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Sectoral Innovation Systems, Complementarities and Productivity in Europe

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Abstract

This paper explores the differences in labour productivity between five firm clusters, distinguished based on firm size, resource capabilities and geographic scope of a firm market (national vs. international), using a k-means clustering approach and panel data for EU Small Medium and Large enterprises. The study is embedded into the framework of sectoral innovation ecosystems, suggesting the importance of complementarities between various pillars of meso-level innovation ecosystems. Our analysis reveals that productivity gains increase jointly with firm scalability and accumulation of organisational and resource capabilities, although individually, firm size is negatively correlated with firm labour productivity. Furthermore, we find a direct positive effect of each of the four pillars of sectoral innovation ecosystems, namely digital, human, innovation and tangible capital capabilities, though statistically, the direct effect of digital capabilities is weaker compared to other pillars. More importantly, via interacting these pillars we find some compelling evidence on complementarities between pairwise sectoral capabilities that have important policy implications for coordination of EU policies, in terms of innovation diffusion, digitalisation and productivity growth in the EU. [1]

[1] Deliverable 3.8 GROWINPRO project funded by the European Union Horizon 2020 Research and Innovation action under grant agreement No 822781, GROWINPRO (https://cordis.europa.eu/project/rcn/218765/factsheet/en). This paper builds upon our previous work, which focused on the determinants of the productivity gap in Europe using a multilevel analysis (see Bruno et al., forthcoming 2021) and assessing the role of SMEs in shaping sectoral productivity growth and innovation patterns (Bruno et. al., 2020). The latter was submitted as Deliverable 3.7 for Task 3.5 of the GROWINPRO

Keywords: labour productivity, innovation ecosystems, clustering, factor analysis, EU

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1. Introduction

This paper explores the role of SMEs as compared to their larger counterparts in firm productivity growth in Europe. We aim to identify clusters of firms underlined by their characteristics and how these are correlated with firm' performance, using a mapping exercise. Hence, we develop different types of sectoral innovation ecosystems explaining the differences in performance of firms of different sizes and other characteristics in order to explore various linkages and mechanisms underlying patterns of SMEs' contribution to productivity growth, especially from the perspective of advanced and converging EU economies.

Earlier work has flagged up concerns about declining productivity in Europe over the past decade. These include specifically human capital deficiencies, including skills' shortages in high-skilled jobs and their changing composition in light of the digitalisation trend; financial constraints and a breakdown in technology diffusion machine across Europe (Berlingieri et al., 2020). Some of these constraints disproportionally more affect the SMEs and serve as potential impediments to their contribution to productivity growth in Europe.

More recent evidence on the role of SMEs in economic performance emphasises the importance of not just single factors in enhancing their contribution to growth, but rather various synergies between different factors underlying the external environment at different levels, which so far has been primarily limited to country or regional levels, and without distinguishing between different firm groups which may require a tailored policy approach depending on what characteristics they have in common (Lafuente et al. 2019; Costa at al. 2021).

The literature on innovation ecosystems which account for the combination of different factors and interaction mechanisms between them spans different research areas and disciplines, including economic geography (regional agglomeration/clustering); innovation studies with focus on national innovation systems; and entrepreneurship and management studies with focus on entrepreneurial ecosystems and competitive advantages of firms' clusters. Since the literature identifies both SMEs/start-ups and incumbents as important drivers of productivity via creative destruction and accumulation processes, we aim to look at how these firms perform in different ecosystem contexts. Also, sectoral ecosystems could be important for different players (SMEs/start-ups vs. incumbents) in explaining productivity differences. The ultimate aim would be to construct a taxonomy of different ecosystems based on the above core elements (a-c). This would enable us to show how different pillars of eco-systems and their interplay impact productivity growth among SMEs, start-ups and incumbents.

We construct firm-industry longitudinal dataset across the EU countries for 2010-2018, based on the Amadeus database provided by the BvD[2], sectoral capital structure indicators from KLEMS and Eurostat. Rich firm-level data allows us to develop firm genotypes, clustering firms based on overlapping resource and organisation capabilities and using a k-means cluster algorithm. More specifically, based on our analysis we distinguish five clusters of firms: (i) small labour-intensive firms; (ii) small capital-intensive firms; (iii) medium-sized domestic firms; (iv) medium foreign firms; (v) large multinationals (MNEs). We observe also commonalities in their performance profiles.

