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Technological novelty and productivity growth: a cliometric approach

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Abstract

This paper aims at providing further empirical evidence on the long-run relationship between technology and productivity by using a cliometric approach based on Granger's causality. We test, for the first time, the sign and direction of causality between technological novelty, which is an important driver of radical technological innovations, and productivity, for the whole 20th century. Technological novelty is here proxied by the degree of component recombination of inventions. We find that the flow and stock of Technologically Novel Inventions (TNI) have an important, but temporary, positive impact on productivity, and that these inventions are originated by a handful of leading technological fields, mainly concentrated in the sectors of specialized suppliers of capital equipment and in science based sectors. Our results also show that, at the aggregate level, there is no causal relationship running from productivity to TNI, which suggests that radical technologies are exogenous, i.e., independent of productivity variations. Yet, at technological field level, we find that productivity may have a positive or negative impact on TNI. This instead suggests that some radical technologies are endogenous and, depending on the field, can rise during periods of growing productivity, when demand is higher, or during periods of decreasing productivity, when the opportunity profits of previous radical technologies are exhausted and demand is lower. However, among endogenous technologies, only those that rise during periods of decreasing productivity have a positive impact on productivity. We conclude by discussing implications on the productivity stagnation since the 1970s and the current productivity slowdown.

Keywords: Technological novelty; Productivity; Radical technologies; Component recombination; Cliometrics; Granger's causality

JEL classification: O33; O40; C32; N12

1. Introduction

The productivity stagnation experienced by advanced economies since the 1970s and the further productivity slowdown since the early 2000s (before the 2008 crisis) have raised interest in better understanding the sources of productivity growth. On the one hand, low productivity growth rates have led to low rates of economic growth and higher unemployment levels, which, in turn, have contributed to the stagnation of wages and demand, as well as to rising inequality. On the other hand, the intensification of the ecological crisis creates increasing pressure on sustained economic growth. Even within a perspective that shifts beyond economic growth as a goal (e.g., Jackson, 2019), productivity growth along selected environmental technologies is of critical importance to enable ecological transition.

This paper aims at providing further empirical evidence on the long-run relationship between technology and productivity. Considering technological change as the primary source of productivity growth, several empirical contributions have analyzed the relationship between technology, usually proxied by R&D or patents, and productivity[1]. However, to our knowledge, none of these studies focuses on the concept of technological novelty. Yet technological novelty is an important driver of radical technological innovations (Verhoeven et al., 2016) and scholars from different approaches, often using different terminologies, have highlighted the role played by radically new technologies in originating long-run productivity growth and economic development (Crafts, 1995; Freeman and Perez, 1988; Helpman and Trajtenberg, 1994; Kuznets, 1930; Mensch, 1979; Mokyr, 1993; Perez, 2010; Schot and Kanger, 2018; Schumpeter, 1939)

In addition, empirical analyses of the relationship between technology and productivity mainly consist of cross-country, cross-industry or cross-firm studies, while we found scarce quantitative evidence adopting a long-run approach. In this work, we try to reduce this gap by using a cliometric approach, which combines economic theory and quantitative methods to the study of historical facts. Cliometrics is, more precisely, the use of causal explanations embedded in economic models in order to screen the relative importance of various factors believed to have been operative in a given historical situation (Diebolt,

[1] Without pretending to be exhaustive, see for example Añón Higón, 2007; Antonelli et al., 2010; Castellacci, 2010; Coad et al., 2016; Crespi and Pianta, 2008; Griliches, 1984; Hall and Mairesse, 1995; Hasan and Tucci, 2010; Verspagen, 1995; Baumann and Kritikos, 2016; Bogliacino and Pianta, 2011; Morris, 2018.

2016). The debate on the determinants of economic growth has always been central among cliometricians (Conrad and Meyer, 1958; Fogel, 1964) and has recently known an important expansion (Diebolt and Hagemann, 2019). Here, we intend to contribute to this debate by analyzing the relationship between technological novelty, a concept developed by innovation scholars, and productivity.

We firstly use patent data to build a number of variables capturing the degree of technological novelty of inventions. Following Verhoeven et al. (2016), technological novelty is measured by the degree of component recombination of inventions, so that an invention is considered to be technologically novel if it combines in an original way existing technological components. Secondly, we test the sign and direction of causality between Technologically Novel Inventions (TNI) and productivity over the whole 20th century, at the aggregate and technological field level, through Granger's analysis. The study is conducted on the USA, the economic and technological leader over the considered time period.

Based on the assumption that radical technologies typically emerge from inventions that introduce a novel technological approach (Arthur, 2007; Verhoeven et al., 2016), our results should provide empirical evidence on the sign and direction of causality between radical technologies and productivity. TNI are an imperfect indicator of radical technologies since not all TNI result in radical innovations. To overcome, at least partly, this limitation, we use a measure of technological novelty validated by previous studies as potentially capable of driving a radical technological change (Verhoeven et al., 2016).

With respect to causality running from radical technologies to productivity, scholars seem to agree that radical technologies cause a temporary acceleration of productivity (Crafts, 1995; Freeman and Perez, 1988; Helpman and Trajtenberg, 1994; Kuznets, 1930; Mensch, 1979; Mokyr, 1993; Perez, 2010; Schumpeter, 1939; Schot and Kanger, 2018). There seems to be agreement also on the causal mechanism behind this relationship: radical technologies generate a stream of investments in more incremental innovations, which originate new, more productive, leading sectors and have a vast impact on user sectors. Though there is a sufficient theoretical consensus on this issue, only a few quantitative studies have tested it adopting a long-run approach.

With respect to causality running from productivity to radical technologies, theoretical consensus is less solid. While most of the authors agree that incremental innovations are endogenous, positions diverge with regard to radical innovations. In some works, radical innovations are random or exogenous (Clark et al., 1981; Crafts, 1995; Helpman and Trajtenberg, 1994; Kuznets, 1930; Mokyr, 1993; Schumpeter, 1939; Silverberg and Lehnert, 1993; Aghion et al., 1998; Caiani et al., 2014), that is, there is no causal relationship running from productivity growth to radical innovations. In other studies, radical innovations are, at least partly, endogenous (Mensch, 1979; Saviotti and Pyka, 2013, 2004; Carlaw and Lipsey, 2006; Perez, 2002; Schot and Kanger, 2018; Schaefer et al., 2014), and, according to many of these works, are more likely to rise during periods of slow productivity growth, when the opportunity profits of former radical technologies are exhausted, market are saturated, and demand for existing products is low. On the other hand, even if they refer to technical change in general (without distinguishing between radical and incremental changes), a number of evolutionary agent-based models (e.g., Dosi et al., 2010; Lorentz et al., 2016) and empirical studies (see Crespi and Pianta, 2008) have highlighted the importance of demand in motivating innovative investments and fostering productivity. Here, radical technologies could also rise during periods of high productivity growth, when demand is higher and risk lower. To provide some empirical evidence on this complex issue, we test whether there is a causal relationship running from productivity to TNI and what is its sign.

In most of the above-mentioned literature, sectoral dynamics plays a central role in determining the relationship between radical technologies and productivity. Therefore, we compute our indicator of technological novelty at the level of technological field (WIPO classification), and test the sign and direction of causality between TNI in each technological field and productivity. This analysis informs us on 1) whether TNI that cause productivity acceleration are concentrated in a restricted number of leading technologies; 2) whether TNI may be endogenous at the level of technological field, that is, whether productivity causes, positively or negatively, TNI in some specific field. Finally, by using a concordance matrix, we link technological fields to their main industrial sectors (NACE 2-digits), and, by relying on the revised Pavitt (1984) taxonomy (Bogliacino and Pianta 2011, 2016), we try to shed light on the mechanisms through which technological novelty in these sectors affects productivity.

Our results indicate that the flow and stock of TNI have an important, but temporary, positive impact on productivity, and that these inventions are originated by a handful of leading technological fields, mainly concentrated in the sectors of specialized suppliers of capital equipment and in science based sectors. Our study also shows that, at the aggregate level, there is no causal relationship running from productivity to TNI, which suggests that radical technologies are exogenous, i.e., independent of productivity variations. Yet, at technological field level, we find that productivity may have a positive or negative impact on TNI. This instead suggests that some radical technologies are endogenous and can rise during periods of growing or decreasing productivity, depending on the field. The rest of the paper is organized as follows. Section 2 reviews the relevant literature and formulate the hypotheses. Section 3 details the data, the indicator of technological novelty, and the methodology. Section 4 illustrates the results of the empirical analysis, and section 5 concludes.

2. Literature review and hypotheses

The idea that radical technologies are at the origin of long-run economic growth and structural change dates back to Kuznets. In his *Secular Movements in Production and Prices* (1930), Kuznets sees revolutionary inventions or discoveries as fundamental changes that mark the beginning of "a new era": "When such a change occurs, the industry grows very rapidly. The innovation is rarely perfect at the start, and further improvements take place continually after the main invention or discovery. The use of the continually improving and cheapening commodity spreads to larger areas, overcoming obstacles which may have limited demand in the past. ... But with all this, after a time the vigorous expansion slackens and further development is not so rapid" (Kuznets 1930, p. 9-10).

According to Kuznets, fundamental innovations are randomly distributed in time. Schumpeter (1939), instead, advanced the hypothesis that radical innovations tend to come about in clusters because of the existence of technical interdependencies among technologies. Such clusters create new fast growing leading sectors and are the main determinants of Kondratieff (1935) long-waves i.e., regular upswings and downswings of economic activity of about 40-60 years. In Schumpeter's view, radical innovations are essentially exogenous: they are introduced by extraordinary individual entrepreneurs that create "new combinations" by using exogenously generated inventions. Although radical innovations also have a disruptive impact on existing technologies and sectors, the "creative impact" eventually prevails, leading to increased investments in innovation and to upswings of economic activity. Nevertheless, after some time, imitators erode the monopoly profits created by radical innovations and new markets saturate, thus the economy enters in the downswing phase of long-waves.

The idea that major inventions are at the origin of industrial revolutions is present in the economic history literature as well. Mokyr (1993) argues that "macro-inventions" were crucial to productivity and economic growth during the First Industrial Revolution. He suggests that "technological definition of the Industrial Revolution is a clustering of macro-inventions leading to an acceleration in micro-inventions", where "macro-inventions are those in which a radical new idea, without clear precedent, emerges more or less ab nihilo" (Mokyr 1993). So, macro-inventions are exogenous, while micro-inventions depend on economic factors and are the main source of productivity accelerations. Nevertheless, micro-inventions are subject to diminishing returns and, in the absence of periodic macro-inventions, productivity growth would ultimately be zero: "Our expectation would be that the technological changes associated with the Industrial Revolution would tend to promote a period of steadily increasing output and productivity growth as learning and diffusion took place followed by decreasing output and productivity growth as micro-inventions ran into diminishing returns" (Crafts, 1995).

