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Political Relations and Trade: New Evidence from Australia, China and the United States[1]

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Abstract

This paper employs structural vector autoregression and local projection methods to examine the impacts of the deterioration in US-China political relations on bilateral trade between Australia and China. Three scenarios are considered to reflect the evolution of US geopolitical strategies in recent years such as "America First", "China Threat Theory" and "The Protection of US Allies". The simulation results illustrate that worsening US-China political relations has a negative impact on Australian exports to and imports from China. It is also found that economic conditions in the US play a more important role in the transmission of this impact than those in China and Australia. In addition, various options are explored to check the robustness of the findings in this paper.

Keywords: Structural vector autoregression, Local projection, Impulse response; US-China political relations; Australia-China trade

JEL Codes: C32, F14, F51

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1. Introduction

The link between political relations and trade has been widely investigated. Earlier studies show that bilateral trade declines as a result of military conflicts (Morrow et al., 1998; Long, 2008; Hegre et al., 2010), disputes over territories (Simmons, 2005) and conflicting political objectives (Pollins, 1989a, b). Although many studies discussed the negative impacts of worsening political relations on trade between two countries, very few investigated the spillovers of a worsening relationship on third-country trade. After World War II, the US became a leading economy, military superpower, and technological innovator. However, China is a rising power with rapid economic growth, especially after joining the World Trade Organisation in 2001. Due to differences in their economic structure, political system, and common values, there are many ongoing disputes between the United States and China.

In recent decades, political relations between the United States and China began with the so-called 'secret trip' by Henry Kissinger in 1971 which broke political ice and paved the way for diplomatic relations. Thereafter, some key events put an abrupt end to the détente, including the US bombing of the Chinese embassy in Belgrade in 1999. The following years witnessed ups and downs in the Sino-US relations. Since former president Donald Trump came to power in 2017, the United States and China have been experiencing the worst diplomatic relations in recent decades. In March 2018, Trump announced massive tariffs on Chinese imports such as clothing, shoes and electronics, which is commonly viewed as the start of a US-China trade war. In addition to these, there are confrontations in other fields such as human rights, technology, and intellectual property, China being labelled a currency manipulator by the US and China's new national security law on Hong Kong's judicial independence. Existing studies such as Du et al. (2017) examined the impacts of political relations on trade between China and its counterparts. However, there is no related literature emphasising the spillover effects of deteriorating political relations.

Since the United States and China are two leading economies in the world, their political relationship could affect the relationship between a third country and China. Although China's influence is increasing, the United States still dominates international affairs and is supported by strong alliances. This paper focuses on the trade between Australia and China for several reasons. First, the United States and China are both important trade partners of Australia. Facing the confrontation between the United States and China, the diplomatic position of Canberra would matter to China's relations with Australia as the latter has a long-standing alliance with the United States. Second, Australian politicians publicly made remarks on China's new national security law on Hong Kong's judicial independence and treatment of Uighurs, which are viewed as interference with Beijing's sovereignty. Furthermore, the Australian government banned the Chinese telecommunications company Huawei from entering the market, while the Chinese government reduced the imports of barley, wine, red meat, cotton, timber, lobster, coal, and so on from Australia. Third, Australia is one of the few developed nations that exports more to China than it imports from China. In other words, trading with China would be beneficial to the domestic economy. Therefore, it would be interesting to determine whether the political tensions between China and the United States have an impact on trade between China and Australia.

To identify macroeconomic shocks, the widely used method is structural vector autoregression (SVAR). The empirical specification and identification strategy is essential to impulse responses. To avoid reverse causality problems, we consider three different scenarios related to political outcomes such as 'America First', 'China Threat Theory', and 'The Protection of US Allies'. Under different scenarios, the variable order is changed accordingly. To solve the misspecification problem, we also utilise a local projection (LP) method proposed by Jordà (2005). In addition, we provide time-varying impulse responses by using a forward expanding method. Finally, we carry out a series of robustness checks to validate the main conclusions.

The empirical findings could be summarised as follows. First, deteriorating US-

China relations could provide a negative shock to Sino-Australian relations with significant spillover effects. Second, Australian exports to and imports from China would decrease as US-China political relations worsen. Third, the transmission of Sino-US political relation shocks turns to be insignificant as we take US economic variables into account. Fourth, by excluding the period of Trump's administration, Australian exports to and imports from China do not react to political tensions. Lastly, within a time-varying analytical framework, bilateral trade is strongly affected by the degradation of political relationships during Trump's presidency.

The remainder of this paper is organised as follows. Section 2 presents a brief theoretical model (Polachek et al., 1999) and discusses the political relation index. Section 3 briefly introduces the SVAR and LP methods. Section 4 describes the source of the dataset and the empirical strategy. Section 6 shows empirical results. The final section provides concluding remarks and policy implications.

2. Theoretical background and measurements

2.1 Theoretical intuitions

The theoretical intuitions of this study are inspired by Polachek et al. (1999). Building on previous work of cooperation and trade, Polachek et al. (1999) and Polachek and Seigle (2007) proposed the following rationale: If deteriorating political relations or conflicts negatively influences trade (through tariffs or quotas), the countries with the greatest gain from trade are also those facing the highest costs of conflicts and hence being least likely to engage in conflicts and most likely to cooperate. In this model, social welfare (*U*) depends on consumption (*C*) and conflicts (*Z*). The country seeks to maximize:

$$U = U(C, Z) .$$

where *C* represents the consumption of *m*-goods produced in a *k*-country world. Each of these countries can initiate conflicts or cooperation with other *k*-1 countries with the level of intensity being denoted by a $1*(k-1)$ vector *Z*.

It is noted that consumption also depends on exports and imports, with a variety of trade partners. Of course, trade (export and imports) depends on the conflicts, as conflicts can provoke tariffs or quotas. It may be important to mention that the welfare gains associated with conflicts can be positive. Consequently, the social welfare function is subject to the balance of payment constraint, as export in value is equal to import in value at the global level.

Finally, the actor may choose the amount of conflict with country *i* so as to equalize conflict marginal costs (that is, related to the reduction in trade) and the marginal benefits (that is, relation to the protection of strategic interest). Thus, in the case of two countries, we have the following equation as the mechanism by which a country decides the amount of belligérance:

$$\frac{\partial U}{\partial z} = \lambda\left[p_z - \left(x_1 + p_1 \frac{\partial x_1}{\partial p_1} \right) \frac{\partial p_1}{\partial z} - \left(m_2 + p_2 \frac{\partial m_2}{\partial p_2} \right) \frac{\partial p_2}{\partial z} \right].$$

where the left-hand side of this equation is the marginal benefit from engaging in conflictuel activities. The marginal cost is given by the right hand side and includes the direct cost of allocating a unit of consumption to z evaluated at the price of z, p_z , as well as the indirect cost of reduction in import and export revenues resulting from the changes in prices as a consequence of international conflict.

Interestingly, Polachek et al. (1999) extended their basic model to Third Party conflicts. Indeed, they distinguish target countries *i* and *j* to consider Third Party conflicts. For example, if an actor is in conflict with country *i* and benefits from this conflict, and if country *i* and country *j* are friends, then, the conflict with *j* reinforces the benefits of an actor's conflict with *i*. Polachek et al. (1999) concluded that 'if rival target countries i and j are friends, conflict with one reinforces conflict with another'. This finding supports the maxim 'a friend of a rival is a rival'.[2]

2.2 Quantifying Political Relations

Measurement of political relations is not an easy task. Fortunately, Yan and Qi (2009) and Yan et al. (2010) first proposed a political relation index (referred to

[2] See Polachek et al. (1999) for more details.

hereafter as PRI) to quantify China's political relations with its counterparts (including the US, Japan, Russia, UK, France, India, Germany, South Korea, Vietnam, Australia, Indonesia and Brazil). The PRI is based on reports of bilateral political events from 'The People's Daily' and official website of Ministry of Foreign Affairs of the People's Republic of China. Furthermore, they also take into account of some key political events that are not covered in "The People's Daily", such as the 'secret trip' by Henry Kissinger in 1971.

The PRI index is a quantitative measurement using scores that provide a general idea about the relationship between China and its counterparts. Yan and his colleagues divided the political relationship into six categories, such as rival (-9 to -6), tense (-6 to -3), disharmonious (-3 to 0), ordinary (0 to 3), good (3 to 6), and friendly (6 to 9). The minimum unit of measure is 0.1 to reflect slight changes in bilateral relations. To calculate the influential score of a given political event, Yan and his colleagues propose the following function,

$$IS = \begin{cases} \frac{N - P_0}{N} IS_0, \text{ while } IS_0 \geq 0 \\ \frac{N + P_0}{N} IS_0, \text{ while } IS_0 < 0 \end{cases}$$

where IS denotes the influential score of an event when the bilateral relation is located at P0, N denotes the absolute range of the bilateral relationship, P_0 represents the initial score when the political event occurs, and IS_0 is the unadjusted influential score which is listed in the event score table. They set the maximum value of N at 9, and IS moves in the range of [−9, 9]. The PRI index calculated using the above function has the following characteristics. First, when $IS_0 > 0$, the positive effects of a given political event decrease as the initial position P0 moves from confrontation to friendship. While P_0 is 9 denoting a friendly relationship, the positive effects will vanish. For example, Nixon's visit to China in 1971 which establishes the diplomatic relationship, is more important than Reagan's visit in 1978 because the United States and China were enemies during the Vietnam War. When $IS_0 < 0$, the negative effects of a political event will increase as the original bilateral relationship P_0 turns from confrontation to friendship. Another point to be highlighted is that military conflict is not equal to confrontation. During the period from the second half of 1953 to earlier 1954, US-China political relations suffered from confrontation, though there are no military conflicts.

Figure 1 shows the PRI indices of the US-China and Australia-China, covering the period from January 1950 to June 2020. According to the evolution of PRI indices, we find that the US-China PRI increases from 1971 when Henry Kissinger visited China. After that, US-China PRI sharply drops in 1989 and the US bombing of the Chinese embassy in Belgrade in 1999. After that, the US-China PRI slowly increased until Donald Trump took office in 2017. The US-China PRI suddenly plunges during Trump's presidency. Compared to the US-China PRI, Australia-China PRI is relatively stable over time. After Kissinger's 'secret trip' in 1971, Australia established diplomatic relations with China in 1972. In the following decades, Australia-China political relations continued to improve till the end of 2016, although we also observed a setback after 1989. After 2017, Australia-China PRI also experienced a sharp drop.

[Figure 1 is here]

According to the evolution of US-China PRI and Australia-China PRI, we can observe some synchronous changes immediately after 1989, the US bombing of the Chinese embassy in Belgrade in 1999 and Trump's trade war started in 2018. Therefore, we intuitively suspect lead-lag effects between them. We utilise the Granger causality test to investigate the causality between US-China PRI and Australia-China PRI. Consider a bivariate VAR model,

$$y_{1t} = c_{10} + \sum_{i=1}^{p} \alpha_{1i} y_{1t-i} + \sum_{i=1}^{p} \beta_{1i} y_{2t-i} + \varepsilon_{1t}$$
$$y_{2t} = c_{20} + \sum_{i=1}^{p} \alpha_{2i} y_{1t-i} + \sum_{i=1}^{p} \beta_{2i} y_{2t-i} + \varepsilon_{2t}$$

where y_{1t} and y_{2t} are stationary processes, c denotes constant term, and p is the maximum lags added to the VAR model. Under the null hypothesis of Granger non-causality from y_{2t} to y_{1t}, that is $y_{2t} \xrightarrow{NG} y_{1t}$, we could test

$$H_0 : \beta_{11} = \beta_{12} = \cdots = \beta_{1p} = 0$$

The above equations mean that the predictions of y_{1t} conditional on its own history cannot be improved by incorporating the past p lags of y_{2t} in the model. Since the PRI is a monthly dataset, we determine p as 12 and use the first difference on the US-China PRI (pri_t^{US-CH}) and Australia-China PRI (pri_t^{AUS-CH}) to ensure the variables are stationary, respectively. The Wald test statistic under the null hypothesis that Δpri_t^{AUS-CH} does not Granger cause Δpri_t^{US-CH} is 0.944 which is insignificant. In contrast, the null hypothesis that pri_t^{US-CH} does not Granger cause pri_t^{AUS-CH} is rejected at 5% significance level with the Wald test statistic. That is, the changes of US-China political relations cause variations in Australia's political relations with China.