The use of sectoral-level data enables us to identify different pillars of sectoral innovation ecosystems to understand how they additionally explain productivity performance of different firm clusters. Based on a factor analysis, we identify four pillars of innovation ecosystems at an industry level, namely (i) digital capabilities; (ii) human capabilities; (iii) innovation capabilities; and (iv) tangible capital capabilities. In the last stage of our analysis we employ a panel regression to study both the direct and indirect effects of these identified clusters on firm performance.

Our core findings suggest the following. First, clustering firms by common capabilities offers some interesting insights on their performance gains with a productivity premium increasing from cluster 1 (small labour-intensive firms) to cluster 5 (large MNEs). The differences in productivity gains are smaller between the top three cluster categories once we control for other firm and sector-level characteristics and sector, country and year fixed effects. Second, we observe that all four pillars of meso-level innovation ecosystems matter for firm productivity both directly, and more so when we allow for further interactions between them. These results have some important policy-making implications for innovation and industrial policy in the EU.

The following section (2) is reviewing the relevant literature structured around three issues: (i) productivity dynamics in Europe and the role of firms of different sizes; (ii) factors exploring productivity dynamics; (iii) innovation ecosystems and productivity patterns. Section three discusses the methodological issues and the data used for assembling our dataset to enable comprehensive analysis. Section four presents stylised patterns of firms' capabilities, and using a clustering algorithm; it identifies five firm genotype groups which

[2] https://www.bvdinfo.com/en-gb

exhibit the best fit on these firm capabilities' indicators. Within this section, we also discuss the "unconditional" firm performance profiles based on the identified typologies. Section five further explores whether such patterns are associated with different sectoral ecosystems' pillars we identify using a factor analysis. Section six investigates econometrically various linkages between firm-level typologies and sectoral pillars of innovation ecosystems in determining productivity growth across Europe. Our key findings are discussed in conclusion, drawing some important policy-making implications of our research.

2. Literature review

2.1 Productivity dynamics in Europe and the role of firms of different sizes

An overview of productivity studies over the past two decades have documented a widening productivity gap between Europe and the US (Aghion and Howitt, 2006; Ortega-Argilés et al., 2014; Castellani et al., 2018). The gap has notably widened in the post-global financial crisis period, leaving most European countries lagging behind the US in terms of both labour and total factor productivity (Adarov & Streher, 2020). The EU's persistent productivity gap is partly driven by the general trend, affecting other economies globally, and described in the literature as 'secular stagnation' (Castellani, et al., 2018). The latter is understood as a downward tendency of the real interest rates signifying an excess of savings over desired investment. Among other reasons, the secular stagnation trend is driven mainly by diminishing technological opportunities (Eichengreen, 2015; Schubert and Neuhäusler, 2018).

In the context of Europe specifically, a persistent productivity gap is also the result of features of its industrial structure that is less high-tech intense than the US (Castellani et al. 2018). Also, the gap reflects a problem of the lower capacity of EU companies in translating R&D investments into productivity gains compared to the US firms (Ortega-Argilés et al., 2014). Thus, using microdata on top R&D-spending companies in the EU and the US both in manufacturing and services between 2004 and 2012, Castellani et al. (2018) show that a ten per cent increase in R&D intensity increases the productivity of a US firm by 2.7%, which is only about one-percent increase for an EU firm. There are even higher disparities observed when firms are split by sector-level R&D intensity.

Several other factors are explaining a slowdown in EU productivity growth. Labour and product market rigidities reduce the entrepreneurial opportunities and inhibit the reallocation of resources from inefficient incumbent firms towards high-growth potential entrants (Aghion and Akcigit; 2015). Heterogeneity of country productivity patterns within the EU and widespread consequences of economic cohesion policies (Castellani et al. 2018) are other important determinants. The quality of human capital, the breakdown of knowledge diffusion machine with not all firms benefiting equally from skill intensity and digitalisation, and low scale of implementation of new managerial practices and organisational investments are also contributing factors (Bonanno, 2016; Castellani et al., 2018; Berlingieri et al., 2020).

