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The Compositional Nature of Productivity and Innovation Slowdown

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Abstract

A growing number of studies identify a generalized slowdown in labor productivity growth. The very existence of the slowdown ignited a series of academic debates suggesting that secular stagnation or ‘mismeasurement’ problems are at the root of the observed trends. We posit that the composition of aggregate productivity matters. In a nutshell, we make the analysis of productivity growth slowdown more fine-grained by shifting the focus to the industry level, considering that the downward trend identified at the macroeconomic level emerges from the aggregation of diverse industry-level productivity trends. We perform an analysis of the structural dynamics of labor productivity by conducting a non-parametric dynamic decomposition exercise that separates within (improvement) and between (structural change) effects for 10 OECD countries. By pooling industries in groups identified according to two different taxonomies — one related to R&D intensities rankings, and the other built upon the Pavitt taxonomy of sources of technological change —, this study assess the industry-level contributions to the slowdown and the trends over time of the within and between components. We interpret our findings highlighting common patterns and suggest two related technological explanations for the productivity slowdown: one based on a Baumol-disease-like effect driven by structural change and another based on implementation lags and/or on an exhaustion of technological opportunities — that is, on decreasing returns in innovative activities. To investigate that, we complement our productivity analysis with evidence on innovation slowdown trends, looking at aggregate and compositional trends. We explore the innovation slowdown using an array of indicators based on the notion of ‘idea-TFP’ and show that there is a generalized evidence for its occurrence. Eventually, we relate productivity and innovation slowdowns deriving tables of trends co-movements, weighted by input-output matrices coefficients, and clustered by Pavitt industry group. We interpret these relationships and highlight patterns and clusters of significant correlations.

Keywords: productivity slowdown; decomposition; industrial dynamics; innovation

JEL Classification: L16; O30; O47

1 Introduction

A growing number of studies identify a generalized slowdown in labor productivity growth (Syverson, 2016). This trend, coupled with evidence of decline in the pace of business dynamism of US firms (Decker et al., 2014) ignited a series of academic debates, revolving around two main issues. The first, more macroeconomic in nature, confronts the hypothesis of secular stagnation (Teulings and Baldwin, 2014) with the ‘mismeasurement’ one (Syverson, 2016); the related debate is summarized in the confrontation between, respectively, ‘techno-pessimists’ and ‘techno-optimists’ (Gordon, 2016; Mokyr, 2014). The second issue, with a more microeconomic flavor, has to do with the ‘black box’ of the nature of productivity (Syverson, 2011; Bartelsman, 2010); in this context, scholars are starting to uncover how firms’ heterogeneity and ‘granularity’ (Gabaix, 2011) and uncorrelated shocks at the micro-level reverberate up to the macro-level (through the structure of production networks) and produce aggregate dynamics — including dynamics of productivity.

In this paper, we take a position in-between these two corners of the research on productivity dynamics, as we address questions usually related to the macroeconomic side of the debate while at the same time shifting the focus at the slightly more granular ‘meso’-level of industries. From the macroeconomic perspective, the analysis of the slowdown is usually based on aggregated measures or on productivity decompositions assessing the contribution of the different production factors (in a source-of-growth framework of analysis) or macro-sectors like IT-producing and IT-using. Here, the arguments to explain productivity slowdown usually echo the classical ‘Solow productivity paradox’ and suggest that IT-related industries are not producing the expected productivity gains or, when productivity growth occurs, it is driven by a faster decline in the denominator of the productivity ratio, rather than in any increase in output or efficiency gain¹. Therefore, a more in-deep analysis of the structural patterns leading to productivity slowdown is needed.

In the paper, we combine two potential explanations of the productivity slowdown and we posit that (a) the composition of aggregate productivity matters, and that (b) productivity dynamics is rooted into more general technological dynamics. To support the first argument, we decompose productivity at the meso level of analysis to show the heterogeneous contribution of industries resulting in aggregate productivity slowdown. To support the second argument, we employ an array of indicators to detect a potential ‘innovation slowdown’. Finally, we relate these two phenomena exploring what we label the ‘innovation-productivity nexus’.

To deal with (a), we dissect the structural composition of the productivity slowdown, checking if it emerges from the aggregation of diverse — and with different weights — industry-level productivity trends. In this first step, we do engage in a throughout assessment of the determinants of the slowdown; while complementary research explores firm-level determinants of productivity dynamics (Bartelsman, 2010) and the role played by skill-biased technical change (Acemoglu and Autor, 2011), ours is an exercise in detection of structural dynamics. Indeed, we focus on capturing the underlying distribution of meso trends and changes resulting in the

¹According to (Acemoglu et al., 2014, p.399), when a differential productivity growth driven by IT-related industries is detected, “. . . it is driven by declining relative output accompanied by even more rapid declines in employment. It is difficult to square these output declines with the notion that computerization and IT embodied in new equipment are driving a productivity revolution, at least in U.S. manufacturing.”

aggregate productivity slowdown.

As concerns our methodological contribution, in order to understand the compositional nature of the aggregate productivity slowdown, we decompose the growth of labor productivity for a sample of 10 OECD countries using non-parametric decomposition techniques (Cantner and Krüger, 2008; Foster et al., 2001; Castaldi, 2009). By doing that, we assess (i) if the generalized productivity slowdown is pulled by the productivity dynamics in a subset of industries and (ii) what is the role played by structural change — namely by the reallocation of labor between industries.

To deal with (b), we limit our insight on the determinants of the slowdown to a conjecture about the role played by profound technological transformations. In fact, the technological (supply-side) explanation of the productivity slowdown should not be overlooked. Indeed, a generalized exhaustion of technological opportunities, one for example characterizing the transition between techno-economic paradigms (Dosi, 1982) could affect the pace of productivity growth.² In this sense, the productivity slowdown could be the proximate outcome of a technological transition yet in the making. This argument goes in line with the recent contribution of Bloom et al. (2017) that — with the aim to test the consensus functional form of idea production in growth models — suggests how research productivity is not constant but decreasing and finds evidence of these decreasing returns of research (and employed researchers) for the whole U.S. economy at a rather disaggregate level. An alternative — though related — explanation is that a technological transition has already taken place, but has yet to show its effects due to implementation lags similar to those to be expected during the establishment of a novel general purpose technology (Brynjolfsson et al., 2017; Cantner and Vannuccini, 2012); according to both views, either a new profound transformation has just occurred or has yet to happen, the productivity slowdown is mirroring decreasing returns in innovative activities within the current established direction of technological development.

To investigate the idea that an exhaustion of technological opportunities or that delayed adoption may be a major driver of the productivity slowdown, we complement our decomposition of aggregate productivity growth with an analysis of trends in innovation-related variables. Being aware that the dynamics and turbulence of the economic and technological domains may not be perfectly synchronous (Cantner and Krüger, 2004), we look for a comparable slowdown in the ‘productivity’ of innovative activities — what we label the ‘innovation slowdown’.

We find evidence that (i) the compositional nature of the productivity slowdown is a common trend in the countries under analysis; that (ii) industry-specific productivity improvements prevail in their magnitude over the effect of structural change; that (iii) the trend of industry-specific productivity improvements is, in general, a declining one. Findings (i)–(iii) suggest that the aggregate productivity slowdown is rather a result of heterogeneous contributions of constituting industries. For what concerns technological dynamics, we find that (iv) there is a generalized (across OECD countries) and compositional innovation slowdown taking place in parallel with the productivity slowdown. All the evidence points to the possibility that the slowdown is driven by the exploitation of established technological opportunities (or implementation lags) in knowledge-intensive industries, coupled with structural shifts of economic activities

²“In other words, whenever the technological paradigm changes, one has got to start (almost) from the beginning in the problem-solving activity.” (Dosi, 1982)

towards services.

The originality of our contribution is threefold: first, we apply decomposition techniques at the industry level; while this is not an absolute novelty (see [Holm \(2014\)](#) and [Castaldi \(2009\)](#), who conducted a similar analysis to assess the role played by manufacturing and services in determining aggregate labor productivity), we are the first to link productivity decompositions and the productivity slowdown literature. In doing so, we apply methods and notions used in the literature on market selection to a novel domain. Second, we combine descriptive evidence on the productivity and innovation slowdowns to explore the innovation–productivity nexus. Third, we exploit the most up–to–date available datasets to gain a throughout understanding of recent productivity dynamics.

The paper proceeds as follows. Section 2 discusses the debate revolving around the productivity slowdown. Section 3 introduces our exploratory analysis and discusses the findings. Section 4 extends our analysis to the innovation slowdown and relates the two phenomena. Section 5 concludes.

2 Productivity Slowdown: What We Know, and What We Don't

Recently, a number of studies has detected a slowdown in labor productivity growth, starting in the year 2004 ([Syverson, 2016](#); [Fernald, 2015](#)). The beginning of this trend predates the beginning of the economic crisis and the great recession, and cannot be fully explained by market ‘bubbles’–related arguments. Furthermore, the slowdown is experienced by most of advanced economies, thus it is not a phenomenon confined to the US. [Fernald \(2015\)](#) estimates that productivity growth trends returned to 1973–1995 level pace, after an acceleration in the period 1995–2004, considered as an ‘aberration’ driven by IT producing and using industries. Therefore, the relevant question is if advanced economies are entering a phase of ‘new mediocre’ ([Dabla-Norris et al., 2015](#)), with the exhaustion of the positive influence on productivity generated by IT diffusion or, in other words, if “the ‘low–hanging fruit’ of IT–based innovation had been plucked” ([Cette et al., 2016](#), p.15).

We now overview the main positions in the debate on the nature of the productivity slowdown. A first position suggests that the productivity slowdown is just the result of a mismeasurement problem ([Brynjolfsson and McAfee, 2014](#); [Mokyr, 2014](#)) and that the task of economists is to estimate correctly the gains produced by a new generation of products and services that are profoundly shaping the economy (e.g. digitization–related goods, Internet and social networks).

A second position rejects the previous idea, pointing out that even the larger estimates that take into account the mismeasurement won't cover the observed output gap generated by the productivity slowdown, hence pointing to the possibility that what hides behind the slowdown is a deeper structural transformation. Such a position is coupled with evidence suggesting a decreasing dynamism (in terms of new ventures formation, workers flow and job creation/destruction) of economic actors in the US, especially for what concerns young firms ([Decker et al., 2014](#)), therefore reinforcing the view that the economy is transitioning to a growth plateau.

A third position, pooling together a smaller set of more heterogeneous studies, connects decreasing economic dynamism and productivity slowdown with intensity of governmental regulation ([Goldschlag and Tabarrok, 2014](#)) and the level of macro–prices, in particular lower interest

rates that allow for the survival of less-efficient firms and, hence, reduce resource reallocation in some European economies (Cette et al., 2016). We direct our attention to the first two positions, as the third set of explanatory variables have been found less cogent and significant and, in any case, it deviates from the focus of this paper on structural dynamics.

For what concerns the mismeasurement hypothesis, Syverson (2016) suggests that the mismeasurement “could take one of two related forms in the data. One would occur if a smaller share of the utility that these products provide is embodied in their prices than was the case for products made before 2004. If this were true, measured output growth would slow even as total surplus growth continued apace. The second form of mismeasurement would occur if the products’ price deflators were rising too fast (or falling too slowly) relative to their pre-2004 changes. This would understate quantity growth as backed out from nominal sales.” (Syverson, 2016, p.2). However, when confronted with the data (for US, in this case), any estimation of the size of the output gap due to the productivity slowdown compensates only for a fraction of the counterfactual missing output that would have been generated if the productivity growth trend would have persisted at the pre-2004 level. Syverson points out further reasons that play down the importance of the mismeasurement hypothesis: first, the trend of productivity slowdown is not confined to the US (see also Cette et al. (2016) for France); second, even the least conservative estimates of Internet-generated consumer surplus cannot account for the trillion dollars magnitude of the output gap; third, the correction of productivity mismeasurement for ICT-related industries would imply a five-time increase in their revenues (and six-fold increase in their value-added), which is hardly justifiable (Syverson, 2016, p.3); fourth, mismeasurement always occurred. The latter point offers a nice argument in favor of the idea that the productivity slowdown can be related to technology non-linear dynamics and adoption lags; in fact, the mismeasurement hypothesis is, in a sense, the re-statement of the Solow paradox with respect to the last wave of IT-related innovations.

While the mismeasurement hypothesis seems not to provide a robust explanation for the labor productivity growth slowdown, Byrne et al. (2017) show that the mismeasurement of high-tech products prices does play a significant role in explaining the patterns and sectoral distribution of multi-factor productivity (MFP) growth (though, not of aggregate MFP growth). However, this evidence only deepens the productivity puzzle, as the upward corrections of the mismeasurement in high-tech sector MFP growth — suggesting a faster pace of technological development for some types of economic activity — do not reverberate into labor productivity growth, that continues to slow down.

Taking stock from the above discussion, the possibility that current slowdown is rooted in long term tendencies rather than in measurement inaccuracies is not to be played down. This has induced a surge in studies on the more structural nature of the phenomenon, creating a divide between techno-pessimists, broadly claiming that technology advances will not contrast the cap to economic growth posed by structural dynamics of advanced economies, and techno-optimists, offering a brighter perspective on the role technological change will have in fostering future growth. In particular, a debate has been fostered by the publication of the book ‘The Rise and Fall of American Growth’ by Robert Gordon (Gordon, 2016). There, the broad issue under analysis is what has been labeled ‘secular stagnation’ (Teulings and Baldwin, 2014). With

secular stagnation — a term firstly introduced by the Keynesian scholar Halvin Hansen — two phenomena are usually conflated together: one on the demand-side (Summers, 2015), and the other on the supply-side.

The supply-side version of secular stagnation is the one discussed by Gordon, that camps on the more techno-pessimist side. Two dynamics are playing against future economic growth. On the one hand, there is the end of a historical phase of ‘great inventions’ ranging from the American civil war to the 1970s. This goes in line with the evidence of non-linearity of technological progress. On the other hand, the emergence of several ‘headwinds’ is threatening future growth prospects. These headwinds are not rooted in technological dynamics, but have to do with increasing inequality, decreasing returns to education, and aging of population. Crafts (2016) and Clark (2016) reinforce this side of Gordon’s argument building up on the evidence that it is the growth of total factor productivity, rather than labor productivity in general, that is slowing down. The reason for that has to do with the massive transition of advanced economies to services. The supporters of the headwinds role as growth constraint highlight how “... (a) surprising share of modern jobs are the timeless ones of the pre-industrial era — cooking, serving food, cleaning, gardening, selling, monitoring, guarding, imprisoning, personal service, guiding vehicles, carrying packages. Food production and serving, for example, now employs significantly more people (9.1 percent) than do production jobs (6.6 percent). One in ten workers is employed in sales. The information technology revolution to date has left these jobs largely untransformed. Workers in these types of jobs in Europe in 1300, if transplanted to modern America, would need little retraining.” (Clark, 2016, p.68). Hence, technological change does not necessarily have to be the *primum movens* of current economic trends.