Radical innovations assume an even more important role in historical analyses of Neo-Schumpeterian scholars (Freeman and Louca, 2001; Freeman and Perez, 1988; Perez, 2010). In this context, clusters of interrelated radical technologies are at the origin of technological revolutions, structural changes, major increases of productivity, and long-term economic growth. Radical innovations also give rise to new "Techno-Economic Paradigms" (TEP), i.e., a new "shared common sense for decision making" (Perez, 2010) that transforms the entire institutional framework of the economy and shapes a new phase of economic development. Similarly, but with a specific focus on sustainable transition, in the Multi-Level Perspective (MLP) framework (Markard et al., 2012; Rip and Kemp, 1998) radical technologies developed at "niche level" play a central role in explaining long-term shifts from one "socio-technical system" to another, and are therefore considered of critical importance in order to enable transition towards a sustainable system of production and consumption.

Bresnahan and Trajtenberg (1995) have used the concept of "General-Purpose Technology (GPTs)" to capture the relationship between major technological changes and productivity growth: "In any given "era" there typically exist a handful of technologies that play a far-reaching role in fostering technical change in a wide range of user sectors, thereby bringing about sustained and pervasive productivity gains" (Helpman and Trajtenberg, 1994, p. 1). Here, periods of slow productivity growth are mainly associated with introduction of some GPTs, which start producing high productivity gains only after an installation period that may be relatively long (David, 1990).

In sum, scholars seem to agree on both the idea that radical technologies (or clusters of radical technologies) are at the origin of long-run productivity growth and the basic causal mechanism behind this relationship: radical technologies generate a stream of investment in more incremental innovations, which create new, more productive, leading sectors and have a vast impact on user sectors, thus determining an acceleration of productivity. There seems to be agreement also on the fact that 1) there exist a lag between the emergence of radical technologies and their impact on productivity; 2) the impact of radical technologies on productivity has limited time length, that is, after some time, it tends to decrease due to diminishing returns. Although there is a sufficient theoretical consensus on these issues, quantitative evidence adopting a long-run approach remains scarce. In order to contribute to fill this gap, and based on the assumption that TNI are a proxy of radical technological innovations (see section 1 and 3), we test the following hypothesis:

HP1: Technologically novel inventions cause a temporary acceleration of productivity

In all the above-surveyed studies, incremental innovations are endogenous, that is, they depend on economic factors. On the contrary, radical innovations are often considered as exogenous (Crafts, 1995; Kuznets, 1930; Mokyr, 1993; Schumpeter, 1939), that is, independent of economic factors: causality runs from radical innovations to productivity growth, but there is no causal relationship running from productivity growth to radical innovations. According to Mensch (1979) instead, radical innovations are endogenous, and, more specifically, dependent on periods of economic depression. In Mensch's view, firms resort to the highly risky strategy of investing in radical innovations only during depression periods, when the opportunity profits of former radical technologies are exhausted, markets are saturated, and demand for existing products is low. Here, causality also runs from economic variables (depression) to innovation (radical innovations).

Although many studies have dealt with the task of empirically testing the Mensch's hypothesis (e.g., Kleinknecht, 1990; Korotayev et al., 2011; Silverberg and Lehnert, 1993; Silverberg and Verspagen, 2003; Solomou, 1986), they have obtained conflicting conclusions. Moreover, the hypothesis has been highly criticized on the theoretical side as well. For example, Clark et al. (1981) argued that the emergence of radical innovations is mainly due to relatively exogenous factors, including scientific and technological breakthroughs, and periods of very strong demand, such as booms and wars, when investing in radical innovation is less risky.

Within the TEP framework, the exhaustion of technological opportunities of a paradigm represents an important endogenous mechanism explaining paradigm shifts, but exogenous factors, in particular government policies, also play a decisive role (Perez, 2002). The MLP acknowledges the same endogenous mechanism of Perez (2002), but emphasizes the importance of exogenous factors in determining the transition to a new socio-technical system, which comes about through "a specific combination and sequence of endogenous and exogenous sources of change" (Schot and Kangera, 2018). Exogenous factors, i.e., the "landscape", include macro-trends such as globalization, urbanization, and climate change, as well as events like wars, natural disasters, and economic crises. As landscape pressures destabilize established regimes, new opportunities are created for niche technologies containing the promise of new regimes, eventually resulting in regime-shifts (Schot and Kangera 2018).

In evolutionary models of technological change and long-run development, the emergence of radical innovations can be either exogenous (Caiani et al., 2014; Silverberg and Lehnert, 1993) or endogenous (Saviotti and Pyka, 2013, 2004). In the latter case, the declining profits opportunities, caused by market saturation and low demand, provide incentives to invest in radically new sectors and technologies. On the other hand, a number of evolutionary agent-based models (Dosi et al., 2010; Lorentz et al., 2016) and empirical studies (see Crespi and Pianta, 2008 for a discussion and references) have highlighted the importance of demand in motivating innovative investment and in fostering productivity, although these works refer to technical change in general, without distinguishing between radical and incremental changes. In this perspective, radical technologies could also emerge in periods of high economic growth, when demand is higher and risk lower.

Finally, within the GPTs framework, in the first works the arrival of GPTs is modelled as exogenous: these arrive at predetermined intervals (Helpman and Trajtenberg, 1994) or with a certain probability (Aghion and Howitt, 1998). However, in more recent articles, economic growth is driven by a succession of endogenously generated GPTs. For example, in Carlaw and Lipsey (2006), GPTs arrive at randomly determined times but with a productivity that is determined by the amount of fundamental research endogenously generated since the last GPT (and a random component), while in Schaefer et al. (2014) GPTs arise stochastically depending on the stock of applied knowledge.

In short, in some works radical innovations are random or exogenous, while in others, they are, at least partly, endogenous. In addition, according to some scholars, firms are more likely to invest in radical innovations during periods of slow economic growth, when the opportunity profits of former radical technologies are exhausted, market are saturated, and demand for existing products is low, while for others, radical innovations may also rise during periods of high economic growth, when demand is higher and risk is lower. In both cases, demand seems to play a key role. In order to provide some preliminary empirical evidence on this complex issue, we test the following hypothesis:

HP2: Technologically novel inventions are exogenous, that is, independent of productivity variations

This issue is important because if radical innovations are exogenous, then technological revolutions, structural changes, and accelerations of economic growth would be the result of random or historically unique events that will not necessarily repeat in the future, e.g., the Second World War (Epicoco, 2020). On the contrary, if radical innovations are, at least partly, endogenous, then the economic system would tend to generate endogenously, and therefore recurrently, technological revolutions, structural change, and accelerations of economic growth (Epicoco, 2020).

Finally, all the above-surveyed literature assigns to sectoral dynamics a central role in determining the relationship between radical technologies and productivity growth: radical technologies are expected to create new, more productive, leading sectors, which drive productivity accelerations. To provide some evidence on such sectoral dynamics, we compute our indicator of technological novelty at the level of technological field (WIPO classification), and test the following hypothesis:

HP3: Technologically novel inventions that cause productivity acceleration are concentrated in a restricted number of leading technological fields

With respect to causality running in the opposite direction, from productivity to radical technologies, we test whether the emergence of radical technologies in some specific technological fields depends on productivity variations. Even if, at the aggregate level, radical innovations may result exogenous, they may be endogenous at the level of technological field, that is, productivity variations may cause (positively or negatively) radical innovations in some specific field. Hence, our last hypothesis to test is the following:

HP4: Technologically novel inventions may be endogenous at the level of technological field, that is, dependent of productivity variations

3. Data, indicator of technological novelty, and methodology

3.1. Data

To test the above-mentioned hypotheses, we have used data on Total Factor Productivity and patent data from 1900 to 2000. The analysis focuses on the USA, the economic and technological leader over the considered time period. Total Factor Productivity measures the growth of total output not caused by traditionally measured inputs of labor and capital, and it is calculated as a residual. It is a measure of the impact on economic growth of all unmeasured factors and, among these, of technological change. Therefore, Total Factor Productivity is a better proxy, compared to labor productivity, of that part of economic growth generated by technological change. For this work, we have used data on total factor productivity per hours worked (TFPHW) provided by Bergeaud et al. (2016).

Patent data have well-known limitations as a proxy of innovative activity because not all innovations are patented and not all patented inventions reach the market. Moreover, the propensity to patent is not constant over time and may be affected by a variety of factors (strategic behavior of firms, changes in IP legislation, wars, etc.). And yet, patent data remain the best proxy of innovative activity available for long time periods and are widely used in innovation studies. In this paper, we have used data on US patents granted by the USPTO by priority year. Data have been extracted from the CRIOS dataset (Coffano and Tarasconi, 2014).

3.2. Indicator of technological novelty

In order to test our hypotheses, we need to identify TNI. According to many innovation scholars, technological novelty is the result of a recombinant search process, that is, a process of continuous recombination of new and existing knowledge and technologies (e.g., Arthur, 2007; Nelson and Winter, 1982; Schumpeter, 1939). The concept of technology brokering (Hargadon and Sutton, 1997) refers, more specifically, to the process of creation of innovations by combining in an original way existing technological components. Therefore, the empirical literature has widely used the degree of component recombination to identify breakthrough inventions and to analyze different aspects of the recombinant process (Arts and Veugelers, 2015; Fleming, 2001; Keijl et al., 2016; Strumsky and Lobo, 2015; Verhoeven et al., 2016).

In this paper, following Verhoeven et al. (2016), an invention is considered to be technologically novel if the applied combination of components is different from those applied in previous inventions. Verhoeven et al. (2016) have tested the validity of this indicator and have shown that the creation of new combinations of components leads to a significantly higher likelihood of breakthroughs. Like in Verhoeven et al. (2016), we have operationalized the above-mentioned indicator by using the IPC-codes (International Patent Classification codes) to which patents are assigned, so that the number of IPC-codes assigned to a patent is a proxy of the components used to develop the invention, while recombination is proxied by the number of new (previously unconnected) pairs of IPC-codes. The number of new pairs of IPC-codes also depends on the number of IPC-codes to which a patent is assigned. This, in turn, depends on the number of existing IPC-codes, which typically grows over time.