It is also imperative to analyse Europe's productivity patterns by performance groups to understand the characteristics of laggards vs. front leaders of productivity. Using firm-level data across 24 OECD countries, Berlingieri et al. (2020) show that smaller and younger firms, positioned at the bottom 40% of the productivity distribution, tend to grow on average higher than the rest of the distribution, suggesting that for them, a catch-up effect is more pronounced. By decomposing aggregate productivity growth using Melitz and Polanec (2015) approach, they show that entrants and existing firms transit through the group of laggards when entering and exiting the economy. Consequently, the bottom productivity growth reflects firm dynamics and captures a broad range of firms, starting from inefficient incumbents with ageing products or technologies to entrants with high productivity potential. Broadly, these findings show that high heterogeneity of firms within the left tail of the distribution of labour productivity calls for a tailored policy approach to firms within the bottom of distribution as these are not all typical 'zombie' firms that should be promoted to exit the market. This urges us to explore some commonalities among firms' characteristics to understand better their performance profiles and how different configurations of the external environment shape them.

The innovation growth-led theories emphasize the critical role played by small and young firms via creative destruction and by larger firms via the process of creative accumulation (Bergek et al., 2013). The notion of technological change through innovation as the main engine of economic growth is well-rooted in the Schumpeterian growth theory (1934; 1942). An innovating entrepreneur challenges an incumbent firm by introducing new inventions that make current technologies and products obsolete. At the same time, larger established firms have a greater R&D capacity, outperforming their smaller counterparts via incremental innovation underlying the process of 'creative accumulation'. The debates on the role of small versus large firms for innovation and productivity are long-standing without offering any conclusive evidence.

In his seminal work on the innovator's dilemma, Christensen (1997) argues that even the power of an outstanding incumbent company can be challenged by new, unexpected competitors who rise fast and take over the market. Innovation activity is a risky undertaking that makes larger businesses less keen to engage in radical innovation. Instead, they often choose a safer strategy of acquiring an innovative high-potential start-up, accumulating their innovation capability quickly without significant business model disruption (Brueller and

Capron, 2021). Unlike larger firms, start-ups are, by their undertaking, more risk-tolerant and are more prepared to fail and exit. Akcigit and Kerr's (2018) develop a theoretical model and, using Census Bureau and patent data for US firms, offer some empirical evidence that smaller firms innovate more radically than incumbent firms and grow (measured by employment growth) on average faster than their larger counterparts. This finding is also rooted in Christensen's (1997) argument that innovation is primarily about creative destruction driven by new entrants.

The decomposition of growth due to different sources of innovation matters for innovation policy. It helps to understand the role of incumbent larger firms engaged in incremental innovation as described above vis-a-vis start-ups, typically small at inception but with high growth potential in driving productivity growth. When further decomposing aggregate growth due to innovation in the context of the US, Akcigit and Kerr (2018: 1377) show that about 26 per cent of growth is due to new entrants; 20 per cent is due to internal efforts of incumbents, and 54 per cent - to external efforts of incumbents.

Garcia-Macia et al. (2019) further distinguish between three main channels of innovation via which growth occurs: (a) 'creative destruction' process, when a new firm innovates and takes over a variety owned by existing firm; (b) 'incremental innovation by incumbents' that improves the quality of existing products firms own; and (c) via the creation of 'brand new varieties'. Employing the U.S. Longitudinal Business Database from 1983-2013, Garcia-Macia et al. (2019) infer the sources of growth indirectly from the patterns of job creation and job destruction. They conclude that most growth comes from incumbents rather than new firms; from improvements rather than brand new varieties with own-variety improvements by incumbents having a more pronounced contribution to growth than creative destruction, which somewhat contradicts the findings from Akcigit and Kerr (2018), emphasising the importance of external innovation.

Overall, the process of 'creative destruction', which is seen as essential to the dynamic market-based economy, does not seem to dominate in the industry dynamics of advanced economies. This can be explained by the heterogeneity of SMEs population in terms of growth and value-adding ambitions, regardless of their important role in employment creation. Our provisional exploratory analysis of SMEs patterns of productivity and market dynamics in the EU reveals that (i) the EU business dynamics are low and stagnant across the EU, with entry rates being lower in the EU North, although these are counterbalanced by higher average employment size of *de novo* firms in the North, reflecting not only their levels of income but also organisational and entrepreneurial capabilities; (ii) exiting firms are relatively old in the EU suggesting 'prolonged creative destruction process': the EU entrants enter larger but then grow at a slower rate and take longer time to exit;

many of SMEs remain 'lifestyle' business whose primary aim is not to grow, making them least resembling conventional Schumpeterian entrepreneur; (iii) small and medium-sized firms tend to underperform larger firms in labour productivity growth (Bruno et al. 2020).

