor income share and using (492a)-(492b) leads to a relationship between the skilled labor income share s_S^j and skilled-biased technological change:

$$\frac{s_S^j}{1 - s_S^j} = \frac{\gamma_S^j}{1 - \gamma_S^j} \left(\frac{A_S^j}{A_U^j} \right)^{\frac{\sigma_L^j - 1}{\sigma_L^j}} \left(\frac{S^j}{U^j} \right)^{\frac{\sigma_L^j - 1}{\sigma_L^j}} \quad (495)$$

We can recover the dynamics $\frac{A_S^j}{A_U^j}$ by using the dynamic responses of s_S^j and $\frac{S^j}{U^j}$.

S.3 Skill-Biased Technological Change (SBTC) and Elasticity of Substitution between Skilled and Unskilled Labor

Costly labor and capital mobility implies a labor and capital cost differential across sectors:

$$\frac{(1 - s_L^j(t)) P^j(t) Y^j(t)}{\tilde{K}^j(t)} = R^j(t), \quad (496a)$$

$$\frac{s_L^j(t) s_S^j(t) P^j(t) Y^j(t)}{S^j(t)} = W^{S,j}(t), \quad (496b)$$

$$\frac{s_L^j(t) (1 - s_S^j(t)) P^j(t) Y^j(t)}{U^j(t)} = W^{U,j}(t), \quad (496c)$$

where $s_S^j(t)$ is the share of skilled labor in labor compensation in sector $j = H, N$, i.e.,

$$s_S^j(t) = \frac{W^{S,j}(t) S^j(t)}{W^j(t) L^j(t)} = \gamma_S^j \left(\frac{A^{S,j}(t) S^j(t)}{A^j(t) L^j(t)} \right)^{\frac{\sigma_L^j - 1}{\sigma_L^j}}. \quad (497)$$

Dividing the demand for skilled labor by the demand for unskilled labor, inserting (497), and denoting the ratio of skilled to unskilled labor income share by $S_S^j(t) \equiv \frac{s_S^j(t)}{1 - s_S^j(t)}$, leads to:

$$S_S^j(t) \equiv \frac{s_S^j(t)}{1 - s_S^j(t)} = \frac{\gamma_S^j}{1 - \gamma_S^j} (\text{SBTC}^j)^{-1} \left(\frac{S^j(t)}{U^j(t)} \right)^{-\frac{1 - \sigma_L^j}{\sigma_L^j}}, \quad (498)$$

where $\text{SBTC}^j(t) = \left(\frac{A^{S,j}(t)}{A^{U,j}(t)} \right)^{\frac{1 - \sigma_L^j}{\sigma_L^j}}$ is skill-biased technological change (SBTC henceforth). We assume imperfect substitution between skill types and one important question is whether skilled and unskilled labor are substitutes or complements. If $\sigma_L^j > 1$, an increase in skilled-relative to unskilled-labor-augmenting productivity increases the demand for skilled labor. When $S^j(t)$ and $U^j(t)$ are gross complements (i.e., if $\sigma_L^j < 1$), higher productivity of skilled workers relative to unskilled workers lowers the demand for skilled labor.

A large span of the literature, see e.g., Acemoglu [2002], Caselli and Coleman [2006], Jones [2014], assume that skilled and unskilled workers as gross substitutes and choose an elasticity of substitution of 1.5. In contrast, the meta analysis by Bazcik et al. [2020] questions the common view that the elasticity exceeds 1. After correcting for the biases, the literature is consistent with an elasticity in the US of 0.6-0.9. When we estimate the elasticity of substitution between skilled and unskilled labor over 1970-2017 for eleven

OECD countries of our sample by using cointegration techniques and sectoral data, our evidence corroborates the findings by Bazcik et al. [2020] as we estimate empirically an elasticity of $\sigma_L^H = 0.77$ for the traded sector and an elasticity of $\sigma_L^N = 0.69$ for the non-traded sector. When we run estimates for one country at a time estimated values display some cross-country dispersion. For example, for the United States, we find a value of $\sigma_L^H = 1.11$ and $\sigma_L^N = 0.91$ which suggests that skilled and unskilled labor are gross substitutes in the traded sector and gross complements in the non-traded sector. In accordance with our estimates, we will assume that skilled and unskilled labor are gross complements. As skilled relative to unskilled labor-augmenting productivity increases (i.e., as $A^{S,j}(t)/A^{U,j}(t)$ rises), the demand for unskilled labor increases when $\sigma_L^j < 1$ which in turn lowers the share of the skilled labor income share in sector j in line with our evidence.