Arguments about the end of the period of great innovations and the increasing burden of headwinds on advanced economies are played down by techno-optimists scholars. They point out that if “... some inventions are more important than others” (Gordon, 2016, p.72), as Gordon claims, nothing prevents new technological revolutions to arrive in the future and ‘rejuvenating’ technological opportunities and unleashing growth by starting a new techno-economic paradigm (Perez, 2010). In fact, the literature on general purpose technologies (Cantner and Vannuccini, 2012) pushes further this argument that the arrival of new pervasive and enabling technologies and productivity dynamics are strictly intertwined, as slowdowns and accelerations in the rate of productivity growth follow the adjustment of the economy to such ‘macro-inventions’ (Mokyr, 1990). Furthermore, also the severity of aging as headwind blowing against growth is questioned. Indeed, Acemoglu and Restrepo (2017) suggest that aging produces no effects on GDP per capita growth due to endogenous responses of technology, where the negative effect on growth of exiting labor force is neutralized by the adoption of robots.

Finally, it is worth mentioning that if the productivity slowdown depends on the transition of advanced economies to services, digitized and immaterial activities, then the problem at stake can be considered a sort of revised version of the classic ‘Baumol disease’ (Baumol, 2012), according to which productivity improvements in service industries cannot be pushed further indefinitely. The structural transformation of advanced economies, in this sense, should naturally lead to a productivity growth slowdown given the relatively decreasing weight of manufacturing in the overall value-added generation.

To sum-up, the detected trend of productivity growth slowdown is found in the literature not to be caused by the Great Recession of the recent years (while the crisis could amplify the slowdown effect by uncovering structural weaknesses in the economies), and most likely not to be due to severe mismeasurements of the welfare gains derived from the digitization of the economy. The productivity slowdown can be a transient and short-term phenomenon, the outcome of advanced economies' restructuring, or a symptom of supply-driven secular stagnation. As already mentioned, the main line of reasoning behind the supply-side view of secular stagnation is that innovations are not all alike. Ironically, while recognizing the heterogeneity among technologies, the studies we cite do not fully take on board the heterogeneity among economic activities that can lead to the observed aggregate trends. In fact, the productivity slowdown may be a generalized trend for the whole economy, or a statistical artifact due to the compensation of trends going in different directions at more disaggregated levels of analysis: stagnation can 'bite' the whole economy, or just some industries, with different magnitudes. For this reason, a structural perspective on the productivity slowdown is necessary to dissect the industry-level sources of productivity growth dynamics.

Put differently, our idea is to investigate, in the field of productivity and innovation, what the classical [Harberger \(1998\)](#) study about mushroom- and yeast-like processes investigated for output growth dynamics. Indeed, our task is to understand if the 'data generating process' behind the productivity slowdown has a mushroom (localized) nature — that is, is generated by few industries — or rather a yeast (generalized) one, where all industries contribute uniformly to the slowdown, and if a common pattern exists across countries. [Napoletano et al. \(2006\)](#) already pointed out using a theoretical model how aggregate output growth is a compositional construct deriving from the combination of sectoral output growths, and how this combination depends on the magnitudes of cross-industry demand elasticities. This renders problematic the empirical identification of what they call 'pure general purpose technology processes' (where the aggregate growth is the result of uniform shifts in growth at the industry level) and 'pure idiosyncratic processes' (where aggregate growth is derived from industry-specific shocks whose reverberation intensities are function of cross-industry elasticities).

In what follows, we take up on the issues raised above by looking at the compositional nature of productivity slowdown.

3 The Compositional Nature of Productivity Slowdown

3.1 Theory

To rationalize our argument, we theoretically connect our expected skewed distribution of industry-level contributions to aggregate productivity dynamics to retardation theory ([Metcalf, 2003](#)). Retardation has been found to be a stylized empirical fact in the evolution of industries; with retardation we mean "the systematic tendency for rates of growth of specific entities or their ensemble to decline with the passage of time" determining "secular or long time movements in the volume of economic activity" ([Metcalf, 2003](#), p.412). In a nutshell, retardation theory suggests that the composition of an aggregate growth rate matters, as the rates of growth of its parts are heterogeneous and vary in time. In our case, the aggregate growth rate

is the one of labor productivity, that we decompose in that of industry groups. Interestingly, retardation theory is conceptually connected to population dynamics, where the growth rate of a given characteristic in a population depends on the structure of the population itself in terms of individual heterogeneity with respect to this characteristic. Usually, such population dynamics are modeled using the replicator dynamics model (Metcalf, 1994) to approximate the working of market selection. Indeed, unlocking the dynamics of an aggregate indicator like productivity is an exercise in understanding economic evolution. Following (Holm, 2014, p.1011), “evolution is the change in the mean characteristic of a population”; in our case, productivity is the characteristic taken into consideration, and its (weighted) mean the evolving indicator of interest.

The economic validity of the replicator dynamics is usually tested by applying indirect methods, such as decomposition techniques (Cantner and Krüger, 2008). Non-parametric decomposition techniques are commonly used in studies of productivity dynamics at the micro (firm) level (see Melitz and Polanec (2015); Cantner et al. (2016) for a review). Usually, either the productivity level is decomposed Olley and Pakes (1992), or the productivity change Foster et al. (2001); Metcalfe and Ramlogan (2006). The latter method, also labeled dynamic decompositions (as opposed to static decompositions of productivity levels) is the one we use in this study. Our novel contribution stands on testing the replicator model through decomposition at the level of analysis of industries.

The theoretical rationale for the decomposition runs as follows. The aggregate growth rate of any relevant economic variable can be expressed as a composite indicator weighting the growth rate of the variable for each component of the aggregate and their respective proportion (share) in the aggregate; this can be expressed as $\sum s_i g_i$, where for each component g_i of the aggregate the growth rate g is weighted by its proportion s_i . Given that, the dynamics (the change over time) of the aggregate variable can be decomposed to highlight different elements contributing to the change; by taking the time derivative of g we obtain

$$\frac{\partial g}{\partial t} = \sum \frac{\partial s_i}{\partial t} g_i + \sum s_i \frac{\partial g_i}{\partial t} \quad (1)$$

In this generic version of the decomposition, we identify two components. The first term on the RHS of the equation captures how aggregate the growth rate changes due to the changing proportion of the elements in the aggregate, that is a how much structural reallocation affect aggregate dynamics. The second term captures how the change in the growth rate of a component contributes to changes growth of the aggregate. While there may be several ways to decompose and aggregate a variable of interest (Metcalf and Ramlogan, 2006), we consider this distinction between a reallocation force and an idiosyncratic force a first illustrative way to identify the structural properties of a given process.

With the theoretical decomposition in mind, we now outline our empirical decomposition. Following Cantner and Krüger (2008), we use a decomposition formula that identifies three components, the so-called within, between, and covariance (or cross-level) components (or effects). The intuition behind the different effects is the following: at the firm level, the within effect is interpreted as learning/innovation (change in productivity between periods ceteris paribus the firm’s market share, corresponding to the second term in 1), the between effect is interpreted

as a measure of reallocation and market selection (the change in firms' market share *ceteris paribus* the productivity of the previous period, compared to a benchmark, corresponding to the first term in 1), and the covariance (the co-movement between periods of firms' productivity indicator and market share) as a proxy for the regime of returns (increasing, decreasing, constant returns to scale) in a particular market. In our case, having industries instead of firms as units of analysis, the within component can be interpreted as the specific industry contribution to productivity change; the between component indicates how reallocation of economic activity (e.g. workers) between industries — that is structural change — affect aggregate dynamics and should not be interpreted as a degree of competition between industries (in this sense, it would rely on a ill-posed conceptualization of competition). Firm-level productivity decompositions (Cantner and Krüger, 2008) usually include additional components accounting for entry and exit dynamics. As the time-span of our study is not enough to observe full obsolescence of industries nor fine-grained enough to observe the entry of completely new economic activities, we rule out these components. Holm (2014) extends the framework of decomposition techniques to account for multi-level selection, that is, a separation amongst reallocation due to firm-level dynamics and to industry-level dynamics. Focusing on industry-level data, our analysis does not allow to follow the same path; however, it is worth stressing the importance of accounting for different levels of economic activity.

Studies of productivity slowdown already engage in decompositions; however, they usually decompose labor productivity change into the contribution of Human Capital (education), capital deepening, and TFP (Gordon, 2016, p.73). The result of this kind of decomposition is usually to highlight how the slowdown in productivity growth is depending almost uniquely on the decrease of TFP. Capital deepening rate is decreasing in the period 2011–2014 as effect of capital devaluation driven by the economic crisis; however, as pointed out by Fernald (2015), it is TFP growth that slows down starting from 2004. This evidence allowed scholars to make inference on the technological nature of productivity slowdown — as TFP remains, besides 'a measure of our ignorance' (Abramovitz, 1989) — also a proxy for technological efficiency. Another kind of distinction operated in the literature is the one between ICT producing and ICT using industries (Fernald, 2015), which however does not provide an in-depth view on the possibly heterogeneous contributions to productivity growth across the industry structure. With our decomposition, we extend these kinds of analyses by looking at the contribution to productivity change due to industries' improvements (as a proxy to measure the magnitude and direction of technological opportunities) and to structural change.

3.2 Data

We conduct our analysis using data for 10 countries retrieved from two versions of the OECD Structural Analysis (STAN) database (ISIC v.4 SNA08 and ISIC v.4 SNA93). Facing the trade-off between, on the one hand, the number of countries to be included in the sample and, on the other hand, the level of detail of the data and the available time-span, we opted for an analysis of the most recent available data, in order to better shed light on the compositional effects driving productivity dynamics. The use of the most up-to-date data is another original contribution of this paper compared, for example, with the similar analysis conducted by Castaldi (2009).

Table 1: Dataset construction

Country	Industries available	From	To	Time span (years)	Data source
Austria	60	1976	2015	40	ISIC 4 SNA08
Czech Republic	62	1994	2015	22	ISIC 4 SNA08
Denmark	63	1970	2015	46	ISIC 4 SNA08
Finland	63	1975	2015	41	ISIC 4 SNA08
Germany	58	1991	2014	24	ISIC 4 SNA08
Italy	58	1992	2014	23	ISIC 4 SNA08
Netherlands	63	1988	2011	24	ISIC 4 SNA93
Norway	55	1975	2014	40	ISIC 4 SNA08
Sweden	50	1993	2014	22	ISIC 4 SNA08
US	30	1987	2010	24	ISIC 4 SNA93
Mean	54	-	-	29.73	-
Minimum	30	1970	2010	20	-
Maximum	63	1994	2015	46	-

We use production (nominal output) and employment tables to determine labor productivity for a selection of industries at the maximum level of disaggregation available. The classification of industries covers a wide spectrum of economic activities from agriculture/natural resources to air and spacecraft, including both manufacturing and services. In order to provide the most comprehensive analysis in terms of periods covered, the time span and set of industries available vary among the countries considered. Our dataset construction is summarized in Table 1.

We set our analysis at the level of aggregation of industries because, despite a detected heterogeneity of economic actors at every level of disaggregation (Dosi and Nelson, 2010) — industry as a level of analysis captures a fair share of variability in economic and innovative behavior, more than firm size and market structure alone do (Cohen, 2010).

In order to ease data interpretation and visualization, we group the industries according to two different taxonomies. First, we follow a novel OECD taxonomy of economic activities based on industries' R&D intensities (Galindo-Rueda and Verger, 2016); this taxonomy results in six groups of industries, that in turn are separated along a manufacturing/non-manufacturing line in order to take care of possible structural differences in behaviors and nature between manufacturing and non-manufacturing economic activities even when ranking similarly in terms of R&D intensity. Formally, in the following these industry groups are numbered from 1 (high R&D intensity) to 6 (low R&D intensity) and with an additional Figure taking the value of 1 for groups of manufacturing industries and 0 for groups of non-manufacturing industries. Thus, for example, group 1.1 stands for high R&D intensity manufacturing industries.

Second, we grouped industries according to the Pavitt taxonomy (Pavitt, 1984). The identified Pavitt groups are, for manufacturing, supplier dominated (SD), scale intensive (SI), science based (SB), and specialized suppliers (SS). For services we distinguish between supplier dominated services (SDS), scale intensive services (in turn divided into physical network (PN) and informational networks (IN)), and knowledge intensive business services (KIBS). In order to attribute the available industries to a particular Pavitt group, we initially followed the assign-

Table 2: Frequencies of R&D-intensity groups

Country	1.0	1.1	2.0	2.1	3.0	3.1	4.0	4.1	5.0	5.1	6.0	6.1	Industries available
Austria	1	3	1	4	0	4	7	10	26	0	4	0	60
Czech Republic	1	3	1	4	0	4	8	11	26	0	4	0	62
Denmark	1	3	1	4	0	4	7	8	31	0	4	0	63
Finland	1	3	1	4	0	4	7	10	29	0	4	0	63
Germany	1	3	1	4	0	4	7	8	26	0	4	0	58
Italy	1	3	1	4	0	4	7	8	26	0	4	0	58
Norway	1	2	1	3	0	3	8	7	26	0	4	0	55
Sweden	0	2	1	4	0	4	4	8	23	0	4	0	50
Netherlands	1	3	1	4	0	4	7	8	31	0	4	0	63
US	0	2	0	4	1	3	2	8	9	0	1	0	30

ment proposed in [Castaldi \(2009\)](#), which already introduced the identification of services groups alongside manufacturing ones. However, in practice, as the set of ISIC v.4 industries we use has a different structure and contains additional branches with respect to previous ISIC versions, for the generic industries not included in the work of Castaldi we estimated and assigned the groups to which these industries belong using on the employment shares of their sub-industries as weights. This procedure led to slightly different classifications of industries in Pavitt classes among the countries in our dataset. For instance, being SDS ‘D77T82: Administrative and support service activities’ industry has the biggest share of employees in ‘D69T82: Professional, scientific and technical activities; administrative and support service activities’, which allows the former to prevail over the other types and makes the latest also to be considered SDS. This holds true, for example, in Germany, while in Denmark the entry D69T82 is classified as KIBS due to the fact that in this country the entry ‘D69T75: Professional, scientific and technical activities’ belongs to KIBS and dominates over D77T82 in terms of the number of employees involved. Thus, each of 118 industries in the dataset was assigned to a particular Pavitt group either by definition or by calculating the mean of employment shares estimation if the industry is composed by different sub-industries belonging to different Pavitt groups.

In order to provide a clear picture of how industries are distributed across our two types of classification (OECD R&D-intensity and Pavitt), [Tables 2 and 3](#) report the frequency of industries falling under each group. Furthermore, [Tables 16–19](#) provide a summary of our assignment to a R&D-intensity and Pavitt group for each industry potentially available in the dataset (recall, however, that not every entry is used for each country).

3.3 Methodology

For the analysis, five years moving averages of the basic variables are computed in order to calculate labor productivity and its growth rate. Robustness checks are performed using one- and three-years moving averages. After the construction of the variables for the analysis, we perform the decomposition exercise; following [Cantner and Krüger \(2008\)](#); [Cantner et al. \(2016\)](#)

Table 3: Frequencies of Pavitt taxonomy groups

Country	SD	SI	SS	SB	SDS	IN	PN	KIBS	Non-market services	Industries available
Austria	12	10	3	1	8	10	8	4	4	60
Czech Republic	12	12	3	1	8	10	8	4	4	62
Denmark	10	10	3	1	12	10	9	4	4	63
Finland	12	10	3	1	12	8	9	4	4	63
Germany	10	10	3	1	8	10	8	4	4	58
Italy	10	10	3	1	8	10	8	4	4	58
Norway	10	8	3	0	8	10	8	4	4	55
Sweden	10	10	3	0	9	8	5	1	4	50
Netherlands	10	10	3	1	12	10	9	4	4	63
US	7	10	3	0	4	3	2	0	1	30

Note: Pavitt categories. SD: supplier dominated; SI: scale intensive; SB: science based; SS specialized suppliers; SDS: supplier dominated services; PN: physical networks; IN informational networks; KIBS: knowledge intensive business services.

we apply the following decomposition formula to aggregate productivity:

$$\Delta \bar{a}_t = \sum_i s_{i,t-\tau} \Delta a_{i,t} + \sum_i \Delta s_{i,t} (a_{i,t-\tau} - \bar{a}_{t-\tau}) + \sum_i \Delta s_{i,t} \Delta a_{i,t}, \quad (2)$$

Where t is a time index, τ is a generic term capturing the period over which the change in productivity is calculated, and i indexes the different industries. As the decomposition equation holds for all the countries under analysis, we drop the country index in order to ease reading.