Therefore, we have normalized our measure of technological novelty by dividing the number of new IPC pairs contained in a patent by the number of possible IPC pairs contained in that patent[2]. Our indicator of Recombinant Novelty (RN) is the following:

$$\mathrm{RN} = \frac{\text{Number of previously unconnected pairs of IPC-codes}}{\text{Number of possible pairs of IPC-codes}}$$

On the basis of this indicator, we have built a number of variables, at the aggregate and technological field level, capturing flows and stocks of TNI. We have then tested the relationship among these variables and productivity (TFPHW) by using Granger's causality. The most important variable is the annual flow of top 1% patents with the highest level of RN (T1rec_flow), which is expected to approximate the annual flow of TNI. T1rec_flow is a subset of a second variable: the annual flow of patents with positive RN (Rec_flow). Rec_flow contains all T1rec_flow patents, but it also includes patents with a lower (even if positive) degree of RN. Besides flows, we have tested the same variables in stocks[3]: the annual stock of top 1% patents with the highest level of RN (T1rec_stock) and the annual stock of patents with positive RN (Rec_stock). Both flows and stocks have been tested in absolute value and as a percentage of annual flows and stocks of patents.

In addition, we have tested causality between TFPHW and 1) the annual flow and stock of patents (Pat_flow and Pat_stock); 2) the annual flow of patents that introduced a new IPC-code (New_ipc). The number of patents may be indicative of the number of inventions, while patent stock should approximate the stock of inventions. New_ipc is a variable that does not directly rely on our indicator of RN since it does not imply any recombination among

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[2] As an example, consider Patent US 4234565 with priority year 1977. The patent is assigned to three IPC codes (A23K001; C08F220; A61K009) from which three combinations can be identified: (A23K001; C08F220), (A23K001; A61K009) and (A61K009; C08F220). Since only the first combination is new (it has never been used by patents with priority year before 1977), the recombinant novelty index is 1/3 = .33, that is, 1/3 of the combinations is new.

[3] The stock has been computed following the perpetual inventory method $K_t = (1-\delta)K_{t-1} + R_t$, where K is the stock of top 1% patents with the highest level of RN at time t, R denotes the flow of top 1% patents with the highest level of RN at time t, and δ is a depreciation rate. For the initial stock, the value is computed based on a depreciation and growth rate as $K_{t=0} \cong \frac{R_0}{\delta+g}$. We applied the depreciation rate (15%) usually used for computing knowledge stocks (Hall et al., 2010).

components. However, since components are approximated by IPC-codes, patents that introduced a new IPC-code should capture inventions that introduced a new component. Therefore, we have tested whether the annual flow of these inventions has a causal relationship with productivity. Tab. 1 contains the list of our variables and their description. Finally, we have calculated our main variable of interest, T1rec_flow, at technological field level by using the IPC8 Technology Concordance Table provided by WIPO, which attributes patents to the 35 technological fields (IPC_35) on the basis of their IPC-codes (Schmoch, 2008). Tab. 1 in the Appendix shows the list of these fields. From CRIOS dataset we have extracted information on the WIPO technological fields to which T1rec_flow patents have been assigned[4], so that to obtain a variable that proxies the annual flow of top 1% patents with the highest level of RN for each technological field.

Tab. 1. List of variables

TFPHW	Annual TFP per Hours Worked
Flows	
Pat_flow	Annual flow of patents granted by the USPTO by priority year
Rec_flow	Annual flow of patents with positive RN
Rec_flow%	Annual flow of patents with positive RN, % of annual patent flow
T1rec_flow	Annual flow of top 1% patents with the highest level of RN
T1rec_flow%	Annual flow of top 1% patents with the highest level of RN, % of annual patent flow
New_ipc	Annual flow of patents that introduced a new IPC-code
Stocks	
Pat_stock	Annual stock of patents granted by the USPTO by priority year
Rec_stock	Annual stock of patents with positive RN
Rec_stock%	Annual stock of patents with positive RN, % of annual patent stock
T1rec_stock	Annual stock of top 1% patents with the highest level of RN
T1rec_stock%	Annual stock of top 1% patents with the highest level of RN, % of annual patent stock

[4] We have applied fractional count to patents assigned to more than one technological field.

3.3. Methodology

Granger's causality requires that we work within the framework of the non-structural VAR introduced into the historical research by (Eckstein et al., 1984)[5]. Non-structural VAR models present the advantage to take into account the intrinsic structure of the series and the dynamical effects between variables offering more reliable analyses at the dynamical level than traditional models.[6] They also offer the possibility of considering all causal relationships between variables without *a priori* on their potential endogeneity. In a VAR model variables are both exogenous and endogenous.[7] Despite their historical opposition, there is a link between non-structural and structural model and it's easy to move from one to another (Hendry and Mizon, 1993; Monfort and Rabemananjara, 1990). In such models each equation describes the evolution of a variable in function of its own lagged values and of the lagged values of other variables of the system.

The use of this type of model requires beforehand to test for various assumptions. First of all it is necessary to work with stationary variables[8]. Therefore, we use the unit root test of Elliott et al. (1996), which is considered more efficient (Salanié, 1999) than the classic test of Dickey and Fuller (1979). Once variables are stationary we select the optimal number of lags which needs to be sufficiently large for residuals to become white noises. Several criteria contribute to determine optimal lags. All of them are based on the maximization of the log-likelihood function. Next, presence of cointegration relationship(s)[9] has to be tested (Engle and Granger, 1991, 1987) and, if necessary, corrected (Vector Error Correction Model) in order to avoid any problem of fallacious regressions (Newbold and Granger, 1974). We use the

[5] "The methodology of vector autoregression appears useful for studying historical series on climatic, economic and demographic variables where we do not yet have a sufficient theoretical foundation for specifying and estimating structural models", p. 295.

[6] The intrinsic structure of the series is related to its identification in the ARIMA classification (Box and Jenkins, 1976; Newbold and Granger, 1974).

[7] Non-structural VAR models are sometimes criticized for requiring to include in the model a number of variables matching the degree of freedom in order to avoid estimation problems (Johnston and Dinardo, 1999), and for the lack of theory on which they rely.

[8] A X_t process is known as stationary if all its moments are invariants for any change of the origin of time. There are two types of non-stationary processes: the TS processes (Trend Stationary Processes) which present non-stationarity of the deterministic type and the DS processes (Difference Stationary Processes) for which non-stationarity is due to a random type. These processes are respectively stationarized by a deviation from the deterministic trend and with a differences filter. In this last case, the number of filters indicates the order of integration of the variable. A variable is integrated of order "D" if it is necessary to differentiate it "D" times to make it stationary.

[9] Variables are said to be cointegrated if they exhibit long-run stable relationship(s), namely if they share common trends.

Johansen test (1988). It is then possible to consider the dynamic analysis and the causality analysis (short term relationship)[10]. There are two approaches to causality (Granger, 1969; Sims, 1980), which are generally equivalent (Bruneau and C., 1996). We choose here a Granger test (1969).

The main difference between correlation and causality is the temporality. Granger-Sims causality relies on the fundamental axiom that 'the past and present may cause the future but the future cannot cause the past' (Granger, 1980, p. 330). It's the temporal ordering that allows interpreting dependence as a causal relationship (Kuersteiner, 2010). It can be explained by the fact that correlation is a symmetric concept without information about the way of influence, whereas causal way is possible through "the arrow of time" (Granger 1980 p. 349). In order to study the direction and sign of causality, we investigate how our variable of interest reacts when a change occurs on the second variable. Consider a two-variable model as follows:

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} A_1 & B_1 \\ C_1 & D_1 \end{bmatrix} \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} A_2 & B_2 \\ C_2 & D_2 \end{bmatrix} \begin{bmatrix} X_{t-2} \\ Y_{t-2} \end{bmatrix} + \cdots + \begin{bmatrix} A_p & B_p \\ C_p & D_p \end{bmatrix} \begin{bmatrix} X_{t-p} \\ Y_{t-p} \end{bmatrix} + [\varepsilon_t]$$

Then, for a causal relationship going from variable X to variable Y, the sign of this relationship is determined by the sign of the following ratio:

$$\sigma_{X \to Y} = \frac{\sum_{i=1}^{p} C_i}{1 - \sum_{i=1}^{p} D_i}$$

These developments are studied in depth by the dynamic analysis, which considers the effects of exogenous variables on endogenous variables. Although VAR models consider all the variables exogenous and/or endogenous, the dynamic analysis requires that innovations are considered as exogenous variables. The simulation of shocks on innovations for each variable helps us to understand how (impulse response function) and to what extent/proportion (variance decomposition) others variables are affected. In other words, we observe how a simulated shock on the innovation of variable X affects the variable Y. To study the direction and sign of causality we investigate how our variable of interest reacts when a change occurs on the second variable.

[10] The definition of causality is given by Granger (1969): the variable X causes the variable Y if the prediction of Y is improved when one incorporates information concerning X and its past into the analysis.

4. Results

4.1. Descriptive statistics

Fig. 1 contains observed and smoothed values of the US annual growth rate of total factor productivity (TFPHW) and labor productivity (LPHW) per hours worked from 1890 to 2012[11]. We observe that the two variables are highly synchronized (i.e., they have the same troughs and peaks) and that both have considerably fluctuated over time, showing periods of accelerated and decelerated growth. This suggests that fluctuations of labor productivity growth, which is the main determinant of output growth, are largely driven by fluctuations of productivity gains originated by technological change.