S.4 Technology Frontier

While we keep assuming that firms within each sector $j = H, N$ decide about the split of capital-utilization-adjusted-TFP $Z^j(t)$ between labor- and capital-augmenting efficiency, we assume that firms choose a mix of skilled- and unskilled-labor-augmenting productivity $A^{S,j}(t)$ and $A^{U,j}(t)$ along a technology frontier (which is assumed to take a CES form):

$$\left[\gamma_Z^{S,j} (A^{S,j}(t))^{\frac{\sigma_Z^{L,j}-1}{\sigma_Z^{L,j}}} + (1 - \gamma_Z^{S,j}) (A^{U,j}(t))^{\frac{\sigma_Z^{L,j}-1}{\sigma_Z^{L,j}}} \right]^{\frac{\sigma_Z^j}{\sigma_Z^{L,j}-1}} \leq A^j(t). \quad (499)$$

where $A^j(t) > 0$ is the height of the technology frontier, $0 < \gamma_Z^{S,j} < 1$ is the weight of skilled labor efficiency in labor-augmenting efficiency and $\sigma_Z^{L,j} > 0$ corresponds to the elasticity of substitution between skilled labor- and unskilled labor-augmenting productivity. The unit cost minimization requires that

$$s_S^j = \gamma_Z^{S,j} \left(\frac{A^{S,j}(t)}{A^j(t)} \right)^{\frac{\sigma_Z^{L,j}-1}{\sigma_Z^{L,j}}}. \quad (500)$$

Inserting this equality into the log-linearized version of the technology frontier shows that labor-augmenting technological change is driven by variations in skilled labor- and unskilled-labor-augmenting technological change (weighted by their contribution to the decline in the unit cost for labor in sector j):

$$\hat{A}^j(t) = s_S^j \hat{A}^{S,j}(t) + (1 - s_S^j) \hat{A}^{U,j}(t). \quad (501)$$

S.5 Calibration

The calibration procedure is identical to that described in sections 4.1-4.2 except that we have to choose values for both production and preference parameters related to workers' skills. Because data for skilled and unskilled labor at a sectoral level are available for eleven countries only over a long enough time length, we calibrate the model to the data by estimating parameters such as ϵ and ϕ and computing ratios for this group of countries only.

Production parameters. Since we choose the initial steady-state in a model with Cobb-Douglas production functions as the normalization point, we set both σ^j and σ_L^j to one. Building on our estimates, the labor income share for the traded and non-traded sectors are set to $s_L^H = 0.636$ and $s_L^N = 0.682$ and for the skilled labor income share to $s_S^H = 0.636$ and $s_S^N = 0.699$.

Preference parameters. We keep assuming $\sigma = 2$ and $\sigma_L = 3$ and choose a value for ζ_S so as to target a ratio of skilled to unskilled labor of $S/L = 56\%$. To pin down the degree of labor mobility of skilled (unskilled) labor across sectors, i.e., ϵ_S (ϵ_U), we run the regression in panel format on annual data of the percentage change in the skilled (unskilled) hours worked share of sector j on the percentage change in the relative share of value added paid to skilled ((unskilled) workers in sector j). In accordance with the evidence documented by

Kambourov and Manovskii [2009] which reveals that industry (and occupational) mobility declines with education, our empirical findings reveal that the elasticity of labor supply across sectors is twice larger for unskilled than skilled workers. More specifically, we set $\epsilon_S = 0.63$ and $\epsilon_U = 1.13$, in line with our panel data estimates. We choose values for ϑ_S and ϑ_U so as to target a weight of skilled and unskilled labor supply of $S^N/S = 69\%$ and $U^N/U = 59\%$, respectively. Note that for the eleven countries of our sample, we set $\epsilon_K = 0.18$ and choose ϑ_K so as to target $K^H/K = 38\%$.

We estimate a value for the elasticity of substitution ϕ between traded and non-traded goods of 0.19 and choose a value for φ so as to target a non-tradable of consumption expenditure $1 - \alpha_C = 58\%$. Keeping assuming $\phi_J = 1$, we choose $1 - \alpha_J = 68\%$. We choose φ^H and ι^H so as to target $\alpha^H = 66\%$ and $\alpha_J^H = 43\%$. Using the fact that $\omega_J = 23\%$, $\omega_C = 57\%$ and $\omega_G = 20\%$, the demand components for home-produced traded goods gives a value added share of tradables $P^H Y^H/Y$ of 35% in line with our estimates.

CES economy. In line with our panel data estimates, we choose for the elasticity of substitution between capital and labor $\sigma^H = 0.86$ and $\sigma^N = 0.83$ and for the elasticity of substitution between skilled and unskilled labor $\sigma_L^H = 0.77$ and $\sigma_L^N = 0.69$.