Having performed the decomposition, we aggregate the values of the within and between effects using our two grouping rules (R&D intensity and Pavitt) and normalize the data in two ways: (i), we calculate the magnitude of the effects per worker; (ii) we provide a normalization in line with [Cantner and Krüger \(2008\)](#), where the size of the effect becomes a percentage of the of the labor productivity level of the previous period.

3.4 Analysis and Discussion of the Results

First of all, we give a closer look at the general development of labor productivity growth for the ten countries under consideration. Doing that, we verify that the data used shows the very features of productivity slowdown which is related to a long-run tendency of productivity growth rates to decline — if not even to become negative.

Table 4 shows for each country the respective time-span average change in labor productivity growth rates (in percentage points). These numbers corroborate the aggregate evidence of productivity slowdown. However, they are averages taken over all industries, whose contribution to the aggregate dynamics could be heterogeneously distributed, as we claimed in the theory Section.

In fact, the percentage point changes in labor productivity growth are rather different among the different industries (see Table 5). Looking at productivity growth trends disaggregated by (Pavitt) groups in Table 5, there are commonalities for all countries involved with respect, for example, SD and SI, which show always a declining tendency, nearly also so in SS. In the other

Table 4: Average change in labor productivity, percentage points per year

Country	Period of analysis	Annual percentage delta LP
US	1991-2010	-0.039
Germany	1995-2014	-0.046
Sweden	1997-2014	-0.154
Norway	1979-2014	-0.049
Netherlands	1992-2011	-0.042
Italy	1996-2014	-0.191
Finland	1979-2015	-0.095
Denmark	1974-2015	-0.003
Czech	1998-2015	-0.115
Austria	1980-2015	-0.052

Table 5: Average change in labor productivity, percentage points per year. Pavitt taxonomy

Country	Period of analysis	IN	KIBS	NMS	PN	SB	SD	SDS	SI	SS
US	1991-2010	-0.043	-	0.015	-0.079	-	-0.114	-0.066	-0.044	0.051
Germany	1995-2014	-0.180	0.096	-0.041	-0.020	-0.417	-0.130	0.059	-0.059	-0.151
Sweden	1997-2014	0.058	-0.076	-0.099	-0.112	-	-0.277	-0.171	-0.076	-0.331
Norway	1979-2014	0.060	-0.168	-0.016	0.054	-	-0.029	0.015	-0.262	-0.016
Netherlands	1992-2011	0.007	-0.145	-0.023	0.005	-0.265	-0.002	-0.132	-0.013	-0.068
Italy	1996-2014	-0.152	-0.356	-0.038	-0.277	0.046	-0.215	-0.243	-0.070	-0.114
Finland	1979-2015	-0.003	-0.055	-0.028	-0.056	-0.050	-0.141	-0.082	-0.098	-0.187
Denmark	1974-2015	-0.017	0.048	0.130	0.030	-0.070	-0.038	-0.049	-0.082	-0.036
Czech	1998-2015	-0.080	0.007	0.005	-0.017	0.145	-0.126	-0.139	-0.249	-0.446
Austria	1980-2015	-0.0618	-0.0752	-0.0355	-0.0256	-0.1394	-0.0248	-0.1004	-0.0741	0.0004

Note: Pavitt categories. SD: supplier dominated; SI: scale intensive; SB: science based; SS specialized suppliers; SDS: supplier dominated services; PN: physical networks; IN informational networks; KIBS: knowledge intensive business services.

classes we find a mixed picture. It appears that in classes related to manufacturing there is a rather general decline whereas in classes related to services we find both directions.

Next, we report the results of analysis for both R&D–intensity and Pavitt–based industry groupings using the Cantner and Krüger (2008) normalization of the data. Furthermore, we limit our discussion to the within and between effects, as the interpretation of the covariance effect at levels of aggregation above the firm level is not straightforward. Figures 1, 2 3 plot the within and between effects for the Pavitt grouping. Figures 4, 5 and 6 do the same for the R&D–intensity industry classification. Figures 7 to 10 provide cross–correlations of the effects at the country level to gain some insights on the commonalities of the patterns observed.

First, we focus on the Pavitt taxonomy. We find that the within effect is generally positive (apart from cases in Denmark, Italy, and Norway, especially during the crisis 2007/8 and its aftermath) and it ranges in a common interval (0;0.06) for all the countries under consideration (with the exception of Norway³). In order, the stronger magnitudes of the effect are found for SI, IN (excluding Italy and Norway), SDS, SD, SS. As for countries cross–correlations (displayed in Figure 7), these are positive and quite strong for Austria, Czech Republic, Denmark, Finland, Germany, Italy and Netherlands, while the USA, Norway and Sweden stand aside and also they are not correlated among each other.

³The peculiarity of Norwegian productivity dynamics might be related to the country specialization in oil production; as it is beyond the scope do this paper, we do not explore the determinants of Norway within and limit ourselves to track its changes.

Table 6: Industry productivity benchmarking with respect to average level

Country	IN	NMS	PN	SI	SB	SDS	SS	KIBS	SD
Germany	1	-1	-1	1	1	-1	1	+1 to -1	-1
Italy	1	-1	-1	1	1	-1	1	+1 to -1	-1 to +1
Netherlands	1	-1	-1	1	1	-1	1	-1	1
Finland	1	-1	-1	1	1	-1	1	+1 to -1	-1 to +1
Czech	1	-1	-1	1	1	+1 to -1	-1 to +1	1	-1
Denmark	1	-1	-1	1	1	+1 to -1	-1 to +1	1	-1 to +1
Sweden	1	-1	-1	1	-	-1	1	-1	1
US	1	-1	-1	1	-	-1	-1 to +1	-	+1 to -1
Norway	1	-1	-1	1	-	+1 to -1	-1 to +1	1	-1 to +1
Austria	1	-1	-1	1	1	+1 to -1	-1 to +1	+1 to -1	-1

Note: Pavitt categories. SD: supplier dominated; SI: scale intensive; SB: science based; SS specialized suppliers; SDS: supplier dominated services; PN: physical networks; IN informational networks; KIBS: knowledge intensive business services. The indicators +1, 1 and -1 show if the Pavitt group's labor productivity is respectively above, equal or below average productivity (aggregate) over all the time period of analysis.

The between effect also ranges across countries in a rather small common interval (-0.06;0.03); it assumes negative values (or close to zero) for SS and fluctuates (Austria, Czech Republic, Denmark, Finland, Germany, Italy) or it is negative (Netherlands, Norway, Sweden, USA) for IN. SI has both the biggest negative and positive contribution in all countries. Finally, the between effect is usually positive for SD. Other Pavitt groups do not show detectable patterns for the between component, and country cross-correlations (see Figure 8) are more scattered. To interpret the between effect, that is given by the changes in sales/employment shares 'weighted' by the deviation of an industries labor productivity from the average labor productivity, the position of an industry or class in this ranking is important. Table 6 indicates for each country and each Pavitt class whether the level of labor productivity is below (-1) or above (+1) the average productivity over the full time span of observation. In most cases, these rankings (with respect to the average) are stable over time; for some classes pattern of development from below to above average (-1 to +1) or the other way round (+1 to -1) can be identified. In most of the Pavitt classes, the position towards the average productivity level in the economy is the same over all countries (IN; NMS; PN, SI, SB) or come to close to that (SDS, SS). A mixed picture is found for KIBS and SD. For the SI class, we usually find negative between effects in all countries. Table 6 tells that SI always has a productivity level above average. This implies for the within effect that SI experiences a decline in sales/employment share, hence loses economic importance. This, of course, contributes negatively to productivity growth dynamics.

Second, we look at the R&D intensity classification. The within effect is generally positive (excluding Denmark, Italy and Norway) and with similar magnitudes. Groups 5.0 and 4.1 have biggest effect (only positive since within is generally positive), excluding Sweden, Norway, Italy where 5.0 is generally negative. For the between effect, again 5.0 and 4.1 groups are the sources of both biggest negative and biggest positive effect (except for Norway). However, different from the Pavitt grouping, country-level effects cross-correlations (Figures 9 and 10) are weak.

From this first decomposition analysis, we summarize the following:

1. productivity slowdown is empirically corroborated, and it displays a compositional nature;

2. within effects prevail in magnitudes over between effects;
3. within effects are usually positive;
4. the negative or small magnitudes of the within effect for SS coupled with positive values for groups of industries that are usually receivers of technological know-how (SD, SDS but also industry groups 4.1 and 5.0) go in the direction suggested in the theoretical part of the study: productivity improvements derive mostly from the ‘plucking of the low-hanging fruits’ of ICT transformations, while the industries that are ‘classic’ sources of deep economic transformations are currently contributing less to productivity growth, suggesting either an exhaustion of technological opportunities or a temporary lag due to re-focusing and implementation of new techniques;
5. the latter trend is technology-driven and not country-specific (even though there are specific cases), as a very similar pattern appears to hold across countries;
6. the between effect is negative in some cases; the principle of market selection we applied at the industry level seems not to hold strictly, as a negative between effect means either that less productive industries gain labor shares or that highly productive industries lose market shares. This is true, for example, for SI industries. While a negative between effect would represent a puzzle in studies of firm-level market shares reallocation, it is an evidence much easier to rationalize in our context of structural change. Indeed, industries with higher productivity levels can, on the one hand, contribute less to productivity growth (an evidence captured by the within effect) and, hence, explain the slowdown due to their decreasing returns in the transformation of technology into productivity improvements. On the other hand, having a productive level higher than the Economy’s average can result from processes of automation and skill-biased technical change that expel labor and produce structural change. Hence, the slowdown of productivity growth may also be affected by a structural dynamics of industrial transformation where labor moves to less productive industries (e.g. services), an evidence in line with our formulation of the slowdown problem as a novel reading of the Baumol disease;
7. the fact that within effects prevail over between effects allow us to claim that the resulting structural changes are not solely demand-driven; in fact, they are more likely to be innovation-driven, otherwise the within effects, capturing industries’ idiosyncratic learning and improvements, would have negligible magnitudes.

As a final step of our analysis of the compositional nature of the productivity slowdown, we check the trend of the within and between effects over time, in order to understand the changing contribution of innovation-related and structural-change-related drivers of productivity dynamics for different industry groups. Once again, we rely on the Cantner and Krüger normalization (percentage values of the components out of previous period levels) and show the results for the Pavitt-based industry grouping.

Figures 11 and 12 display respectively the trends of the within and between effects. To estimate the trend, we plotted the fitted value of a simple time-trend regression, selecting

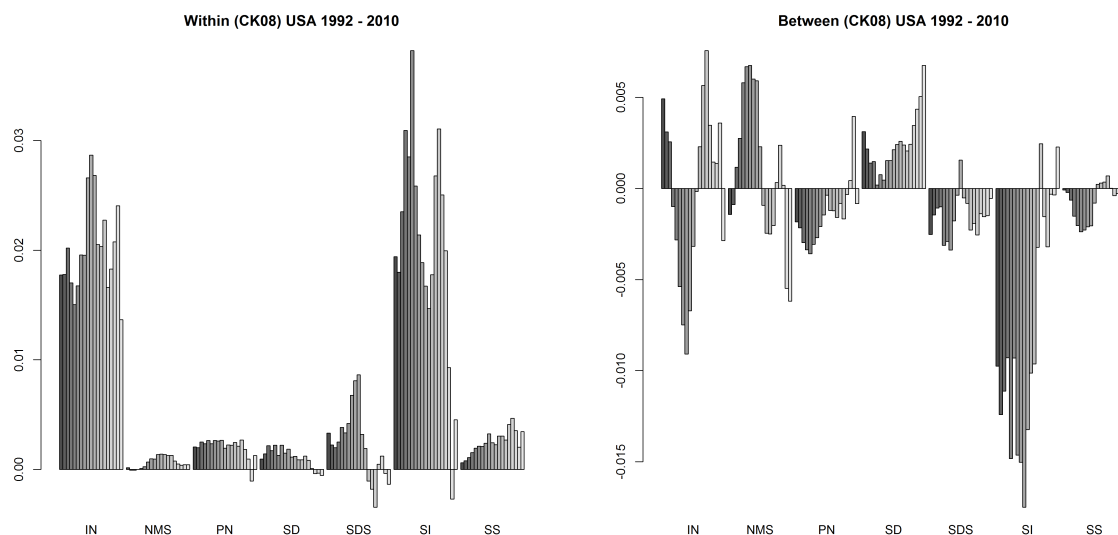


Figure 1: Between and Within effects, USA, 5-years moving average

Note: Labels on the x-axis represent Pavitt's industry types.

between a linear or a quadratic regression model according to the highest value of the goodness-of-fit. Boxes colored in blue indicate linear and non-linear increasing trends, while the opposite holds for red lines.

In general, even though the within effect is generally positive in terms of the contribution to productivity growth, its trend are mostly negative or inverted-U shaped. Positive trends are concentrated in manufacturing (SI, SS) but most of them follow an inverted-U non-linear trend that could turn negative in the near future. The trend for the SB industries is overall positive, but it applies to a small magnitude of the effect. From the trend analysis of the within effect, we obtain another piece of evidence for the idea that decreasing returns to innovation-based improvements are at currently work, a fact we link to the possibility of an ongoing exhaustion of technological opportunities (or time-lags before the emergence of a new general purpose technology-driven economic dynamism).

The evidence for the between effect is more scattered and display a more equal distribution of positive and negative trends. Roughly, the between effect has positive trends in manufacturing for some countries (like Austria, Denmark, US), and positive trends in services for others (like Italy, Netherlands, Norway). In the first case, industries groups characterized by higher-than-average productivity levels gain from structural change; in the second case, our informed guess about the Baumol disease-style dynamics is showing up, with services (usually displaying lower-than-average productivity levels) gaining labor shares in the economy. We reiterate here a consideration about the sign of the between effect: when analyzing structural change dynamics, the between component should be expected to be negative, as labor-saving technological change in industries that are source of innovation pushes workers to other sectors, less productive in levels. Industries with high productivity lose labor shares (hence, have a negative between component) as structural change and reallocation is function of (relative) productivity levels, while their within component is positive but displays a negative trend, as it is function of the change in productivity, which is in turn affected by technological dynamics.