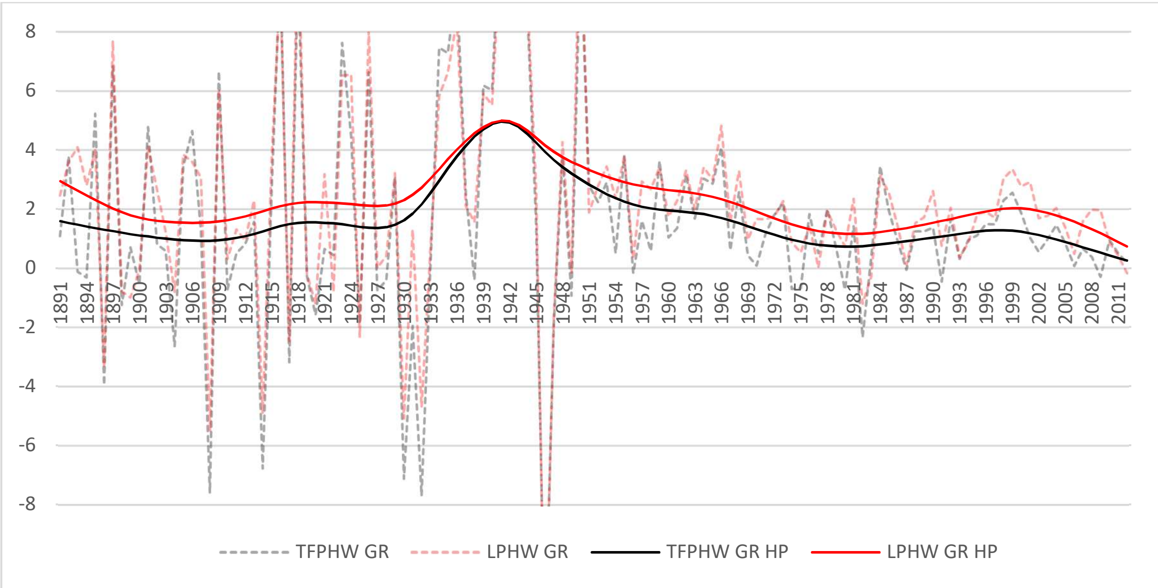


Fig. 1. US Annual growth rate of labor productivity per hours worked (LPHW GR) and total factor productivity per hours worked (TFPHW GR): observed and smoothed values (%)

The wave that accelerates during the 1980s and the 1990s, with a peak in 1998, is commonly associated to the ICTs (Information and Communication Technologies) revolution, while the big wave expanding from the end of the 19th century to the 1970s is usually associate to the second industrial revolution, based on innovations like electricity, internal combustion engine, and chemistry (Bergeaud et al. 2016). As we can see, since the 1970s productivity

[11] Data have been provided by Bergeaud et al. (2016). Following this work, data have been smoothed by using the HP filter (lambda = 500).

growth has been substantially lower than the previous decades and it has slowed down further since the early 2000s, before the 2008 financial crisis. Tab. 2 shows that the average growth rate of LPHW and TFPHW since the 1970s has been lower than any other time period since 1891, even when we consider only the period 1970-2000, well before the 2008 crisis.

Tab. 2. Average annual growth rate of labor productivity per hours worked (LPHW GR) and total factor productivity per hours worked (TFPHW GR), USA (%)

	TFPHW GR	**LPHW GR**
1891-2012	1.68	2.26
1891-1929	1.45	2.14
1930-1969	2.74	3.23
1970-2012	0.89	1.48
1970-2000	0.99	1.50

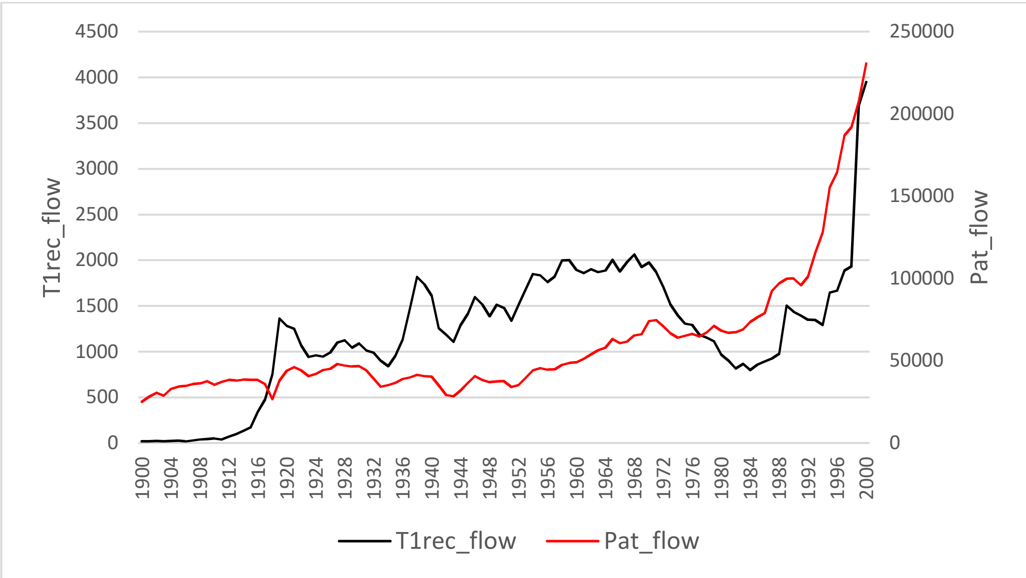


Fig. 2. Annual flow of patents granted by the USPTO by priority year (Pat_flow) and annual flow of the top 1% patents with the highest level of RN (T1rec_flow)

Fig. 2 shows our main variable, T1rec_flow, which should approximate the annual flow of TNI, and Pat_flow, which is indicative of the annual flow of total inventions. T1rec_flow represents only 2.02% of total patents granted between 1900 and 2000. We can see from fig. 2 that the annual flow of TNI increases rapidly in the late 1910s, and, after a 15-year stagnation, it rises again from the mid-1930s to the early 1970s. We then observe a strong decline until the mid-1980s, followed by an exponential increase. The annual flow of total patents, instead, fluctuates slowly until the 1940s, grows during the 1950s and 1960s, and, after a short decline in the 1970s, starts exponentially increasing in the mid-1980s. The literature mainly ascribes that growth to the increase of firms' propensity to patent for strategic reasons (Hall and Ziedonis, 2001). Thus, the increase in the flow of TNI since the mid-1980s may be largely due a more general increase in the flow of strategic patents.

Fig. 3. compares T1rec_flow with the annual flow of patents with positive RN (Rec_flow) and the annual flow of patents that introduced a new IPC-code (New_ipc). Rec_flow and New_ipc represents the 6.14% and the 0.12% of total patents granted between 1900 and 2000, respectively. So, almost 94% of patents have RN=0, that is, have not combined any new IPC-pair. We can see from the figure that Rec_flow and T1rec_flow start importantly diverging since the 1950s. This suggests that since the second half of the 20th century, the number of patents with the highest level of RN (T1rec_flow) has grown much slower than the number of patents with a lower level of RN (Rec_flow). Patents that introduced a new IPC-code, instead, are highly concentrated in one decade, the 1910s. This suggests that during the 1910s have been invented those main components - possibly the core technologies of the second revolution - that in the subsequent years have been recombined. New_ipc rises, to a much smaller extent, also during the 1960s and 1970s, probably because of the emergence of ICTs.

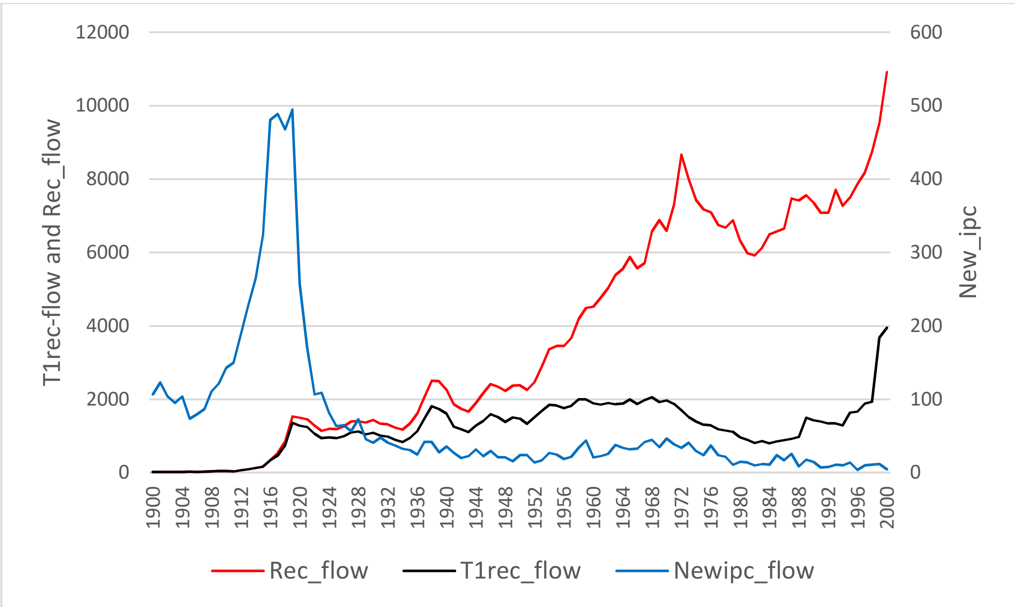


Fig. 3. Annual flow of the top 1% patents with the highest level of RN (T1rec_flow), annual flow of patents with positive RN (Rec_flow), and annual flow of patents that introduced a new IPC-code (New_ipc)

Fig. 4. shows our variables in stock: the annual stock of total patents (Pat_stock), the annual stock of patents with positive RN (Rec_stock), and the annual stock of the top 1% patents with the highest level of RN (T1rec_stock), which should approximate the annual stock of TNI. We see that, coherently with the evolution of variables in flow, all these variables reach a peak in the early 1970s, then decline or stagnate up to mid-1980s, and finally start growing very rapidly.

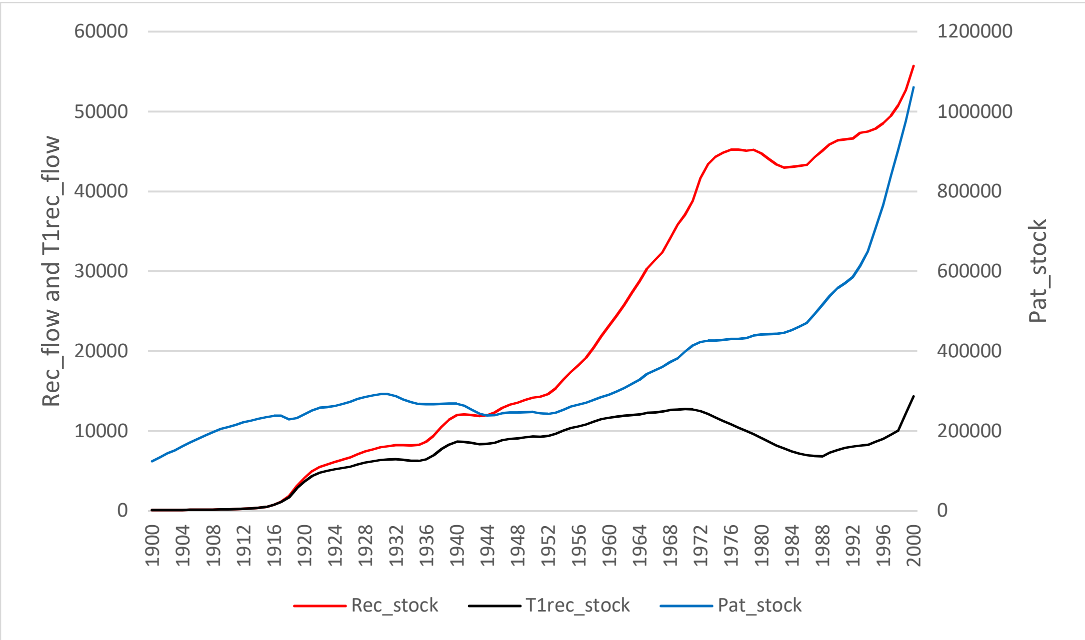


Fig. 4. Annual stock of patents granted by the USPTO by priority year (Pat_stock), annual stock of patents with positive RN (Rec_stock), annual stock of top 1% patents with the highest level of RN (T1rec_stock).