There are various internal factors, such as, for example, human capital and skill deficiency; managerial competencies; the capital intensity of projects bound by financing constraints; and external factors that may impact the SMEs/start-ups contribution to economic performance. Among the commonly cited external factors are access to finance, legal and business regulation constraints (Beck & Demirguc-Kunt, 2006; Beck et al. 2006) The recent evidence also suggests the critical role played by skill deficiencies which disproportionally more affect the SMEs (OECD, 2017), and which inhibit the transfer of technology and knowledge as economies become increasingly exposed to digital technologies and as knowledge increases (Berlingieri et al., 2020). The following section discusses determinants of productivity to classify different factors.

2.2 Determinants of productivity

Productivity is a multi-level phenomenon. By this, we mean that its determinants are operating at the firm and sector levels and include linkages among firms. From a Schumpeterian economics perspective, productivity is determined by the interaction between micro, mezzo, and macro factors. We briefly review each of these levels. However, the majority of the literature explores determinants of productivity only at either country level or only at sectoral or micro levels.

Firm-level factors as determinants of productivity

An extensive literature review suggests that the firm-level variables and idiosyncratic firm-factors play a significant role in explaining productivity differences within industries (Syverson 2011). A pervasive empirical finding in the recent literature is the existence of significant and persistent productivity differentials across establishments in the same narrowly defined industry (e.g. at four-digit level). These differences dwarf inter-industry differences (Foster et al., 2001). Factors that explain these differences are various and include size, age, location, managerial abilities, innovation capacity, etc., and we try to account for the most important of these factors.

In the EU context, Gorodnichenko et al. (2018) show that the firm-level characteristics alone account for 11.2 per cent of the total variation in the log of marginal revenue product of capital and 27.1 per cent of the variation in the log of marginal revenue product of labour. When they allow firm-level characteristics to have different effects by sector or country, they show that firm-level variables explain most of the variation in marginal products within the EU. They conclude that the firm-level characteristics coupled with the fixed sector and country features explain most observed dispersion.

The relationship between firm size and productivity is known as “Schumpeterian Hypothesis” which underpins the idea that large firms in concentrated markets are more likely to support innovation. This hypothesis is justified by the argument that large firms may support a more substantial portfolio of R&D efforts, increasing the likelihood of developing improved products or processes. However, theoretical research also indicates that a monopolist can have less incentive to innovate. Results on the relationship are inconclusive (for example, Fisher and Peter Temin, 1979; Levin et al., 1985; Soete 1979; Gayle 2003; Acs and Audretsch, 1988; Kinugasa, 1998).

There is some scant evidence that total factor productivity (TFP) in emerging economies tends to increase with firm size (see OECD, 2014, figure 3.12). On the other hand, we would expect that firms’ size should not be positively related to TFP when firms move towards the technology frontier. Also, increasingly available cross-country firm-level evidence suggest that the distributions of productivity and size exhibit a positive correlation, i.e. more productive firms tend to be larger than less productive ones. Bartelsman et al. (2013) show positive covariance between productivity and size across countries, across industries and over time and show a considerable variation in the strength of the nexus. The latter is the highest in US manufacturing; it is much lower in the Western European countries and even lower in Central and Eastern Europe (CEE). They explain these differences by a misallocation hypothesis developed by Hsieh and Klenow, (2009), which suggests that policy-induced distortions affect the allocation of resources across firms and the selection of firms producing in each market. However, they also show that the relationship between size and productivity increased substantially in the CEE economies over time, less in Western Europe and much less in the United States.

Within the EU, there are significant differences in the size of firms. For example, microenterprises account for a significantly larger share of employment and value-added in Southern EU than in other EU countries. They are also much less productive than other parts of the EU (Ridao-Cano and Bodeweg, 2018). For example, if the South had the size-mix of other EU15 (‘old EU’) countries, and its microenterprises had the productivity level of other EU15 countries, its productivity gap with the rest of EU15 would be reduced by 40 per cent (ibid).