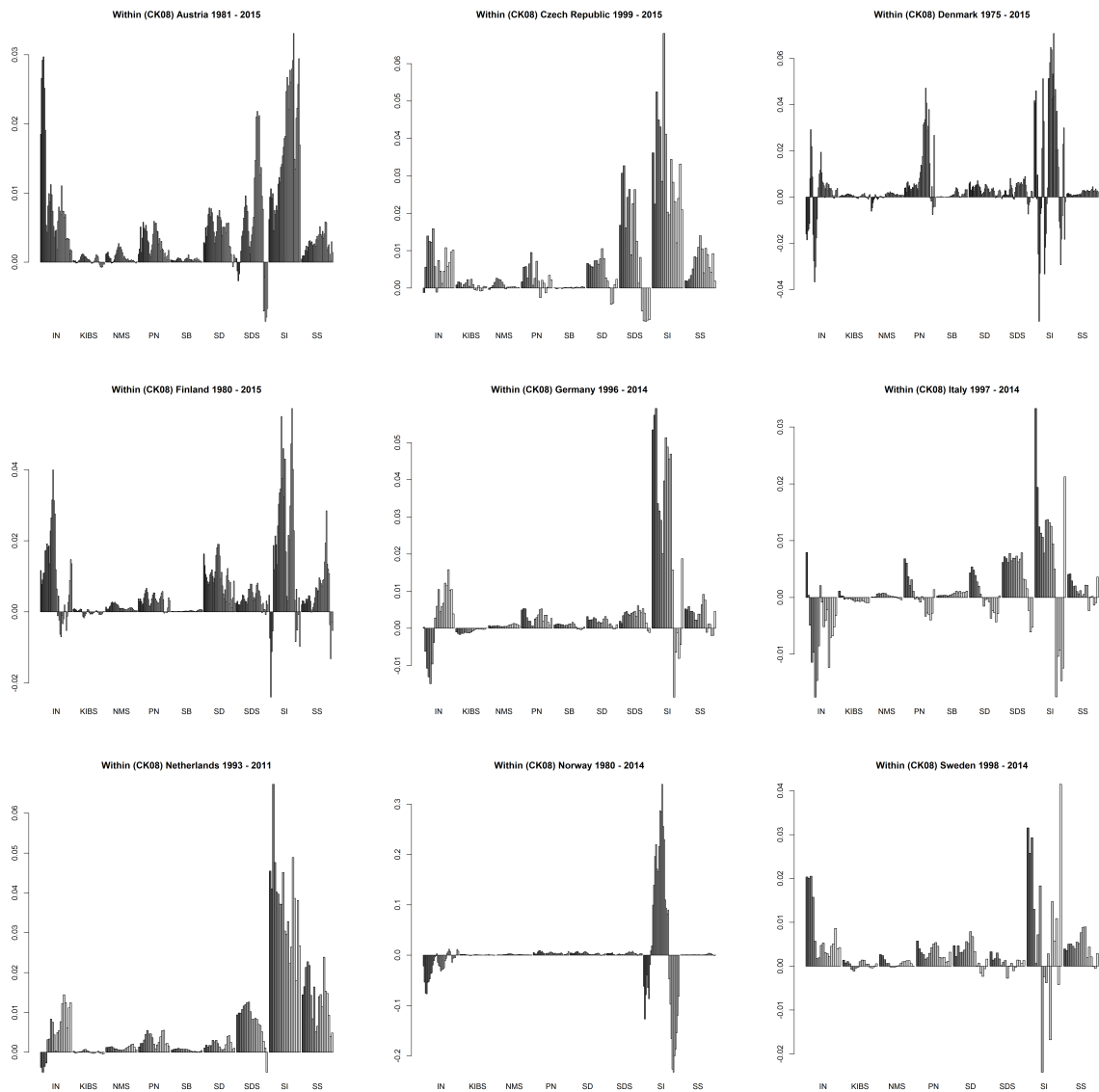


Figure 2: Within effect for 9 OECD countries, 5–years moving averages, Pavitt groups
Note: Labels on the x-axis represent Pavitt’s industry types.

To summarize the results so far, the aggregate productivity slowdown is a compositional *collage* of innovation–driven and structural change–driven weights varying across industries and over time. We posit that all this results from structural technological mechanisms related to the shifting between techno–economic paradigms. If this holds true, the productivity slowdown might be coupled with a parallel dynamics in the realm of innovative activities that should be detectable. Hence, next Section takes a look at the innovation slowdown.

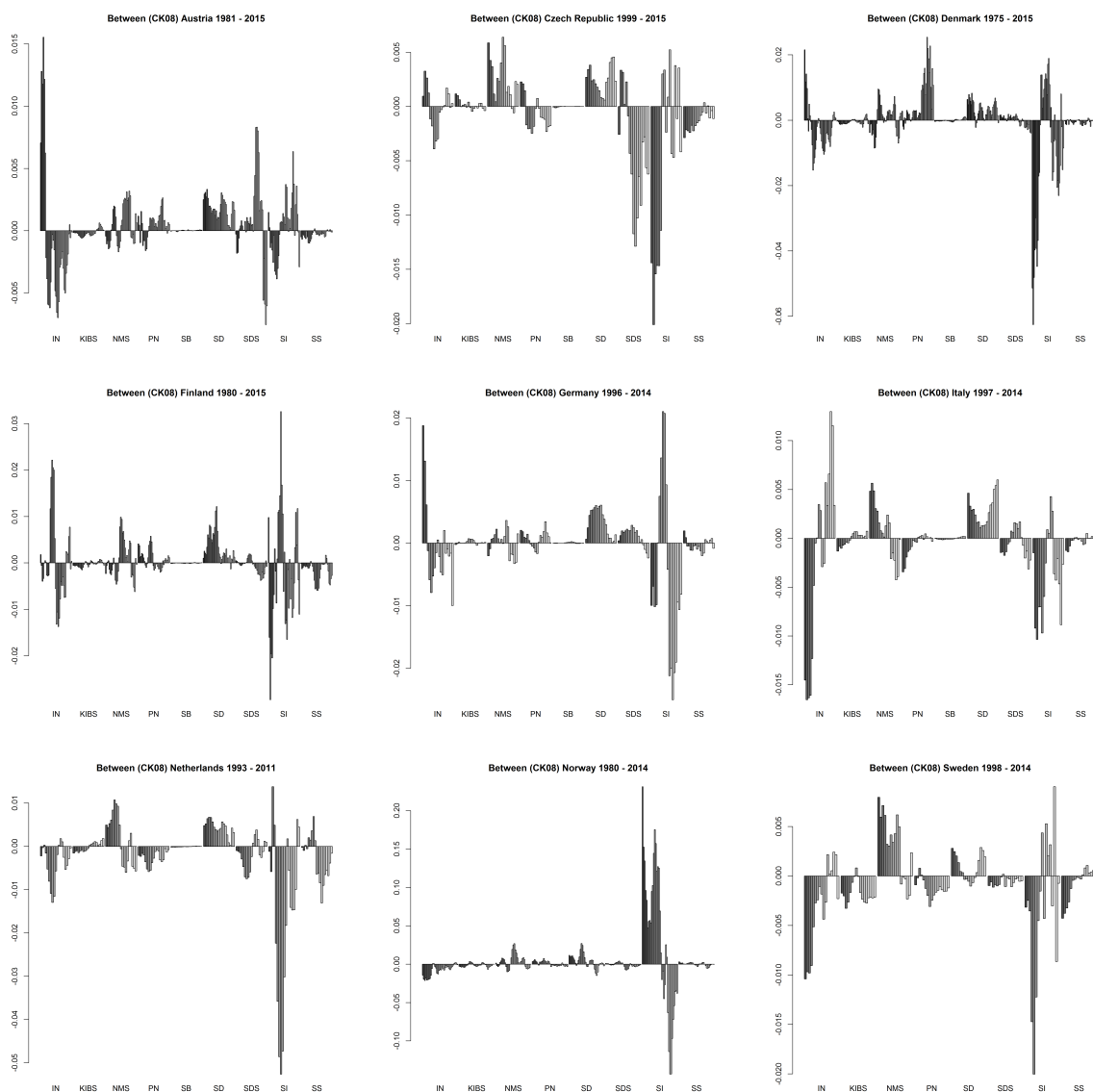


Figure 3: Between effect for 9 OECD countries, 5–years moving averages, Pavitt groups
Note: Labels on the x-axis represent Pavitt’s industry types.

4 The Detection of Innovation Slowdown and Its Impact on Productivity Dynamics

4.1 Theory

In this Section, we focus on what we label the innovation slowdown. With innovation slowdown we mean the occurrence of a trend of declining intensity in innovative activities; in what follows, we trace such trend at different level of analysis, look at its compositional nature as we did for the productivity slowdown and later on we relate it to the productivity dynamics discussed in previous sections.

A reduction in the rate of innovative activities can be driven by a large set of factors. First, the evidence of innovation slowdown can be the result of mismeasurement, if the choice of innovation measures used to assess the slowdown is inappropriate or biased. In our empirical

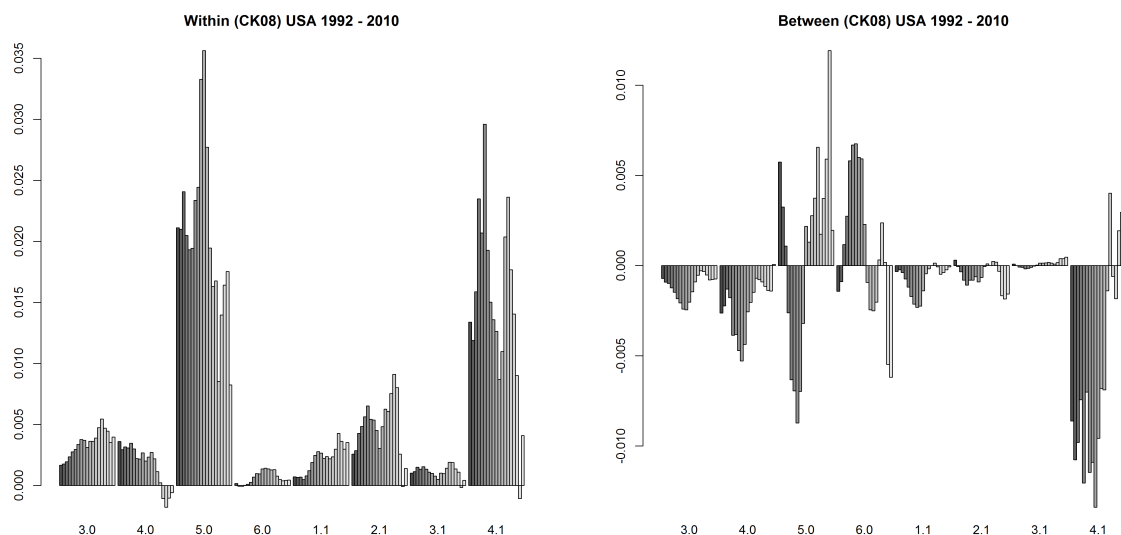


Figure 4: Between and Within effects, USA, 5–years moving average, R&D–intensity groups.

Note: Values on the x–axis code the R&D classification of industries, ranging from 1 (highest intensity) to 6 (lowest intensity). Decimal values indicate if the group is belonging to manufacturing (.1) or non–manufacturing (.0). For example, 1.0 indicates the group pooling highest R&D intensity non–manufacturing industries.

analysis, we build on a measure — the ‘idea TFP’ or, alternatively, ‘research productivity’ indicator — used by Bloom et al. (2017). In order to increase the robustness of such measure, we develop alternatives formulations of the same indicator. However, other pieces of evidence on the trends of innovative activities that are built around alternative indicators, such as the declining rate of innovator shares (for Germany, see Cantner (2016)) or pn measures of decreasing firm dynamism (Decker et al., 2014) produce similar results.

Second, starting with Arrow (1962) and following the classic literature on patent races (Reinganum, 1989), different market structure could be more or less conducive of innovative activities, where under the term ‘market structure’ we summarize here both the static nature of the market in terms of concentration and the dynamic conditions of competition for the market (e.g. appropriability, pre–emption). The debate on the so–called Schumpeter hypotheses (Cohen, 2010) continues until today (see Aghion et al. (2005)) and started to look at the trade determinants of R&D expenditures; for example, Dorn et al. (2016) corroborate the idea that R&D is complementary to manufacturing by showing a declining trend in research expenditures connected with changing patterns of international trade and specialization. Furthermore, very recently and at the very microeconomic level, the rise of markups has been considered a potential driver of macroeconomic consequences like the fall of labor share or the slowdown in output growth (De Loecker and Eeckhout, 2017) and, in the field of micro analysis of productivity, the surge of superstar firms, by increasing the gap in labor productivity (and multi–factor productivity) between the global frontier and the laggards may result in decreasing intensity in innovative activities (Andrews et al., 2016).

Third, innovation can slowdown because economic actors redirect resources from exploitation to exploration, in an effort related to the discovery of new innovation ‘directions’ (Cantner, 2016) that require experimentation, learning, policy support and that, most important, are deeply

rooted in uncertainty with respect to the possible outcomes.

Finally, a fourth possibility is that, following Gordon’s hypothesis already discussed in Section 2, a decreasing importance of capital investments in TFP growth results in diminishing rates of innovation. In the latter case, it is not the rate of innovative activity (or knowledge creation) itself that slows down; it is, instead, the ability of economic actors to effectively exploit current ideas and technological opportunities that slows down. If this is a permanent phenomenon or a transient one — where innovation slowdown is experienced in the time lag occurring while the needed adjustments (through learning and understanding) take place — is once again a question that divides techno-optimists and techno-pessimists.

In what follows, we assess the structural dynamics generated by these potential ‘data generating processes’ in order to describe the nature and composition of the innovation slowdown.

4.2 Methodology

We claim that the labor productivity growth slowdown discussed earlier on in the paper might have roots in learning lags or exhaustion of technological opportunities; in turn, these may result from an increasing difficulty in finding new ideas. In other words, to create new knowledge and keep the current pace of technological development, it is necessary to exploit an increasing amount of resources — decreasing returns ‘bite’ more and more in the production of new know-how. In order to have an idea of the magnitude of this phenomenon, we adopted a measure suggested by Bloom et al. (2017) labeled idea TFP. The evidence in Bloom et al. (2017) suggests that idea TFP captures the slowing down of research productivity occurred due to a faster growth of employed researchers (‘idea input’) compared with TFP growth rate (‘idea output’). Despite some shortcomings of this statistic and, in general, of the explanatory power of TFP (the measure of our ignorance, to cite Abramovitz (1989)) to capture technological dynamics, we consider idea TFP a useful proxy to capture the innovation slowdown.

To provide a more robust analysis, we calculate other close measures that retain the idea output-to-input ratio concept, along with a precise replication of the idea TFP indicator. A summary of the measures we use can be found in Table 7. Indeed, TFP, being a measure of the efficiency of transformation of input into output, reflects either the efficiency of usage or the quality of the embodied knowledge expressed in applied technology or/and processes. Thus, there are other possible proxies for both idea input and output such as respectively, R&D expenditures and labor productivity (hereinafter LP) growth.

The slowdown in knowledge creation can have as well a compositional nature as we found in Section 2 for labor productivity trends. Macro trends at the country level may result either from similar patterns among industries (yeast-like process) or heterogeneous dynamics of industries (mushroom-like process). The more or less evenly-distributed nature of the industries’ contribution to aggregate dynamics of a variable of interest (being it productivity of idea productivity) depends on different factors; for example, the accumulated knowledge — the history dependent path of accumulation or the potential for a new GPT emergence (Cantner and Vannuccini, 2012) in a particular industry, the sources, direction and structure of knowledge flows among sectors (Pavitt, 1984), the cross-industry demand elasticities, and so on. In general, such interdependent and connected nature of industrial structures which results in aggregated

macro pattern is certainly important to account for, as for instance the pervasiveness of GPTs induces multidimensional and inter-temporal structural changes leading to non-linearities in innovation and economic inducements and reactions. Furthermore, once a technology showing the properties of a GPT appears, its influence spreads through the economy’s structure which differs across countries and, thus, producing different speed, directions and overall patterns of structural changes.