Finally, fig. 5 shows the distribution among technological fields (WIPO IPC_35) of both total patents and the top 1% of patents with the highest degree of RN (T1rec_flow) from 1920 to 2000[12]. We observe that technological fields considerably diverge in terms of both size (as proxied by Pat_flow) and degree of technological novelty (as proxied by T1rec_flow). The largest technological fields are: Electrical machinery, apparatus, energy (IPC_35 1), Transport (IPC_35 32), Other special machines (IPC_35 29), Measurement (IPC_35 10). The technological fields with the highest degree of technological novelty are: Mechanical elements (IPC_35 31),

[12] The information on technological fields to which patents belong is only available since 1920.

Machine tools (IPC_35 26), Transport (IPC_35 32), Electrical machinery, apparatus, energy (IPC_35 1).

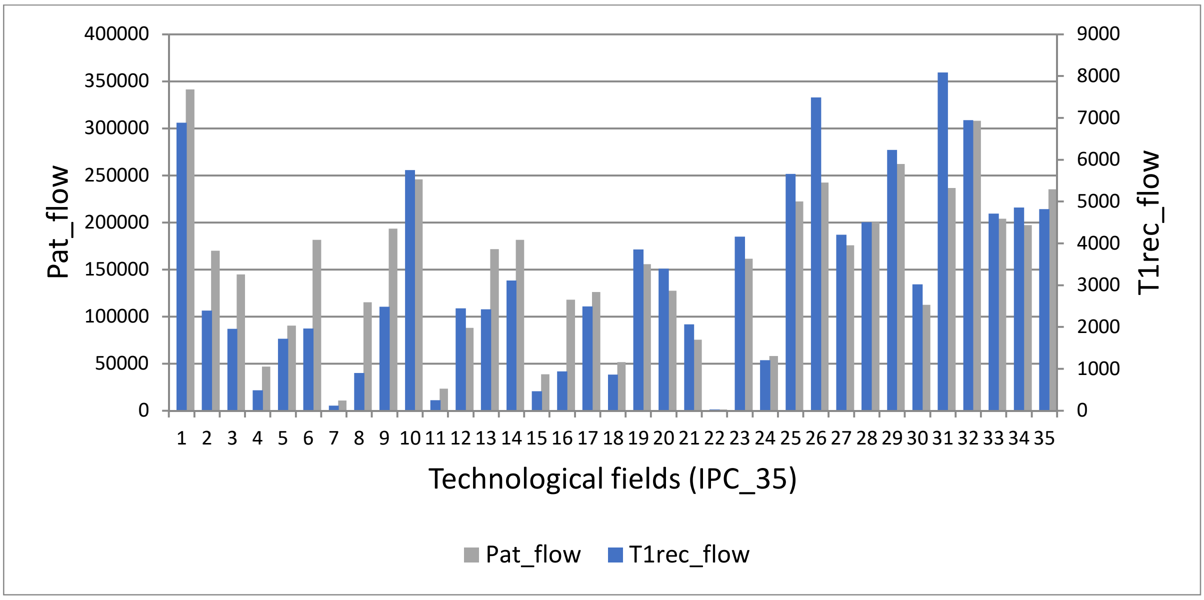


Fig. 5. Distribution among technological fields (IPC_35) of total patents (Pat_flow) and of patents with the highest degree of technological novelty (T1rec_flow), 1920-2000.

4.2. Aggregate analysis

In order to test HP1 and HP2, we have detected the direction and sign of causality between TFPHW and the variables listed in Tab. 1, by using Granger's test. We find that only three variables have a causal relationship with TFPHW. These are Rec_flow, T1rec_flow, and T1rec_stock (all with significance: $p < 5\%$). In all three cases, the sign of the causal relationship is positive and the direction of causality only goes from technological variables (Rec_flow, T1rec_flow, and T1rec_stock) to economic variables (TFPHW). Hence, both the flow and stock of TNI, as measured by our indicator of RN, have a positive impact on productivity, but productivity has no impact on the flow and stock of TNI. This result seems to provide support for our HP2: Technologically novel inventions are exogenous, that is, independent of productivity variations. In order to further prove this hypothesis, we have performed an exogeneity test, which confirmed that the flow of TNI does not depend on productivity: only 5% of T1rec_flow variations depend on productivity variations.

All three significant variables are not cointegrated with TFPHW, meaning that the flow and stock of TNI do not share a common stable long-run trend with productivity levels. For all three variables, the optimal lag equals 5, so that the impact of technological variables on productivity occurs after 5 years, with a peak on the sixth year. Fig. 6 shows the impulse response function of TFPHW when we simulate a positive shock on our three technological variables. The overall duration of the impact on productivity appears to be similar for all variables, and it is about 15 years. Instead, the amplitude of the impact of both T1rec_flow and T1rec_stock is much higher than the impact of Rec_flow. We can also see that, before reaching a peak on the sixth year, TFPHW shows an initial negative reaction to a positive shock of both T1rec_flow and T1rec_stock[13]. We propose that this reaction may be interpreted as the result of the disruptive impact of radical technologies. Indeed, radical technologies create a new stream of incremental innovations that should drive productivity acceleration. However, at the same time, radical technologies have a disruptive impact on existing technologies, by replacing them. This may have a negative impact on productivity during the emergence phase of radical technologies, when their productivity gains are typically low compared to established technologies (Christensen, 1997). Our results suggest that while the creative impact is generally predominant, during the first 5 years after the appearance of a radical technology, it is its disruptive impact that prevails.

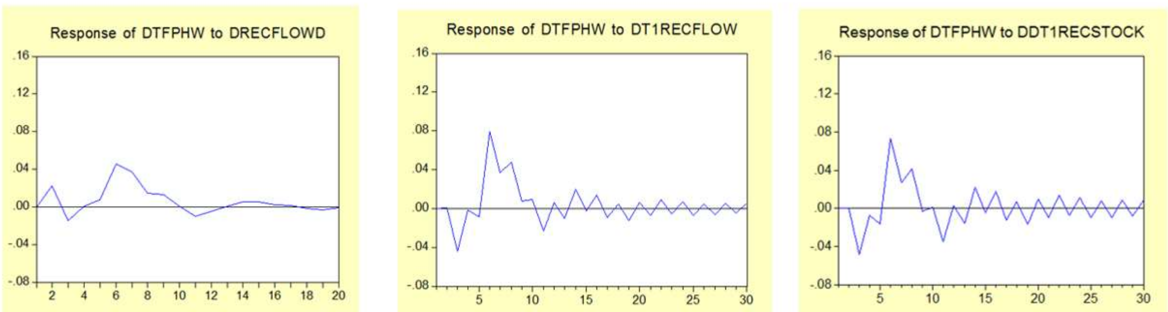


Fig. 6. Impulse response function of TFPHW after a simulated positive shock on Rec_flow, T1rec_flow, and T1rec_stock

[13] Although TFPHW initially shows a positive reaction to a positive shock of Rec_flow, we observe even in this case a subsequent negative reaction before the peak.

Tab. 3 shows the variance decomposition of TFPHW according to our technological variables. We observe that TFPHW variations are due to:

- 2.5% of Rec_flow variations the third year, 8.7% the sixth year, and 13% after about 15 years, when the explained variance stabilizes
- 7% of T1rec_flow variations the third year, 22.7% the sixth year, and 31% after about 15 years, when the explained variance stabilizes
- 8% of T1rec_stock variations the third year, 21.7% the sixth year, and 30% after about 15 years, when the explained variance stabilizes

The variance explained by T1rec_flow and T1rec_stock is similar and important: after 15 years more than 30% of productivity variations are explained by the variations in the flow and stock of TNI. Moreover, the variance explained by T1rec_flow and T1rec_stock is more than twice the variance explained by Rec_flow.

Overall, these results provide support for our HP1: Technologically novel inventions cause a temporary acceleration of productivity. Indeed, both the flow and stock of TNI, as measured by our indicator of RN, cause an acceleration of productivity that occurs after 5 years and lasts about 10 years. Moreover, the variations in both the flow and stock of TNI explain an important part of productivity variations. The fact that T1rec_flow and T1rec_stock have a higher impact on TFPHW and explain TFPHW variations much more than Rec_flow further supports HP1: compared to T1rec_flow, Rec_flow patents have a lower degree of technological novelty (see section 3.2.) and coherently with HP1, they have a lower impact on TFPHW and explain TFPHW variations to a lesser extent.

The flow and stock of total patents are not significant, suggesting that the number and stock of total inventions have no impact on productivity. The same holds for the stock of patents with positive RN (Rec_stock) and the flow of patents that introduced a new IPC-code (New_ipc). The latter result suggests that inventing a new component have no direct impact on productivity, what matters in terms of productivity is recombining in a novel way such components. However, there may be an indirect impact (not captured by our analysis), because recombination would be limited without the periodic creation of new components. Finally, the variables in percentage are never significant, which might perhaps confirm that the total number of inventions is not important in order to explain productivity.

