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Radical technologies, recombinant novelty and productivity growth: a cliometric approach

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Abstract

Using inventions with a high degree of recombinant novelty as proxy for radical technologies, this work provides a long-run quantitative analysis of the relationship between radical technologies and productivity growth. The empirical analysis is based on a cliometric approach and relies on Granger's causality to test the sign and direction of causality between the flow of radical technologies and productivity levels, in the USA between 1920 and 2000. At the aggregate level, results show that radical technologies cause a temporary acceleration of productivity growth and explain a considerable part of productivity variations. At technology-field level, the analysis indicates that productivity growth is driven by a few technological fields, mainly concentrated in science based sectors and in the sectors of specialized suppliers of capital equipment. Finally, with respect to the controversial issue of the endogeneity of radical technologies, at the aggregate level we find no causal relationship running from productivity to radical technologies, suggesting that these are exogenous. However, at technology-field level, we find a few endogenous technologies. Most of these are "demand-driven" as their flow increases when productivity grows, but they have no impact on productivity. Only in one technological field, the flow of radical technologies increases when productivity decreases and, at the same time, has a positive impact on productivity. This latter case may explain why technological revolutions and the whole process of long-run economic development are partly endogenous.

Keywords: Radical technologies; Recombinant novelty; Productivity growth; Cliometrics; Granger's causality; Technological revolutions; Long-run economic development.

JEL classification: O33; O40; C32; N12

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1. Introduction

“In many industries there comes a time when the basic technical conditions are revolutionized. When such a fundamental change takes place, a new era begins” (Kuznets, 1930 p.9). Since the work of Kuznets, scholars from different approaches, often using different terminologies, have highlighted that radical technologies (steam engine, electricity, computers, ...) are the main source of 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). According to these studies, radical technologies, or cluster of radical technologies, are at the origin of technological revolutions, as well as of structural and institutional changes. The succession in time of technological revolutions, in turn, is at the origin of both the long-run increasing trend of productivity and its associated long-run fluctuations.

This paper aims at analyzing the long-run relationship between radical technologies and productivity growth by using an indicator of technological novelty of inventions as (imperfect) proxy of radical technologies, and a cliometric approach based on Granger’s causality. More precisely, we are interested in the three related research questions. First, to what extent radical technologies explain productivity growth observed at macroeconomic level? Second, is there a causal relationship running from productivity to radical technologies? If yes, what is the sign of this relationship? This question is important because it provides information on whether radical technologies are exogenous or endogenous. Third, to what extent productivity growth observed at macroeconomic level can be explained by radical technologies at sectoral level? In other words, are radical technologies concentrated in a restricted number of sectors that contribute to macroeconomic growth or are they spread across many sectors?

With respect to the first question, scholars seem to agree that radical technologies cause a temporary acceleration of productivity growth². Radical technologies generate a wave of investments in more incremental innovations, which originate new, more productive, leading sectors and have a vast impact on user sectors. The acceleration is temporary because of diminishing returns of investment in innovation. However, empirical works on the relationship between technology and productivity rarely focus on radical technologies, and, when this is done, the analysis is mainly based on cross-country, cross-industry or cross-firm studies³. To the best of our knowledge, we found no quantitative evidence adopting a long-run approach.

With respect to the second question, theoretical consensus is less solid. In some works radical technologies are exogenous or random (Aghion et al., 1998; Caiani et al., 2014; Clark et al., 1981; Crafts, 1995; Helpman and Trajtenberg, 1994; Kuznets, 1930; Mokyr, 1993; Schumpeter, 1939; Silverberg and Lehnert, 1993), meaning that variations in economic variables like productivity levels have no impact on radical technologies, which mainly result from luck, inventors’ genius or other (relatively) exogenous events, like wars. In other studies,

² See for example Crafts, 1995; Freeman and Perez, 1988; Helpman and Trajtenberg, 1994; Kuznets, 1930; Mensch, 1979; Mokyr, 1993; Perez, 2010; Schumpeter, 1939; Schot and Kanger, 2018.

³ Without pretending to be exhaustive, see for example Añón Higón, 2007; Antonelli, Krafft, Quatraro, 2010; Castellacci, 2010; Coad et al., 2016; Crespi and Pianta, 2008; Scherer, 1984; Hall and Mairesse, 1995; Hasan and Tucci, 2010; Verspagen, 1995; Baumann and Kritikos, 2016; Bogliacino and Pianta 2011; Morris, 2018; Juhász et al., 2020.

radical technologies are, at least partly, endogenous (Carlaw and Lipsey, 2006; Mensch, 1979; Perez, 2002; Saviotti and Pyka, 2013, 2004; Schaefer et al., 2014; Schot and Kanger, 2018). In most of these cases, radical technologies depend negatively on productivity growth because they are assumed to rise during periods of recession, when the opportunity profits of former radical technologies are exhausted, markets are saturated, and demand for existing products is low. On the other hand, even if they refer to technical change in general, 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. Here, radical technologies could also rise during periods of productivity growth, when demand is higher and risk lower.

Our final question discusses the role of sectoral dynamics in determining the relationship between radical technologies and productivity. As mentioned before, radical technologies are expected to create new, more productive sectors, which drive productivity growth acceleration. As a consequence, productivity growth observed at macroeconomic level should be explained by the dynamics of a few leading sectors. This Schumpeterian view is compatible with a “mushroom” dynamics of the growth process (Harberger, 1998), according to which the largest share of macroeconomic productivity growth is driven by innovation and growth concentrated in a few sectors. On the contrary, the process of productivity growth may rather follow a “yeast” dynamics, according to which productivity growth is mainly driven by economies of scale and knowledge externalities, and therefore, evenly spread across economic sectors. Empirical investigations on this issue are inconclusive⁴ and do not focus explicitly on technological change.

This work intends to contribute to the above-mentioned literature in two ways. First, we explicitly focus our analysis on radical technologies. We base on the assumption that radical technologies typically emerge from inventions introducing technological novelty, that is, a novel technological approach (Arthur, 2007; Verhoeven et al., 2016), and rely on the idea that technological novelty results from a recombinant search process (Arthur, 2009; Schumpeter, 1939). Hence, we approximate radical technologies by using an indicator of recombinant novelty based on the degree of component recombination of inventions. The indicator, developed by innovation scholars, has been validated by previous studies as potentially capable of driving a radical technological change (Verhoeven et al., 2016). Second, we test, for the first time, the sign and direction of causality between the flow of radical technologies and productivity levels in the USA between 1920 and 2000, at aggregate and technology-field level. To this end, we use a cliometric approach that combines economic theory and quantitative methods to the study of history. 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, 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

⁴ See for example Harberger, 1998; Timmer et al., 2011; Bakker et al. 2015.

(Diebolt and Hagemann, 2019). Here, we intend to contribute to this debate by analyzing the relationship between recombinant novelty and productivity growth.

At the aggregate level, results show that radical technologies cause a temporary acceleration of productivity growth and explain a considerable part of productivity variations. At technology-field level, the analysis indicates that productivity growth is driven by a few technological fields, mainly concentrated in science based sectors and in the sectors of specialized suppliers of capital equipment. Finally, with respect to the controversial issue of the endogeneity of radical technologies, at the aggregate level we find no causal relationship running from productivity to radical technologies, suggesting that these are exogenous. However, at technology-field level, we find a few endogenous technologies. Most of these are “demand-driven” as their flow increases when productivity grows, but they have no impact on productivity. Only in one technological field, the flow of radical technologies increases when productivity decreases and, at the same time, has a positive impact on productivity. This latter case may explain why technological revolutions and the whole process of long-run economic development are partly endogenous. The rest of the paper is organized as follows. Section 2 reviews the relevant literature and formulate the hypotheses. Section 3 details the indicator of technological novelty, the variables, and the methodology. Section 4 illustrates the results of the empirical analysis, section 5 provides a summary and a discussion of the results, and section 6 concludes.

2. Literature review and hypotheses

Our first research question asks to what extent radical technologies explain productivity growth observed at macroeconomic level. On this issue, scholars from different theoretical approaches agree that radical technologies cause a temporary acceleration of productivity growth (Crafts, 1995; Freeman and Perez, 1988; Helpman and Trajtenberg, 1994; Kuznets, 1930; Mensch, 1979; Mokyr, 1993; Perez, 2010; Schot and Kanger, 2018; Schumpeter, 1939). The basic idea, often developed using different terminologies, is that radical technologies, or clusters of radical technologies, evolve over time following a logistic curve: at the beginning they emerge slowly, then grow rapidly, and finally develop slowly again during the maturity phase. Radical technologies emerge slowly because “an innovation is rarely perfect at the start” (Kuznets 1930, p. 9), different variants compete with each other and with incumbent technologies, and there is great uncertainty about the winning technology. As a consequence, costs are high and demand is low.