Given the discussion above, we conduct the analysis at both the macro (country) and meso (industry) levels of analysis. If the causal relation between knowledge and technological slowdown exists, given the obtained results in Section 3.4, it is reasonable to assume similar patterns of idea TFP and LP.

Table 7: Indicators of innovation slowdown

Macro level	
Measure	Description
Indicator 1	Idea TFP R&D = TFP growth rate (annual)/R&D expenditures
Indicator 2	Idea TFP Researcher = TFP growth rate (annual)/Number of researchers
Indicator 3	Idea LP R&D = Labor productivity growth rate (annual)/R&D expenditures
Indicator 4	Idea LP Researchers = Labor productivity growth rate (annual)/Number of researchers
Meso level	
Measure	Description
Indicator 1	Idea LP R&D = Labor productivity growth rate/R&D expenditures. 5 years moving average

4.3 Data

As mentioned above, we perform the analysis at two levels of (dis)aggregation: macro and meso. For the macro-level measures based on LP growth rate (Indicators 3 and 4, see Table 7) we collected annual data on the same variables used for the productivity slowdown analysis, namely production (nominal output) and employment, retrieved from the OECD Structural Analysis (STAN) database (ISIC v.4 SNA08 and ISIC v.4 SNA93). To construct the indicators, we collected additional data on R&D expenditures (OECD STAN ISIC v.4), number of researchers (OECD Research and Development Statistics database), and multifactor productivity (OECD Productivity Database). Using several ways to measure the innovation slowdown helps to increase the validity and robustness of results against potential mismeasurement problems. Table 8 summarizes the sets of countries and time spans used to compute the different indicators.

For what concerns the meso-level indicator, that we employ to assess the compositional nature of the innovation slowdown, we use our previous calculations of LP growth rates (5-years moving averages) to exclude industry-specific shocks potentially distorting the innovation slowdown dynamics. The number of countries for which LP growth rates were available decreases from 10 to 7 because of data gaps and due to different industries classifications of the data on production and employment in OECD STAN ISIC v.4 SNA08 and ISIC v.4 SNA93 (used for idea output) and R&D expenditures in OECD STAN ISIC v.4 (used for idea input) which makes

Table 8: Set of countries under analysis

Countries	Indicator 1	Indicator 2	Indicator 3	Indicator 4
Australia	1	1	0	0
Austria	1	0	1	0
Belgium	1	1	1	1
Canada	1	1	0	0
Czech Republic	0	0	1	0
Denmark	0	1	0	1
Finland	1	0	1	0
France	0	1	0	1
Germany	1	1	1	1
Italy	1	1	1	1
Japan	1	1	1	1
Korea	1	1	0	0
Mexico	0	0	1	0
Netherlands	0	1	0	1
Norway	0	0	1	0
Portugal	1	1	1	1
Slovakia	0	0	1	0
Slovenia	0	0	1	0
Spain	1	1	0	0
United Kingdom	0	1	0	0
United States	1	1	1	1
Number of countries	12	14	13	9
From	1997	1987	1997	1987
To	2013	2013	2014	2014

data matching rather cumbersome at this fine-grained level of analysis. A precise description of the data is reported in Table 14 and 15.

Table 9: Industries dataset description

Country	Number of industries	From	To
Austria	23	2002	2013
Czech Republic	23	2000	2014
Finland	17	1999	2014
Germany	22	1999	2014
Italy	23	1997	2014
Norway	17	1991	2014
USA	24	2002	2011

We grouped industries according to the Pavitt taxonomy in order to ease visualization and, most important, to capture a gist of industries' supplier-user structure. By applying this classification we want to understand whether there is a localization of the innovation slowdown and how the structure of knowledge flows shapes the aggregated pattern. As there is a prevalence of manufacturing sector over services in the sample (see Table 10), our conclusions from the analysis can be reliably attributed to the manufacturing sector only, while a thorough analysis of services will require additional data.

Table 10: Pavitt taxonomy groups

Pavitt	Austria	Czech Republic	Finland	Germany	Italy	Norway	USA
SI	10	8	7	10	10	6	10
SD	7	7	4	5	5	5	4
SB	1	1	0	1	1	0	0
SS	3	3	3	3	3	3	3
PN	1	1	1	1	1	1	2
KIBS	1	1	1	1	1	1	0
IN	0	1	1	1	1	1	3
SDS	0	1	0	0	1	0	2
Total	23	23	17	22	23	17	24

4.4 Analysis and Discussion of the Results

First of all, it is important to highlight our evidence at the macro level. We detect the innovation slowdown in a overwhelming majority of countries, irrespective of the indicator used. The evidence is summarized in Table 11. This consistent pattern across measures signals that the innovation slowdown exists beyond potential mismeasurement issues.

Table 11: Summary of results on innovation productivity. Macro level

Country	Indicator 1	Indicator 2	Indicator 3	Indicator 4
Australia	↘	↘	-	-
Austria	↘	-	↘	-
Belgium	↘	↘	↘	↘
Canada	↘	↘	-	-
Czech Republic	-	-	↘	-
Denmark	-	↘	-	↘
Finland	↘	-	↘	-
France	-	↘	-	↘
Germany	↘	↘	↘	↘
Italy	↘	↘	↘	↘
Japan	↗	↘	↘	↘
Korea	↘	↘	-	-
Mexico	-	-	↘	-
Netherlands	-	↘	-	↘
Norway	-	-	↘	-
Portugal	↘	↘	↘	↘
Slovakia	-	-	↘	-
Slovenia	-	-	↘	-
Spain	↗	↘	-	-
United Kingdom	-	↘	-	-
United States	↘	↗	↘	↘
Total	12	14	13	9

Note: The direction of the arrows indicates the sign of the trend-line fitting the indicators series, with ↗ ↘ pointing respectively to an increasing or decreasing trend of the indicator. For cells with (-) the respective indicator could not be calculated with the available data.

If we give a closer look at Indicator 2 in Table 11, which is a precise replication of (Bloom et al., 2017) idea TFP, one may see that all countries, except for the USA, are experiencing the slowdown in the idea production with respect to employed research effort. However, the USA shows an upward trend mostly because the available data covers the time span from 1987 to 2007 and the lack of more recent data can explain the ‘exception’. Furthermore, while the generalized pattern shows an increase (flat positive slope), real annual numbers for Indicator 2

after 2003 sharply went down. For a visual inspection see the bottom rightmost chart in the Figure 13 plotting the described calculation results on Indicator 2.

Moving to the more disaggregated level of industry, we obtained less consistent results for services, as it was presumed due to the insufficient representativeness of industries from this sector in the sample. For the manufacturing sector, the tendency of slowing-down research productivity is clearer; however, it is rather non-linear in comparison with the country level results as displayed in Figure 13. Table 12 summarizes the evidence at the industry level.

Table 12: Summary of results on innovation productivity. Meso level

Pavitt	Austria	Czech Republic	Finland	Germany	Italy	Norway	USA
Manufacturing							
SI	↘	↘	→	→ / ↘	↘	→ / ↘	U-inverted
SS	↘	↘	↘	↘	↘	↘	U-inverted
SD	↘	↘	↘	→	↘	↘	↘
SB	↘	↗	-	↘	→	-	-
Services							
PN	-	↘	↘	↗ ↘	↘	↘	→
IN	-	↘	↗	↘	↘	↘	↘
KIBS	↘	U-shaped	→	↘	→	→	-
SDS	-	→	-	-	↘	-	↘

Note: The direction of the arrows indicates the sign of the trend-line fitting the indicators series, with ↗ → ↘ pointing respectively to an increasing, constant or decreasing trend of the indicator. For cells with (-) the respective indicator could not be calculated with the available data.

In sum, the innovation slowdown exists, its detection is robust to an array of different proxies used to capture it, and it emerges both at the macro and at the meso level of analysis. As for the productivity slowdown, also the innovation slowdown is generalized and displays a compositional nature.

A final issue to tackle has to do with the structural relationship between productivity and innovation slowdown. In this sense, our clustering of industries into the Pavitt taxonomy becomes key to identify the possible direction of the relationships and to hypothesize in which cases and to what extent patterns of innovation slowdown may influence patterns of productivity slowdown. For example, a selection of Germany and USA supplier dominated (SD), specialized suppliers (SS) and scale intensive (SI) Pavitt groups in Figures (respectively) 14 and 15 illustrate co-directed movement of manufacturing industries dynamics among these classes.

Theoretically, if the slowdown in knowledge creation initiates in the specialized suppliers group (innovation producers/sellers), then it may be transferred in form of productivity slowdown to application industries (e.g. SD) that are buyers of SS research outcomes. Such effect of innovation slowdown on productivity dynamics might be less strong if it starts in industry groups that receivers, rather than creators, of new knowledge, as the vertical upstream-to-downstream transmission channel of innovation flows is missing. In a nutshell, being a final link in the knowledge flow chain, if one observes a decreasing research productivity in the group of knowledge-receivers industries, e.g. the SI group, this might have negligible impact on labor productivity of this or other groups as technological improvements (and hence knowledge) are mainly exogenously received and used for ‘consumption’ within this SI group.

To elaborate further on these insights, however, we need to explore the relationship between

the productivity and the innovation slowdown. We provide a first correlation analysis in the following Section.

4.5 The Relationship between the Innovation and Productivity Slowdown

In order to assess the relationship between the two structural dynamics we observed in this study, we opt for an exploratory measurement of the intra- and inter-industry correlations among productivity and innovation slowdown. In general, this task can be addressed by adopting a parametric approach in line with classic studies on inter-industry spillovers (Bernstein and Nadiri, 1989) or by capturing interdependencies through using input-output methods such as those used in studies on technology flow matrices (Verspagen and De Loo, 1999).

In this paper, we limit ourselves to uncovering co-movements in trends between productivity and innovation slowdown across groups of industries. We attempt to capture the structure of connections among industries in order to localize potential sources/origins of innovation slowdown and to identify its transmission channels to productivity slowdown. The non-parametric method applied in this section is a table constructed as a product of, on the one hand, correlation matrices between innovation and productivity measures and, on the other hand, OECD input-output tables describing sales and purchases relationships among industries. The rationale behind the construction of this more elaborated representation is that a co-movement of innovation and productivity measures time series can occur just by chance; by accounting for the input-output relations, we exclude spurious correlations, as input-output coefficients register the existence and the strength of actual trade relations between any two industries. In a nutshell, to test the hypothesis of innovation-productivity nexus, we assume that there is a transmission unit which embodies the result of innovation activity of the selling sector and that, through implementation, may influence productivity of buyer sectors. Thus, here we consider upstream-downstream relations among industries as a premise/precondition for the innovation-productivity nexus. In light of this interpretation, the Pavitt taxonomy offers a meaningful structure of industrial relations that might be a starting point for the analysis of innovation-productivity nexus.

The procedure we implement runs as follows: on a first stage for each of 7 countries available we constructed correlation tables, where on the vertical axis there is the innovation measure for n industries and on the horizontal axis productivity. Thus, each cell contains a correlation coefficient between innovation measure of row-industry i and productivity measure of column-industry j . Eventually, we have a non-symmetric ($a_{ij} \neq a_{ji}$) matrix of size $n \times n$ where the empty cells indicate statistically insignificant coefficients. The main diagonal shows intra-industry innovation-productivity nexus while off-diagonal values represent inter-industry relations. Inter-industry correlations have to be considered because, as we pointed out in the previous section, given the assumption that some industries are producers of new knowledge-embodied capital while others are buyers of this capital, the consideration of only intra-industry correlations (diagonal values) would ignore the phenomenon we aim at uncovering, namely the structural nature of the innovation-productivity nexus.

In Table 13 we report a summary of calculated correlation coefficients for Germany; industries are clustered according to Pavitt taxonomy.

Table 13: Summary of significant innovation–productivity correlations, Germany

DEU			Manufacturing				Services			
	Inno	Prod N	SS 3	SI 10	SD 5	SB 1	SDS 0	PN 1	KIBS 1	IN 1
Manuf.	SS	3	100%	70%	60%	100%		33%	100%	0%
	SI	10	67%	56%	28%	70%		30%	60%	0%
	SD	5	53%	34%	48%	60%		20%	40%	20%
	SB	1	100%	50%	20%	100%		0%	100%	0%
Services	SDS	0								
	PN	1	67%	40%	40%	100%		100%	0%	100%
	KIBS	1	100%	40%	20%	100%		0%	100%	0%
	IN	1	0%	30%	0%	0%		0%	0%	100%

Note: Color scheme: 50–100% — green, 30–50% — yellow, < 0 — red, not in the sample — gray

The top left and bottom right quadrants represent intra–sectoral connections between innovation and productivity measures within manufacturing and services respectively. The top right quadrant shows inter–sectoral connections between innovation measure for manufacturing and productivity measure in services while the bottom left quadrant shows the opposite connection. N is a number of industries assigned to the respective Pavitt group. The values in cells indicate the share of statistically significant coefficients calculated for industries which belong to a pair of Pavitt groups. For example, cell a_{12} indicates that between innovation measure for 3 SS industries and productivity measure for 10 SI industries we obtained 70 percent of significant correlations, which means 21 coefficients out of 30. Colors highlight the possible structure of the connections where shares of significant coefficients are high and either positive (green and yellow) or negative (red). For all 7 countries within the manufacturing sector we found that the correlation between innovation and productivity measures is high, significant for a big share of cross–correlations and in all cases positive. The results within services sector and manufacturing–services interconnections are rather mixed across countries.

However, correlations grasp only co–movement, tell nothing about causality, and can also be spurious. The use of input–output data can resolve these problems by indicating the existence of channels for transmission of innovation slowdown to productivity slowdown and, therefore, allows advancing insights regarding causality. Besides, the magnitude of input–output index shows the potential transmission capacity of the channel. Indeed, even if a correlation coefficient is high and positive — indicating co–movement of innovation and productivity measures for a pair of industries —, if the these industries have a weak seller–buyer relationship it means that this channel barely can transmit slowdown from innovation to productivity.

Given that, in a second step we took OECD Leontief Inverse input–output matrices as a measure of inter–industry connections. The Leontief Inverse contains indices showing rise in output of an industry i due to the unit increase in demand of industry j . Therefore, these matrices reflect the structure and importance (the magnitude) of each connection.

Eventually, to display uncovered structures we construct heatmaps (following [Acemoglu et al. \(2016\)](#)) as an insightful visualization tool for the product of correlation and input–output matrices.

The heatmap in Figure 16, displaying the structural properties for Germany, shows strong

intra-industry connection with high values on the main diagonal. This outcome is a result of high input-output coefficient because of high ‘self-demand’ share for each industry. The heatmaps for the remaining 6 countries are displayed in Figure 17 in the Appendix. The main pattern that the majority of countries share regards evidence of structure within the manufacturing sector; this holds true for all countries apart from Finland and Norway. This suggests that innovation and productivity measures are co-moved and the trade structure among industries allows for the transmission of the slowdown effect. The other regularity, taking place in Germany, Italy, USA and Finland, is that PN industries, for example logistics and warehousing, play a role in affecting the productivity of the manufacturing sector. The same holds true for KIBS industries in Austria, Germany, Italy and Norway.