3. VAR and LP Methods

A vector autoregression (VAR) is widely used by empirical scholars with different applications. By imposing a restriction matrix, the model is supposed to represent the structure of an economy. Consider a structural VAR(p) model,

$$y_t = \boldsymbol{\alpha} + \boldsymbol{\Phi}_1 y_{t-1} + \boldsymbol{\Phi}_2 y_{t-2} + \cdots + \boldsymbol{\Phi}_p y_{t-p} + \mathbf{e}_t$$

where $\boldsymbol{\alpha} = \mathbf{A}_0^{-1} c$, $\boldsymbol{\Phi}_i = \mathbf{A}_0^{-1} \mathbf{B}_i y_{t-i}$ for $i = 1, 2, \cdots, p$ and $\mathbf{e}_t = A_0^{-1} \varepsilon_t$. Here, we normalize the variance-covariance matrix of the structural residuals as $\mathbf{E}(\varepsilon_t^{'} \varepsilon_t) = \Sigma_\varepsilon = \mathbf{I}_k$ (in the empirical work, Breusch-Pagan-Godfrey tests are conducted to ensure the existence of homogeneity). In addition, the variance-covariance matrix of the reduced-form could be presented as $\mathbf{E}(\mathbf{e}_t^{'} \mathbf{e}_t) = \Sigma_{\mathbf{e}} = \mathbf{A}_0^{-1} \mathbf{A}_0^{-1'}$. To establish the relationship between SVAR and the reduced-form VAR, we should pre-know $\mathbf{A}_0$ which represents contemporaneous impacts of the model variables or of its inverse. In this study, we use a recursive identification strategy and assume a lower-triangular $k \times k$ matrix $\mathbf{Q}$ with a positive main diagonal, which satisfies $\Sigma_{\mathbf{e}} = \mathbf{A}_0^{-1} \mathbf{A}_0^{-1'} = \mathbf{Q}\mathbf{Q}^{'}$, and such that $\mathbf{A}_0^{-1} = \mathbf{Q}$. To recover $\mathbf{A}_0$, we use a typical Cholesky decomposition method.

Jordà (2005) suggests that the misspecification problem in a typical SVAR model leads to inaccurate impulse response estimates. He proposes a so-called 'local projections' method using a horizon-specific regression rather than the iterated regression method used in the traditional model. Ramey and Vine (2006) and Plagborg-Møller and Wolf (2021) point out that the local projections sometimes provide erratic impulse responses, Jordà (2005), Ramey (2016) and Montiel-Olea and Plagborg-Møller (2021) confirm that the local projection method is considerably robust against empirical specifications compared to a typical SVAR model.

The LP method is expressed as follows,

$$y_{k,t+h} = \alpha_{k,h} \cdot \varepsilon_{k,t} + \mathbf{controls} + \eta_{h,t}, \quad h = 0, 1, 2, \cdots$$

where $\alpha_{k,h}$ is the estimate of the impulse response of a variable $y_{k,t+h}$ at horizon h to a shock on $\varepsilon_{k,t}$. The control variables include deterministic trends such as constant term, lags of the $y_{k,t+h}$ and other variables that are necessary. Here, we use the method of Newey and West (1987) to correct potential serial correlation in $\eta_{h,t}$. In addition, the LP impulse response still relies upon the identification of $\varepsilon_{k,t}$ in a typical SVAR model. Plagborg-Møller and Wolf (2021) present that SVAR and local projections provide closely tied patterns in the shorter horizons. However, in the longer horizons, the specification with a small lag will generate observable gaps between SVAR and LP methods.[3]

Other empirical specification strategies can be summarised as follows. First, we determine the optimal lags as 4 thanks to the Akaike Information Criteria corrected (AICc) proposed by Hurvich and Tsai (1993) in both SVAR and LP. Second, we use the wild bootstrap method to generate error bands for the typical SVARs and Newey-West standard errors to generate confidence level error bands for LP estimates.

4. Data and Empirical Specifications

4.1 Data

The PRI of US-China and Australia-China can be found on the official website of

[3] It is noted that this gap does not affect the main conclusions in this study. Many authors in their theoretical work also pointed out the gap between LP and SVAR in the longer horizons.

the Institute of International Relations of Tsinghua University: http://www.imir.tsinghua.edu.cn/. The dataset of Australian exports to and imports from China is available in the Direction of Trade Statistics operated by International Monetary Fund (IMF). In addition, we also include gross domestic production (GDP) and real effective exchange rate (REER) in the baseline model. The GDP and REER are drawn from the International Financial Statistics database of the IMF. To deflate GDP and trade statistics, we utilize the Consumer Price Index (CPI) at constant prices, which is also available in the IFS database.[4] Although Yan and Qi (2009) and Yan et al. (2010) measure the PRI at a monthly frequency, we convert it into a quarterly frequency due to the unavailability of macroeconomic indicators of China and Australia at a monthly frequency.

All data used in this study are seasonally adjusted and cover the period from 1992Q1 to 2020Q2 (for more details, refers to the appendix). We choose the following notations for the involved variables: pri_t^{US-CH}, pri_t^{AUS-CH}, gdp_t^{CH}, gdp_t^{AUS}, $reer_t^{CH}$, $reer_t^{AUS}$, ex_t and im_t denote the political relation index between US and China, the political relation index between Australia and China, the real GDP of China, the real GDP of Australia, the real effective exchange rate of China, the real effective exchange rate of Australia, the Australian exports to China and the Australian imports from China, respectively. Due to the negative values in PRI, we utilize the following use $pri_t + \sqrt{1 + pri_t^2}$ to replace the original PRI series.[5]

4.2 Identification

The empirical specifications are crucial to impulse response analyses of the SVAR model. The eight variables that we have considered can be divided into 4 groups which are pri_t^{US-CH}, Chinese variables, pri_t^{AUS-CH}, and Australian variables. Since the contemporaneous relation matrix $\mathbf{A}_0$ in Section 3 relates to identifying the structural shocks, we implement a recursive identification scheme and recover $\mathbf{A}_0$ by

[4] We also use US GDP deflator for robustness checks.
[5] Another linear transformation of PRI is used for robustness checks.

using the Cholesky decomposition.[6] Therefore, variable orders should be carefully determined. Since our interest is the Sino-US political relation shock, the location of pri_t^{US-CH} is needed to be discussed. We consider three scenarios for the ordering of pri_t^{US-CH}.[7]

Scenario I: Sino-US political relations are determined by the US.

Although China is a rising power with rapid economic growth, its political influences are still nondominant in US-China political relations. The unresolved concerns between Washington and Beijing are mainly about the role of democracy and human rights in China. Furthermore, the 'America First' movement also affects the US politics and diplomatic policies. 'America First' refers to a policy in the United States that focusses on nationalism and non-interventionism. 'America First' policies are inspired by Thomas Jefferson who promoted the Embargo Act of 1807 which aims to resist the impressment of Americans to serve on foreign warships. After that, this slogan has been used by both Democrats and Republicans. During World War II, the America First Committee opposed the entry into the war with the exacerbation of American nationalism and unilateralism. Donald Trump revived this slogan during his election campaign and presidency, though with considerable differences. Some critics even describe Trump's 'America First' as 'America Alone'. In other words, Trump's 'America First' endows more isolationism and nativism. It is assumed that the government policies of the United States are influenced by this slogan and focused on domestic economic benefits. In this case, the political relations are exogenous and are not instantaneously affected by other countries. Therefore, the model is specified as follows:

[6] Jordà (2005) presents that model misspecification could lead to inaccurate impulse response estimates and further proposes a Local Projection method. Although Jordà (2005) proposes an LP method which could solve the problem of model misspecification by choosing lags, it also relies upon the identification scheme in the SVAR model.

[7] According to the Australian Bureau of Statistics 2019, total exports of Australian goods to China were 150,488 million dollars; however, its total imports from China were only 80,876 million dollars. Australia enjoyed a large surplus with China. Thus, the Australian economy could be influenced both by the sluggish Chinese demand and the deterioration of bilateral political relations. Therefore, we locate Chinese variables (gdp_t^{CH} and $reer_t^{CH}$) and Sino-Australia political relation index (pri_t^{AUS-CH}) before Australian economic indicators (gdp_t^{AUS} , $reer_t^{AUS}$, ex_t and im_t).

$$y_t = [pri_t^{US-CH}, gdp_t^{CH}, reer_t^{CH}, pri_t^{AUS-CH}, gdp_t^{AUS}, reer_t^{AUS}, ex_t, im_t]'.$$

where the order of variables implies that shocks contemporaneously influence the rest of variables in the VAR.

Scenario II: Sino-US political relations are affected by both US and China.

China's rise not only creates development opportunities but also poses challenges to the international structure. The 'China threat theory' emerged as a response to China's rapid economic growth. Concerns have previously been expressed about a strong China, which may threaten East Asian security. The 'China threat theory' has gained wider attention since December 2001 after China joined the WTO. In fact, joining the WTO probably contributed to accelerate China's growth. Although the 9/11 terrorist attacks temporarily diverted the US's attention to terrorism, many scholars focused on the "China threat" issue. Since Donald Trump came to power, the "China threat theory" revived quickly across western countries. Another problem that affects the US-China political relationship is the exchange rate of the Chinese currency (RMB) because some US politicians view RMB as a challenge to the enduring dominance of US dollar in the international monetary system. Donald Trump even formally labelled China as the 'currency manipulator' in August 2019.

Although we implement a series of pairwise Granger non-causality tests under the null hypothesis, it is still necessary to assume that pri_t^{US-CH} is contemporaneously influenced by China's economic situation given above discussions. To complement *Scenario I*, we locate pri_t^{US-CH} at the third position in the SVAR model. That is shocks of gdp_t^{CH} and $reer_t^{CH}$ have instantaneous impacts on pri_t^{US-CH}. Thus, we have the following variable order,

$$y_t = [gdp_t^{CH}, reer_t^{CH}, pri_t^{US-CH}, pri_t^{AUS-CH}, gdp_t^{AUS}, reer_t^{AUS}, ex_t, im_t]'.$$

where the variables of Australia are located after pri_t^{US-CH}. Therefore, the identified pri_t^{US-CH} shocks could have contemporaneous influences on pri_t^{AUS-CH}, gdp_t^{AUS}, $reer_t^{AUS}$, ex_t, and im_t, but the reverse impacts take time. This ordering implies that Australia-China political relations have no instantaneous impacts on US-China political relations. This scenario is more realistic because the global influence of Australia is not comparable to that of the United States and China. In Section 2, we found a unidirectional causality running from pri_t^{US-CH} to pri_t^{AUS-CH}, which supports this ordering.

Scenario III: Sino-US political relations are not only determined by themselves, but also another ally.

The Australia, New Zealand, United States Security Treaty (ANZUS) is a collective security nonbinding agreement to cooperate on military matters in the Pacific Ocean region. The ANZUS is a military alliance that aims to provide military support when one of the allies is attacked by other countries. The original treaty is a three-way defense pact, that is, Australia-New Zealand, Australia-US and New Zealand-US. Due to the disputes between New Zealand and the United States over visiting rights for ships and submarines capable of carrying nuclear arms in 1984, the treaty exists only between Australia-US and Australia-New Zealand. Although the treaty was split in 1984, the Australia-US alliance remains intact.[8]

In addition to military cooperation, Australia and the United States also maintain strong economic links. The Australia - United States Free Trade Agreement (AUSFTA) came into force in January 2005 and widely met a mixed reception. The agreement is strongly supported by the former Howard government and is commonly viewed as a continuation of the Australia-US alliance. However, the results of this agreement in the following year are declining Australian exports to the United States but increasing US exports to Australia. The worsening Australian trade deficit and the improving US trade deficit with Australia could not be solely attributed to the free trade agreement because of the lagged effects of the appreciation of the Australian dollar over the period from 2000 to 2003. One could suspect that both Australia and the United States would keep a watchful eye on each other's national interests.