When the winning technology is established, the heuristics of search and the vision of the community of practitioner are clear. Hence, uncertainty is greatly reduced and a wave of investments in more incremental innovations takes place. This creates new leading sectors, with a vast impact on user sectors, and drives the acceleration of productivity growth, which, in turns, pushes income and demand growth. “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. 10). This is mainly due to market saturation and diminishing

returns of investment in innovation: the rate at which, on the basis of existing technologies, costs can be lowered, quality can be improved, and new markets can be created slackens after some time.

This basic pattern of evolution is at the origin of the process of long-run economic development based on technological revolutions, structural and institutional changes. The succession in time of technological revolutions, in turn, is at the origin of both the long-run increase of productivity and its associated long-run fluctuations. Although there is a wide theoretical consensus on these issues, empirical works on the relationship between technology and productivity rarely focus on radical technologies, and when this is done, the analysis is mainly based on cross-country, cross-industry or cross-firm⁵ studies, while we find no quantitative evidence adopting a long-run approach. In order to contribute to fill this gap, we use the degree of recombinant novelty of inventions as proxy of radical technologies and test the following hypothesis:

Hypothesis 1: Radical technologies cause a temporary acceleration of productivity growth

As for our second research question, i.e., whether radical technologies are endogenous or exogenous, theoretical consensus is less solid. While most of the authors agree that incremental technologies are endogenous, that is, dependent on economic variables like productivity and economic growth, positions diverge with regard to radical technologies. In the first works, radical technologies are often considered as exogenous, meaning that their emergence does not depend on economic variables: causality runs from radical technologies to productivity growth, but there is no causal relationship running from productivity variations to radical technologies. According to Kuznets, for example, fundamental innovations are randomly distributed in time, and in Schumpeter (1939), radical innovations, even though clustered, remain exogenous: they are introduced by extraordinary individual entrepreneurs that create “new combinations” by using exogenously generated inventions. Radical technologies are essentially exogenous also in more recent historical analyses of industrial revolutions (Mokyr, 1993; Crafts, 1995). Here, “macro-inventions are those in which a radical new idea, without clear precedent, emerges more or less ab nihilo” (Mokyr, 1993 p. 22). Macro-inventions are “essentially exogenous and unpredictable, often resulting from strokes of genius or luck” (Craft, 1995 p. 757).

The first argument put forward in favor of endogenous radical technologies was provided by Mensch (1979), and further developed by Kleinknecht and Panne (2008). According to these scholars, radical technologies are endogenous because 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 (negative variation of productivity) to technological variables (emergence of radical technologies). This “depression trigger hypothesis” has been highly criticized. 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.

⁵ See references on note 3.

Conversely, more recently, there seems to be a tendency to endogenize, at least partly, radical technologies. Within the Techno-Economic Paradigms framework (Freeman and Perez, 1988; Perez, 2010), 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 Multi-Level Perspective framework (Markard et al., 2012; Rip and Kemp, 1998) 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 Kanger, 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 Kanger 2018).

Within the General-Purpose Technology framework (Bresnahan and Trajtenberg, 1995), 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 et al., 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.

Finally, 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, therefore, in fostering productivity. Though these works refer to technical change in general, without distinguishing between radical and incremental changes, here radical technologies could also emerge during periods of economic growth, when demand is higher and risk lower.

In short, in some works radical technologies are random or exogenous, while in others, they are, at least partly, endogenous, and may depend positively or negatively on productivity variations: according to some scholars, firms are more likely to invest in radical innovations during periods of recession, when the opportunity profits of former radical technologies are exhausted, market are saturated, and demand is low, while for others, radical technologies may also rise during periods of productivity 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:

Hypothesis 2: Radical technologies are endogenous, that is, dependent on productivity variations

Our final question concerns the role of sectoral dynamics in determining the relationship between radical technologies and productivity growth. All the above-surveyed literature assigns to sectoral dynamics a central role: radical technologies are expected to create new, more productive, leading sectors, which drive productivity growth accelerations. As a consequence, economic growth may not be uniformly spread across all sectors within an economy, but may be instead concentrated in, and driven by, a limited number of sectors during a given time period. This vision, mainly based on the Schumpeterian process of creative destruction, is compatible with a “mushroom dynamics” of the growth process (Harberger, 1998), according to which aggregate productivity growth is mainly driven by innovation and growth concentrated in a few sectors, while other sectors have zero or even a negative contribution to aggregate growth. Here, growth is mainly explained by “real cost reduction” which stems from “1001 different causes” (Harberger, 1998), such as technical improvements and technical innovations. Conversely, according to some scholars, the growth process may instead follow a “yeast dynamics”, in which productivity growth is rather evenly spread across sectors and driven by economies of scale and broad externalities applicable to the entire economy, basically related to the global stock of knowledge or human capital.

These competing views have been empirically tested by numerous studies, which mainly analyze whether TFP growth is widely spread among sectors or rather concentrated in some industries. Their findings are inconclusive and do not specifically focus on technological change or on radical technologies. For example, Harberger (1998) finds a mushroomy dynamics with a high degree of concentration: aggregate TFP growth in USA over the period 1950-1990 is fully accounted for by the growth of a subset of industries representing less than half the economy. These findings are supported by firm level data, which point to highly diverse experiences regarding the distribution of technical advances and explain the wide dispersion not only within industries but also across industries. For a more recent period (1980-2005), Timmer et al. (2011) find that TFP growth is rather widespread across industries in the US and Anglo-Saxon countries, while it is more localized and mushroomy in Europe. Finally, Bakker et al., (2015) find a mushroom dynamics for the US manufacturing sector over the period 1899-1941, with a few sectors such as electricity, automobile, chemicals, and entertainment that accounted for a large share of aggregate TFP growth. In this work, we compute our indicator of recombinant novelty at the level of technological field (WIPO classification), so that we explicitly focus our analysis on the contribution of sectoral radical technologies to productivity growth, and, test the following hypothesis:

Hypothesis 3: Radical technologies that cause productivity growth acceleration are concentrated in a restricted number of technological fields

3. Indicator of technological novelty, variables, and methodology

3.1. Indicator of technological novelty

Following the Schumpeterian tradition, technological novelty is here considered as the result of a recombinant search process through which new and existing knowledge, components, and functionalities are

continuously recombined (e.g., Arthur, 2007; Nelson and Winter, 1982; Schumpeter, 1939; Youn et al., 2015). The empirical literature has increasingly used measures of recombinant novelty to identify radically new and breakthrough inventions (Arts and Veugelers, 2015; Fleming, 2001; Keijl et al., 2016; Strumsky and Lobo, 2015; Verhoeven et al., 2016). The main advantage of this approach is that it enables to identify technological origination, i.e., technological novelty. Conversely, as explained by Strumsky et al., (2012), citations serve primarily a legal function, which enables to reveal the technological impact of a given invention by tracing back its relationships with subsequent inventions. In our case, the focus on the basic technological components of a patent enables to identify both the introduction of new or potentially radically new combinations of components, and, indirectly, the new knowledge that such combinations of components create. In addition, citations may not provide a full picture when the analysis concerns long time periods because they are rather sparse (Strumsky et al., 2012).

In order to operationalize the concepts of recombinant novelty and radical technologies, as a first step, we use the CRIOS dataset (Coffano and Tarasconi, 2014) and extract all US patents granted from the USPTO by priority year for the period 1920-2000⁶. Patent data have well-known limitations as a proxy of technology because not all technologies are patented. 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 technology available for long time periods and are widely used in innovation studies. As a second step, we follow Verhoeven et al. (2016) and their “novelty in recombination” indicator, for which an invention is considered to be technologically novel if a technological combination is applied for the first time in an invention. Verhoeven et al., (2016) have tested the validity of this indicator and compared it with traditional measures of impact of innovations, concluding that those few inventions “that are “more novel”, i.e. those that make more and more different types of new combinations, are more likely to be sources for technological breakthroughs” (Verhoeven et al., 2016 p.721).

The indicator is based on 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 by the patent to develop the invention, while recombination is proxied by the number of new (previously unconnected) pairs of IPC-codes. Since the number of patents typically grows over time, the number of IPC-codes and of possible pairs of IPC-codes grow over time as well. Therefore, we have normalized our measure of recombinant novelty by dividing the number of new pairs of IPC-codes contained in a patent by the number of possible pairs of IPC-codes contained in that patent⁷. Hence, in this work, our indicator of *Novelty in Recombinant (NR)* is:

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

⁶ The choice of the analyzed period (1920-2000) depends on the availability of data in the CRIOS dataset.

⁷As 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 NR index is $1/3 = .33$, that is, 1/3 of the combinations is new.

This measure ranges from 0 to 1; it takes the value 1 when all pairs of IPC-codes are novel combinations, and 0 when none is a novel combination. Using the IPC classification has a number of advantages and drawbacks. Regarding the advantages, in order to define the scope of patent protection, the IPC classification relies on various technological information contained in the patent document, including the description of the invention, examples, drawings, and claims, while the US Patent Office Classification relies only on claims (Gruber et al., 2013; Verhoeven et al., 2016). This is particularly important for our purpose, because the number of IPC-codes assigned to a patent is often positively correlated with the patent scope. In addition, IPC classification has been designed to be aligned with the industry-based definitions of technologies (Strumsky and Lobo, 2015), which is again very useful for our analysis as we seek to explore the link between technological novelty, sectoral dynamics, and productivity growth. The drawback is that the IPC classification is top down and remains fixed until it is revised. Revisions, nevertheless, occurs on a regular basis. Finally, it is important to note that in both classification systems, retroactive reclassification of existing patents occurs⁸.