In sum, after we sorted out potentially spurious correlations by multiplying correlation tables with input-output indices, the structure of connections between innovation and productivity measures remains, especially for the manufacturing sector. This does not allow ruling out the hypothesis about innovation-productivity nexus and keeps it under further investigation.

5 Conclusion

In this paper, we contribute to the ongoing discussion on labor productivity growth slowdown in a novel way. We assessed the structural properties of productivity dynamics by (i) looking at a more disaggregated pictures — the industry level —, (ii) by applying a non-parametric decomposition technique usually performed to distinguish between learning and reallocation effects at the firm-level, and iii) by interpreting the skewed and compositional nature of the slowdown in an evolutionary manner. We grouped our industry-level analysis using two different classifications, the Pavitt taxonomy and a taxonomy capturing industries’ R&D intensities, in order to assess the robustness of our findings across different logics of aggregation of economics activities. We performed the analysis on a dataset of ten OECD countries, using the most recent available data.

The findings suggest that (i) the compositional nature of the productivity slowdown is a common trend in the countries under analysis, that (ii) within effects prevail over between effects, suggesting that the driver of productivity dynamics have to be searched in the heterogeneous and skewed contributions of different industry groups to aggregate productivity growth rather than to selection (structural change) effects due to reallocation. The latter, however, when present, tend to go again the principles of selection and the replicator dynamics, with labor shares moving to less productive industry groups. All the evidence points to the possibility that the slowdown is driven by the exploitation of established technological opportunities in knowledge-intensive industries coupled with structural shifts of economic activities towards services, in a ‘Baumol disease-like’ fashion.

For what concerns the innovation slowdown, we find a generalized decreasing trend of research productivity across countries and Pavitt industry groups. While the indicator used and suggested by Bloom et al. (2017) to capture the innovation slowdown can be subject to criticism, we derived four alternative specifications of the measure, and all of these follow a comparable dynamics.

Our analysis, though exploratory, is the first to offer a fresh view on the productivity slowdown and to link the tools and concepts of market selection with meso-economic analysis. As

mentioned in Section 1, we are interested in the structural dynamics lying behind slowdown in productivity and innovative activities rather than in their specific determinants. In this sense, we do not delve into causal explanation but rather offer an ‘informed guess’ about the nature of the phenomena. Some issues might have therefore received not enough attention. For example, we do not discuss how import–export dynamics (that is the international distribution of production) can affect the PS. Nonetheless, issues such as the effects of international trade on productivity growth falls into our explanation of the trends in terms of structural change — as international competition pushes labor to flow across industries with consequent compositional effects on aggregate productivity growth.

In sum, the paper supports an explanation of productivity slowdown that adds to the long–run threat of growth headwinds highlighted by Gordon, namely the closure of the technological opportunities set available in the current techno–economic paradigm. Such explanation relies on the detected trends of innovation slowdown, but it should not be interpreted as the last word on the long–run trends of productivity developments. Decreasing returns of innovation and discovery due to exhausted technological opportunity are only one side of structural transformations; however, for these transformations to be unleashed new directions of innovative change might be worth exploring. Thus, in conclusion, if the productivity slowdown is a symptom of a deeper technological slowdown, concerns from scholars and policy–makers should be directed to how to open–up new opportunities and, therefore, give a future to economic growth.

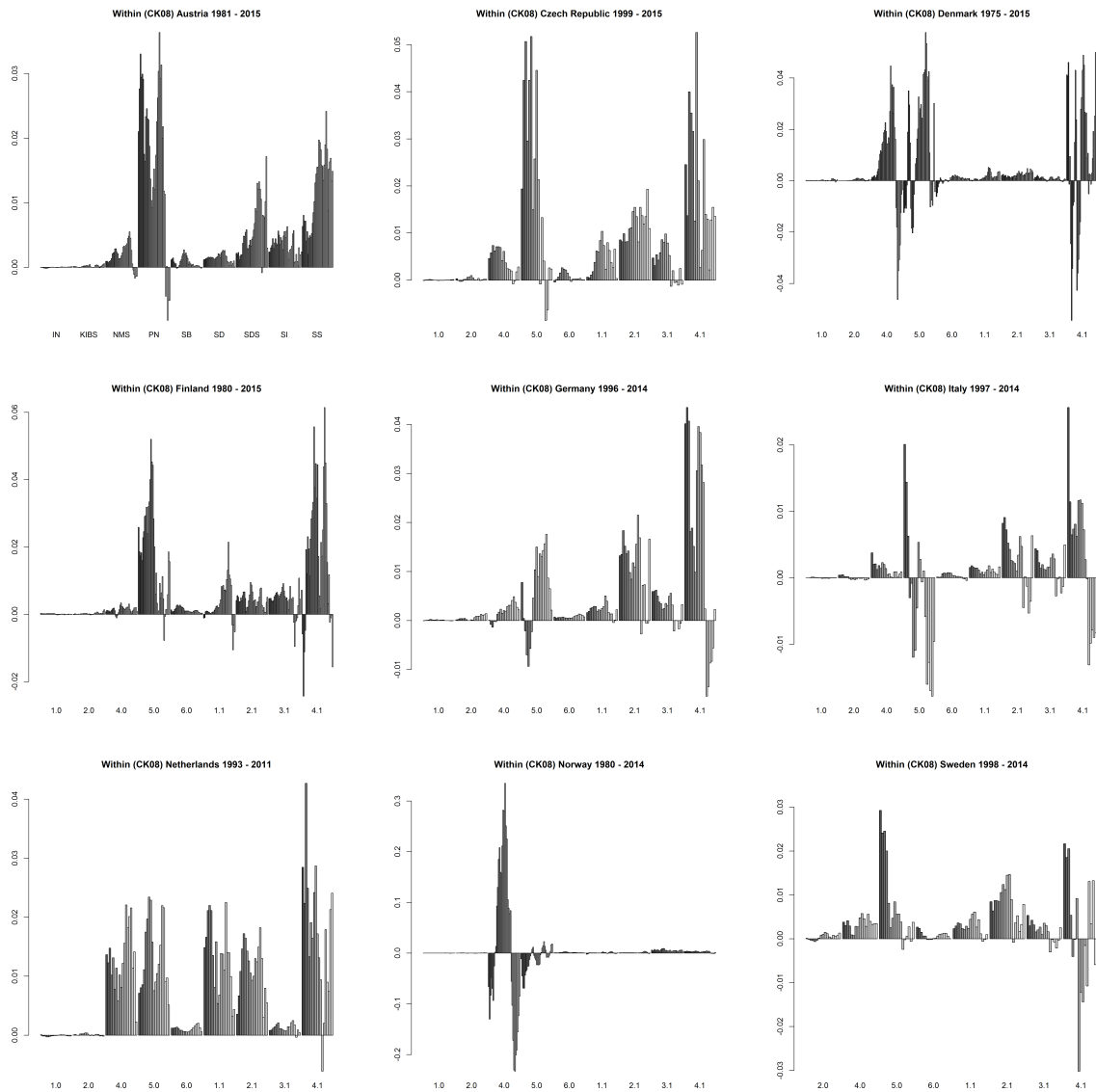


Figure 5: Within effect for 9 OECD countries, 5-years moving averages, R&D-intensity groups
Note: Values on the x-axis code the R&D classification of industries, ranging from 1 (highest intensity) to 6 (lowest intensity). Decimal values indicate if the group is belonging to manufacturing (.1) or non-manufacturing (.0). For example, 1.0 indicates the group pooling highest R&D intensity non-manufacturing industries.

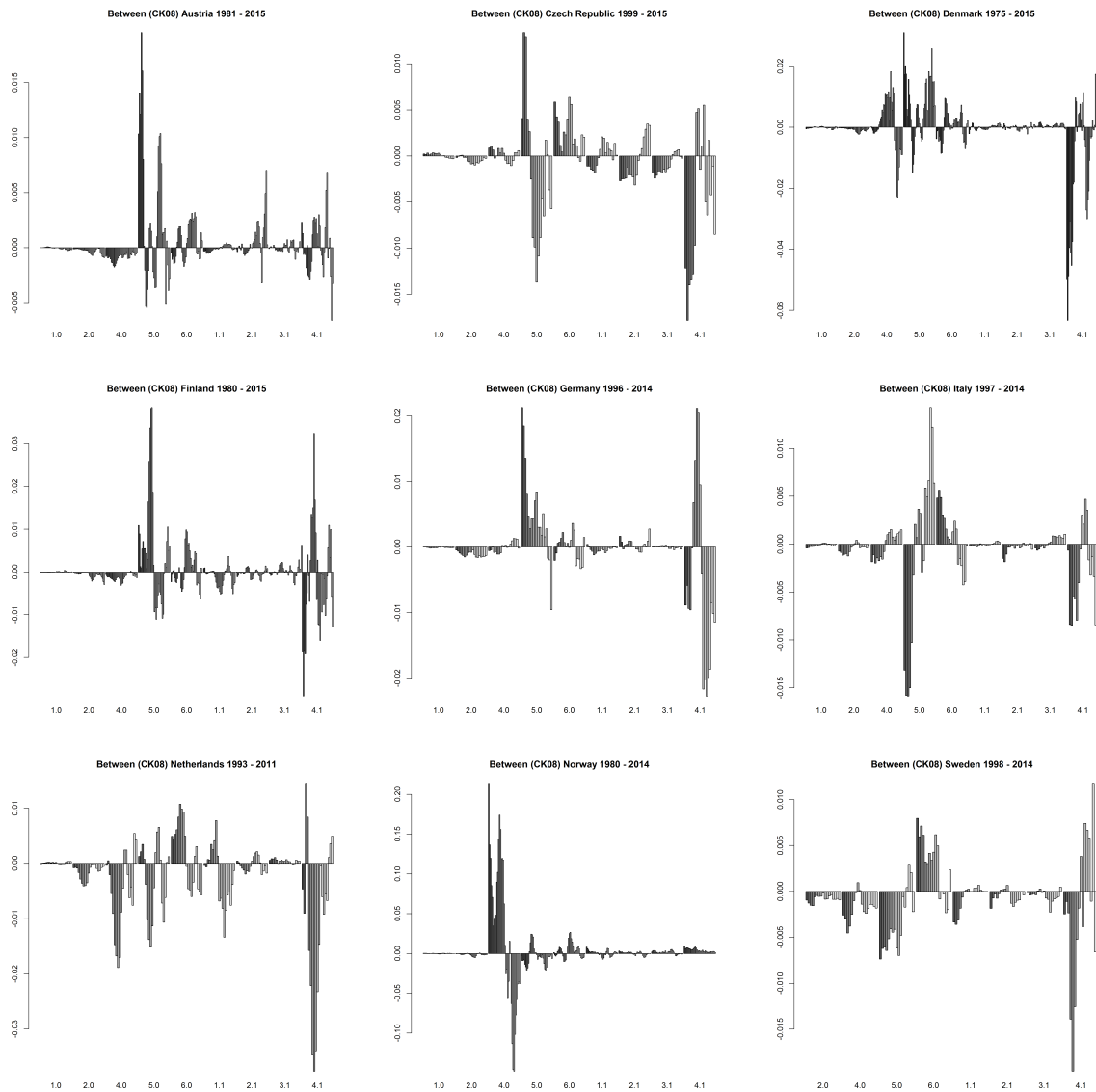


Figure 6: Between effect for 9 OECD countries, 5-years moving averages, R&D-intensity groups
Note: Values on the x-axis code the R&D classification of industries, ranging from 1 (highest intensity) to 6 (lowest intensity). Decimal values indicate if the group is belonging to manufacturing (.1) or non-manufacturing (.0). For example, 1.0 indicates the group pooling highest R&D intensity non-manufacturing industries.

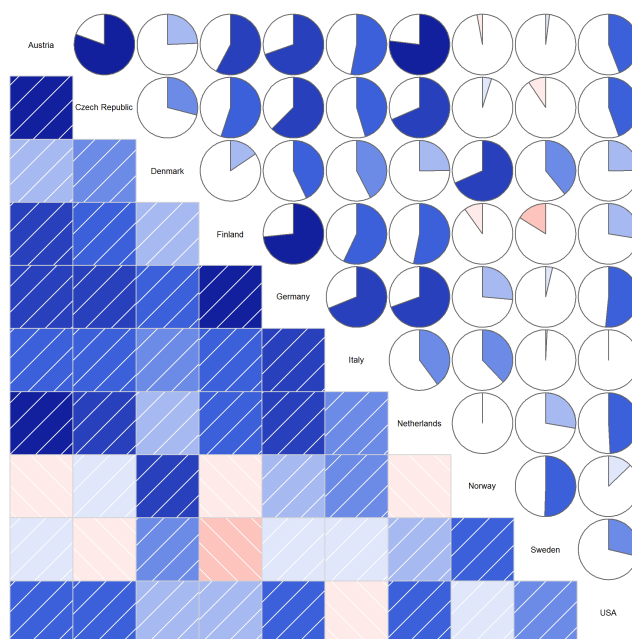


Figure 7: Between effect (Pavitt groups), country-level cross-correlations.

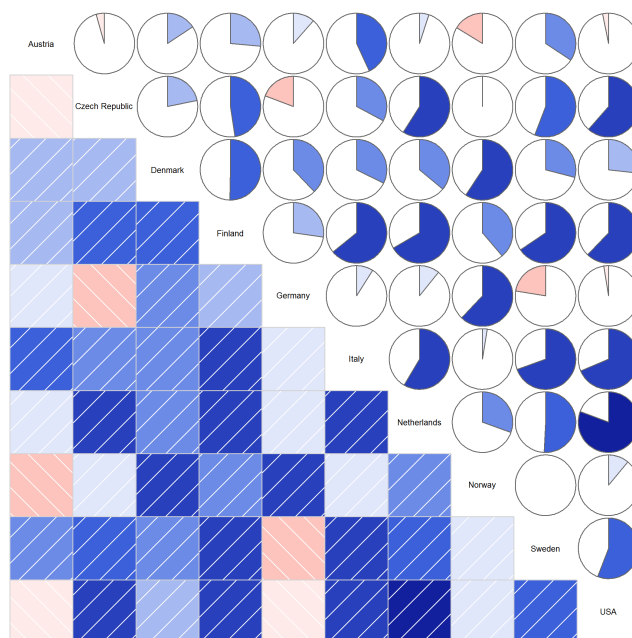


Figure 8: Between effect (Pavitt groups), country-level cross-correlations.