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[8] As shown by the recent AUKUS partnership (with the US and the UK) and the turnaround about the deal on nuclear submarine negotiated between Australia and France.

Meanwhile, China is the largest trade partner of Australia. As the leading economy in the world, the United States is careful with his strategic competitor and ally. Therefore, we specify the model as follows,

$$y_t = [gdp_t^{CH}, reer_t^{CH}, pri_t^{AUS-CH}, gdp_t^{AUS}, reer_t^{AUS}, ex_t, im_t, pri_t^{US-CH}]'.$$

where we put the pri_t^{US-CH} variable in the last position in the SVAR model. That means that the shocks caused by other variables could contemporaneously affect US-China political relations. However, the reverse effects take time.

4.3 Granger non-causality tests

Ramey (2016) shows that structural shocks should be exogenous with respect to other current and lagged variables in the model, and thus the ordering of variables is easily challenged. The US government policies affect not only their domestic affairs, but also the development and political affairs of foreign countries. To verify this point, we carry out a battery of pairwise Granger non-causality tests spanning from fiscal and economic variables to political relation index between US and China. The lags are set at 4 which is adequate to capture potential dynamics. The large p-values show that the non-causality hypothesis cannot be rejected.

Other practical issues are summarised as follows. First, some previous studies impose unit root and cointegrated relations to pretest the variables; however, Elliott et al. (1996) suggests that this procedure could lead to size distortions. Another key issue is the selection of the lag length.[9] Ramey (2016) suggests that although LP avoids the misspecification problem, it suffers from less precise estimates due to fewer restrictions being imposed. Recent studies such as Plagborg-Møller and Wolf (2021) and Montiel-Olea and Plagborg-Møller (2021) suggest that SVAR and LP could give the same estimates in short- and medium-horizons. However, in longer horizons, the impulse response estimates of SVARs and LP disagree substantially. Plagborg-Møller

[9] Although Jordà (2005) suggests using AICc proposed by Hurvich and Tsai (1993) to determine the optimal lags used in local projections, recent studies by Plagborg-Møller and Wolf (2021) and Montiel-Olea and Plagborg-Møller (2021) present that typical SVAR and local projections should deliver consistent impulse response estimates especially in the short and medium run. Based on their findings, the choice of lags should satisfy their conditions. The robustness checks are implemented by incorporating shorter and longer lags.

and Wolf (2021) also issue a series of warnings about the use of SVAR and LP. To balance the so called "bias-variance" trade-off presented by Plagborg-Møller and Wolf (2021), we fix the lags at 4 in the baseline estimates and check the robustness by using other lags such as 2 and 6. In addition, impulse response horizons are determined as 20.[10] Second, we use wild bootstrap procedure to generate confidence interval for SVAR model and utilize Newey-West standard errors to generate error bands for LP. Finally, the baseline estimates are built upon a quarterly dataset due to unavailability of monthly data for some macroeconomic variables of China and Australia.

5. Empirical Results

5.1 Preliminary analysis

We first provide the plots of identified US-China PRI shocks over time-variation under the three different scenarios in Figure 2. The shocks are normalised by their mean and standard deviation. Obviously, the evolution of the identified shocks under the three different scenarios is consistent over time. This is interesting, since we consider different orderings of the variables in the SVAR model. If there are potential causal impacts running from other variables to the US-China political relation index, the evolution of the normalized residuals would dramatically change under different scenarios.

[Figure 2 is here]

5.2 Baseline results

Figure 3 plots the Impulse Response Functions (IRFs) of pri_t^{US-CH}, pri_t^{AUS-CH}, ex_t and im_t given 1% unexpected decrease in pri_t^{US-CH}. This shock represents the deterioration of US-China political relations. By considering pri_t^{US-CH} at different positions, we find the IRFs patterns are highly consistent. Our results are explained by using one standard error band (around a 66% confidence level).

[10] Prior to determining the lags as 4, we put other lags into the model, such as 2 and 6 lags. We find significant gaps between SVAR and LP in short- and medium-run when we use shorter lags. As the recent study by Plagborg-Møller and Wolf (2021) shown, SVAR and LP should estimate the similar impulse response, especially in short and medium horizons. When we add the lags to 6, the impulse responses of SVAR and LP methods are similar.

Given an immediate decrease of pri_t^{US-CH}, the IRFs of pri_t^{AUS-CH} in the short-run (the first 6 quarters) is not significant, but the decrease persists in the medium and long run. The deterioration of US-China political relations causes significant spillovers to Australia-China political relation in the medium and long run. The reason for the insignificant results in the short term can be attributed to political motivation, such as 'wait and see'. For example, in the earlier stage of the US-China trade war, conflicts are maintained at the diplomatic level. Countries, such as Australia, are not aware of the underlying motivations, which means that the deterioration of US-China political relations cannot cause a significant decrease in the PRI of Australia-China in the short run. Another interesting point is that the IRFs of pri_t^{AUS-CH} under the two other scenarios are very similar.

Turning to the IRFs of exports and imports, the shocks have significant and negative impacts on Australian exports to China, with the maximum impacts of 0.1% being reached in the eighth quarter (two years). Such negative effects are long-lasting and still appear after 5 years. In other words, political tensions between China and the US decrease Australian exports to China. With respect to Australian imports from China, the median impulse response is significant, negative, and persistent. The maximum impact occurs in the seventh quarter after an immediate decrease in pri_t^{US-CH}. These results suggest that the deterioration of US-China political relations decreases bilateral trade between Australia and China. Under the other scenario (by allocating pri_t^{US-CH} from the front to the back), the IRFs patterns do not change significantly. At this point, it is worth pointing out that, though US-China political relation deteriorated in recent years, Australia-China trade in fact expanded. This observation however does not invalidate the findings from the above impulse response analysis. The patterns of exports and imports in Figure 3 imply that, without the deterioration of US-China political relation (a negative shock), trade between Australia and China would have increased more than what we observed in reality.

We also plot the results of the forecast error variance decomposition (FEVD) in

Figure 4 which shows that the FEVD is sensitive to the ordering of the variables. In other words, the FEVD results are becoming smaller as we move the pri_t^{US-CH} variable from the first position to the last position. Under *Scenario I*, the contribution of pri_t^{US-CH} shocks to pri_t^{AUS-CH} variations increase as horizons expand. Furthermore, the shock could contribute roughly 5% to export fluctuations of exports after 2 years and around 10% to the variations of imports of imports after the second quarter. In *Scenario II* and *III*, the pri_t^{US-CH} shocks account for a smaller proportion of variations in Australian exports to and imports from China.

[Figures 3 and 4 are here]

Jordà (2005) argues that the misspecification significantly affects the estimates of the SVAR model. The typical SVAR uses an iterated method to forecast errors, rather than a direct forecasting method used by Jordà (2005). Subsequently, we implement the LP method which provides the empirical results in Figure 5. The SVAR and LP methods present the same impulse response in the short and medium horizons; however, the patterns in the long-run differ substantially. Our findings reconfirm the conclusions of Plagborg-Møller and Wolf (2021). Furthermore, there is a slight difference in the pattern of imports between SVAR and LP. That is, the median impulse response based on SVAR is significant; however, the LP impulse response of imports is insignificant in the long term.[11] Regarding the results of FEVD shown in Figure 6, we find that the paths are highly consistent in different scenarios. Specifically, the pri_t^{US-CH} shocks could roughly contribute, at the peak to 18% variations in pri_t^{AUS-CH}, 18% variations in ex_t and 10% of variations in im_t.

[Figures 5 and 6 are here]

We report the IRFs of the remaining variables in Figures A.2 and A.3 in the Appendix. Given the pri_t^{US-CH} shocks, the median responses of gdp_t^{CH} and $reer_t^{CH}$ drop. This indicates that worsening US-China political relations could decrease gdp_t^{CH} and depreciate the RMB. In addition, the median response of gdp_t^{AUS} is not significant. The

[11] Ramey (2016) suggests implementing the LP method as robustness checks against the typical SVAR model. In fact, there are no clear explanations as to why SVARs and LP are inconsistent in the longer horizons.

IRFs of $reer_t^{REER}$ goes down when pri_t^{US-CH} decreases.

To capture the impacts of pri_t^{US-CH} shocks on total trade between Australia and China, we repeat the exercises for the different scenarios. The results are available in Figure 7. According to the IRFs results of the SVAR model, the pri_t^{US-CH} shocks decrease Australian trade under all hypotheses. As for the IRFs of the LP model, the pri_t^{US-CH} shocks have significant and negative impacts on trade in the short- and medium-run. However, the long-term estimates of SVAR and LP disagree substantially.

[Figures 7 is here]

The baseline results are derived based on different scenarios which are reflected by changing the ordering of pri_t^{US-CH}. Although we sequentially move pri_t^{US-CH} from the first to the end of the VAR system, the impulse response functions of Australian exports and imports do not change dramatically. According to the recursive identification scheme of the VAR, we usually order the most exogenous variable at the first. If pri_t^{US-CH} is independent to other variables in the VAR, its location does not matter to the IRFs results. Beyond that, Figure 2 presents the evolution of identified structural US-China political relation shocks are highly consistent. These confirm that US-China political relation is not determined by Chinese and Australian economic conditions regardless the status of the country being a rival or ally to the US. In spite of these, it is natural to suspect that the political relation is solely determined by the attitude of the US government and the economic conditions in the United States. To verify this point, we augment the VAR model with US economic variables in the following section.

5.3 Augmented VAR model with the US variables

The benchmark model does not include the US economic variables. To extend the model, we supplement the VAR model with the US real gross domestic production (gdp_t^{US}) and the real effective exchange rate ($reer_t^{US}$). Only minor changes are made in the three scenarios. We put gdp_t^{US} and $reer_t^{US}$ in the first two positions. This ordering implies that the shocks of gdp_t^{US} and $reer_t^{US}$ could have contemporaneous impacts on other variables in the VAR system. The ordering of the rest of variables is the same as the benchmark model. In addition, the empirical specifications are unchanged.

By adding the gdp_t^{US} and $reer_t^{US}$ into the VAR system, the newly identified pri_t^{US-CH} shocks exclude the effects of gdp_t^{US} and $reer_t^{US}$ shocks. In other words, if US economic variables have impacts on pri_t^{US-CH}, there should be changes in the impulse responses. If not, the results of the augmented VAR are quantitively similar to those from the model without US variables (baseline results). The results of SVAR are displayed in Figures 8. We first look at the median response of a typical SVAR model, which shows that Australian exports to China slightly increase in the short run and decrease after that. Furthermore, the median response of Australian imports from China also drops, although it slowly recovers in the long term. According to the confidence intervals in the SVAR model, the IRFs results are insignificant in most cases. There are observable changes in the IRFs pattern after we incorporate the US variables into the model. These results are interesting because two sovereign states have less control on their bilateral trade than a third country. In the meanwhile, above analyses greatly support the discussions of *Scenario I*.

[Figures 8 is here]

The above-discussed findings verify our suspicion that US economic variables significantly matter to the transmission from US-China political relation to bilateral trade between Australia and China.[12] Together with the results presented in section 5.2, some important policy implications can be drawn. Unlike the US, Australia has for a long time benefited from a trade surplus with China. The bilateral relation between Australia and China was also continuously improved before Trump's administration. For Australia, China is more likely an economic opportunity. But for the US, China's rise has been treated as a real threat to the superpower's leading position in the globe. Our empirical results illustrate that the US-China political

[12] These findings do not contradict the baseline impulse response results and, instead, complement the baseline results. The political relation is decided by multiple factors.

relation is not affected by the economic conditions of China (strategic competitor) and Australia (ally). After including US economic variables, the impulse responses of Australian exports and imports turn to be insignificant. These reconfirm that US economic variables play a key role in the transmission. The "America First" is still dominant in the bilateral trade between Australia and China even though it shouldn't be. Both Chinese and Australian governments need to better handle their bilateral trade when US-China political relation deteriorates again. Although "China Threat Theory" is prevailing among western countries, the impacts of US-China political relation shocks on Australian trade with China are not a core problem. Domestic economic uncertainties in the US are the key to the transmission.