3.2. Variables and descriptive statistics

Based on the Novelty in Recombination indicator, we construct our variables as follows. From the dataset of US granted patents, at first we compute *the annual flow of patents that introduce at least one new technological combination (Rec_flow)*. This variable captures all patents for which our indicator of Novelty in Recombination has a positive value ($NR > 0$). Then, as we expect that patents with a higher degree of Novelty in Recombination have a higher impact on productivity, we compute *the annual flow of the top 1 % of patents with highest values of Novelty in Recombination (T1rec_flow)*. This is our variable of interest and our proxy for the annual flow of radical technologies at the aggregate level. The annual flow of patents with positive value of Novelty in Recombination (*Rec_flow*) is instead used to proxy more incremental technologies as, by definition, it includes technologies with lower values of recombinant novelty than radical technologies. In order to calculate the annual flow of radical technologies (*T1rec_flow*) at the level of technological field, we use the IPC8 Technology Concordance Table provided by WIPO, which attributes patents to 35 technological fields (*IPC_35*) on the basis of their IPC-codes (Schmoch, 2008). Table 1A in the Appendix shows the list of these fields. We used the information on the WIPO technological fields as provided by the CRIOS dataset.

In addition, among the technological variables, we include the *annual flow of patents (Pat_flow)* and the *annual flow of patents that introduce a new IPC-code (New_ipc)*. The flow of patents is indicative of the number of inventions, while *New_ipc* captures the emergence of a new technological component⁹. The final sample includes 5,315,044 granted patents over the period 1920-2000. Among these, 6.92% introduce at least a new technological combination (*Rec_flow*) and 2.23 % are radical technologies (*T1rec_flow*). So, about 93% of patents

⁸ Lobo and Strumsky (2015) give the example of nanotechnology, which has been introduced in 2004 in the USPC system and has led to recodification of previous patents, thus the first nanotechnology patent was granted in 1986.

⁹ We also have computed all these variables in stocks using a perpetual inventory method (Hall et al., 2010). Econometric results were very similar to those of variables in flow and, therefore, are not here reported.

have introduced no novel combination of components (NR = 0), and radical inventions only represent 2% of total inventions. Patents that introduce a new IPC-code (New_ipc), instead, represent 0.052% of total granted patents and 2.35% of radical technologies.

Our last variable is productivity, and, more specifically, Total Factor Productivity (TFP). TFP growth measures the growth of total output not explained by the growth of traditionally measured inputs of labor and capital. TFP growth is calculated as a residual and, therefore, is a proxy of the contribution to economic growth of all unmeasured factors and, among these, of technological change. **For this reason, we consider that, compared to labor productivity growth, TFP growth is a better proxy of the part of economic growth generated by technological change.** In this work, we have used data on *the annual level of TFP* from 1920 to 2000, in the USA. These data have been provided in Bergeaud et al. (2016)¹⁰. Table 1 contains the list of our variables, their description, and the basics descriptive statistics.

Table 1. List of variables

Variables	Description	Mean	Std. Dev.	Min	Max
TFP	Annual level of Total Factor Productivity	6.49	2.70	2.39	11.01
T1rec_flow	Annual flow of radical technologies (top 1% of patents with the highest value of NR)	1466.45	532.85	801	3951
Rec_flow	Annual flow of patents with NR > 0	4541.28	2664.94	1147	10922
Pat_flow	Annual flow of patents granted by the USPTO by priority year	66263.6	41271.37	28450	230803
New_ipc	Annual flow of patents that introduce a new IPC-code	34.58	35.65	4	258

Period: 1920 – 2000

We now show the evolution over time of our variables. Figure 1 contains observed and smoothed values of the US annual growth rate of total factor productivity (TFP) and labor productivity (LP) from 1890 to 2012¹¹. We observe that the two variables have considerably fluctuated over time, showing periods of accelerated and decelerated growth. 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 associated 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 growth has been substantially lower than the previous decades and it has slowed down further since the early 2000s, before the 2008 financial crisis. Table 2 shows that the average growth rate

¹⁰ In Bergeaud et al. (2016), TFP is computed assuming the following Cobb–Douglas production function: $TFP = Y/(K^\alpha * L^\beta)$, where α and β are the elasticities of output with respect to the inputs K and L. Assuming unitary returns to scale ($\alpha + \beta = 1$), TFP is then calculated as a residual according to the following equation: $TFP = Y/(K^\alpha * L^{1-\alpha})$. Three basic series have been used: GDP (Y), labor (L), and capital (K). Labor (L), is calculated by using data on total employment (N) and working time (H). The capital indicator is constructed by the perpetual inventory method (PIM). α is computed by assuming that production factors are remunerated at their marginal productivity (at least over the medium to long term). Given that labor costs (wages and related taxes and social security contributions) represent roughly two-thirds of income, we have $\beta=0.7$ and $\alpha=0.3$.

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

of TFP and LP 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.

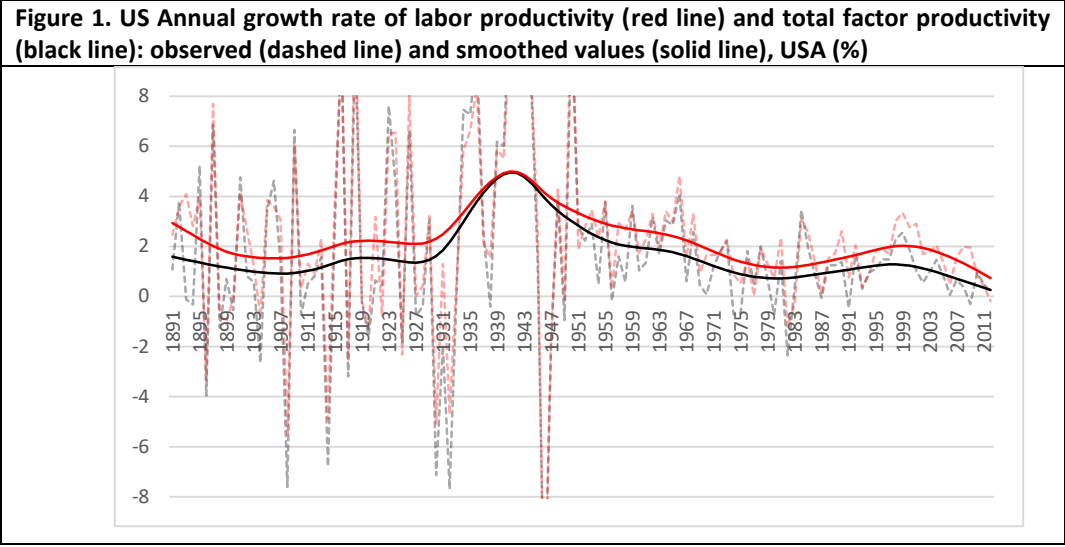


Table 2. Average annual growth rate of total factor productivity (TFP) and labor productivity (LP), USA (%)

Periods	TFP	LP
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

Figure 2 shows our variable of interest, the annual flow of radical technologies (T1rec_flow), together with the flow of total patents (Pat_flow). The flow of radical technologies increases from the mid-1930s to the early 1970s. We then observe a strong decline until the mid-1980s, followed by an exponential increase. The 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 this exponential growth to the increasing propensity of firms to patent for strategic reasons (Hall and Ziedonis, 2001). Thus, the increase in the flow of radical technologies since the mid-1980s may be largely due to a more general soaring in the flow of strategic patents.

Figure 2. Annual flow of radical technologies (T1rec_flow) and annual flow of patents granted by the USPTO by priority year (Pat_flow)

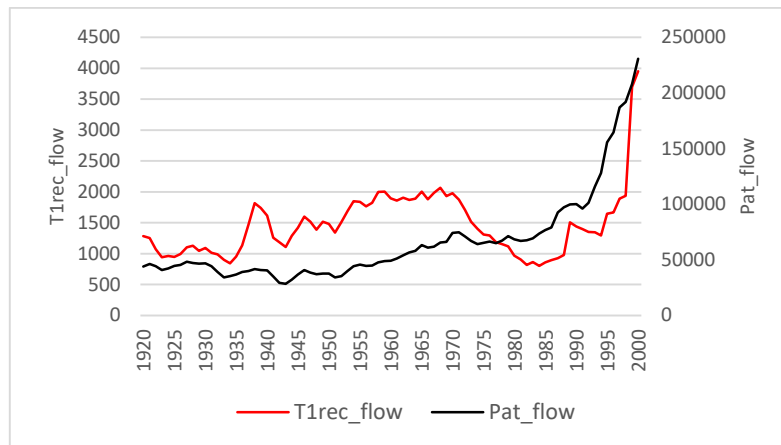


Figure 3. compares the flow of radical technologies (T1rec_flow) with the flow of patents with a positive value of Novelty in Recombination (Rec_flow) and with the flow of patents that introduce a new IPC-code (New_ipc). We observe that the flow of patents with NR > 0 and the flow of radical technologies start diverging significantly since the 1950s. This suggests that since the second half of the 20th century radical technologies (T1rec_flow) have grown much slower than technologies with lower values of novelty or radicalness (Rec_flow). Patents that introduce a new IPC-code, instead, are highly concentrated before 1920¹². New_ipc rises, to a much smaller extent, also during the 1960s and 1970s, probably because of the emergence of ICTs.