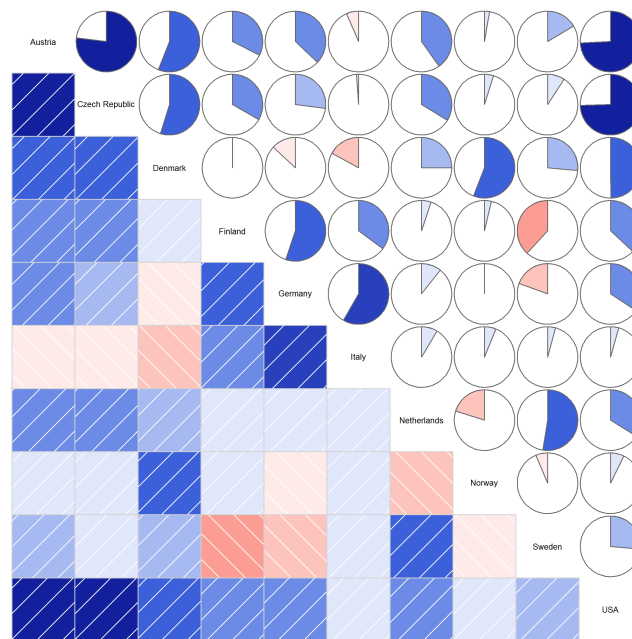


Figure 9: Within effect (R&D-intensity groups), country-level cross-correlations.

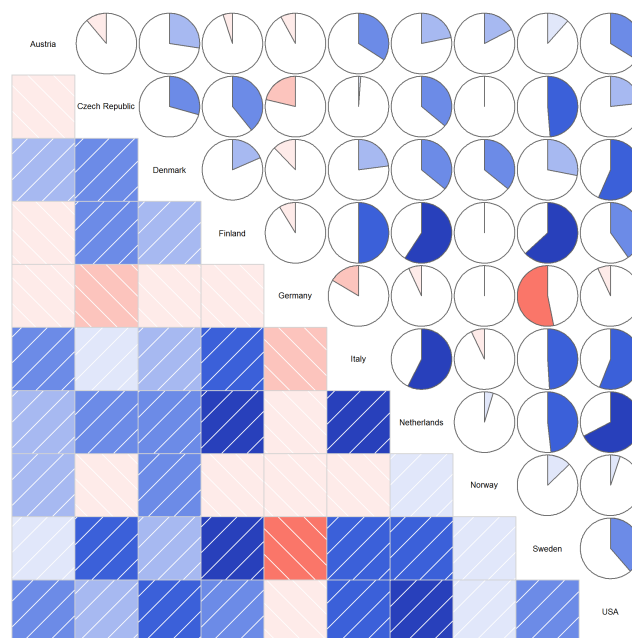


Figure 10: Between effect (R&D-intensity groups), country-level cross-correlations.

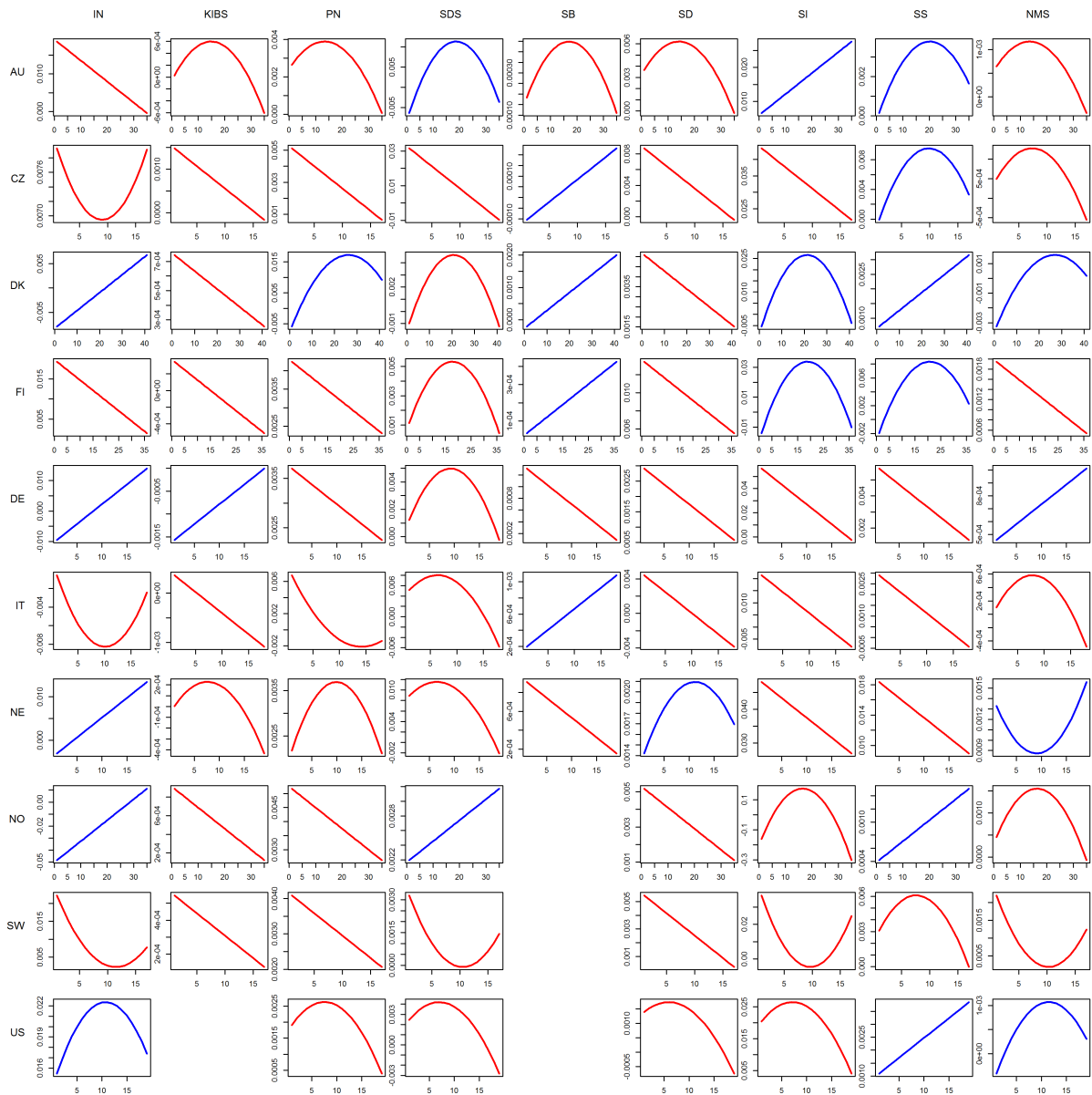


Figure 11: Within effect — trends

Note: The trend of the component is obtained from the fitted values of a linear or quadratic regression using the time-series of within effect for each country-group pair. The choice of the regression model is based on the higher goodness-of-fit (F-stat); line colors indicate an increasing (blue) or decreasing (red) trend.

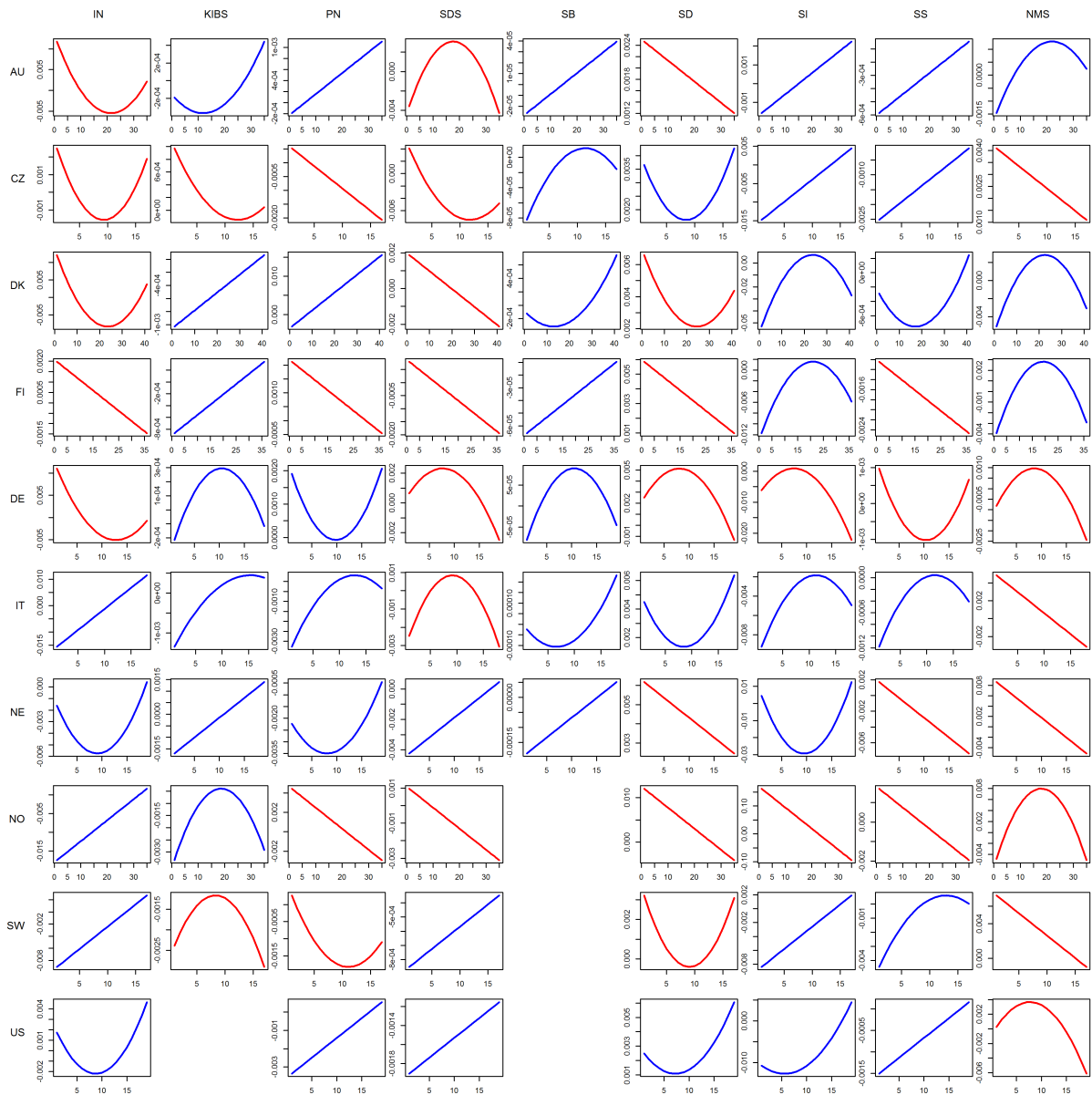


Figure 12: Between effect — trends

Note: The trend of the component is obtained from the fitted values of a linear or quadratic regression using the time-series of between effect for each country-group pair. The choice of the regression model is based on the higher goodness-of-fit (F-stat); line colors indicate an increasing (blue) or decreasing (red) trend.