It is common to use age as a proxy for the learning curve and accumulated capabilities. One may expect that, on average, firms that have been long in existence have old and probably lower quality capital. However, age may also be a proxy for productivity as firms invest in learning by doing. Hence, we may also expect that old firms will have higher levels of TFP due to the accumulation of technological capabilities (Jensen et al., 2001). Also, new exciting evidence shows that firms' ageing drives the increase in average firm size and concentration (Hopenhayn et al., 2018).

Therefore, the aggregate outcome of differences in size, age, technology and globalisation are increased dispersion in productivity, whether measured as a real value-added per worker (labour productivity) or as multi-factor productivity (MFP) (Berlingeri et al., 2017). Most of the increase is driven by within-sector across firms' productivity differentials rather than cross-sectoral differences (ibid).

The firm organisation is another significant determinant of productivity. Navaretti and Venables, 2004 show that productivity is higher in the sector where there is a high share of multiplant and multinational firms (see Navaretti and Venables, 2004). The multinationalisation as the form of firm organisation is more likely to occur in the context with high firm scale economies are combined with relatively low plant scale economies

Differences in performance between foreign-owned and domestic firms can be substantial (Navaretti and Venables, 2004; Hanousek et al., 2010; Lipsey, 2002; Damijan et al., 2013). For example, foreign presence through FDI, domestic R&D and firm size are among the most critical factors to enhance TFP in Chinese industries (Liu and Wang, 2003). However, higher performance of MNCs disappears' or is significantly reduced after controlling for firms and industry characteristics as a structural effect or industry composition effect, not foreign ownership, account for most of the variation (see Bellak, 2004 for a review).

Sector-level determinants of productivity

The recognition of the importance of meso or industry levels in determining productivity is of a relatively recent origin. Industry dynamics literature shows that technology and industry structure co-evolve (Nelson, 1995), and hence, levels and dynamics of productivity are intimately related to changes in industry structure.

In the literature, industry concentration is typically treated as a result of technological determinants like scale economies, sunk costs, product life cycles, market size, or firm-specific determinants like the organisation structure and accumulated capabilities (learning curve). It is increasingly recognised that industry structure is an endogenous variable, suggesting that the relationship between industry concentration and its various determinants is non-linear. Sutton (1998) shows that technological and demand-related factors determine industry concentration through the interplay between exogenous and endogenous sunk costs. A concentrated or dispersed market structure is by itself not a priory promoting or hindering productivity catch-up, i.e. it is industry-specific and dependent on the size of the market.

A market structure may affect convergence in productivity through its effects on incentives for firms to engage in R&D and innovation. As reflected in different market structures, the degree of competition may affect positively or negatively innovative behaviour and, thus, closure of the productivity gap. Cheung et al. (2001) show a significant market structure effect on the persistence of productivity differential at the macro level. Using data on 11 industries in 17 OECD countries shows that a concentrated market structure tends to hinder convergence. However, there is no simple relationship between market structure and innovation (Acemoglu et al., 2006; Aghion et al., 2009). Aghion et al. (2005) show an inverted-U relationship, so only a certain degree of competition positively induces innovative behaviour. On the technology frontier, competition may be conducive to growth but not behind the technology frontier, where competition dampens innovation by lowering the successful innovators' mark up (ibid). This is consistent with the earlier finding from Scherer (1967).

Increased concentration accompanied by increased differences between firms regarding their relative sales, productivity and wages could be interpreted as increased market power. However, an alternative explanation is that this may be due to globalisation and new technologies (cf. 'winner takes all' industry structure) rather than a generalised weakening of competition due to relaxed anti-trust rules or regulation (van Reenen 2018). Globalisation and economic integration can also affect productivity distribution, but trade may both increase and decrease productivity dispersion. A recent persuasive explanation is that this may be due to the increased ageing of companies, i.e. consolidation of industry dynamics (Hopenhayn et al., 2018).

In the EU context, Bruno et al (2021) show that highly concentrated markets at the country-level have adverse effects on productivity gap closure, but highly concentrated markets at the EU-level help close such gap. Local oligopolies at the country-level (when most EU countries are relatively small markets) may affect productivity growth negatively. In contrast, at the level of the much larger EU market, "economies of scale" may have more of an impact. These results are compatible with the notion that there is no simple one to one relationship between industry structure, innovation and productivity growth (Aghion et al., 2005).