Tab. 3. Variance decomposition of TFPHW: VAR Model with TFPHW and RECFLOW; VAR Model with TFPHW and T1RECFLOW; VAR Model with TFPHW and T1RECSTOCK

Period	S.E.	DTFPHW	DRECFLOW
1	0.155026	100.0000	0.000000
2	0.164198	98.21994	1.780059
3	0.167183	97.47349	2.526514
4	0.167689	97.48786	2.512139
5	0.173812	97.48743	2.512575
6	0.179678	91.28340	8.716599
7	0.183415	87.61245	12.38755
8	0.184091	87.04654	12.95346
9	0.187046	86.99720	13.00280
10	0.187280	87.02921	12.97079
11	0.187562	86.77515	13.22485
12	0.187626	86.71938	13.28062
13	0.188009	86.77310	13.22690
14	0.188129	86.70729	13.29271
15	0.188195	86.64760	13.35240
16	0.188214	86.63484	13.36516
17	0.188316	86.64302	13.35698
18	0.188336	86.63619	13.36381
19	0.188363	86.61150	13.38850
20	0.188368	86.60810	13.39190

Period	S.E.	DTFPHW	DT1RECFLOW
1	0.154212	100.0000	0.000000
2	0.160780	99.99704	0.002959
3	0.167749	93.01991	6.980087
4	0.168376	93.05986	6.940137
5	0.174017	93.26641	6.733591
6	0.191212	77.27953	22.72047
7	0.195227	74.56023	25.43977
8	0.201671	70.47611	29.52389
9	0.204078	71.03691	28.96309
10	0.204453	70.93389	29.06611
11	0.205822	70.00933	29.99067
12	0.205975	69.95834	30.04166
13	0.206590	69.89731	30.10269
14	0.207568	69.24559	30.75441
15	0.207592	69.23610	30.76390
16	0.208082	68.94695	31.05305
17	0.208356	68.81608	31.18392
18	0.208401	68.78797	31.21203
19	0.208808	68.53063	31.46937
20	0.208907	68.47376	31.52624

Period	S.E.	DTFPHW	DT1RECSTOCK
1	0.155303	100.0000	0.000000
2	0.162252	99.99998	2.24E-05
3	0.170479	91.89915	8.100851
4	0.171408	91.80933	8.190673
5	0.177374	91.50554	8.494456
6	0.191850	78.24439	21.75561
7	0.193986	76.80977	23.19023
8	0.198624	73.62843	26.37157
9	0.200326	74.04564	25.95436
10	0.200370	74.05435	25.94565
11	0.203569	71.84146	28.15854
12	0.203707	71.85905	28.14095
13	0.204757	71.57441	28.42559
14	0.205947	70.75544	29.24456
15	0.206007	70.72276	29.27724
16	0.206818	70.22577	29.77423
17	0.207256	69.98709	30.01291
18	0.207360	69.92090	30.07910
19	0.208045	69.47546	30.52454
20	0.208251	69.34696	30.65304

4.3. Analysis at technological field level

In order to test HP3 and HP4, we have estimated the direction and sign of causality between TFPHW and the 35 variables that represent the annual flow of TNI (T1rec_flow) for each technological field (WIPO IPC_35). We find that only 5 out of 35 fields have a positive causal relationship with productivity. This suggests that those TNI that contributed to productivity growth during 1920-2000 are concentrated in a handful of technological fields. These are labeled as "leading technological fields" because of their positive impact on productivity. These are the following (as described by Schmoch 2008):

IPC_35 1. Electrical machinery, apparatus, energy (signif.: p<1%): it primarily covers the non-electronic part of electrical engineering, e.g., the generation, conversion and distribution of electric power, electric machines, and basic electric elements (resistors, magnets, capacitors, lamps or cables)

IPC_35 3. Telecommunications (signif.: p<5%): it is a very broad field covering a variety of telecommunications techniques and products

IPC_35 19. Basic materials chemistry (signif.: p<5%): it primarily covers typical mass chemicals such as herbicides, fertilizers, paints, petroleum, gas, detergents etc.

IPC_35 25. Handling (signif.: p<5%): it comprises elevators, cranes or robots, but also packaging devices; in terms of research intensity, the field is quite heterogeneous

IPC_35 28. Textile and paper machines (signif.: p<1%): it includes machines for specific production purposes; textile and food machines represent the most relevant part of these machines.

Fig. 7 shows the impulse responses function of TFPHW after a simulated positive shock on our 5 leading technological fields, while Tab. 4 contains the variance decomposition of productivity obtained by building a model where TFPHW is explained by the 5 field variables. We can see from fig. 7 that the fields differ in terms of both duration and amplitude of the impact on productivity: "Electrical machinery, apparatus, energy" has the highest impact, and together with "Basic materials chemistry", it also has the longest impact. For all the 5 fields, optimal lag equals to 6 or 7 years (one or two years more than the lag at the aggregate level), and, before reaching their peak, all fields, except “Handling”, display the same initial negative impact, more or less pronounced, that we have observed at aggregate level.

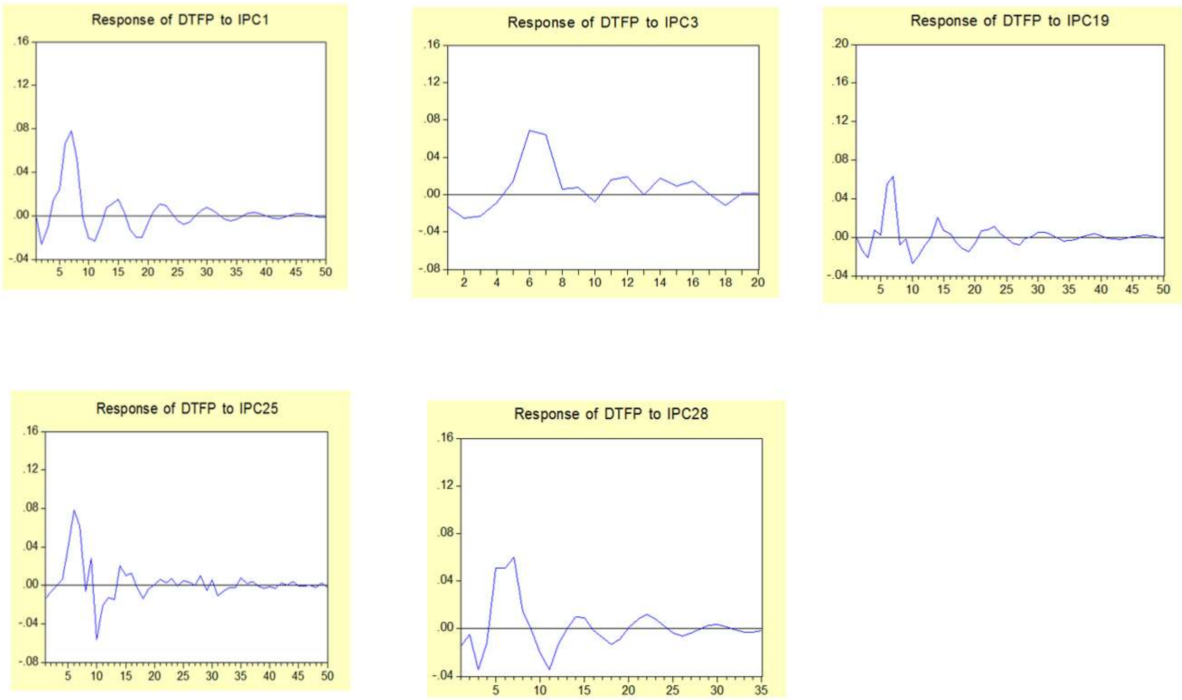


Fig. 7. Impulse responses function of TFPHW after a simulated shock on IPC1, IPC3, IPC19, IPC25, IPC28

Tab. 4. Variance decomposition of TFPHW: Global VAR Model with TFPHW and the 5 leading technological fields

Variance Decomposition of DTFPHW:							
Period	**S.E.**	**IPC1**	**IPC3**	**IPC19**	**IPC25**	**IPC28**	**TFP**
1	0.16	0.00	2.36	1.53	0.57	3.63	91.91
2	0.16	0.82	2.19	1.44	3.74	5.59	86.21
3	0.17	1.62	2.62	2.27	3.66	6.39	83.44
4	0.17	1.67	4.00	2.29	7.48	6.05	78.51
5	0.18	1.50	3.62	4.76	6.97	10.58	72.57
6	0.19	9.38	4.25	4.94	7.60	9.62	64.22
7	0.22	22.96	5.42	7.94	6.02	8.17	49.49
8	0.23	26.09	5.00	7.72	5.59	7.86	47.73
9	0.24	26.33	4.75	9.38	6.10	7.58	45.86
10	0.24	26.53	4.76	9.31	6.08	7.52	45.81

By looking at TFPHW variance decomposition in Tab. 4, we observe that after 10 years, the variations in the flow of TNI in the 5 leading fields explain together a very important part (54%) of TFPHW variations. The most influencing field is “Electrical machinery, apparatus, energy”, whose variations explain alone 26.5% of TFPHW variations. “Telecommunications” is the sector that explains least productivity variations, with only 4.7% of TFPHW variations explained. This result is consistent with those studies that attribute the low rate of productivity growth since the 1970s to the low importance of ICTs compared to the technologies of the second technological revolution (Gordon, 2012). Overall these results provide evidence for our HP3: Technologically novel inventions that cause productivity acceleration are concentrated in a restricted number of leading technological fields.

In order to identify the industrial sectors corresponding to our leading technological fields and shed light on the mechanisms through which technological novelty in these fields may affect productivity growth, we adopt a two-step approach. First, we link technological fields to their industrial sectors by using the Neuhäusler, Frietsch and Kroll (2019) concordance matrix between WIPO IPC_35 fields and NACE (Rev.2, 2-digit) industrial sectors. Second, we rely on Pavitt (1984) taxonomy, as revised by Bogliacino and Pianta (2011, 2016), to identify the innovation patterns characterizing each sector[14]. The concordance matrix provides, for each technological field, the percentage of patents originated by each of the 99 2-digit NACE sectors. Tab. 5 shows such percentages for the main industrial sectors in which our 5 leading technological fields are concentrated[15]. As we can see, only 4 out of 99 industrial sectors have significant shares (>10%): “Manufacture of chemicals and chemical products” (NACE 20), “Manufacture of computer, electronic and optical products” (NACE 26), “Manufacture of electrical equipment” (NACE 27), and “Manufacture of machinery and equipment” (NACE 28).

[14] One limitation of this analysis is that we use a contemporaneous concordance matrix in order to interpret patterns dating back to the 1920s. However, we are not aware of any such concordance matrix relating technological fields and industrial sectors over such a long period of time. Our analysis thus relies on the hypothesis that these sectors have broad patterns of innovation that persist over long periods, which is not so heroic when comparing Pavitt’s (1984) analysis and the more recent analysis by Bogliacino and Pianta (2011, 2016).