Figure 3. Annual flow of radical technologies (T1rec_flow), annual flow of patents with positive NR (Rec_flow), and annual flow of patents introducing a new IPC-code (New_ipc).

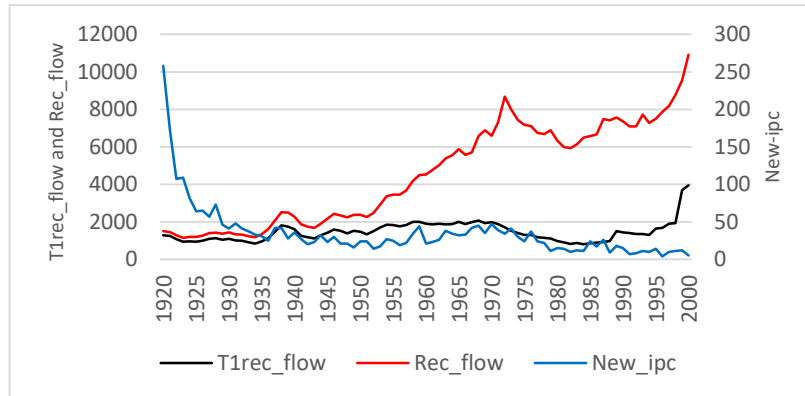


Figure 4 shows the distribution among technological fields (WIPO IPC_35) of both total patents (Pat_flow) and radical technologies (T1rec_flow) from 1920 to 2000. We observe that technological fields considerably diverge in terms of both size (as proxied by Pat_flow) and degree of Novelty in Recombination (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), and Measurement (IPC_35 10). The technological fields that

¹² Note that retroactive reclassification of existing patents occurs on a regular basis. See the example on note 8.

display the highest number of radical technologies are: Mechanical elements (IPC_35 31), Machine tools (IPC_35 26), Transport (IPC_35 32), and Electrical machinery, apparatus, energy (IPC_35 1).

Finally, Figure 5 and 6 show the evolution over time of the average number of IPC-codes and technological fields (IPC_35) per patent, respectively, for four groups: all granted patents (Pat_flow), patents that make no novel combination (No_recomb), patents that make at least one new combination, i.e., patents with a positive value of Novelty in Recombination (Rec_flow), and radical technologies (T1rec_flow). We can see that technologies introducing new combinations (Rec_flow and T1rec_flow) are in general more complex (average number of IPC_codes per patent) and cross-fields (average number of technological field per patent) than both all patents and patents that make no novel combination. The complexity of patents that make at least one combination (Rec_flow) appears particularly high and experience a significant increase since 1950s up to reach nearly six codes per patent on average in 2000. With respect to radical technologies, Figure 5 shows that they are concentrated among those patents that have only two IPC codes up to the 1990s (76 % of all radical technologies have only two codes) and then experience a steep increase to reach nearly four codes in 2000¹³. These trends seem to indicate that technologies introducing new combinations have become increasingly complex and cross-fields and that, up a recent period, radical technologies (T1rec_flow) have been more technologically focused (less complex and less cross-field) than technologies with a positive, but, by definition, lower degree of recombinant novelty or radicalness (Rec_flow).

Figure 4. Distribution among technological fields (IPC_35) of radical technologies (T1rec_flow) and of total patents (Pat_flow), 1920-2000.

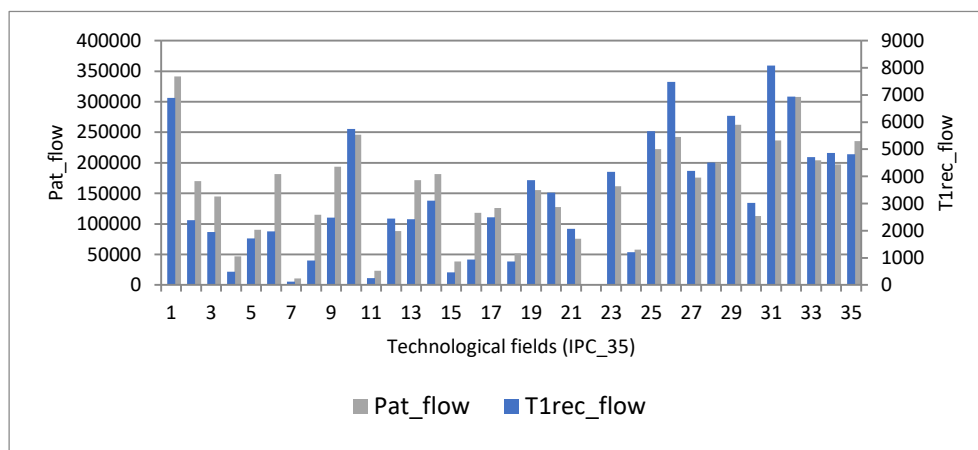


Figure 5. Annual average number of IPC-codes per patent

¹³ Also note that 48 % of all granted patents have only one IPC code, which corroborates previous studies (Verhoeven et al., 2016). Among the remaining patents that have at least two codes, the majority, namely 46%, have only two codes and one combination.

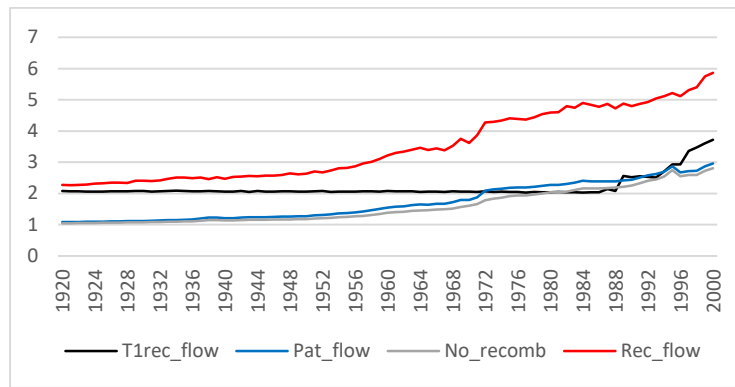
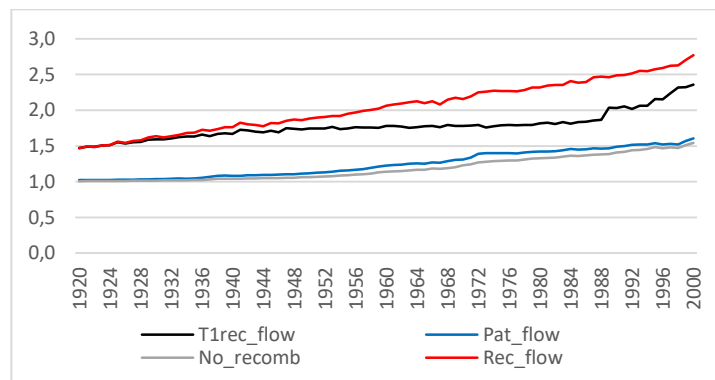


Figure 6. Annual average number of technological fields (IPC_35) per patent



3.3. Methodology

In order to test the sign and direction of causality between radical technologies and productivity, we rely on Granger’s causality, which requires that we work within the framework of the non-structural VAR, introduced into the historical research by Eckstein et al., (1984)¹⁴. Non-structural VAR models are particularly suited for answering our questions because they present the advantage of accounting for the intrinsic structure of the series and the dynamical effects between variables offering more reliable analyses at the dynamical level than traditional models.¹⁵ These models are appropriated for our analysis also because they offer the possibility of

¹⁴ “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.

¹⁵ The intrinsic structure of the series is related to its identification in the ARIMA classification (Box and Jenkins, 1976; Newbold and Granger, 1974).

considering all causal relationships between variables without *a priori* on their potential endogeneity. In a VAR model, variables are both exogenous and endogenous¹⁶. 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. So, with two variables, the model can be written as:

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

Formally, the causality analysis relies on the statistical test of the hypothesis:

$$\begin{cases} X_t \text{ does not cause } Y_t \leftrightarrow C_1 = C_2 = \dots C_p = 0 \\ Y_t \text{ does not cause } X_t \leftrightarrow B_1 = B_2 = \dots B_p = 0 \end{cases}$$

Indeed, according to Granger (1969), the variable X (resp. Y) causes the variable Y (resp. X) if the prediction of Y (resp. X) is improved when one incorporates information concerning X (resp. Y) and its past into the analysis. This means that in the above VAR model, coefficients C_i (resp. B_i) are significantly different from zero. 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:

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

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.