Among other meso-level factors, the literature also suggests the important role played by the capital stock composition, distinguishing between tangible (fixed capital) and intangible capital (R&D intensity and human capital) (Griffith et a. 2004; Corrado et al. 2017). A number of studies emerging post 1990s specifically emphasized the role of ICT capital played in enhancing productivity (Oliner & Sichel, 2000; Spiezia 2013). Using EU KLEMS data on capital structure at a sectoral-level, Adarov and Streher (2020) further distinguish between tangible ICT and intangible ICT (i.e. software and databases), suggesting that the latter is even more conducive to productivity. Therefore, in a dynamic market setting digitalisation proves to be instrumental for enhancing firm performance. In section 2.3 we continue this discussion further.

A step further in understanding determinants of productivity at the sectoral level came with the notion of sectoral systems of innovation (Malerba, 1992) and it has been further developed (at least conceptually) through research on innovation ecosystems. The underlying idea is that differences in economic performance cannot be linked causally to isolated "key factors" such as firm R&D investments or openness of the economy. Any 'success factors' are embedded and are part of the relationships in the systems in which firms operate. So, whatever is considered 'success factors,' they work well because many other factors support them. Understanding differences in productivity and economic performance requires looking at the sectoral or innovation ecosystems, not just some of its components.

2.3 Innovation ecosystems

The literature on productivity determinants of firms has recently evolved to emphasise the importance of the combination of factors and complementarities between them for enhancing productivity growth. Primarily, such studies explore complementarities either at a firm level (Costa et al. 2021) or various interactions of sectoral, regional and country-level factors which affect the quality of the business environment and firms' performance (Griffith et al., 2004; Aghion et al. 2009; Aghion and Akcigit 2015; Lafuente et al. 2019; Adarov and Streher, 2020; Bruno et al., forthcoming 2021). Thus, Costa et al. (2021) employ a survey of Italian firms over 2016-2018 and develop firm taxonomies based on overlapping profiles of their organisational capabilities and strategies. For each genotype of firms, they map their performance patterns, measured by productivity and employment growth. They conclude that belonging to different clusters defined by the combination of firm organisational capabilities and behaviours matters for firm performance rather than individual firm-level characteristics per se.

Using a panel of industries across OECD countries over the 1970-1990 period, Griffith et al. (2004) show the critical role of complementarity between investment in R&D and human capital for enhancing sectoral productivity growth. Bruno et al. (forthcoming 2021) study the impact of different types of industrial innovation capabilities on a firm productivity gap in Europe across four sectors of the economy (food manufacturing, basic metals; chemicals; and computing). They show that, individually, disembodied (in-house) R&D and R&D embodied in purchased equipment and machinery matter for closing a productivity gap. However, jointly, there is a lack of complementarity between the two pointing to possible mismatches between two types of innovation activities in reducing a productivity gap.

Along with in-house R&D and R&D embodied in investment in machinery and equipment, inward foreign direct investments are often seen as another crucial driving force of productivity primarily via a technology transfer channel, as discussed in Section 2.2. In their study of productivity determinants in Europe, Adarov and Stehrer (2020) identify possible mismatches between FDI and absorptive capacities. Namely, they show a lack of complementarity between FDI and various indicators of 'absorptive capacity, including educational attainment, government effectiveness and control for corruption, quality of infrastructure, and financial development, and between FDI and participation (forward and backward) in global value chains (GVCs). However, the direct effect of backward GVCs on labour productivity has proven to be significant.

Reviewing the literature on the interaction of macroenvironmental factors in Europe, Aghion et al. (2009) find that the complementarity of structural reforms and investment in education significantly impacts productivity gains. More specifically, they show that simultaneously liberalising product and labour markets are essential to labour market flexibility. Aghion and Akcigit (2015)[3] further show that in countries that grow based on frontier innovation, R&D-driven investment alone does not suffice. Instead, R&D investments need to be coupled with competition, property rights, financial development, education, and macroeconomic stability. They emphasise specifically the importance of competition and

[3] http://www.coeure-book.ceu.edu/Innovation.pdf. See also Aghion and Howitt (2006) for early work on the impact of institutional frameworks, distance to technology frontier and growth in the context of Europe.

entry, labour mobility and education in promoting growth in Europe. Countercyclical budgetary policies are more growth-enhancing in countries with lower financial development.