5.4 The IRFs before Trump's administration

Since Donald Trump came to power in 2016, the political relations between the United States and China have been significantly worsened. During his presidency, the US Treasury Department labeled China a "currency manipulator". Trump also ratcheted up tariffs on Chinese goods and further launched the trade war against China. Furthermore, he also frequently criticized China's new national security law on Hong Kong's judicial independence and human rights problem. These moves have profound and negative impacts on the US-China relationship. Therefore, it is interesting to examine the impact of US-China political relations on Australia-China trade before Trump's administration (1992Q1-2016Q4) and compare it with the finding from the benchmark analysis which covers the period of Trump's Presidency (1992Q1-2020Q2). For this purpose, we use the same specifications of the benchmark model by setting the lag order as 4 and considering the different scenarios. For a better understanding, we only report the median responses of pri_t^{US-CH}, pri_t^{AUS-CH}, ex_t and im_t in Figure 9.

Given one percentage decrease in the pri_t^{US-CH} index, the median response of the pri_t^{AUS-CH} index briefly moves up and drops persistently afterwards. This pattern is similar to the benchmark results. That is, even before Trump's administration, a deterioration in US-China political relations could affect relations between Australia and China. As for export IRFs, the median responses under different scenarios increase over horizons and are not significant at the 66% significance level. These results are inconsistent with the reference estimates. The median response is a short drop followed by a slow increase in imports, before approaching zero. Likewise, import IRFs are not significant at the 66% level.

[Figure 9 is here]

The above results imply that a worsening of US-China political relations does not significantly affect bilateral trade between Australia and China when we exclude the period of Trump's administration. Contrary to these findings, the benchmark IRF shows that the deterioration of Sino-American relations could decrease both Australian exports to and imports from China. In other words, the worsening of political relations between the US and China during Trump's administration plays a pivotal role in the decline of bilateral trade between Australia and China.

5.5 Sensitivity and robustness checks

The robustness checks are carried out with various factors affecting the baseline estimates, such as the selection of lag-order, data misreporting, SVAR model in first difference, adding a time trend, GDP deflator, and the transformation of the political relation index.

Selection of lag-order: Since the estimates of the SVAR model are sensitive to the lag-order, we choose other lags such as 2 and 6 for robustness checks. The results are available in Figure A.4 of the appendix. The main conclusions that use these lags do not changed according to the baseline findings. Slight differences are found in the median impulse response in longer horizons. Therefore, the results are robust against different lags.

Misreporting problem: Another concern is the misreporting of exports and imports between China and Australia. Because the baseline model uses exports and imports data provided by Australia, we also consider the dataset provided by China. In fact, the data on trade reported by both countries differ considerably. Other empirical specifications are the same as those used in the baseline model. Therefore, we check the robustness against the misreporting problem of the trade dataset. The results are provided in Figure A.5. Specifically, the median export responses are similar when different datasets are utilised. In terms of the response of imports, we find a gap between the two median responses.

SVAR in first difference: The benchmark model is constructed using log level dataset. Gospodinov et al. (2013) and Ramey (2016) suggest that a log-level specification is the safest approach when the magnitude of the roots is unknown. In spite of these, we re-estimate the VAR model in first difference. We report the IRFs results in Figure A.6. We find significant differences in the median responses between the log-level specification and first difference specification. The IRFs of SVAR in the first difference imply that tense US-China political relations improve the political relations between Australia and China. This is unexpected. As one of the allies of the US, Canberra always keeps a close tie with Washington when it comes to international affairs. According to Elliott (1988) and Ramey (2016), imposing the unit root and cointegrating relation amongst the variables can lead to large size distortions. Gospodinov et al. (2013) further discuss how large the size distortions can be in theory.

Adding a time trend: Since the variables in the model contain a deterministic trend, Ramey (2016) suggests that the common methodology to solve the problem of non-stationary variables in the VAR is adding a time trend. Therefore, we reestimate the VAR system with both constant and time trend. The results are available in Figure A.7. Overall, the impulse response patterns of adding time trend are consistent with the baseline results.

GDP deflator: In the baseline model, we deflate the trade dataset with US CPI index. However, the GDP deflator has more advantages over CPI index because it covers prices of all goods and services produced. Thus, we re-estimate VAR by using the trade dataset deflated by US GDP deflator. The results are reported in Figure A.8 of the appendix. The impulse responses are both qualitatively and quantitively similar to the baseline results.

Transformation of PRI index. Another concern is the non-linear transformation of US-China political relation index by using the equation $pri_t + \sqrt{1+pri_t^2}$. To check potential biases, linear transformation by using $100 + pri_t$ is adopted. The results using the new transformation are reported in Figure A.9 of the appendix which are qualitatively similar to the baseline results (in Figure 3).

6 Time-varying Impulse Response Functions

With political relations between the US and China changing over time the transmission of pri_t^{US-CH} shocks to the economy could be time-varying. As we have previously stated, the pri_t^{US-CH} index sharply decreases in 1989, the US bombing of the Chinese embassy in Belgrade in 1999 and Trade War in 2016. To provide time-varying impulse responses, we utilise forward-expanding and recursive-evolving methods. In terms of the forward expanding method, the starting point S_1 is fixed at the first observation (i.e., S_1=1). We further expand the end point S_2 from the window size S_w to T. We set the window size S_w to 48 and the lag length to 4 which is consistent with the baseline model. Therefore, impulse responses over the period from 2004Q1 to 2020Q2 are available.

Figure 10 delivers the overall evolution of impulse responses given the identified shocks over time. Figure 11 plots the horizontal IRFs (referred to as HIRF hereafter) from 2004Q1 to 2020Q2. For the results of pri_t^{US-CH}, we could conclude some main features. First, there are some differences in the horizontal IRFs given different scenarios before 2009. Second, the HIRFs are consistent after 2009. Third, we find a significant drop in transmission after 2017 in the HIRFs.

Figure 11 shows the HIRFs of pri_t^{AUS-CH} in different horizons. The results illustrate that the identified shocks have positive impacts on pri_t^{AUS-CH} in 4 quarters.

From the perspective of a longer span, such shocks negatively affect the evolution of pri_t^{AUS-CH}. This could be due to the Australian government using wait-and-see tactics. Since the US and Australia are allies, they would adopt the same attitude in the long run. Therefore, the HIRFs of pri_t^{AUS-CH} in the 8, 12 and 20 quarters are below zero. Another interesting point worth stressing is that the HIRFs of different horizons drop significantly after 2017. In other words, relatively stable transmission changes during Trump's administration.

[Figures 10 and 11 are here]

Regarding the HIRFs of Australian exports to and imports from China, some characteristics could be summarised as follows. First, there are significant fluctuations during the period from 2004Q1 to 2009Q1. Especially in 2008Q3, there are sudden drops in the HIRFs of exports and imports under *Scenario I*, which could be attributed to the suppression effects of the financial crisis. However, such decreases were quickly curbed and the HIRFs in the following years remained relatively stable until 2017. Since then, export and import HIRFs have experienced a downward trend during Trump's presidency and hit the bottom in 2019 Q3. During Trump's administration, the political relations between the US and China got worse as the trade war intensified and this deterioration had spillovers into the bilateral trade. Obviously, the sharp decreases in HIRFs of exports and imports are transitory. However, the downward turn after 2017 is persistent and intensifying. That is to say, Australia-China bilateral trade is significantly distorted by the deterioration of US-China political relations.

7 Conclusions

In this study, we use a recursive identification strategy to isolate shocks from the US-China political relationship in several scenarios. The empirical results show that the sudden cooling of US-China political relations has persistent negative impacts on Australia-China political relations. Such deterioration of the political relations also decreases Australian exports to and imports from China. When we focus on the period prior to Trump’s administration, the IRFs of exports and imports are not significant. Furthermore, we employ a forward-expanding strategy to obtain time-varying IRFs and the empirical results demonstrate two sharp drops during the 2009 economic downturn and Trump’s presidency. However, the first drop was quickly fixed, but the last sharp decrease is more persistent. In other words, the worsening political relations between the United States and China during Trump’s administration had persistent negative impacts on Australian exports to and imports from China.

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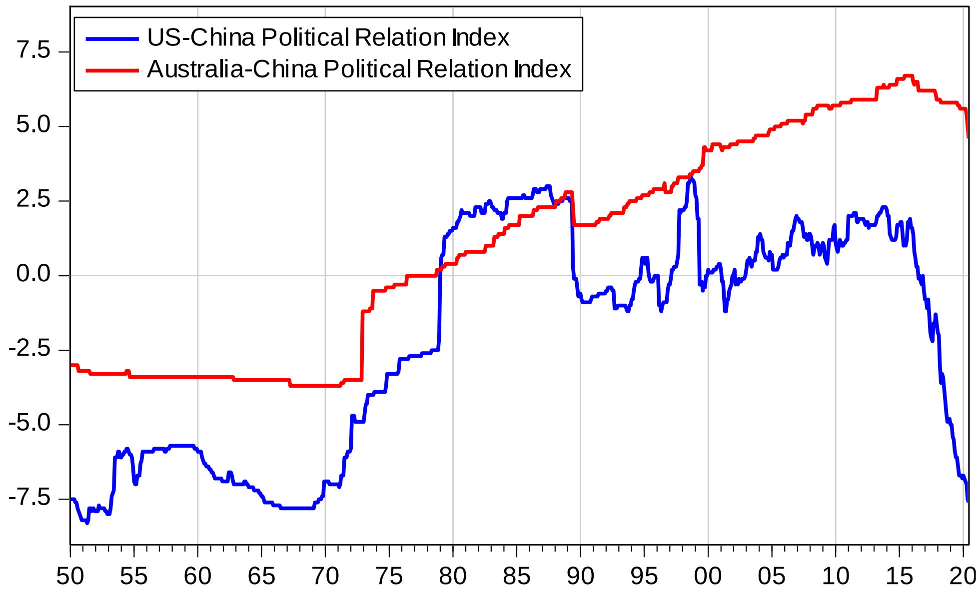
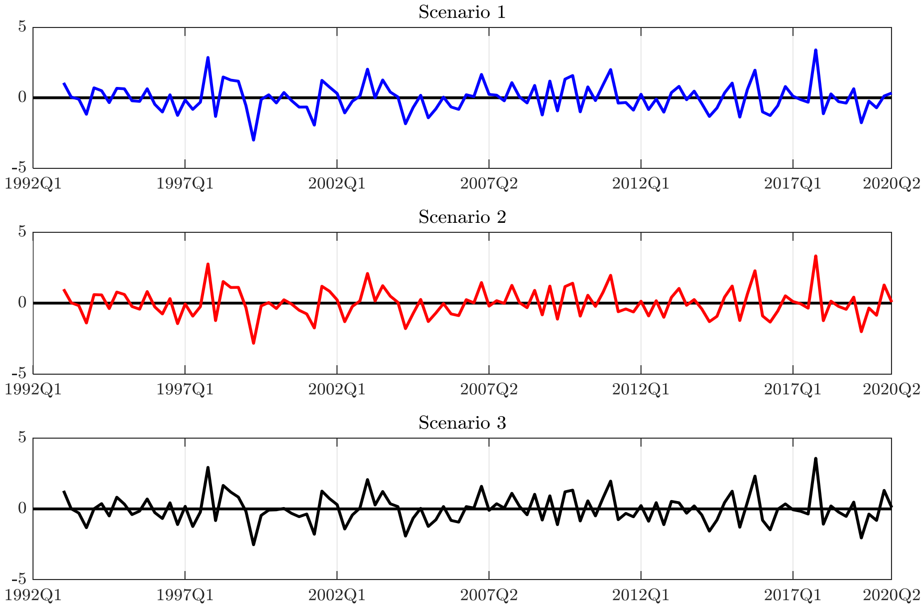
Figure 1 Political Relation Index



Note: The dataset is available on: http://www.imir.tsinghua.edu.cn/. The PRI index is monthly and covers the period from January 1950 to June 2020.