However, the use of this type of model requires beforehand to test for various assumptions. For the interested reader, all intermediate econometric results are available in supplementary materials (SM). First of all it is necessary to work with stationary variables¹⁷. Therefore, we use the unit root test of Elliott et al., (1996),

¹⁶ 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.

¹⁷ 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. In our tests, a variable X_t which is stationarised with a difference

which is considered more efficient (Salanié, 1999) than the classic test of Dickey and Fuller (1979). These tests consist in determining whether the variables are stationary or not and if not, where the non-stationarity comes from: a deterministic trend or the presence of a unit root (SM, part 1)¹⁸. 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. We select as optimal, the lag that satisfies the most criteria (SM, part 2).

Next, presence of cointegration relationship(s) 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). Indeed, variables are said to be cointegrated if they exhibit long-run stable relationship(s), namely if they share common trends. In this case, causal relationship may be only due to this common trend. So, it is necessary to detect if there is cointegration and to correct it in order to highlight the real link between variables. A necessary condition of cointegration between two variables is that they are integrated of the same order. We use the Johansen test (1988), which consists in testing long run common trend between integrated variables of the same order; this test is performed on gross variables. Thus, at the aggregate level, we apply it to the following variables: levels of total factor productivity (TFP), flow of radical technologies (T1rec_flow), and flow of inventions with positive value of novelty in recombination (Rec_flow). Johansen test indicates that these variables are not cointegrated (SM, part 3).

It is then possible to consider the causality analysis. There are two approaches to causality (Granger, 1969; Sims, 1980), which are generally equivalent (Bruneau 1996). We choose here a Granger test (1969). It is a binary test that consists in highlighting the causal relationships and its impact (positive or negative) between two stationary variables. Impacts are calculated with coefficients of the associated VAR models. Models are estimated with stationary variables at the aggregate level (SM, part 4).

Finally, it is possible to make a dynamic analysis. We observe how a simulated shock on the variable X affects the variable Y. The simulation of shocks on each variable helps us to understand how (impulse response function) and to what extent/proportion (variance decomposition) others variables are affected. By this way, we can, for example, observe the variations over time of TFP levels after a simulated technological shock, like an increase in the flow of radical technologies. And, by the same way, we can observe to what extent variations in TFP levels are explained over time by the technological shock.

In sum, in order to test our three hypotheses, we test the existence of a causal relationship, and eventually the direction and the sign of this relationship, between TFP levels and each of the technological variables listed in table 1: the annual flow of radical technologies (T1rec_flow), the annual flow of invention with a positive value

filter is noted DX_t ; a variable Y_t which is stationarised with a deviation from a linear trend is noted SY_t . A variable Z_t which needs to be stationarised with a difference filter and a deviation from a linear trend is noted SDZ_t

¹⁸ At the aggregate level ERS tests indicate that TFP, Rec_flow, T1rec_flow are non-stationary because of a unit root (DS processes); New_ipc is non-stationary because of a linear trend (TS process) and Pat_flow is non-stationary because of the two (Mixed process). Thus, stationary variables are now respectively noted DTPF, DRECFLOW, DT1RECFLOW, SNBNEWPIC, and SDPATFLOW.

of Novelty in Recombination, the annual flow of total patents, and the annual flow of patents that introduce a new IPC-code. This should provide us information on the eventual existence of a long-run relationship between productivity and our technological variables, in particular the flow of radical technologies. Moreover, for significant variables, we should be able to provide information on the direction of the causal relationship (which variables are endogenous or exogenous) and its sign (positive or negative). Finally, the dynamic analysis will provide information on the length and amplitude of the impact on our variables of interest of a simulated shock, as well as information on the magnitude of the explained variations over time.

4. Results

4.1. Aggregate analysis

In this section we present the results of the causality analysis and the dynamic analysis at the aggregate level for the period 1920-2000. With respect to the causality analysis¹⁹, we find that, among all our technological variables, only the annual flow of radical technologies (T1rec_flow) has a causal relationship with TFP levels ($p < 5\%$, see Appendix 2). The flow of total patents is not significant, indicating that the number of total inventions or technologies has no impact on productivity. The same holds for the flow of patents with positive values of Novelty in Recombination (Rec_flow)²⁰ and for patents that introduce a new IPC-code (New_ipc). These results suggest that only technologies with the highest values of recombinant novelty or radicalness have a significant impact on productivity, while more incremental inventions (Rec_flow) have not. In addition, it seems that inventing a new component does not have a direct impact on productivity as well, though there may be an indirect impact (not captured by our analysis) because recombination would be limited without the periodic creation of new components.

The causality analysis also reveals that the direction of causality only goes from radical technologies to TFP and that the sign of this relationship is positive. Hence, a positive variation in the flow of radical technologies causes a positive variation in productivity levels, that is, productivity growth. However, the opposite is not true, because a variation (positive or negative) of productivity levels has no impact on the flow of radical technologies. This result appears to provide no support for our hypothesis 2, which states that “Radical technologies are endogenous, that is, dependent on productivity variations”. In order to further test this hypothesis, we have performed an exogeneity test, which confirms that the flow of radical technologies does not depend on productivity variations: only 5% of variations in flow of radical technologies depends on productivity variations. For the estimated model, the optimal lag equals 5, so that the impact of radical technologies on productivity

¹⁹ Here, we test the existence of causal links between $D(TFP)$, $D(recflow)$, $D(T1recflow)$, $SD(patflow)$ and $S(nbnewipc)$. See note 17.

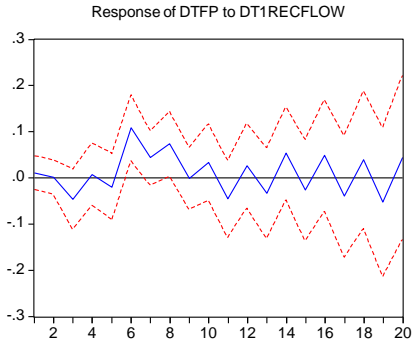
²⁰ There is a causal relationship from Rec_flow to TFP with a significance level of 10%.

occurs after 5 years, with a peak on the sixth year. This explains the important jump that we will observe in the dynamic analysis.

With respect to the dynamic analysis, Figure 7 shows how TFP levels react when we simulate a positive shock on the annual flow of radical technologies (T1rec_flow), like for example the introduction of a radical technology. We can observe that the impact on productivity levels is temporary (it is about 15 years) and it is not constant over time. At the beginning of the introduction of a radical technology, productivity declines (we see a negative variation of TFP levels), possibly because an invention typically takes some times before to be perfected and productive. Then, we observe an acceleration of productivity growth (we see a large positive variation of TFP levels) up to the sixth year, possibly as a result of the establishment of a dominant standard/paradigm. After the peak of the sixth year, the productivity growth generated by the radical technologies decelerates (the variations of TFP levels are sometimes positive, but smaller, and sometimes negative), and, finally, disappears.

The dynamic analysis also provides us the variance decomposition of TFP levels according to the annual flow of radical technologies (Appendix 3). Results show that variations in the flow of radical technologies explain a considerable part of TFP level variations: after 15 years, more than 50% of productivity variations are explained by the variations in the flow of radical technologies. Overall, these results provide support for our hypothesis 1: “Radical technologies cause a temporary acceleration of productivity growth”. In addition, the fact that productivity growth produced by radical technologies is low or negative at the beginning, then very high, and, finally, declining seems to indirectly support the idea that radical technologies evolve following a logistic curve and confirms the existence of diminishing returns of innovation.

Figure 7. Impulse response function of productivity levels (TFP) after a simulated positive shock on the flow of radical technologies (T1rec_flow) (in red: confidence bands)



4.2. Technology-field analysis

To test whether radical technologies that cause productivity growth acceleration are concentrated in a restricted number of technological fields (hypothesis 3), we perform the same analyses of section 4.1., i.e., causality analysis and dynamic analysis, at the technology-field level. Therefore, we test whether there is a relationship of causality between TFP levels and the flow of radical technologies in each of the 35 WIPO

technological fields (IPC_35)²¹. We find that only 5 out of 35 fields have a positive causal relationship with productivity (Appendix 4). This suggests that those radical technologies that contributed to productivity growth during 1920-2000 period are concentrated in a handful of “leading technological fields”. These are, as described by Schmoch (2008):