Lafuente et al. (2019) distinguish between Kirznerian entrepreneurs who drive growth via increasing market efficiency, helping an economy catch up to the technology frontier, and Schumpeterian entrepreneurs, who create the prospect for disruptive product technology pushing the existing technology frontier outwards. They explore further how different national systems of entrepreneurship trigger different sources of total factor productivity, namely market efficiency due to more efficient resource allocation, Kirznerian entrepreneurship, and technological efficiency associated with Schumpeterian entrepreneurship. Their results support the importance of a solid entrepreneurial ecosystem for developing and commercialising innovations that drive total factor productivity and call for exploring complex and systemic interactions that drive entrepreneurial actions.

Overall, the evidence on the importance of complementarities (or mismatches) of different elements of the external environment and firms' features and capabilities is still far from conclusive. There is a growing consensus among academic scholars that firms creating value from complex propositions would require different complementary ecosystems. For example, start-ups and smaller firms, which are typically capital constrained, may benefit substantially from a competitive environment, the growing importance of ICT technologies and digitalisation (Aghion et al., 2015; Autio et al. 2018; Adarov and Streher, 2020). At the same time, larger and more labour-intense firms may benefit more from better-developed transport infrastructure to facilitate their growth potential via a growing distribution network domestically and exporting. At the same time, incumbents operating in intense innovation environments are likely to continue growing via continuous engagement in incremental innovation via R&D investment, conditional on the available human capital. Although the literature on innovation ecosystems is growing, to the best of our knowledge, there is no empirical evidence to offer a holistic picture of the role different types of innovation ecosystems play in explaining differences in firms' performance across Europe. Below, we introduce the innovation ecosystem concept as the backbone of the theoretical framework for our empirical analysis.

The concept of innovation ecosystems has grown in popularity over the past few decades, spanning several disciplines and levels of analysis. Its distinct origins are rooted in innovation system studies exploring it from national (Freeman, 1987; Lundvall, 1992), regional (Asheim et al., 2005), or sectoral innovations systems' perspectives (Breschi and

Malerba, 1997). However, the increasing importance of lead firms that form a dense network of knowledge links with other companies led to the notion of the innovation ecosystem.

The key idea that underpins the notion of an innovation ecosystem is that the innovation process is collaborative or social. According to Adner (2006), an innovation ecosystem is “the collaborative arrangements through which firms combine their individual offerings into a coherent, customer-facing solution” (p. 98). This does not seem new, as the gist of the innovation system is about the interactive or collaborative nature of the innovation process. So, what is new about it? Unlike Yawson (2009), who sees the rationale for the ecosystem framework in the inability of ‘traditional innovations models’ ‘to identify the successful policy strategies that drive innovations at the national level’ we see it in dynamic nature of the notion of the ecosystem as opposed to static analyses of the overall innovation system. As pointed out by Bessant et al (2014), national innovation system does look at the detailed dynamics of knowledge flows within the system but the notion of an innovation ecosystem, in contrast, ‘directs attention not only to the internal structure and operation of the system but also its *evolution through time, as well as in relation to other ecosystems’* (italics ours). (See also Moore, 1993 on this issue including a taxonomy of stages of innovation ecosystem (birth, expansion, leadership, self-renewal (or death)). The innovation ecosystem perspective focuses on the innovation community of interacting firms and infrastructure institutions engaged in generating and exploiting technological knowledge (Durst and Poutanen,2013). Its analytical level is not a priory national or sectoral but is given by the nature of technology, making it similar to the technology system approach (Carlsson and Stankiewicz, 1995).

The other reason for the increasing popularity and use of this approach is not academic but empirical. Namely, we have seen the emergence of platform economics or the rise of big IT-based market players (Google, Apple, etc) who are engaged in interactive innovation. This new perspective shows that it is an innovation ecosystem rather than new technology-based firms or large firms per se driving innovation. In other words, large firms (such as Apple) interact with small technology-based firms (such as software companies developing apps for Apple products), which innovate based on large firms’ stable technology platforms (Mandel, 2011, p.6). Whether used inside firms, across supply chains or as building blocks of new industrial architectures, the emergence of platforms is a broad new phenomenon affecting most industries today, from products to services (Gawer, 2009). The recognition of the dynamic and interactive nature of the innovation ecosystem has already led to the emergence of policy platforms, including many within the smart specialisation support activities (Cooke, 2007; Asheim et al., 2011). The biological metaphor behind the notion points to the interaction between firms and their environment.