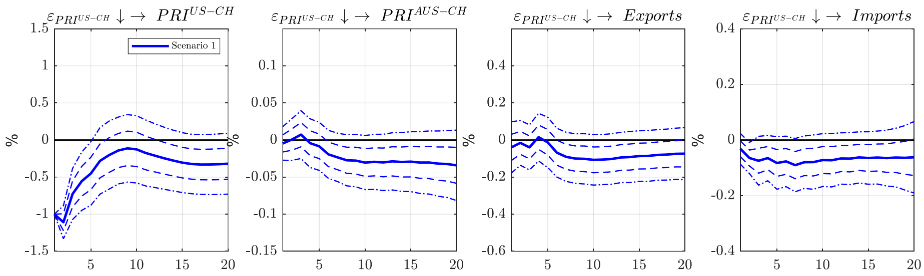
Figure 2 Identified US-China PRI shocks under different scenarios



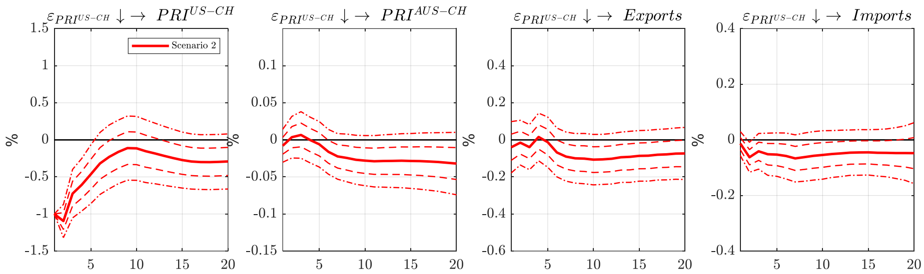
Note: the lags for the VAR system are determined as 4.

Figure 3 Impulse response functions of the typical SVAR model

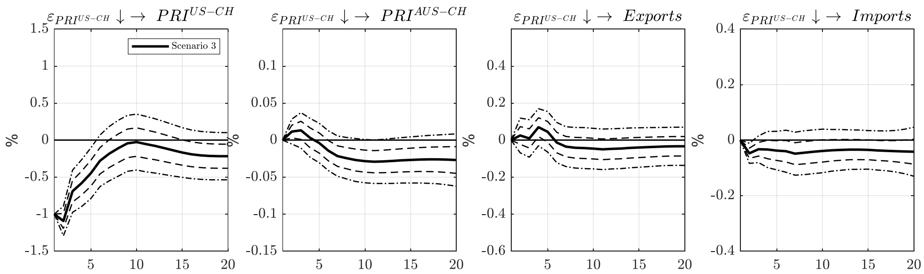
(a) Scenario I



(b) Scenario II



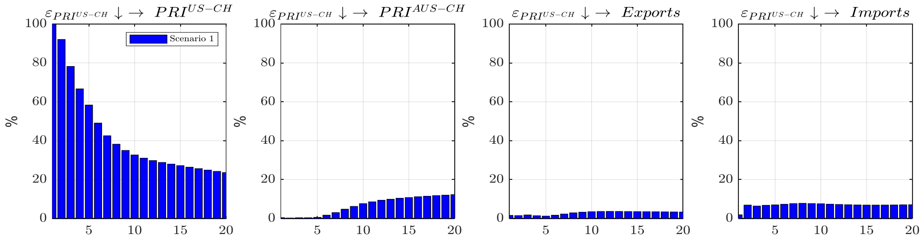
(c) Scenario III



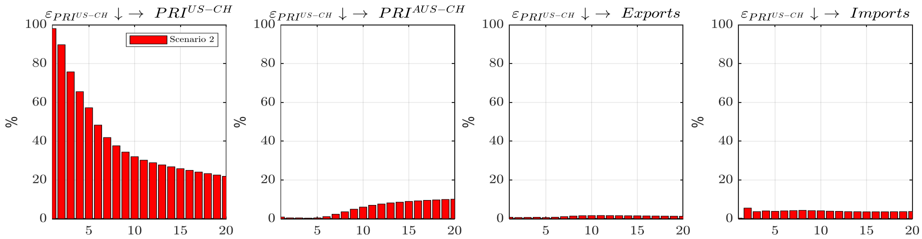
Note: the confidence intervals are constructed by using a wild bootstrapping method proposed by (Kilian, 2009) at 66% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determined as 4.

Figure 4 Forecast error variance decomposition of the typical SVAR

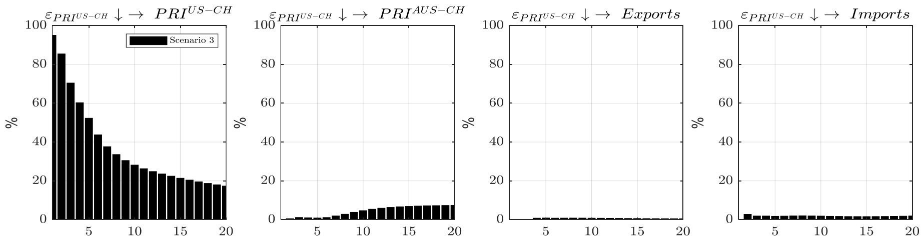
(a) Scenario I



(b) Scenario II



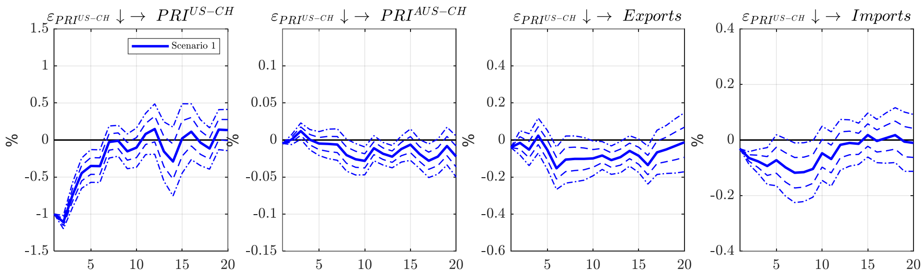
(c) Scenario III



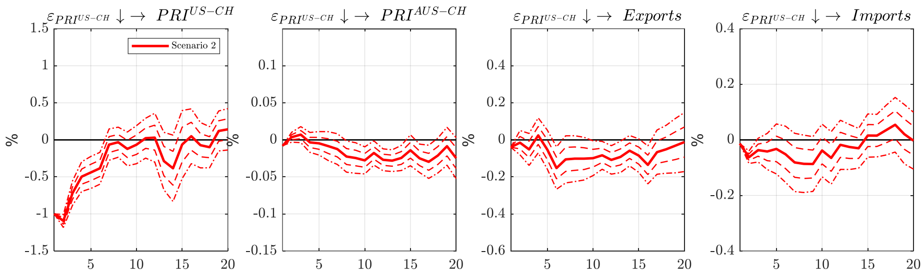
Note: the horizons are quarterly.

Figure 5 Impulse response functions of the local projections

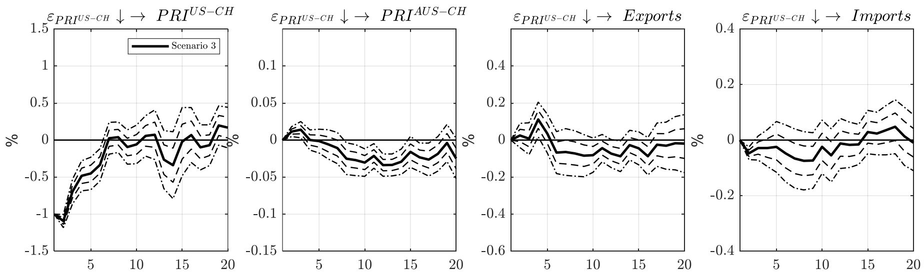
(a) Scenario I



(b) Scenario II



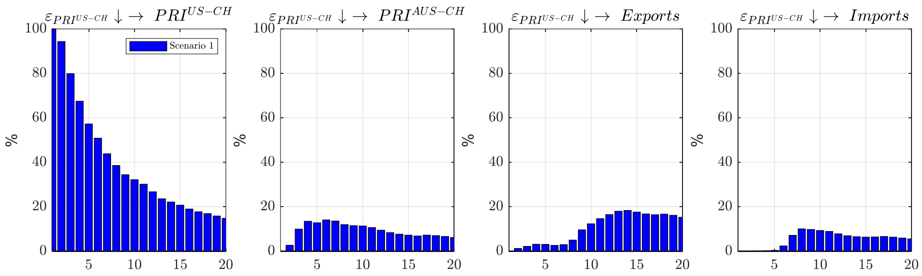
(c) Scenario III



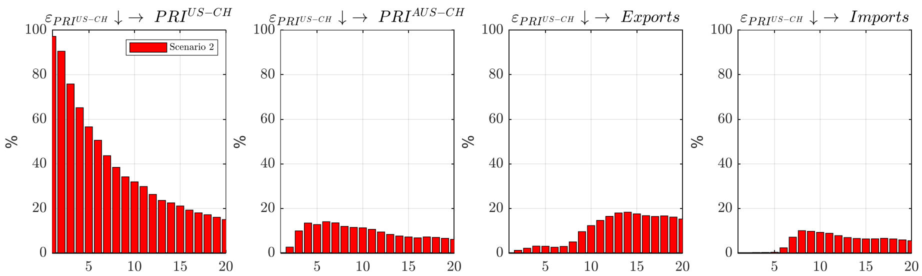
Note: the confidence intervals are constructed by using the error bands of Newey and West (1987) at 66% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determined

Figure 6 Forecast error variance decomposition of the local project

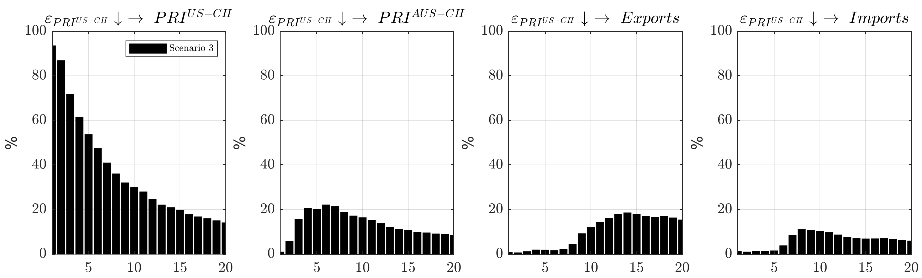
(a) Scenario I



(b) Scenario II



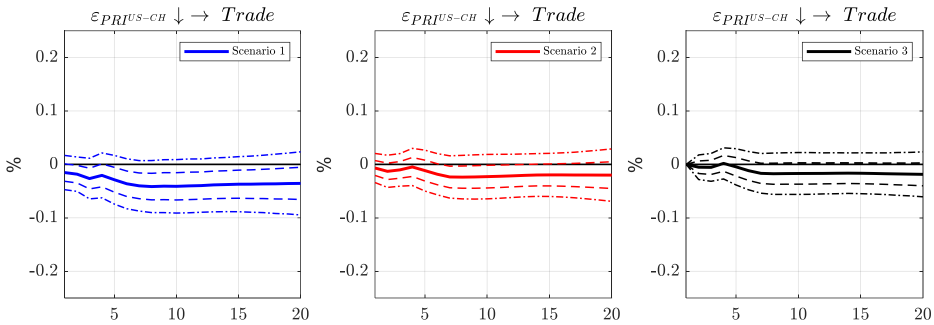
(c) Scenario III



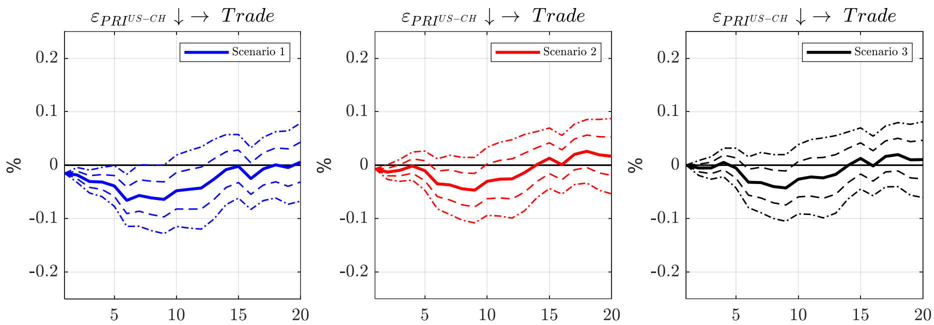
Note: the lags for the VAR system are determined as 4.