[15] For example, the technological field 3 (Telecommunications) is highly concentrated in the NACE sector 26 “Manufacture of computer, electronic and optical products”, which originates 68% of all Telecommunications patents. The remaining sectors related to this technological field have a share between 0% and 5%. Similarly, for the technological field 19 (Basic materials chemistry), patents originate at 45 % from NACE sector 20 “Manufacture of chemicals and chemical products”, the remaining sectors have a share between 0% and 5%.

Tab. 5 also contains the innovation pattern of each sector, as provided by Bogliacini and Pianta (2011): “Manufacture of computer, electronic and optical products” (NACE 26), “Manufacture of chemicals and chemical products” (NACE 20) are both classified as Science Based industries, while “Manufacture of electrical equipment” (NACE 27) and “Manufacture of machinery and equipment” (NACE 28) are classified as Specialized Suppliers. Following Pavitt (1984), Science Based sectors, like the computer and chemical sector, draw their main source of innovation from intense in-house R&D activities, based on the rapid development of underlying science, to produce both product and process innovations. Their technologies are pervasive and have a large range of applications. The main focus of Specialized Suppliers, instead, is the generation of product innovations in intermediate goods or capital equipment for use in a variety of user sectors. These industries are a particularly important source of process innovations for Scale Intensive sectors (food products, metal manufacturing, shipbuilding, motor vehicles …) as they supply them with machines allowing to replace labor and to lower production costs. Specialized Suppliers rely on in-house R&D activities, highly skilled labor and strong user-producer relationships.

Tab. 5. Leading technological fields, related industrial sectors and patterns of innovation

Technological field (WIPO IPC_35 fields)	**Related industrial sectors** (WIPO IPC_35 – NACE concordance)	**Patterns of innovation** (Bogliacino and Pianta 2016)
1. Electrical machinery, apparatus, energy	26. Manufacture of computer, electronic and optical products (26%*)	Science based
	27. Manufacture of electrical equipment (15%)	Specialized suppliers
	28. Manufacture of machinery and equipment (14%)	Specialized suppliers
3. Telecommunications	26. Manufacture of computer, electronic and optical products (68%)	Science based
19. Basic materials chemistry	20. Manufacture of chemicals and chemical products (45%)	Science based
25. Handling	26. Manufacture of computer, electronic and optical products (11%)	Science based
	28. Manufacture of machinery and equipment 31%)	Specialized suppliers
28. Textile and paper machines	20. Manufacture of chemicals and chemical products (16%)	Science based
	26. Manufacture of computer, electronic and optical products (22%)	Science based
	28. Manufacture of machinery and equipment (25%)	Specialized suppliers

*% of patents originated from the NACE 2-digit sectors

In examining how different industries contribute to labor productivity growth, Bogliacino and Pianta (2011) show that both Science Based sectors and Specialized Suppliers rely on two distinct, but complementary, "engines" leading to increased competitiveness and reduced costs: a strategy of technological competitiveness – based on intense R&D activities to innovate in products and open up new markets – and a strategy of cost competitiveness, based innovation in processes and machinery, with the objective of increasing efficiency through labor saving investment, flexibilization of production, and cut-price competition. Bogliacino and Pianta (2011) also highlight that while the latter strategy emerges as a strong aspect of innovative activities in all industries, its impact on productivity growth is inferior to that of a search for new products and markets, typical of Science Based and Specialized Suppliers industries alone. Hence, our analysis seems to indirectly suggest that the main source of productivity growth during the 20th century has been the creation of new R&D intensive products, including capital products (machinery), and new markets.

For the leading technological fields, the direction of causality goes from technological variables to economic variables, like at the aggregate level. At the aggregate level, we found no causal relationship going from economic variables to technological variables. At the level of technological field, instead, we found this relationship. More precisely, TFPHW has a positive impact on the flow of TNI in three fields and a negative impact in one field. We label as "demand-driven" those technological fields for which the sign of the causal relationship is positive, based on the idea that investments in radical technologies in these fields rise during period of growing productivity because demand is higher and innovation risk lower (see section 2). These sectors are (following Schmoch's definition):

IPC-35 21. Surface technology, coating (signif.: $p<1\%$): the coating of metals, generally with advanced methods, represents the core of this field

IPC-35 27. Engines, pumps, turbines (signif.: $p<1\%$): it covers non-electrical engines for all types of applications, in quantitative terms, applications for automobiles dominate

IPC-35 31. Mechanical elements (signif.: $p<5\%$): it covers fluid-circuit elements, joints, shafts, couplings, valves, pipe-line systems or mechanical control devices.

However, TNI in these 3 technological fields are not pervasive as they do not generate productivity growth at the aggregate level (as shown by results on the leading technological fields). Fig. 8 shows the impulse responses function of demand-driven fields when we simulate a positive shock on productivity and Tab. 6 contains the variance decomposition of the three fields. We can see that demand-driven sectors are more heterogeneous in terms of optimal lag, which is 11, 2, and 5 years for IPC21, IPC27 and IPC31, respectively. The amplitude of the impact for "Engines, pumps, turbines" and "Mechanical elements" is higher, but shorter than for "Surface technology, coating". In addition, if we look at the explained variance in Tab. 6, we see that productivity variations explain the 26% of the variations in the flow of TNI of "Surface technology, coating", while for "Engines, pumps, turbines" and "Mechanical elements" the explained variance is only 13% and 14%, respectively.

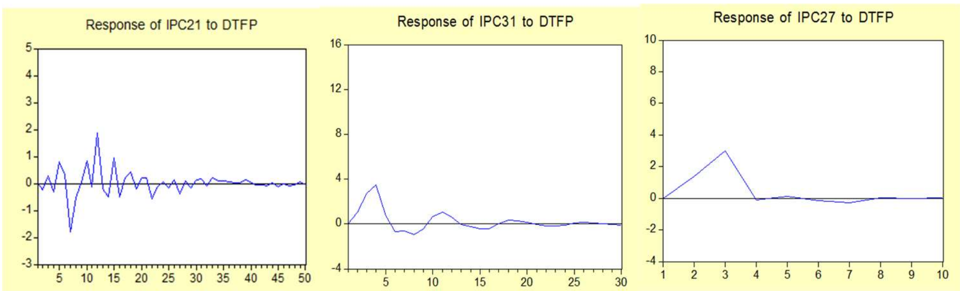


Fig. 8. Impulse responses function of IPC21, IPC31, IPC27 after a simulated shock on TFPHW

Like for the leading technological fields, we show, in Tab. 7, the industrial sectors and the pattern of innovation associated with demand-driven technological fields. Interestingly, among demand-driven sectors we find 3 of our leading industrial sectors – the computer, chemical and machinery sectors – but we also see some new sector, i.e., the manufacture of motor vehicles and of other transport. The latter is included by Bogliacino and Pianta (2011) among the Scale and Information Intensive industries[16]. These industries benefit from large economies of scale and are characterized by oligopolistic markets in which technological change is often incremental. Such industries mainly rely on a cost competitiveness strategy with a major role played by the share of firms indicating the suppliers of equipment as the source of their process innovation (Bogliacino and Pianta 2011).

[16] They comprise motor vehicles, mineral oil refining, coke and nuclear fuel, rubber and plastics, basic metals, and financial services related to information technology

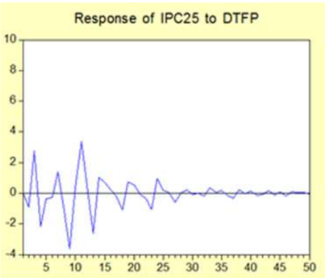
Tab. 6. Variance decomposition of IPC21, IPC27 and IPC31 (VAR Model with TFPHW and IPC21; VAR Model with TFPHW and IPC27; VAR Model with TFPHW and IPC31)

Period	S.E.	IPC21	TFP	Period	S.E.	IPC27	TFP	Period	S.E.	IPC31	TFP
1	4.09	100.00	0.00	1	7.92	100.00	0.00	1	12.52	100.00	0.00
2	4.57	99.71	0.29	2	8.66	97.42	2.58	2	12.69	99.29	0.71
3	4.61	99.35	0.65	3	9.18	87.01	12.99	3	13.31	95.22	4.78
4	4.86	98.94	1.06	4	9.18	87.00	13.00	4	13.77	89.12	10.88
5	4.95	96.34	3.66	5	9.21	87.07	12.93	5	13.99	89.18	10.82
6	4.97	95.97	4.03	6	9.21	87.06	12.94	6	14.27	89.37	10.63
7	5.30	84.84	15.16	7	9.22	86.99	13.01	7	14.29	89.23	10.77
8	5.48	84.93	15.07	8	9.22	86.99	13.01	8	14.56	89.20	10.80
9	5.52	85.15	14.85	9	9.22	86.99	13.01	9	14.58	89.14	10.86
10	5.66	83.77	16.23	10	9.22	86.99	13.01	10	14.68	89.08	10.92
11	5.67	83.77	16.23	11	9.22	86.99	13.01	11	14.72	88.62	11.38
12	6.04	76.15	23.85	12	9.22	86.99	13.01	12	14.74	88.47	11.53
13	6.06	76.19	23.81	13	9.22	86.99	13.01	13	14.76	88.50	11.50
14	6.09	75.80	24.20	14	9.22	86.99	13.01	14	14.76	88.48	11.52
15	6.17	74.07	25.93	15	9.22	86.99	13.01	15	14.80	88.44	11.56
16	6.19	73.63	26.37	16	9.22	86.99	13.01	16	14.81	88.38	11.62
17	6.20	73.59	26.41	17	9.22	86.99	13.01	17	14.81	88.38	11.62
18	6.24	73.50	26.50	18	9.22	86.99	13.01	18	14.81	88.33	11.67
19	6.32	74.02	25.98	19	9.22	86.99	13.01	19	14.82	88.30	11.70
20	6.32	73.98	26.02	20	9.22	86.99	13.01	20	14.82	88.30	11.70

Tab. 7: Demand-driven technological fields, related industrial sectors and patterns of innovation

Technological field	Related industrial sectors	Patterns of innovation
21. Surface technology, coating	20. Manufacture of chemicals and chemical products (21%)	Science based
	26. Manufacture of computer, electronic and optical products (17%)	Science based
	28. Manufacture of machinery and equipment (10%)	Specialized suppliers
27. Engines, pumps, turbines	28. Manufacture of machinery and equipment (39%)	Specialized suppliers
	29. Manufacture of motor vehicles, trailers and semi-trailers (18%)	Scale and information intensive
	30. Manufacture of other transport equipment (11%)	Specialized suppliers
31. Mechanical elements	28. Manufacture of machinery and equipment (29%)	Specialized suppliers
	30. Manufacture of motor vehicles, trailers and semi-trailers (19%)	Scale and information intensive

Bogliacino and Pianta (2011) shows that demand is a key factor for explaining the contribution to labor productivity of all types of industries. However, the authors also highlight that while demand growth is highly important for Science Based (relevance of increasing returns), Specialized suppliers (relevance of interaction with clients) and, even more, for Scale and information intensive industries (relevance of new expanding service markets), it is much less important for the last category of the Pavitt taxonomy, namely Suppliers Dominated industries. In fact, these industries, characterized by a model of cost competitiveness with the search for more flexible production, do not appear among our demand-driven sectors.