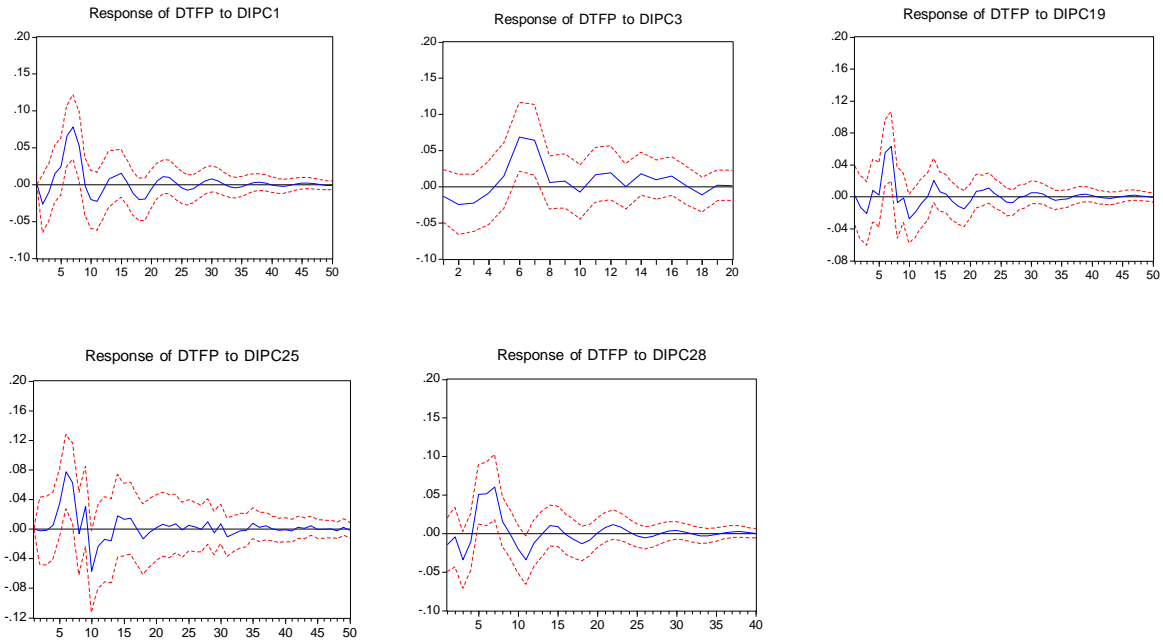
- “Electrical machinery, apparatus, energy” (IPC_1, signif.: $p < 1\%$): it primarily covers the non-electronic part of electrical engineering, e.g., the generation, conversion and distribution of electric power, electric machines, and basic electric elements (resistors, magnets, capacitors, lamps or cables);
- “Telecommunications” (IPC_3, signif.: $p < 5\%$): it is a very broad field covering a variety of telecommunications techniques and products;
- “Basic materials chemistry” (IPC_19, signif.: $p < 5\%$): it primarily covers typical mass chemicals such as herbicides, fertilizers, paints, petroleum, gas, detergents etc.;
- “Handling” (IPC_25, signif.: $p < 5\%$): it is a quite heterogeneous field comprising elevators, cranes, robots, but also packaging devices;
- “Textile and paper machines” (IPC_28, signif.: $p < 1\%$): it includes machines for specific production purposes; textile and food machines represent the most relevant part of these machines.

Figure 8 shows how TFP levels react after a simulated positive shock on our 5 leading fields. Although the evolution of TFP in the 5 cases is broadly similar to the evolution observed at the aggregate level (in section 4.1.), we can also note some differences among technological fields. “Electrical machinery, apparatus, energy” has the highest impact, and together with “Basic materials chemistry”, it also has the longest impact. For all 5 fields, optimal lag equals up to 6 or 7 years (one or two years more than the lag at the aggregate level), and, before reaching their peak, all fields display the same initial negative impact, more or less pronounced, that we have observed at the aggregate level.

In order to analyze how each of the 5 leading sectors contributes to explain TFP variations, we build a model where TFP variations are explained by 5 variables, each corresponding to the annual flow of radical technologies in the 5 leading fields (Appendix 5). We find that after 10 years, the variations in the flow of radical technologies in the 5 leading fields explain together a very important part (54%) of TFP variations. The most influencing field is “Electrical machinery, apparatus, energy”, which explains 26.5% of TFP variations on its own. “Telecommunications” is the sector that contributes the least (4.7%). This may be partially due to fact that these are still relatively “young” technologies, which in future will produce higher productivity gains. However, this result may also reflect to the so-called productivity paradox, i.e., the surprisingly low productivity gains associated with ICTs. Overall, these results provide evidence for our Hypothesis 3: “Radical technologies that cause productivity acceleration are concentrated in a restricted number of technological fields”.

Figure 8. Impulse responses function of TFP after a simulated positive shock on IPC1, IPC3, IPC19, IPC25, IPC28

²¹ As for the aggregate analysis, all the intermediary tests performed are presented in the supplementary materials. ERS tests are presented in SM, part 5 ; cointegration tests are in SM, part 6 ; VAR Models estimations are in SM, part 7.



Unlike the aggregate level, for which we found no causal relationship going from productivity to radical technologies, at technology-field level, we find a positive impact of productivity levels on the flow of radical technologies in three fields and a negative impact in one field (Appendix 4). We label the first three fields as “demand-driven” since, in this case, a positive variation in TFP levels cause a positive variation in the flow of radical technologies. Hence, during periods of growing productivity, investments in radical technologies in these fields increase, possibly because demand is higher (pushed by productivity and income growth) and innovation risk is lower (see section 2). These sectors are (Schmoch’s definition):

- “Surface technology, coating” (IPC_21, signif.: $p < 1\%$): the coating of metals, generally with advanced methods, represents the core of this field;
- “Engines, pumps, turbines” (IPC_27, signif.: $p < 1\%$): it covers non-electrical engines for all types of applications, in quantitative terms, applications for automobiles dominate;
- “Mechanical elements” (IPC_31, signif.: $p < 5\%$): it covers fluid-circuit elements, joints, shafts, couplings, valves, pipe-line systems or mechanical control devices.

However, radical technologies in these 3 technological fields do not generate productivity growth at the aggregate level: as we have seen before in this section, they are not among the leading technological fields. Figure 9 shows the impulse response function of demand-driven fields when we simulate a positive shock on productivity levels. 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 (Appendix 6), productivity variations explain 26% of the variations in the flow of radical technologies for “Surface technology, coating”, while for “Engines, pumps, turbines” and “Mechanical elements” the explained variance is only 13% and 14%, respectively.

Figure 9. Impulse responses functions of IPC21, IPC31, IPC27 after a positive simulated shock on TFP

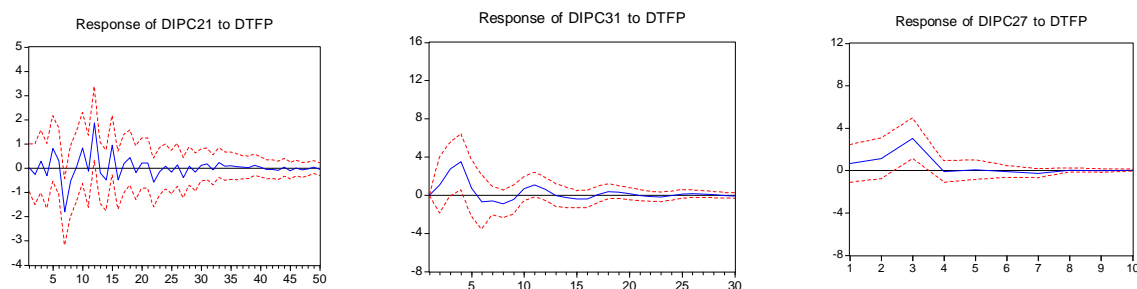
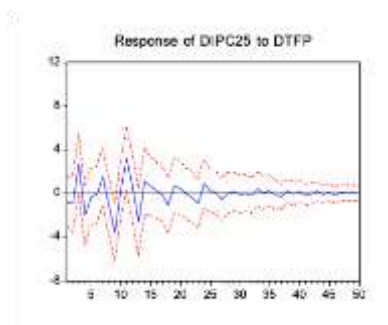


Figure 10. Impulse responses function of IPC25 after a positive simulated shock on TFP



Finally, as mentioned before, we find one sector, “Handling” (IPC_ 25) which has a negative causal relationship with productivity levels (signif.: $p < 5\%$, see also Appendix 4). Hence, in this case, a negative variation of TFP levels causes an increase in the flow of radical technologies in this field, possibly because decreasing productivity levels signal that predominant technologies are mature and do not offer sufficient gains any more (see section 2). What is interesting for this field, is that it is also one of the leading technological fields. Therefore, this is the only field having a double causal relationship with productivity: it is negatively caused by productivity, but it also positively causes productivity. Figure 9 shows how the flow of radical technologies in this field reacts when we simulate a positive shock on TFP levels. Optimal lag, in this case, is the highest one, i.e., 13 years, after which the negative impact of productivity growth on the flow of radical technologies starts disappearing. The variance decomposition (Appendix 7) indicates that, after 20 years, TFP variations explain an important part (almost 33%) of the variations in the flow of radical technologies in the field.

Overall, these results provide partial empirical evidence supporting our hypothesis 2: “Radical technologies are endogenous, that is, dependent on productivity variations”: the flow of radical technologies in 4 out of 35 technological fields depends (positively or negatively) on TFP variations, and therefore these technologies can be considered as endogenous, while the remaining 31 technologies should be considered as exogenous.