Figure 7 IRFs of trade by employing SVAR and LP methods

(a) SVAR model



(b) LP model



Note: the confidence intervals are constructed by using a wild bootstrapping method proposed by (Kilian, 2009) at 66% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determine

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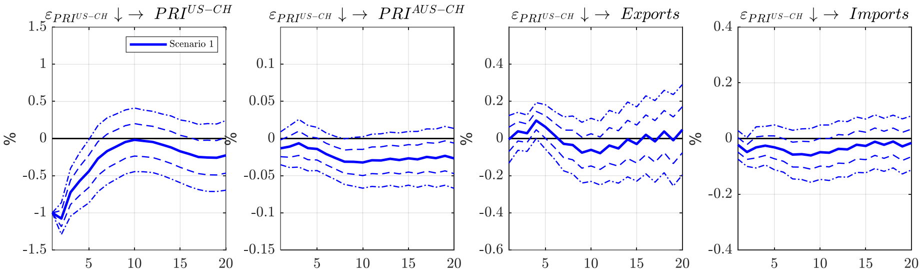
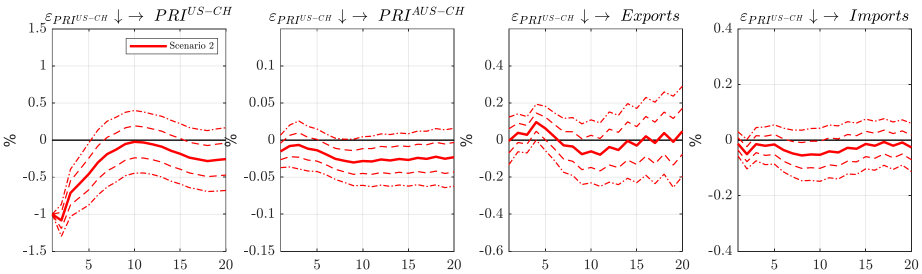
Figure 8 IRFs of an augmented SVAR model

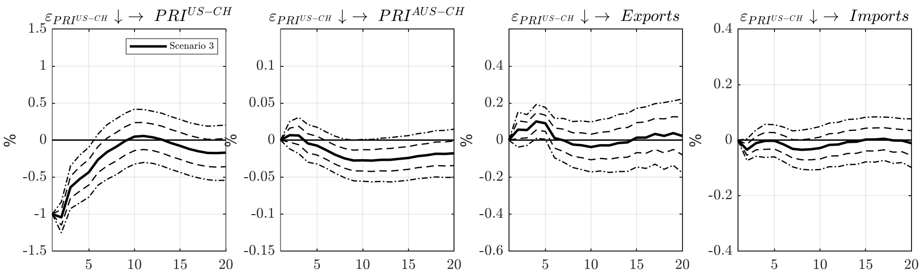
(a) Scenario I



(b) Scenario II



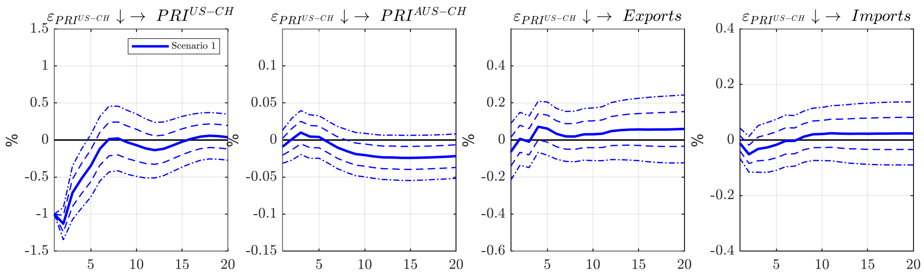
(c) Scenario III



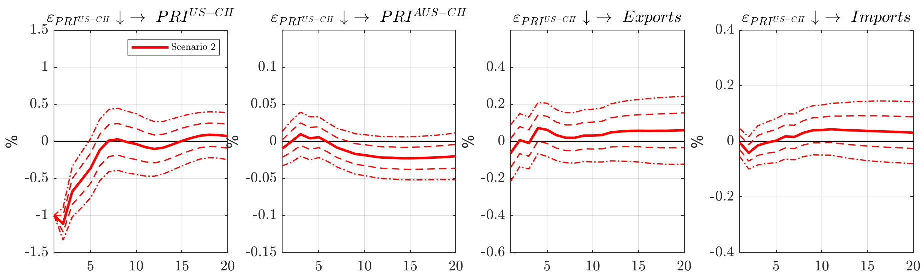
Note: the confidence intervals are constructed by using a wild bootstrapping method proposed by (Kilian, 2009) at 66% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determine

Figure 9 IRFs of the typical SVAR model (Prior to Trump's administration)

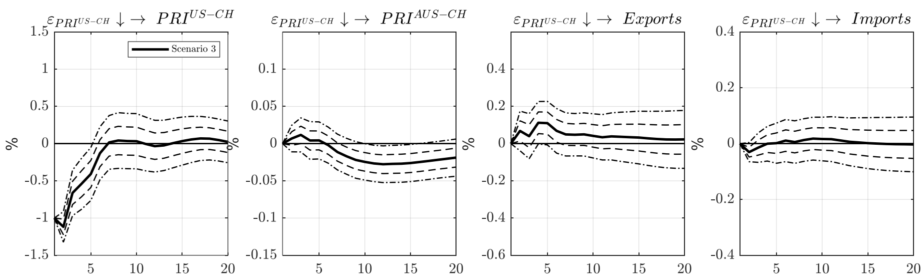
(a) Scenario I



(b) Scenario II



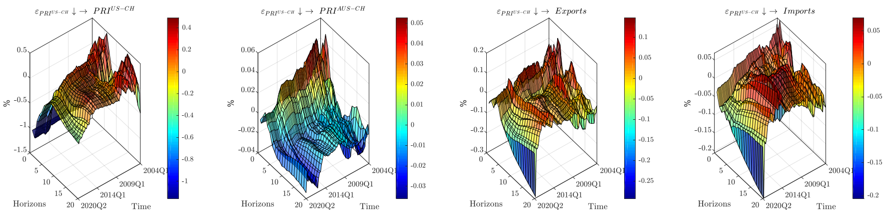
(c) Scenario III



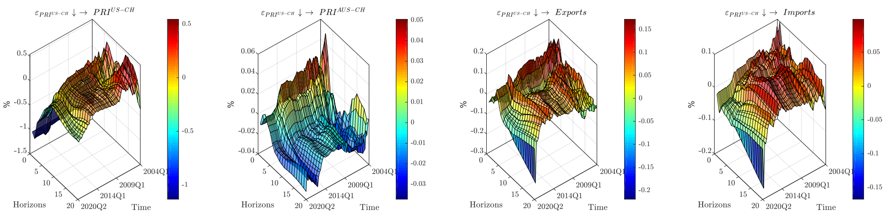
Note: the confidence intervals are constructed by using a wild bootstrapping method proposed by (Kilian, 2009) at 66% and 95% significance levels. The horizon is quarterly. The lags for the VAR system are determine

Figure 10 Time-varying IRFs of the typical SVAR model

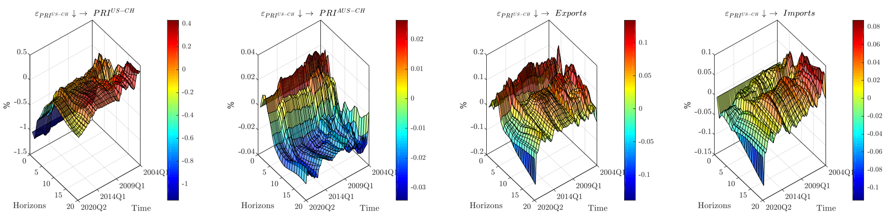
(a) Scenario I



(b) Scenario II



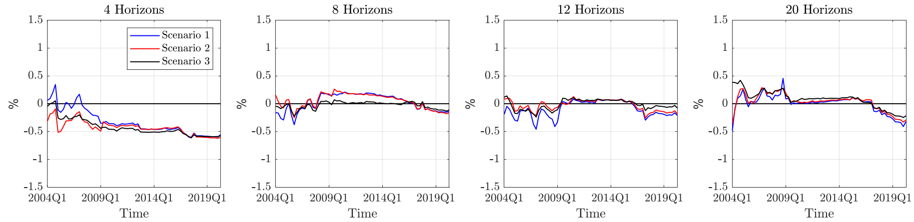
(c) Scenario III



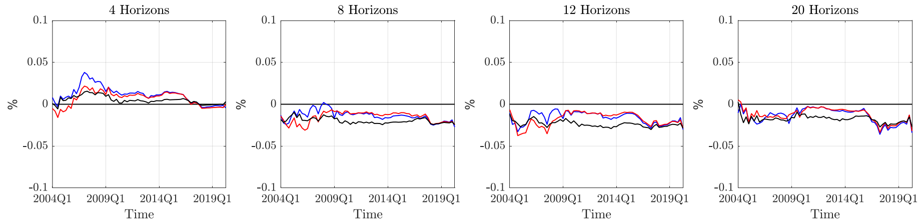
Note: the lags for the VAR system are determined as 4. To obtain time-varying impulse response functions, we use a forward-expanding method by setting the window size to 48. Therefore, the estimates start from 2004Q1 and end up with 2020Q2.

Figure 11 Time-varying IRFs of the typical SVAR model (Horizontal)

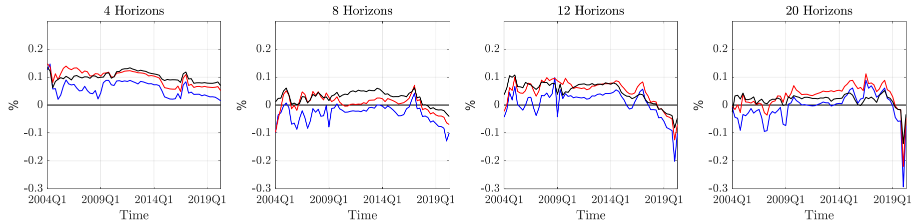
(a) The responses of pri_t^{US-CH}



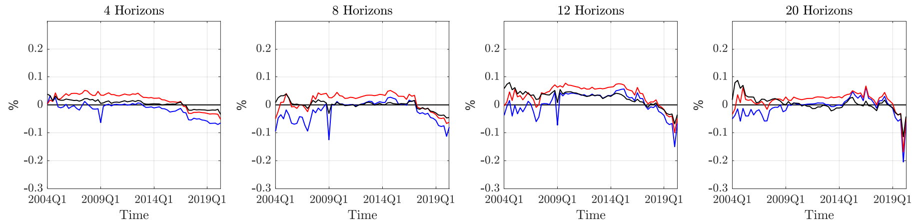
(b) The responses of pri_t^{AUS-CH}



(c) The responses of ex_t



(d) The responses of im_t



Note: the lags for the VAR system are determined as 4. To obtain time-varying impulse response functions, we use a forward-expanding method by setting the window size to 48. Therefore, the estimates start from 2004Q1 and end up with 2020Q2.

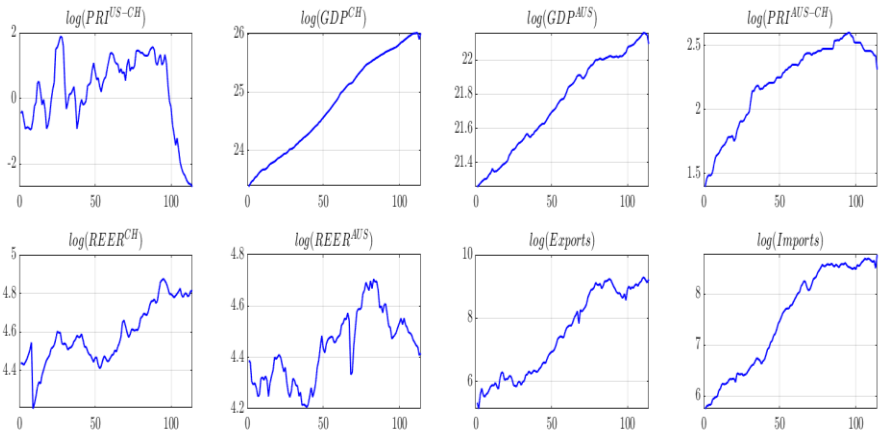
Appendix: Supplementary Materials

In this appendix, we provide additional materials about the dataset, additional results and robustness checks.