Factor-augmenting efficiency. We assume that factor-augmenting productivity is made up of a symmetric component across sectors denoted by the subscript S and an asymmetric component denoted by the subscript D . To recover the dynamics of $B^j(t)$ and $A^j(t)$, and the dynamics of $A^{S,j}(t)$ and $A^{U,j}(t)$, we proceed as in section 4.2. Because the equations are identical for $B^j(t)$ and $A^j(t)$ (see eq.s (47a)-(47b)), we focus on labor-augmenting efficiency across workers' skills. Log-linearizing the demand for skilled labor relative to the demand for unskilled labor (495), this equation together with the log-linearized versions of the technology frontier (501) can be solved for deviations of $A_c^{S,j}(t)$ and $A_c^{U,j}(t)$ relative to their initial steady-state values:

$$\hat{A}_c^{S,j}(t) = \hat{A}^j(t) - \left(1 - s_S^j\right) \left[\left(\frac{\sigma_L^j}{1 - \sigma_L^j} \right) \hat{S}_S^j(t) - \left(\hat{S}^j(t) - \hat{U}^j(t) \right) \right], \quad c = S, D \quad (502a)$$

$$\hat{A}_c^{U,j}(t) = \hat{A}^j(t) + s_S^j \left[\left(\frac{\sigma_L^j}{1 - \sigma_L^j} \right) \hat{S}_S^j(t) - \left(\hat{S}^j(t) - \hat{U}^j(t) \right) \right], \quad c = S, D. \quad (502b)$$

Plugging estimated values for σ_L^j and empirically estimated responses for $s_S^j(t)$, $S^j(t)/U^j(t)$, following a symmetric (asymmetric) technology shock across sectors into above equations enables us to recover the dynamics for $A_S^{S,j}(t)$ ($A_D^{S,j}(t)$) and $A_S^{U,j}(t)$ ($A_D^{U,j}(t)$) consistent with the demand for factors of production (498) and the technology frontier (501).

Share of symmetric technology shocks across sectors. By using the fact that technology improvements are a weighted average of symmetric and asymmetric technology shocks, we find that a value of $\eta = 80\%$ minimizes the discrepancy between the empirical response of $Z^A(t)$ following a permanent technology improvement and its response computed from $\hat{Z}^A(t) = \eta \hat{Z}_S^A(t) + (1 - \eta) \hat{Z}_D^A(t)$. Note that the capital utilization rates are found to quite muted after a technology improvement for the eleven countries of our sample, we let $\xi_{2,S}^j$, $\xi_{2,D}^j$ tend toward infinity.

S.6 Taking the Model to the Data

Labor composition effects across workers' skills. In Fig. 31, we contrast the dynamics effects of a 1% permanent technology improvement we estimate empirically (shown in the solid blue line) with the responses we compute numerically in the baseline model (shown in black line with squares). To give a sense of the role of FBTC and SBTC in driving the effects of a permanent technology improvement, we also consider a restricted version of our model shown in dashed red lines which imposes Cobb-Douglas production functions to produce sectoral goods and to aggregate both types of labor so that both FBTC and SBTC are shut down.

A permanent increase in utilization-adjusted-aggregate-TFP shown in Fig. 31(a) leads agents to work less as displayed by Fig. 31(b). Quantitatively, hours worked decline by 0.45% on impact and such a dramatic decline is caused by the importance of symmetric

technology shocks which account for 80% of technology improvements. Intuitively, when technological change is evenly spread across sectors, higher productivity puts downward pressure on sectoral prices which curbs the increase in sectoral wages. Because the substitution effect is small, the wealth effect lowers significantly hours worked. Fig. 31(c) shows that the skilled labor share of labor income $\alpha_S(t) = s_S^H(t)\alpha_L(t) + s_S^N(t)(1 - \alpha_L(t))$ decreases over time which reflects the fact that most of the decline is driven by the fall in skilled labor. In contrast, as shown in the dashed red lines, a model abstracting from SBTC predicts a flat skilled labor income share. As displayed by Fig. 31(d), the restricted model tends to understate the fall in skilled labor. In contrast, a model with SBTC reproduces well the adjustment in skilled labor, in particular the dynamics for skilled hours worked in the traded sector, as can be seen in Fig. 31(e). The reason behind the decline in the skilled labor income share is the gradual decrease in the skilled labor income shares in both the traded and the non-traded sector. As shown in the dashed red lines in Fig. 31(g) and Fig. 31(h), only the baseline model assuming SBTC can generate a decrease in the intensity of production of both sectors in skilled labor.

Fig. 31(i) reveals that skilled labor shifts away from traded industries and the cause of this movement is twofold. First, because the decrease in s_S^H is more pronounced in the traded than in the non-traded sector, the demand for skilled labor declines more rapidly in the traded than in the non-traded sector. Second, the decrease in the skilled labor income share amplifies the fall in $S^H(t)/L(t)$. While the tradable content of unskilled labor income, $\alpha_U^H(t)$ is quite muted, the tradable content of skilled labor income, $\alpha_S^H(t)$, experiences a pronounced decline that our model reproduces reasonably well. And therefore, the reallocation of labor toward the non-traded sector shown in Fig. 31(j) is mostly driven by the shift of skilled labor away from traded industries and toward the non-traded sector. As shown in Fig. 31(o), to compensate for the labor mobility costs, non-traded industries pay higher wages relative to the traded sector. The reallocation of labor is driven by the productivity growth differential between tradables and non-tradables which leads to an appreciation in the relative price of non-tradables, as displayed by Fig. 31(m).