Variance Decomposition of IPC25:			
Period	**S.E.**	**IPC25**	**TFP**
1	9.26	100.00	0.00
2	9.31	99.02	0.98
3	9.72	91.07	8.93
4	10.01	86.88	13.12
5	10.02	86.78	13.22
6	10.13	86.99	13.01
7	10.32	85.69	14.31
8	10.41	84.78	15.22
9	11.02	75.59	24.41
10	11.15	76.04	23.96
11	11.95	71.13	28.87
12	12.07	71.53	28.47
13	12.35	68.27	31.73
14	12.43	67.93	32.07
15	12.45	67.74	32.26
16	12.46	67.74	32.26
17	12.47	67.76	32.24
18	12.52	67.29	32.71
19	12.55	67.11	32.89
20	12.6	67.21	32.79

Fig. 9. Impulse responses function of IPC25 after a simulated shock on TFPHW and Variance decomposition of IPC25 (VAR Model with TFPHW and IP25)

Finally, we find that one field, “Handling” (IPC_35 25), has a double causal relationship with TPHHW: it positively causes TFPHW (as showed by results on the leading technological fields), but it is also negatively caused by TFPHW (signif.: p<5%), which means that a negative (positive) variation of productivity would cause an increase (decrease) of TNI in this field. Among the 5 leading technological fields, only handling, also displays a relationship running from productivity to TNI. Fig. 9 shows the impulse responses function and the variance decomposition of the field. Optimal lag, in this case, is the highest one, i.e., 13 years, after which the negative impact of productivity on TNI starts dumping. The variance decomposition indicates that, after 20 years, TFPHW variations explain an important part (almost 33%) of the variations in the number of TNI in the field. As shown in Tab. 5, patents in this field are mainly concentrated in the machinery (31%) and computer (11%) sectors.

Overall these results provide empirical evidence for our HP4: Technologically novel inventions may be endogenous at the level of technological field, that is, dependent of productivity variations. In fact, we have seen that productivity variations may cause positive variations in the flow of TNI in some fields (demand-driven fields), or it may cause negative variations, like for the field handling. This suggests that some radical technologies can be endogenous. With respect to sign of endogeneity, these results seem to indicate that some radical technologies rise during periods of growing productivity, when demand is higher and risk lower, while, some other radical technologies rise during periods of decreasing productivity, when the opportunity profits of former radical technologies are exhausted, market, are saturated and demand for existing products is low. Hence, demand seems to play a role, either positive or negative, on radical technologies depending on the field. However, it seems that, among endogenous technologies, only those that rise during periods of decreasing productivity have a positive impact on productivity.

5. Conclusions

This paper tries to provide empirical evidence on the long-run relationship between technology and productivity by testing, for the first time, the sign and direction of causality between technological novelty and productivity over the whole 20th century. Our results intend to contribute to research on technological change and long-run economic development through a cliometric approach, based on Granger's causality, that proposes an otherwise lacking perspective. On the other hand, by providing a deeper characterization of technology that focuses on the concept of recombinant novelty, we try to contribute to cliometric studies on the determinants of economic growth.

With respect to causality running from technologically novel inventions (TNI) to productivity, we find that: 1) the flow and stock of TNI cause an acceleration of productivity that occurs after 5 years and lasts about 10 years; 2) variations in the flow and stock of TNI explain an important part of productivity variations. To the extent that the degree of technological novelty of inventions approximates the degree of radicalness of technologies, these results provide empirical support to the hypotheses that radical technologies have a positive, but temporary, impact on productivity, and that there is a lag between the emergence of radical technologies and their effect on productivity (Crafts, 1995; Freeman and Perez, 1988; Helpman and Trajtenberg, 1994; Kuznets, 1930; Mensch, 1979; Mokyr, 1993; Perez, 2010; Schot and Kanger, 2018; Schumpeter, 1939)

Our results also show that those TNI that contribute to productivity growth are originated by only five leading technological fields, whose patents are mainly concentrated in the sectors of specialized suppliers of capital equipment (machinery and electrical sectors) and in science based sectors (computer and chemical sectors). Variations in the flow of TNI in these fields explain together about 54% of productivity variations. This result indicates that radical technologies at the origin of productivity growth are concentrated in a handful of leading technological fields and sectors. As highlighted by Bogliacino and Pianta (2011), the contribution to productivity growth of these sectors relies essentially on the creation of new products, including capital products (machinery), and new markets based on intense R&D activities. Hence, our analysis seems to indirectly suggest that the main source of productivity growth during the 20th century has been the creation of new R&D-intensive products and markets. In addition, we find that inventing a new component has no direct impact on productivity, what matters in terms of productivity is recombining in a novel way such components. Also, the flow and stock of inventions, as proxied by the flow and stock of total patents, have no impact on productivity.

With respect to causality running from productivity to TNI, our analysis shows that, at the aggregate level, there is no causal relationship, meaning that productivity variations have no impact on the variations in the flow of TNI. This could suggest that radical technologies are exogenous, as proposed by various scholars (Kuznets, 1930; Schumpeter, 1939; Clark et al., 1981; Mokyr, 1993; Craft, 1995), in the sense that they do not depend on economic variables like productivity. However, when we looked at the flow of TNI at the level of technological field, we find more complex relationships. Productivity has a positive impact on the flow of TNI in three fields, labeled as demand-driven fields, which, nevertheless, are not the fields that drive productivity growth. This seems to indicate that some radical technologies are more likely to rise during periods of growing productivity, when demand is higher and innovation risk lower. Demand-driven technological fields are mainly concentrated in the automotive sector (a scale intensive sector) and in three of the leading sectors mentioned above, i.e., the computer, chemical, and machinery sectors.

Finally, we find that productivity has a negative impact on the flow of TNI in one field, i.e., Handling. Interestingly, this is also one of the five leading fields that contribute to productivity growth and, as such, its patents are mainly concentrated in the machinery and computer sectors. This result could instead provide support to the idea that some radical technologies rise during periods of decreasing productivity, when the opportunity profits of former radical technologies are exhausted, market are saturated, and demand for existing products is low (Mensch, 1979; Perez, 2002; Saviotti and Pyka, 2004; 2013; Schot and Kangera, 2018). More in general, these results indicate that some radical technologies can be endogenous and that demand plays a role, either positive or negative, on radical technologies depending on the field. However, among endogenous technologies, only those that rise during periods of decreasing productivity have a positive impact on productivity. These differences among technological fields, in turn, may partially explain why, at aggregate level, productivity appears to have no impact on TNI.

Overall, this analysis suggests that one of the causes of the productivity stagnation since the 1970s may be a comparatively low degree of technological novelty of prevailing technologies, namely ICTs (as proposed by Gordon, 2012). With respect to the more recent productivity slowdown, since 2000s, our study suggests that it can have a negative impact on TNI in some demand-driven fields. Although these fields appear to have no direct impact on productivity growth, many of their patents are concentrated in industrial sectors (computer, chemical and machinery) that importantly contribute to productivity growth. Hence, a productivity slowdown may have the effect of abating a positive spiral: higher productivity leads to more radical technologies, which lead to higher productivity. However, at the same time, such slowdown may provide incentive to the emergence of TNI in some other fields, like handling - whose patents are also concentrated in the machinery and computer sectors - that are negatively caused by productivity, but that have a positive impact on it.

Of course this work has limitations. First, patents are an imperfect indicator of inventive and innovative activity, and it is likely that our indicator of recombinant novelty, though validated by previous studies, captures only some aspects of both the degree of technological novelty of inventions and the degree of radicalness of technologies. Research on more sophisticated indicators of radicalness can improve our knowledge of the relationship between radicalness and productivity. Second, our analysis is likely to show only some average results on the relationship between productivity and technological novelty. These average results provide a synthetic and quantitative perspective that would otherwise be lacking, but they can also hide important differences in the degree of radicalness of technologies and in their impact on productivity. Finally, and most importantly, our results hide the rich set of institutional and historical factors that are behind the relationship between productivity and technological novelty. Integrating at least some of these factors in a global model could provide promising opportunities for further research. Another extension may consist in using alternative econometric techniques, like the outliers methodology, in order to detect events (real shocks) affecting the evolution of productivity and technological novelty.

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Appendix

Tab. 1. List of technological fields (IPC8 -Technology Concordance)
Source: WIPO Statistics Database (Last update: March 2018)

Field_number	Sector	Field
1	Electrical engineering	Electrical machinery, apparatus, energy
2	Electrical engineering	Audio-visual technology
3	Electrical engineering	Telecommunications
4	Electrical engineering	Digital communication
5	Electrical engineering	Basic communication processes
6	Electrical engineering	Computer technology
7	Electrical engineering	IT methods for management
8	Electrical engineering	Semiconductors
9	Instruments	Optics
10	Instruments	Measurement
11	Instruments	Analysis of biological materials
12	Instruments	Control
13	Instruments	Medical technology
14	Chemistry	Organic fine chemistry
15	Chemistry	Biotechnology
16	Chemistry	Pharmaceuticals
17	Chemistry	Macromolecular chemistry, polymers
18	Chemistry	Food chemistry
19	Chemistry	Basic materials chemistry
20	Chemistry	Materials, metallurgy
21	Chemistry	Surface technology, coating
22	Chemistry	Micro-structural and nano-technology
23	Chemistry	Chemical engineering
24	Chemistry	Environmental technology
25	Mechanical engineering	Handling
26	Mechanical engineering	Machine tools
27	Mechanical engineering	Engines, pumps, turbines
28	Mechanical engineering	Textile and paper machines
29	Mechanical engineering	Other special machines
30	Mechanical engineering	Thermal processes and apparatus
31	Mechanical engineering	Mechanical elements
32	Mechanical engineering	Transport
33	Other fields	Furniture, games
34	Other fields	Other consumer goods
35	Other fields	Civil engineering