A.1 Dataset

The PRI of US-China and Australia-China are drawn from the official website of the Institute of International Relations of Tsinghua University: http://www.imir.tsinghua.edu.cn/. The dataset of Australian exports to and imports from China can be found in the Direction of Trade Statistics operated by the International Monetary Fund (IMF). The nominal GDP and real effective exchange rate are available at International Financial Statistics dataset operated by IMF. To deflate the nominal dataset, we utilize the consumer production index at constant price which is also available in the IFS database. All variables are seasonally adjusted where necessary. Before implementing the SVAR model and local projections, we transform the data into logarithms. We plot all variables used in the benchmark model in Figure A.1. The sample covers the period from 1992Q1 to 2020Q2。

Figure A.1 Plots of variables

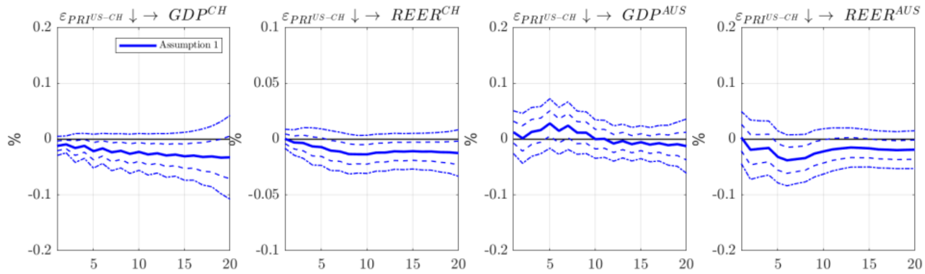


A.2 Additional IRFs results

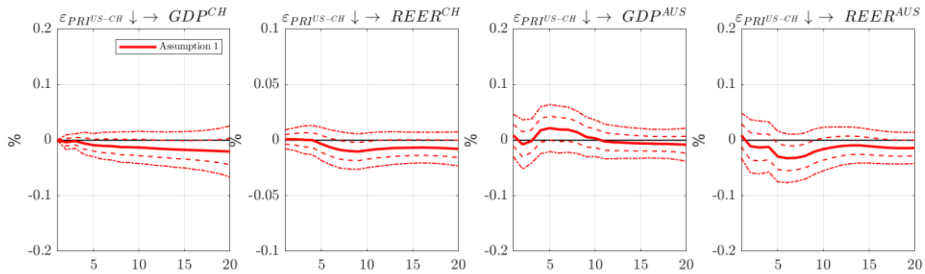
Additional IRFs of the remaining variables given oil supply shocks are reported here. The empirical specifications are the same as the ones shown in the benchmark model. The results based on a typical SVAR and LP methods are available in Figures A.2 and A.3.

Figure A.2 IRFs of the rest of variables in the typical SVAR

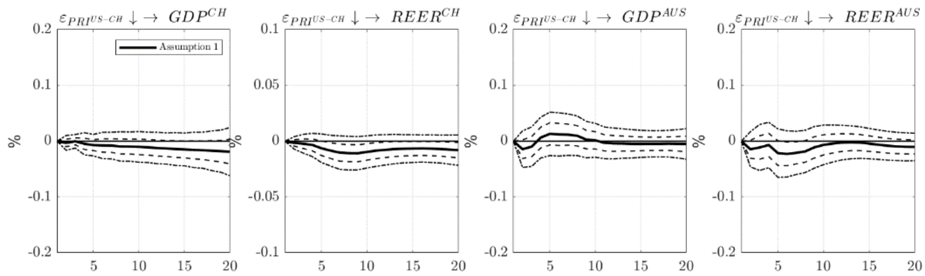
(a) Scenario 1



(b) Scenario 2



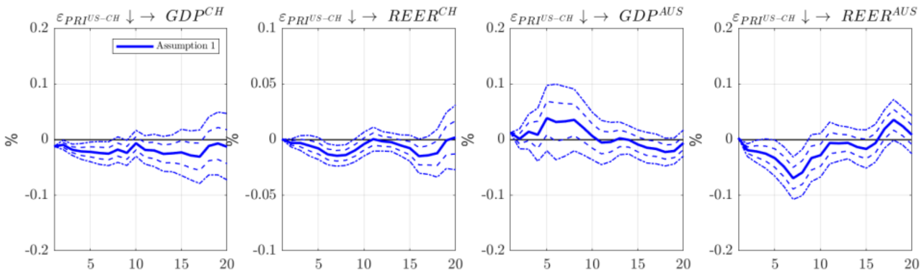
(c) Scenario 3



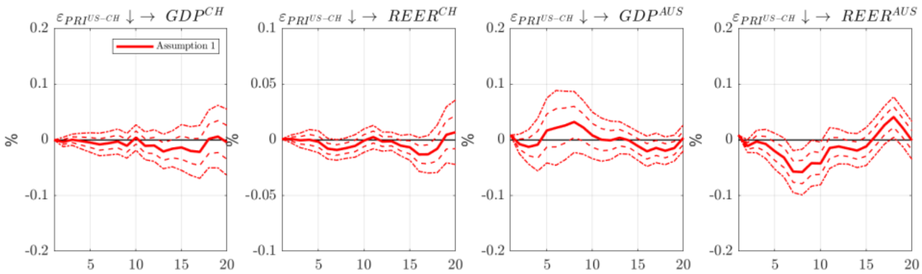
Note: the horizon is quarterly. The lags for the VAR system are determined as 4.

Figure A.3 IRFs of the rest of variables in LP Methods

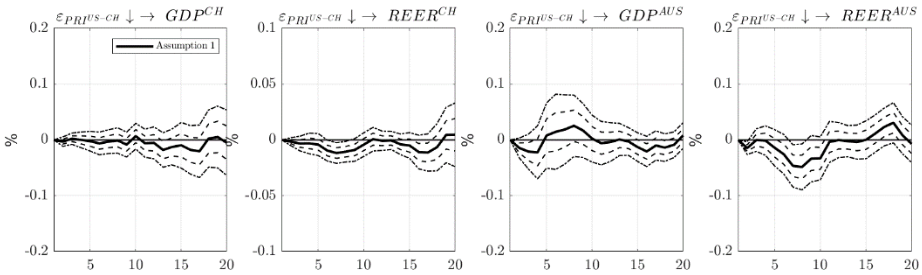
(a) Scenario 1



(b) Scenario 2



(c) Scenario 3



Note: the horizon is quarterly. The lags for the VAR system are determined as 4.

A.3 Robustness checks

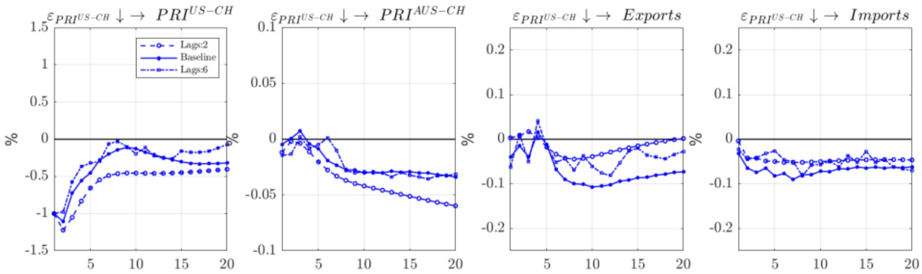
The results of robustness checks by considering different empirical specifications, such as lag-order, data misreporting, VAR in first-differenced data and adding time tend, are presented here. In the benchmark model, the results are obtained by setting the lag order to 4 quarters. In the robustness check, we incorporate fewer and more lags into the model, such as 2 and 6 lags. Other empirical specifications are the same as the baseline specifications. The robustness results of lag-order specifications under different scenarios are available in Figure A.4.

Due to different statistical standards in measuring trade between China and Australia, there is a misreporting problem. In the benchmark model, we consider the datasets from Australia. However, in the robustness checks, we utilize the dataset reported by China. In other words, China's exports are viewed as Australian imports and the imports of China are Australian exports. The results are available at Figure A.5.

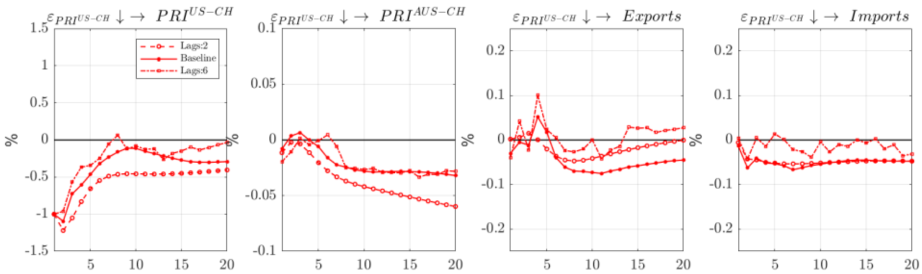
The benchmark model is estimated in log level specifications, Sims et al. (1990) suggest that the log level specifications can deliver consistent estimates when the variables in the VAR system have stochastic trends and are cointegrated. Furthermore, Elliott (1998) shows that imposing the unit root and cointegration relationships in the model could lead to large size distortions. Peersman (2018) estimates a food market model based on the log level specifications. In this sensitivity analysis, we provide results of the VAR estimated in differenced data in Figure A.6. In addition, we also implement Johansen cointegration tests which suggest 8 cointegration relations at the 5% level according to the Trace statistics. Finally results adding a time trend are reported in Figure A.7.

Figure A.4 Robustness of lag-order

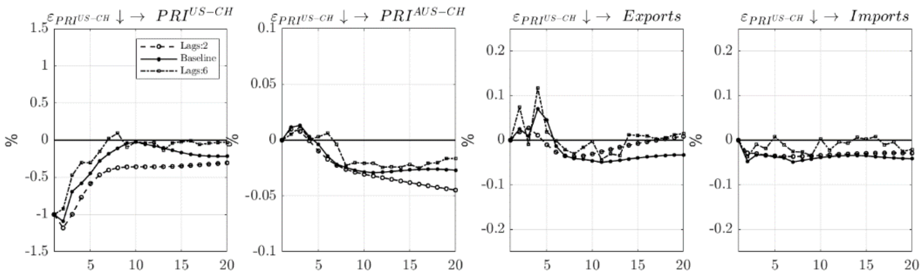
(a) Scenario 1



(b) Scenario 2



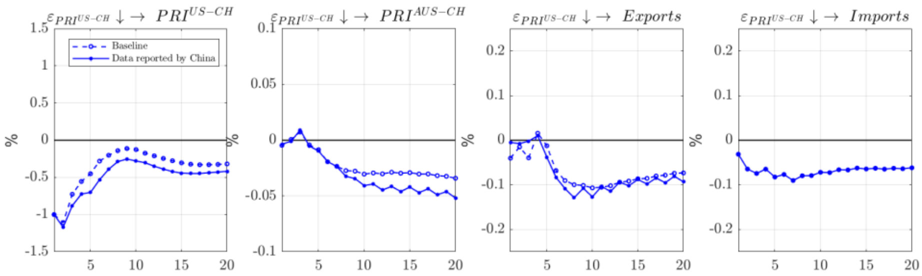
(c) Scenario 3



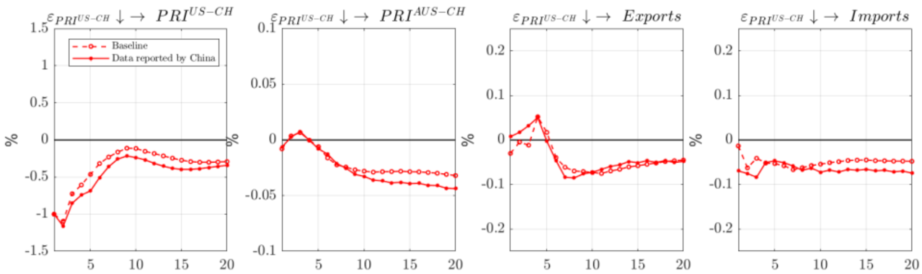
Note: the horizon is quarterly.