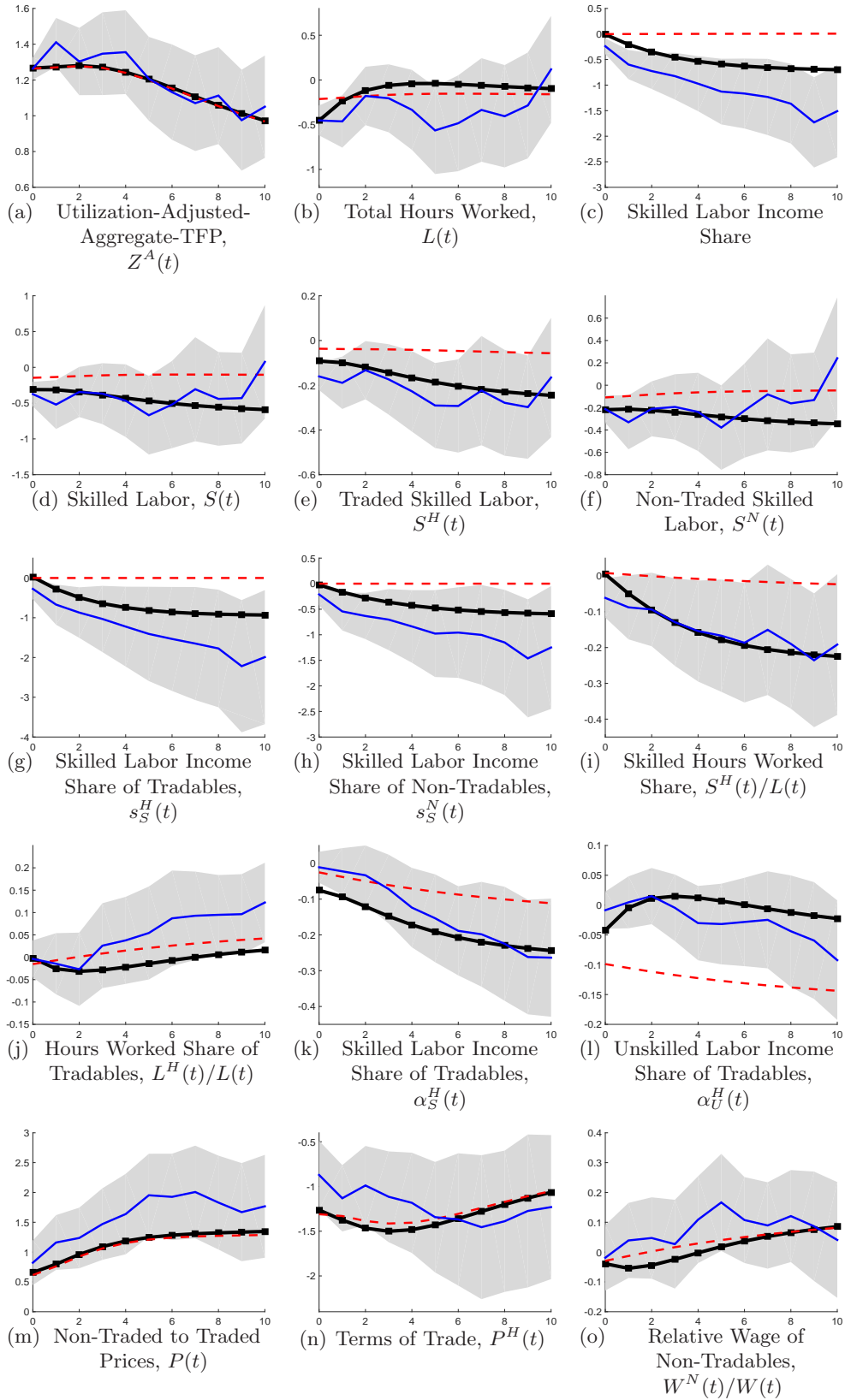


Figure 31: Theoretical vs. Empirical Responses Following a Technology Shock: Labor Composition Effects across Workers' Skills. **Notes:** The solid blue line which displays point estimate from local projections with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario with FBTC and SBTC, while the dashed red line shows predictions of a model with Cobb-Douglas production functions (which amount to shutting down FBTC and SBTC). In line with the evidence for the eleven countries of our sample, we let $\xi_{2,S}^j, \xi_{2,D}^j$ tend toward infinity so that the capital utilization rates are muted in both sectors.

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