4.3. Innovation patterns of technological fields and industry dynamics: an interpretation

In this section, we try to identify the industrial sectors associated to leading technological fields and demand-driven fields in order to understand the innovation patterns that may explain how these technologies affect or are affected by productivity. We adopt a two-step approach. First, we link technological fields to their industrial sectors by using the Neuhäusler et al. (2019) concordance matrix, which links 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. We are conscious of the important limitation of this analysis because in order to interpret patterns dating back to the 1920s, we use a contemporaneous and a time invariant concordance matrix. However, we are not aware of any such concordance matrix relating technological fields and industrial sectors over such a long period of time. This 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).

The concordance matrix provides, for each technological field, the percentage of patents originated by each of the 99 2-digit NACE sectors. Table 3 shows such percentages for the main industrial sectors in which our five leading fields are concentrated²². As we can see, only four out of the 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). Table 3 also contains the innovation pattern of each sector, as provided by Bogliacino and Pianta (2011), and shows that two sectors are Science-Based (26 and 20) and two are Specialized Suppliers (27 and 28). Following Pavitt (1984), Science-Based sectors 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.

Table 3. Leading technological fields, related industrial sectors and patterns of innovation

Technological field (WIPO IPC_35)	Related industrial sectors (WIPO IPC_35 – NACE concordance)	Patterns of innovation ¹
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

²² 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%.

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		
¹ Bogliacino and Pianta (2016)		

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 on 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, only typical of Science Based and Specialized Suppliers industries. Hence, our analysis seems to indirectly suggest that the main source of productivity growth during most of the 20th century has been the creation of new R&D intensive products, including capital products (machinery), and new markets.

Like for the leading fields, we show, in Table 4, the industrial sectors and the patterns of innovation associated with demand-driven fields. Interestingly, among demand-driven sectors we find three of our leading industrial sectors – the computer, chemical and machinery sectors – but we also see some new sectors such as manufacture of motor vehicles and manufacture of other transport equipment. While the latter is a Specialized Supplier sector, the former is included by Bogliacino and Pianta (2011) among the Scale and Information Intensive industries²³. 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 suppliers of equipment as the source of their process innovation (Bogliacino and Pianta 2011). Bogliacino and Pianta (2011) also highlight that while demand growth is highly important for Science-Based sectors (relevance of increasing returns), Specialized suppliers (relevance of interaction with clients) and, even more, for Scale and information intensive industries (relevance of new mass 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.

²³ They comprise motor vehicles, mineral oil refining, coke and nuclear fuel, rubber and plastics, basic metals, and financial services related to information technology

Table 4: 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

5. Summary and discussion

This work provides, for the first time, a long-run quantitative analysis of the relationship between radical technologies, as proxied by the degree of recombinant novelty of inventions, and productivity growth. By using a cliometric approach based on Granger’s causality, we test the sign and direction of causality between the flow of radical technologies and productivity levels between 1920 and 2000, at the aggregate and technology-field level, in the USA.

Our analysis shows that, at the aggregate level, radical technologies cause a temporary acceleration of productivity growth and explain a considerable part of productivity variations. This result provides long-run quantitative evidence supporting what claimed by different historical studies and theoretical models (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 analysis also suggests that only technologies with the highest values of recombinant novelty or radicalness have a significant impact on productivity, while the total number of technologies (as proxied by the flow of total inventions) and more incremental technologies (as proxied by inventions with a lower degree of recombinant novelty) have not. Moreover, it seems that inventing a new component does not have a direct impact on productivity as well, though there may be an indirect impact (not captured by our analysis) because recombination would be limited without the periodic creation of new components. The fact that the acceleration of productivity growth is temporary also provides evidence that radical technologies tend to develop following a logistic curve and indirectly confirms the existence of diminishing returns of investment in innovation, as highlighted by the above-mentioned studies and models. If so, in the absence of periodic radical technologies, productivity growth would ultimately cease (Crafts, 1995).

Our technology-level analysis provides a more detailed picture. Actually, those radical technologies that contributed to aggregate productivity growth appear to be concentrated in only 5 out of 35 technological fields (WIPO fields). These 5 “leading technological fields” explain together about 54% of productivity variations, while the field “Electrical machinery, apparatus, energy” explains alone 26.5% of productivity variations. By relying on a concordance table and the revised Pavitt (1984) taxonomy (Bogliacino and Pianta, 2016), we find that patents

in the 5 leading fields are mainly concentrated in science based sectors (computer and chemical sectors) and in the sectors of specialized suppliers of capital equipment (machinery and electrical 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, and new markets, based on intense R&D activities. Hence, our analysis seems to indirectly suggest that the main source of productivity growth during most of the 20th century has been the creation of new R&D-intensive products and new markets.

More in general, this evidence seems to clearly support the idea behind the Schumpeterian process of creative destruction (Schumpeter, 1939), where a few leading sectors drive productivity growth acceleration during a given time period, by improving and further developing initial radical technologies. Although results are not directly comparable because issued by different methodological approaches, our findings are also compatible with a “mushroom vision of the growth process” (Hardenberg, 1998), according to which the largest share of macroeconomic productivity growth is explained by innovation and growth in a few sectors, rather than by economies of scale and knowledge externalities spreading all over economic sectors.

Finally, with respect to the controversial issue of the endogeneity of radical technologies, we find that at the aggregate level, there is no causal relationship running from productivity levels to the flow of radical technologies. So, while the flow of radical technologies positively causes productivity variations, the opposite is not true. This would suggest that, at least during the analyzed time period, radical technologies are exogenous, because their emergence does not depend on productivity variations. However, when we look at the relationship between productivity levels and the flow of radical technologies in each of 35 technological fields, we find a more complex dynamic. Most of technologies remains exogenous, as stated by some works (e.g., Kuznets, 1930; Schumpeter, 1939; Clark et al., 1981; Mokyr, 1993; Craft, 1995; Helpman and Trajtenberg, 1994; Aghion et al., 1998; Caiani et al., 2014; Silverberg and Lehnert, 1993), but a few are endogenous, as claimed by others works (e.g; Mensch, 1979; Kleinknecht and Panne 2008, Saviotti and Pyka, 2013, 2004; Carlaw and Lipsey, 2006; Schaefer et al., 2014).

Among endogenous technologies, most are positively caused by productivity growth, while only one technology is negatively caused by productivity growth. We have labelled the first technologies as "demand-driven" because the flow of radical technologies in these fields increases (decreases) as productivity, and therefore income and demand, increase (decrease). 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 (e.g., Clark et al. 1981; Dosi et al., 2010; Lorentz et al., 2016; Crespi and Pianta, 2008). Demand-driven technologies are mainly concentrated in the automotive sector (a scale intensive sector) and in three of the 5 leading sectors mentioned above, i.e., the computer, chemical, and machinery sectors. However, it is worth noting demand-driven field have no impact on productivity. Hence, our interpretation is that these technologies mainly act as amplifier of long-run fluctuations, thus increasing the instability of the economic system: during expansion periods (positive variations of productivity levels), investment in radical demand-driven technologies increases, attracted by the growing demand, possibly creating over-investment and over-production. On the contrary,

during recession periods (negative variations of productivity), investment in demand-driven radical technologies will decrease, in the absence of attractive demand, thus deepening recessions.

Finally, the existence of one technological field that negatively depends on productivity growth suggests that some radical technologies may 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; Kleinknecht and Panne 2008, Saviotti and Pyka, 2013, 2004). This technological field, i.e., Handling, is very heterogeneous (it includes technologies ranging from elevators to robots), and its patents are mainly concentrated in the machinery and computer sectors. What seems interesting for this field is that it also one of the 5 leading fields. Therefore, Handling is the only technology having a double causal relationship with productivity: it positively causes productivity variations and, at the same time, it is negatively caused by productivity variations. As a consequence, a negative (positive) variation of productivity levels would cause an increase (decrease) of radical technologies in this field, which, in turn, should lead to a positive variation of productivity levels. If so, during recession periods (negative variation of productivity), this technology may have the potential to stimulate new radical technologies and, eventually, a new technological revolution.

6. Conclusion

Despite our findings should be taken with caution because of the limitations of this work, they may have a number of theoretical implications, which are also relevant in the light on the current debate on a possible fourth technological revolution based on Artificial Intelligence. First, in section 1, we have highlighted that radical technologies are the origin of technological revolutions, of structural and institutional changes, and, ultimately, of the fluctuating increasing trend of productivity and production. As such, radical technologies are at the core of the process of long-run economic development. If some radical technologies are negatively endogenous, i.e., they rise during periods of decreasing productivity, then also the process of long-run economic development should be partly endogenous: during recession periods, some new radical technologies can rise and eventually positively contribute to start a new technological revolution and a new phase of economic development. And, if the process of long-run economic development is partly endogenous, then also technological revolutions, structural change and long-run economic fluctuations should be partly endogenous: the economic system tends to generate itself, and therefore recurrently, the forces that transform it and that determine its long-run development (Epicoco 2021). It is important to highlight that this conclusion has nothing deterministic and in no way reduces the important role that exogenous factors can play on the process of long-run development. On the contrary, the role that relatively exogenous factors – random events (wars, epidemics, natural disasters ...), public policies, and socio-institutional actors – may play in orienting long-run development should be strengthened by a better understanding of the endogenous forces at play.