Figure A.5 Robustness of data misreporting

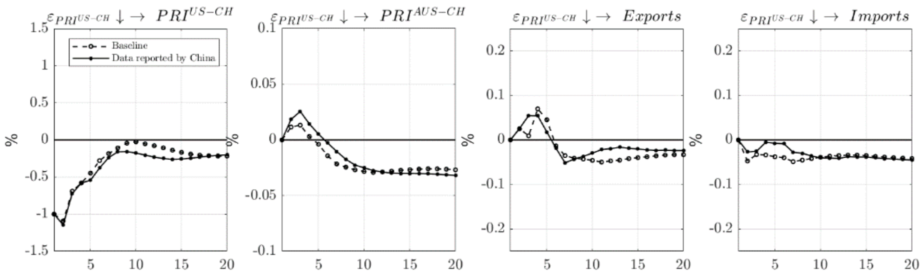
(a) Scenario 1



(b) Scenario 2



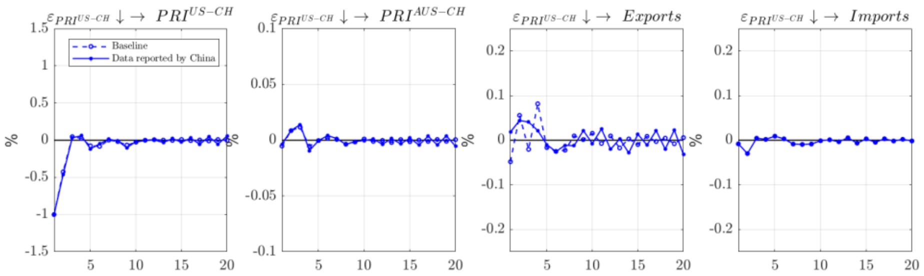
(c) Scenario 3



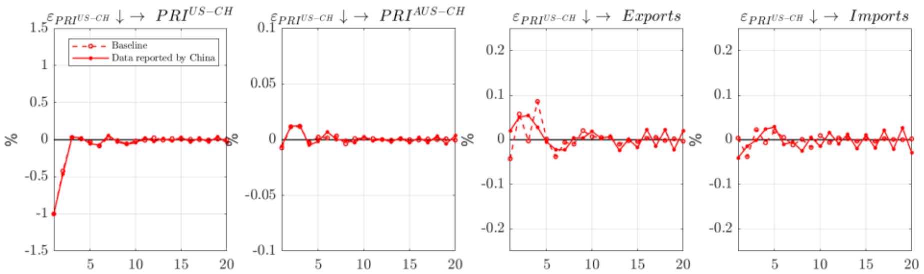
Note: the horizon is quarterly. The lags for the VAR system are determined as 4.

Figure A.6 Robustness of first-differenced data

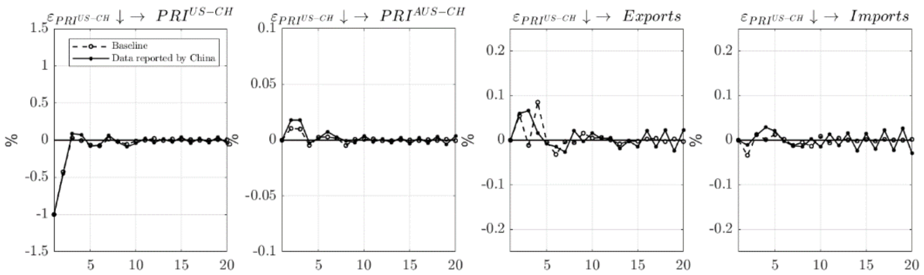
(a) Scenario 1



(b) Scenario 2



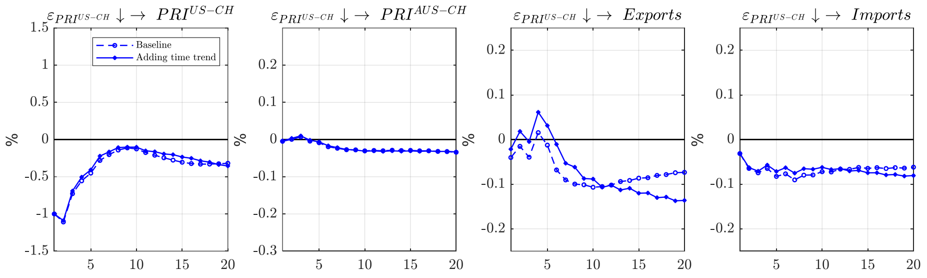
(c) Scenario 3



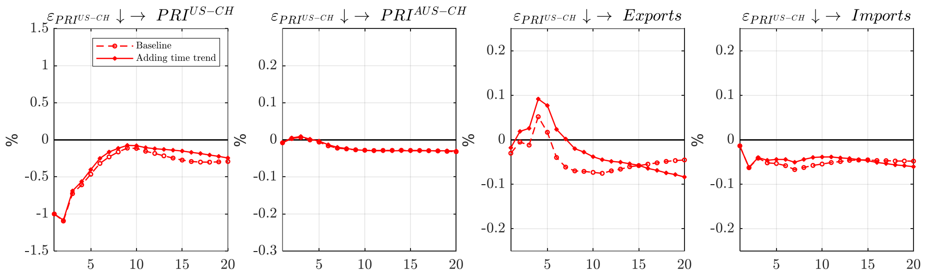
Note: the horizon is quarterly. The lags for the VAR system are determined as 4.

Figure A.7 Robustness of adding a time trend

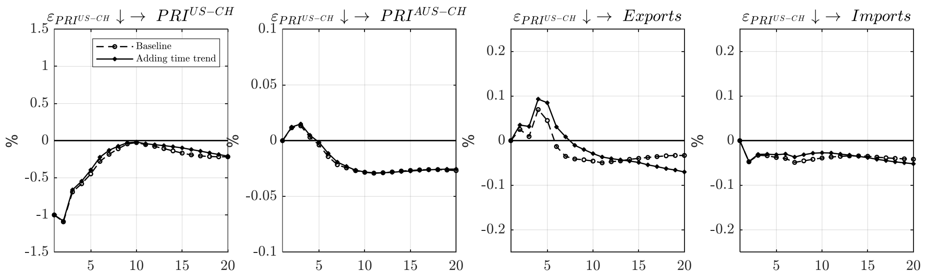
(a) Scenario 1



(b) Scenario 2



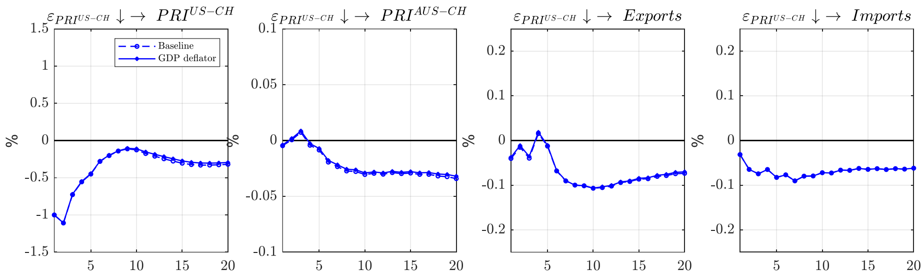
(c) Scenario 3



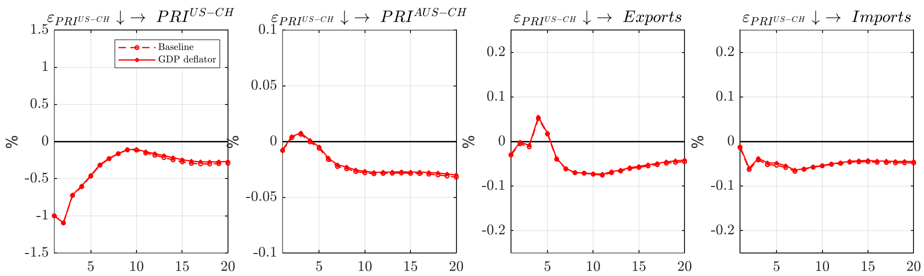
Note: the horizon is quarterly. The lags for the VAR system are determined as 4.

Figure A.8. Robustness of GDP deflator

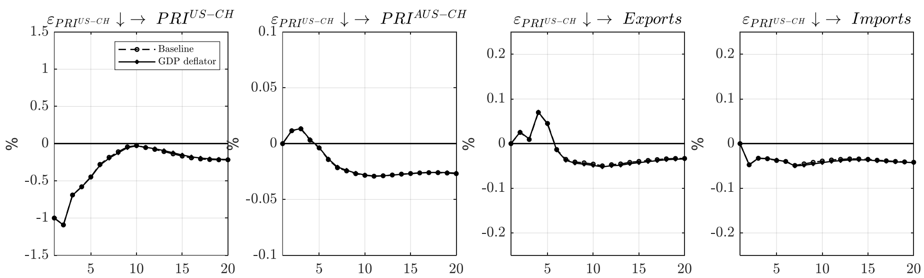
(1) Scenario 1



(2) Scenario 2



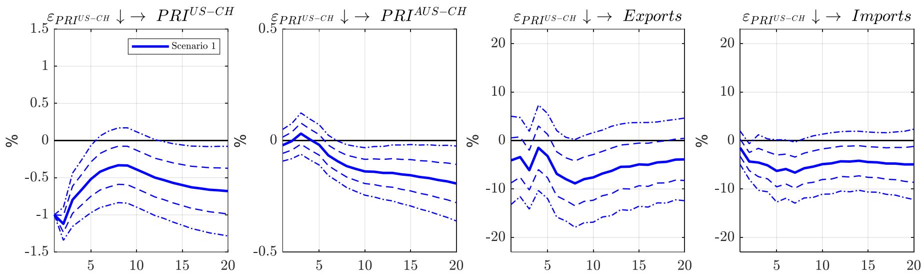
(3) Scenario 3



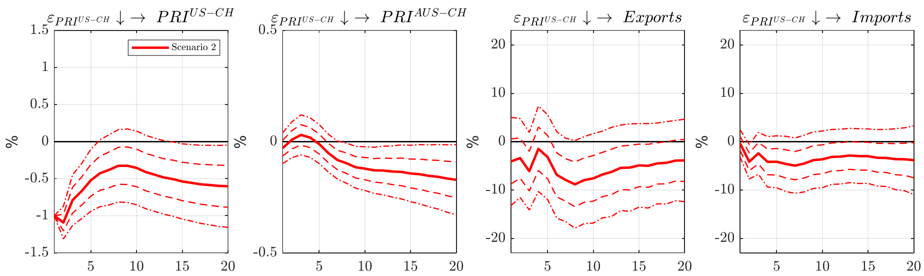
Note: the horizon is quarterly. The lags for the VAR system are determined as 4. The exports and imports are deflated by GDP deflator.

Figure A.9. Robustness of linear transformation of PRI

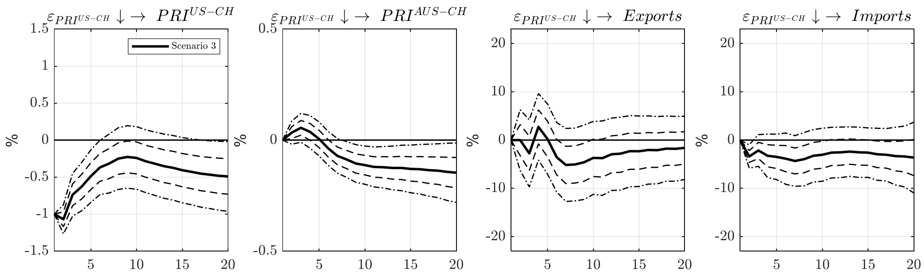
(4) Scenario 1



(5) Scenario 2



(6) Scenario 3



Note: the horizon is quarterly. The lags for the VAR system are determined as 4. The exports and imports are deflated by GDP deflator.