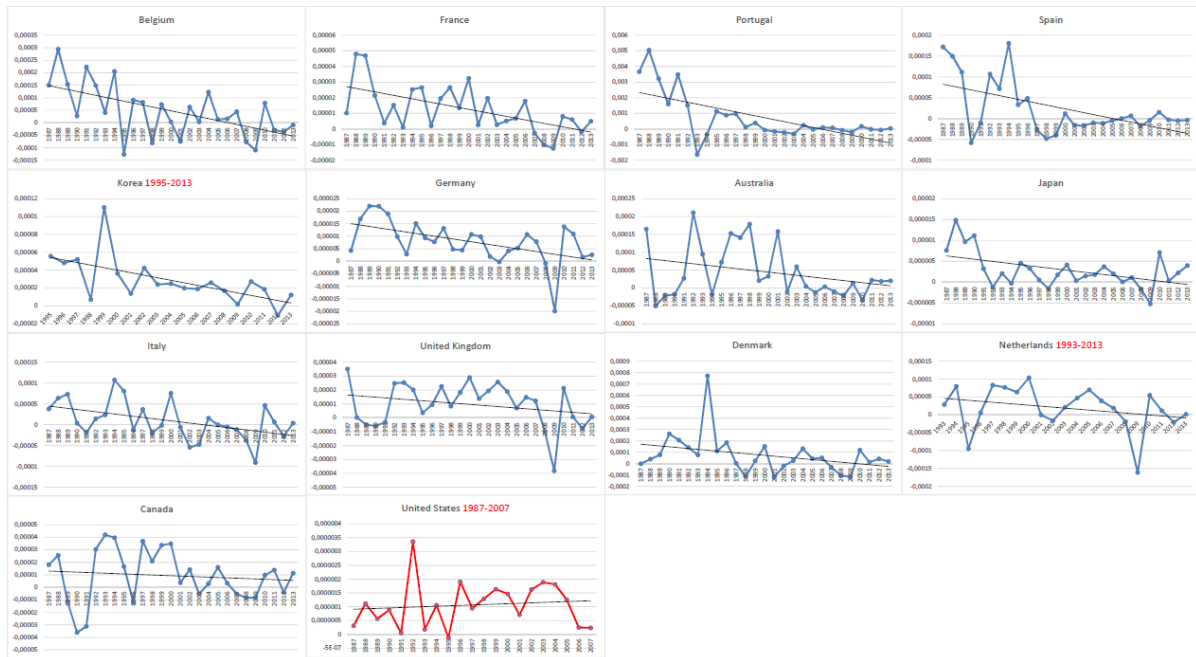


Figure 13: Indicator 2 dynamics — whole sample, macro

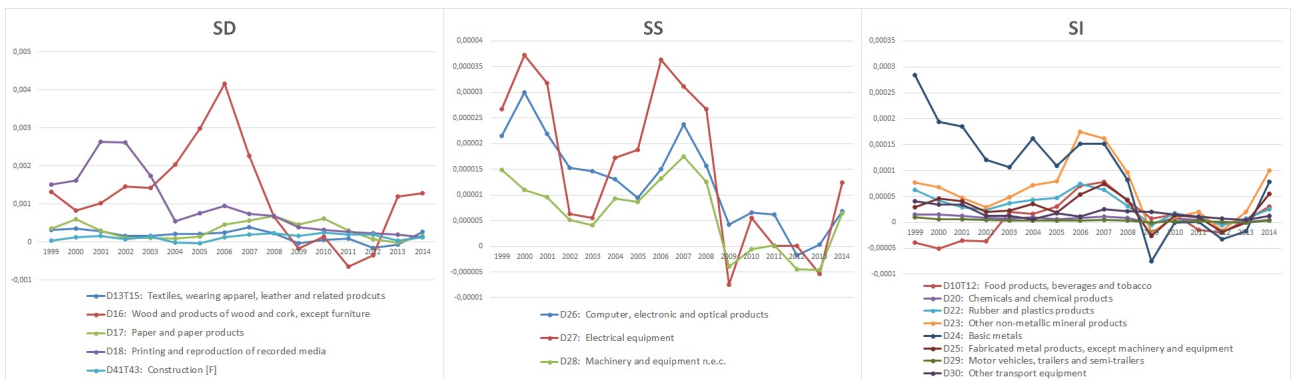


Figure 14: Indicator 1 dynamics for Pavitt groups. Germany



Figure 15: Indicator 1 dynamics for Pavitt groups. USA

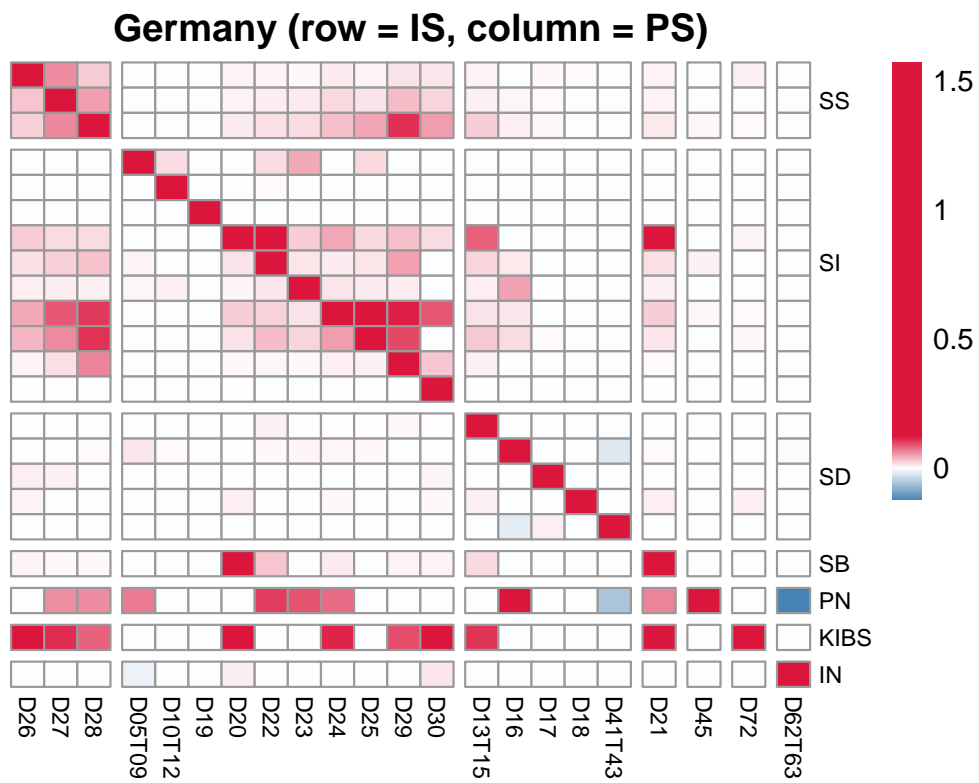


Figure 16: Correlation table weighed by input-output coefficients. Germany

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6 Appendix

Table 14: Variables description. Country level

Variable	Description
TFP growth rate	Multifactor productivity, annual growth rate
ANBERD	Research and Development (R&D) expenditures are expressed in national current prices, millions
Number of researchers	Measured in full-time equivalent are researchers in the business enterprise sector by industry according to the International Standard Industrial Classification (ISIC) revision 3.1
LP growth rate	$(LP_t - LP_{t-1})/LP_{t-1}$, where $LP = PRDK/EMP_N$
PRDK	Production (PRDK) is a volume measure expressed in current price of the reference year 2010, millions
EMP_N	Total employment is displayed as thousands of persons (headcounts) engaged

Table 15: Variables description. Industry level

Variable	Description
ANBERD	Research and Development (R&D) expenditures are expressed in national current prices. Millions, 5 years moving averages
LP growth rate	$(LP_t - LP_{t-1})/LP_{t-1}$, where $LP = PRDK/EMP_N$, 5 years moving averages
PRDK	Production (PRDK) is a volume measure expressed in current price of the reference year 2010, millions
EMP_N	Total employment is displayed as thousands of persons (headcounts) engaged

Table 16: Assignment of industries to taxonomy groups

Industries	R&D group	RxMy	Pavitt
D01T99: Total	-	-	-
D01T03: Agriculture, forestry and fishing [A]	5	5.0	SD
D01T02: Agriculture, hunting and forestry	5	5.0	SD
D01: Crop and animal production, hunting and related service activities	5	5.0	SD
D02: Forestry and logging	5	5.0	SD
D03: Fishing and aquaculture	5	5.0	SD
D05T09: Mining and quarrying [B]	4	4.0	SI
D05T06: Mining and quarrying of energy producing materials	4	4.0	SI
D07T08: Mining and quarrying except energy producing materials	4	4.0	SI
D09: Mining support service activities	4	4.0	PN
D10T33: Manufacturing [C]	3	3.1	na
D10T12: Food products, beverages and tobacco	4	4.1	SI
D10T11: Food products and beverages	4	4.1	SI
D10: Food products	4	4.1	SI
D11: Beverages	4	4.1	SI
D12: Tobacco products	4	4.1	SI
D13T15: Textiles, wearing apparel, leather and related products	4	4.1	SD
D13T14: Textiles and wearing apparel	4	4.1	SD
D13: Textiles	4	4.1	SD
D14: Wearing apparel	4	4.1	SD
D15: Leather and related products	4	4.1	SD
D16T18: Wood and paper products, and printing	4	4.1	SD
D16: Wood and products of wood and cork, except furniture	4	4.1	SD
D17: Paper and paper products	4	4.1	SD
D18: Printing and reproduction of recorded media	4	4.1	SD
D19T23: Chemical, rubber, plastics, fuel products and other non-metallic mineral products	3	3.1	SI
D19: Coke and refined petroleum products	4	4.1	SI
D20T21: Chemical and pharmaceutical products	2	2.1	SI
D20: Chemicals and chemical products	2	2.1	SI
D21: Basic pharmaceutical products and pharmaceutical preparations	1	1.1	SB
D22T23: Rubber and plastics products, and other non-metallic mineral products	3	3.1	SI
D22: Rubber and plastics products	3	3.1	SI
D23: Other non-metallic mineral products	3	3.1	SI
D24T25: Basic metals and fabricated metal products, except machinery and equipment	4	4.1	SI
D24: Basic metals	3	3.1	SI
D241T31: Iron and steel	3	3.1	SI
D242T32: Non-ferrous metals	3	3.1	SI
D25: Fabricated metal products, except machinery and equipment	4	4.1	SI

Table 17: Assignment of industries to taxonomy groups

Industries	R&D group	RxMy	Pavitt
D26T28: Machinery and equipment	2	2.1	SS
D26T27: Electrical, electronic and optical equipment	2	2.1	SS
D26: Computer, electronic and optical products	1	1.1	SS
D27: Electrical equipment	2	2.1	SS
D28: Machinery and equipment n.e.c.	2	2.1	SS
D29T30: Transport equipment	2	2.1	SI
D29: Motor vehicles, trailers and semi-trailers	2	2.1	SI
D30: Other transport equipment	1	1.1	SI
D301: Building of ships and boats	3	3.1	SI
D303: Air and spacecraft and related machinery	1	1.1	SI
D304: Military fighting vehicles	2	2.1	SI
D302A9: Railroad equipment and transport equipment n.e.c.	2	2.1	SI
D31T33: Furniture; other manufacturing; repair and installation of machinery and equipment	4	4.1	SD
D31T32: Furniture, other manufacturing	4	4.1	SD
D33: Repair and installation of machinery and equipment	3	3.1	SD
D35T39: Electricity, gas and water supply; sewerage, waste management and remediation activities [D-E]	5	5.0	SDS
D35: Electricity, gas, steam and air conditioning supply [D]	5	5.0	SDS
D36T39: Water supply; sewerage, waste management and remediation activities [E]	5	5.0	SDS
D36: Water collection, treatment and supply	5	5.0	SDS
D37T39: Sewerage, waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services	5	5.0	SDS
D41T43: Construction [F]	5	5.0	SD
D45T56: Wholesale and retail trade; repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities [G-I]	5	5.0	PN
D45T47: Wholesale and retail trade, repair of motor vehicles and motorcycles [G]	5	5.0	PN
D45: Wholesale and retail trade and repair of motor vehicles and motorcycles	5	5.0	PN
D46: Wholesale trade, except of motor vehicles and motorcycles	5	5.0	PN
D47: Retail trade, except of motor vehicles and motorcycles	5	5.0	PN
D49T53: Transportation and storage [H]	5	5.0	PN
D49: Land transport and transport via pipelines	5	5.0	PN
D50: Water transport	5	5.0	PN
D51: Air transport	5	5.0	PN

Table 18: Assignment of industries to taxonomy groups

Industries	R&D group	RxMy	Pavitt
D53: Postal and courier activities	5	5.0	IN
D55T56: Accommodation and food service activities [I]	5	5.0	SDS
D58T63: Information and communication [J]	3	3.0	IN
D58T60: Publishing, audiovisual and broadcasting activities	5	5.0	IN
D58: Publishing activities	4	4.0	IN
D59T60: Audiovisual and broadcasting activities	5	5.0	IN
D61: Telecommunications	4	4.0	IN
D62T63: IT and other information services	2	2.0	IN
D62: Computer programming, consultancy and related activities	2	2.0	IN
D63: Information service activities	2	2.0	IN
D64T66: Financial and insurance activities [K]	5	5.0	IN
D64: Financial service activities, except insurance and pension funding	5	5.0	IN
D65: Insurance, reinsurance and pension funding, except compulsory social security	5	5.0	IN
D66: Activities auxiliary to financial service and insurance activities	5	5.0	IN
D68T82: Real estate, renting and business activities [L-N]	5	5.0	SDS/KIBS
D68: Real estate activities [L]	5	5.0	IN
D69T82: Professional, scientific and technical activities; administrative and support service activities [M-N]	4	4.0	SDS/KIBS
D69T75: Professional, scientific and technical activities [M]	4	4.0	KIBS
D69T71: Legal and accounting activities; activities of head offices; management consultancy activities; architecture and engineering activities; technical testing and analysis	4	4.0	IN/KIBS
D69T70: Legal and accounting activities; activities of head offices; management consultancy activities	4	4.0	IN/KIBS
D69: Legal and accounting activities	4	4.0	IN
D70: Activities of head offices; management consultancy activities	4	4.0	KIBS
D71: Architectural and engineering activities; technical testing and analysis	4	4.0	KIBS
D72: Scientific research and development	1	1.0	KIBS
D73T75: Advertising and market research; other professional, scientific and technical activities; veterinary activities	4	4.0	KIBS
D73: Advertising and market research	4	4.0	KIBS
D74T75: Other professional, scientific and technical activities; veterinary activities	4	4.0	KIBS

Table 19: Assignment of industries to taxonomy groups

Industries	R&D group	RxMy	Pavitt
D74: Other professional, scientific and technical activities	4	4.0	KIBS
D75: Veterinary activities	4	4.0	SDS
D77T82: Administrative and support service activities [N]	5	5.0	SDS
D77: Rental and leasing activities	5	5.0	SDS
D78: Employment activities	5	5.0	SDS
D79: Travel agency, tour operator, reservation service and related activities	5	5.0	PN
D80T82: Security and investigation activities; services to buildings and landscape activities; office administrative, office support and other business support activities	5	5.0	SDS
D84T99: Community, social and personal services [O-U]	6	6.0	NMS
D84T88: Public administration and defence; compulsory social security; education; human health and social work activities [O-Q]	6	6.0	NMS
D84: Public administration and defence; compulsory social security [O]	6	6.0	NMS
D85: Education [P]	6	6.0	NMS
D86T88: Human health and social work activities [Q]	6	6.0	NMS
D86: Human health activities	6	6.0	NMS
D87T88: Residential care and social work activities	6	6.0	NMS
D90T99: Arts, entertainment, repair of household goods and other services [R-U]	5	5.0	SDS
D90T93: Arts, entertainment and recreation [R]	5	5.0	SDS
D90T92: Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling and betting activities	5	5.0	SDS
D93: Sports activities and amusement and recreation activities	5	5.0	SDS
D94T96: Other service activities [S]	5	5.0	SDS
D94: Activities of membership organizations	5	5.0	SDS
D95: Repair of computers and personal and household goods	5	5.0	PN
D96: Other personal service activities	5	5.0	SDS
D97T98: Activities of households as employers; undifferentiated activities of households for own use [T]	5	5.0	SDS

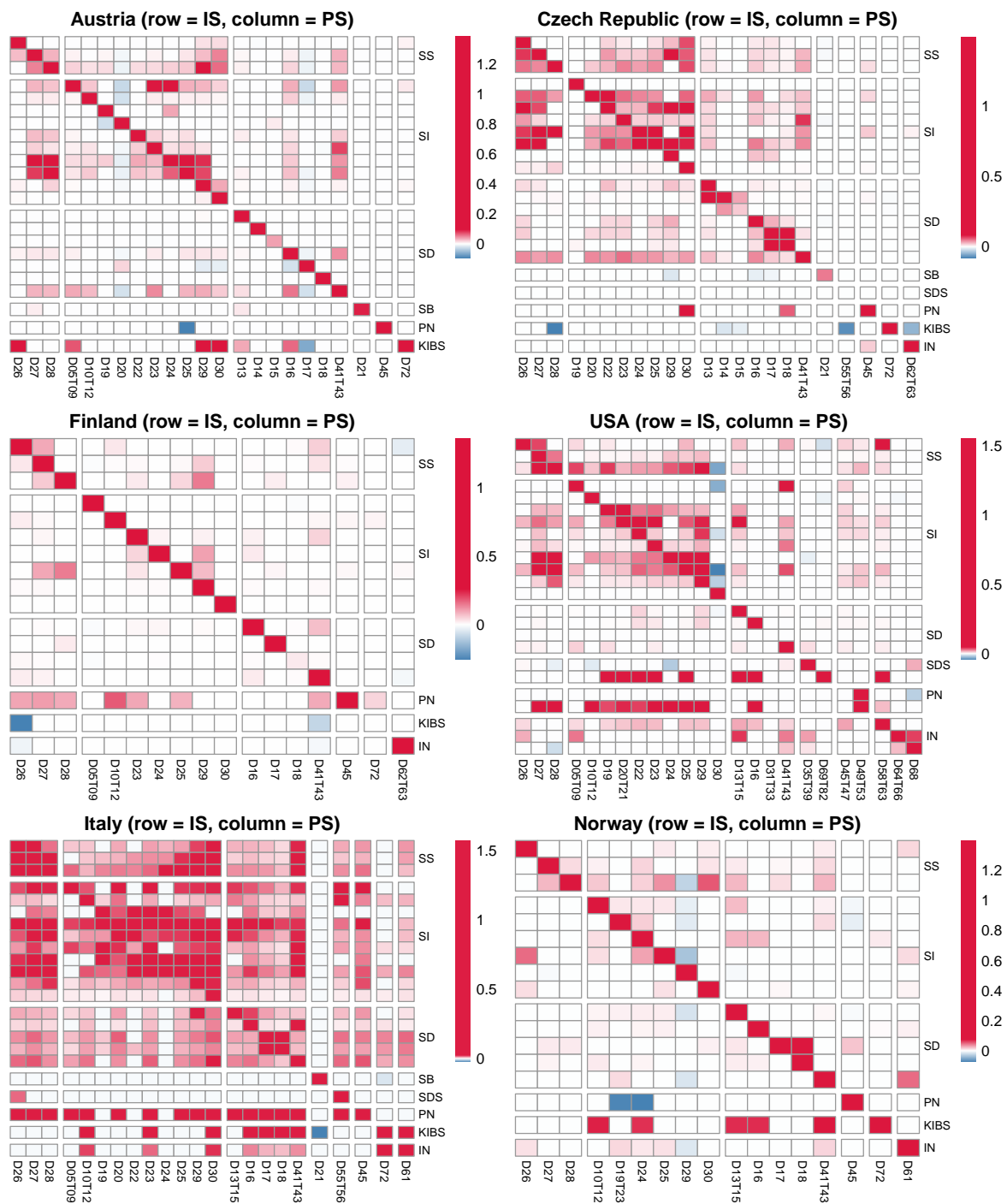


Figure 17: Correlation matrices

Note: Rows indicate measures of innovation productivity (growth of labor productivity over R&D input); Columns indicate measures of labor productivity growth.