A second implication of our study is about the relationship between meso level, that is the technological or sectoral level, and macro level, that is, aggregate productivity growth. According to Dopfer et al. (2004), the meso level is the fundamental unit of economic evolution in a complex system because it is the primary locus of

change of the economic system: “an evolutionary economic process ultimately depends upon the introduction of a novel generic rule that begins a meso trajectory” (Dopfer et al., 2004 p. 278). The macro level essentially adapts itself to changes introduced at meso level and constrains these changes, thus defining the evolutionary coordination problem: “This results in the growth of knowledge and, therefore, the growth of economic systems” (Dopfer et al., 2004 p. 278). In this perspective, change is essentially endogenous and driven by the (possibly overlapping) succession of logistic curves at technological or sectoral level, while long-run economic fluctuations occur when “rules” become excessively rigid and the structure of “meso units” begins to fall apart, leading to recessions. Broadly speaking, our analysis seems to provide some empirical evidence in favor of these arguments. Firstly, because only a few technologies, and one in particular, have driven productivity growth during the examined time-period, and, secondly because each of these technologies produced a temporary, and not a permanent, acceleration of productivity, which suggests that, after some time, “rules” become too rigid. Finally, our work shows that some technologies are endogenous, and that, among them, one is potentially capable of explaining endogenously why changes in dominant technologies and paradigms are possible. However, more sophisticated analyses are needed to empirically show this meso-macro relationship. Such work would require to explicitly integrate into the analysis the logistic curves of leading technologies and/or to gather time-series sufficiently long to test relationships during different sub-periods of time.

Of course this work has limitations. First, patents are an imperfect indicator of technology, 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. Second, our analysis is likely to show only some average estimates on the relationship between productivity and radical technologies. These estimates provide a synthetic and quantitative perspective that would otherwise be lacking, but they can hide important differences in the degree of radicalness of technologies and in their impact on productivity. Research on more sophisticated indicators of radicalness can improve our knowledge of the relationship between radical technologies and productivity. Third, our method does only provide average estimates for the whole time period under examination and is not able to integrate the life cycles of technological fields²⁴. Finally, and most importantly, our results hide the rich set of institutional and historical factors that are behind the relationship between productivity and radical technologies. Integrating at least some of these factors in a global model could provide promising opportunities for further research.

Compliance with Ethical Standards:

This paper respects ethical standards and in particular it has been submitted to JEEC only.

Ethical Conduct:

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²⁴ We thank one anonymous referee for this important comment.

Data Availability Statement

The data that support the findings of this study are not publicly available but were provided by Bocconi ICRIOS. See Coffano, Monica and Tarasconi, Gianluca, Crios - Patstat Database: Sources, Contents and Access Rules (February 1, 2014). Available at SSRN: <http://ssrn.com/abstract=2404344>

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Appendix 1. List of technological fields

Table 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

Appendix 2. Causality test for aggregate models

Pairwise Granger Causality Tests : 1920-2000	Obs	F-Statistic	Prob.	Lag	Sign
Null Hypothesis:					
DTFP does not Granger Cause DRECFLOW DRECFLOW does not Granger Cause DTFP	75	0.88795 2.03684	0.49451 0.08522	5	+
DTFP does not Granger Cause DT1RECFLOW DT1RECFLOW does not Granger Cause DTFP	75	1.05102 2.88883	0.39584 0.02054*	5	+
DTFP does not Granger Cause SDPATFLOW SDPATFLOW does not Granger Cause DTFP	79	1.62032 0.12464	0.20693 0.72503	1	
DTFP does not Granger Cause SNEWIPC SNEWIPC does not Granger Cause DTFP	76	0.37247 1.33790	0.82747 0.26504	4	

* significance at 5%

Appendix 3. Variance decomposition of TFP

VAR Model with TFP and T1RECFLOW

Variance Decomposition of DTFP:			
Period	S.E.	DT1RECFLOW	DTFP
1	0.157148	0.556998	99.44300
2	0.165163	0.506200	99.49380
3	0.173102	8.767873	91.23213
4	0.173943	8.913487	91.08651
5	0.183706	9.349787	90.65021
6	0.217845	35.51668	64.48332
7	0.223046	38.37395	61.62605
8	0.238325	44.85286	55.14714
9	0.240548	44.02831	55.97169
10	0.244055	45.00751	54.99249
15	0.261907	51.62544	48.37456
20	0.284367	58.54662	41.45338

Appendix 4. Causality test at the sectoral level

Pairwise Granger Causality Tests : 1900-2000	Obs	F-Statistic	Prob.	Sign	Lag
Null Hypothesis: DIPC1 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC1	74	4.02570 1.03979	0.00115** 0.41365	+	7
DIPC2 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC2	80	0.75679 0.03463	0.38704 0.85287		1
DIPC3 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC3	75	2.45599 0.64038	0.03399* 0.69747	+	6
DDIPC4 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DDIPC4	78	0.34614 1.21960	0.70857 0.30130		2
DIPC5 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC5	80	0.03207 3.39034	0.85834 0.06943		1
SDIPC6 does not Granger Cause DTFPHW DTFPHW does not Granger Cause SDIPC6	80	0.54062 0.30277	0.46441 0.58375		1
SIPC7 does not Granger Cause DTFPHW DTFPHW does not Granger Cause SIPC7	76	0.52304 0.51831	0.75796 0.76149		5
SDIPC8 does not Granger Cause DTFPHW DTFPHW does not Granger Cause SDIPC8	80	0.01074 0.50721	0.91773 0.47850		1
DIPC9 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC9	80	1.26569 0.02517	0.26407 0.87435		1
DIPC10 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC10	80	0.77628 1.09347	0.38102 0.29897		1
DIPC11 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC11	80	0.05182 0.00070	0.82053 0.97899		1
DIPC12 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC12	80	2.58322 2.76415	0.11209 0.10046		1
DIPC13 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC13	80	0.91104 0.18398	0.34283 0.66917		1
DIPC14 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC14	77	0.43878 2.29456	0.78014 0.06811		4
DIPC15 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC15	80	0.07642 0.67149	0.78295 0.41506		1
DIPC16 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC16	80	0.21792 0.81446	0.64195 0.36962		1
DIPC17 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC17	80	0.54610 0.00518	0.46216 0.94284		1

DIPC18 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC18	75	1.67997 1.24985	0.14093 0.29374		6
DIPC19 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC19	73	2.27223 1.33192	0.03510* 0.24712	+	8
DIPC20 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC20	80	0.02581 0.02276	0.87277 0.88048		1
DIPC21 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC21	70	0.65594 4.15382	0.77144 0.00027**	+	11
SDIPC22 does not Granger Cause DTFPHW DTFPHW does not Granger Cause SDIPC22	80	0.59819 0.01382	0.44164 0.90672		1
DIPC23 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC23	80	0.66027 0.35726	0.41897 0.55179		1
DIPC24 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC24	80	0.21637 1.46068	0.64313 0.23052		1
DIPC25 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC25	68	2.21687 2.15471	0.02647* 0.03103	+ -	13
DIPC26 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC26	80	0.19113 2.92610	0.66320 0.09118		1
DIPC27 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC27	79	2.81863 9.17459	0.06611 0.00028**	+	2
DIPC28 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC28	75	3.57520 1.53708	0.00417** 0.18108	+	6
DDIPC29 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DDIPC29	72	1.35098 1.02444	0.23873 0.42905		8
SIPC30 does not Granger Cause DTFPHW DTFPHW does not Granger Cause SIPC30	80	2.58781 0.09678	0.11178 0.75657		1
DIPC31 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC31	76	2.13277 2.84369	0.07252 0.02203*	+	5
DIPC32 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC32	80	0.08396 0.00739	0.77277 0.93171		1
IPC33 does not Granger Cause DTFPHW DTFPHW does not Granger Cause IPC33	80	0.60861 0.72028	0.43770 0.39868		1
SIPC34 does not Granger Cause DTFPHW DTFPHW does not Granger Cause SIPC34	80	0.07242 0.04325	0.78857 0.83581		1
DIPC35 does not Granger Cause DTFPHW DTFPHW does not Granger Cause DIPC35	80	0.31524 0.07792	0.57611 0.78088		1

*, ** significance at 5%, 1%

Appendix 5. Variance decomposition of TFP: Global VAR Model with TFP 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

Appendix 6. Variance decomposition of IPC21, IPC27 and IPC31

VAR Model with TFP and IPC21				VAR Model with TFP and IPC27				VAR Model with TFP 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

Appendix 7. Variance decomposition of IPC25 (VAR Model with TFP and IP25)

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
10	11.15	76.04	23.96
15	12.45	67.74	32.26
20	12.6	67.21	32.79