In contrast, in the social world, this interaction includes various market and non-market actors with different objectives (Jackson, undated). However, the more we go towards the macro-level, the advantage of the innovation ecosystem diminishes, and the notion becomes indistinguishable from the notion of the sectoral or national innovation system. When successful, the innovation ecosystem has the potential for value creation which is much more significant when compared to the potential of individual firms. However, strategic issues in managing networks of firms are also increasingly complex. However, the most important is that the business ecosystem is a social, not biological construct and thus involves issues of culture, power, learning, dependence and autonomy.

The issue of complementarities and relationships has led to the exploration of entrepreneurial propensity or propensity of individuals and systems to engage in discovery or creation of profitable market, technological and institutional opportunities (Radosevic & Yoruk, 2013; Mason & Brown, 2014); Autio et al., 2018; Stam & van de Ven, 2019; Audretsch et al., 2019). These are also concerns of innovation ecosystems literature. Autio et al. (2018: 72) claim that entrepreneurial ecosystems differ from traditional systems of innovation or knowledge clusters by "*their emphasis on the exploitation of digital affordances; by their organisation around entrepreneurial opportunity discovery and pursuit; by their emphasis on business model innovation; by voluntary horizontal knowledge spillovers; and by cluster-external locus of entrepreneurial opportunities*". Digital affordances are viewed as a combination of digital artefacts embedded in a new product or service, platforms and infrastructure, which facilitate the formation of new product ideas and business models and allow for a dynamic enactment of new opportunities (Nambisan 2017; Nambisan et al. 2019). A compelling body of research has shown that digitalisation substantially affects the nature and type of entrepreneurial activity and how it influences economic development (Autio et al., 2018). This calls for further understanding of how digital technology can help young firms develop digital capabilities (Rosin et al., 2020).

In this report, we follow Granstand & Holgersson (2020) conceptualisation of innovation ecosystems. Their framework is close to business ecosystems emphasising the importance of collaborative arrangements through which firms, drawing upon their set of capabilities and resources, offer product and service solutions to customers (Moore, 1983; Adner, 2006).

A majority of studies in this field have the following components in common to define innovation ecosystems: ***(i) actors; (ii) activities; (iii) artefacts; (iv) institutions,*** *and* ***(iv) relations*** underlying the complexity of interactions between different stakeholders of an ecosystem with implications for individual or aggregate innovation performance and value creation (Granstand & Holgersson, 2020).

Firms or groups of firms (if looked at from the perspective of mezzo or macro-levels) are commonly viewed as continuously evolving ***actors*** of innovation ecosystems who generate, acquire and diffuse knowledge to establish their competitive advantages in dynamic marketplaces (Alvarez and Barney, 2007). Via engaging in high-performing strategic ***activities*** such as, for example, product and process innovation, they engage in learning to allow them to capture profitable opportunities (Bingham et al. 2007; Estrin, Korosteleva, and Mickiewicz, 2020). Firms translate this content further into heuristics and organisational routines and continue engaging in search and discovery activities, leading to the emergence of new products and production methods (Costa et al., 2021).

Artefacts are products or services or other systems inputs and outputs that also include innovations (Granstand & Holgersson, 2020). Thus, in a multi-level system, artefacts range broadly from firm capabilities underlying the production of competitive products and services to sectoral, regional or national resources, innovation inputs and outputs. The importance of a different set of firm and sectoral capabilities for influencing firms' co-evolution and performance within their ecosystems also depends on the stages of ecosystem development, which Autio (2021) describes as initiation, scaling and control. Our study captures this by distinguishing between different firm capabilities as depicted by the stage of their life cycle. First, we include *firm age* that allows us distinguishing between initiation and growth stages. Second, *firm size* and the number of domestic and foreign subsidiaries capture firms' scaling capabilities within domestic and foreign markets. Third, the *intensity of using a mix of capital and labour resources underlie managerial capabilities of a firm or its degree of control and authority over allocating* scarce resources towards their productive use. Based on the identified firms' capabilities, we further construct their genotypes characterised by the profile of their capabilities and consider these in terms of firms' performance profile and how this is conditional on different pillars of sectoral innovation ecosystems.

Multi-layered contextual ***institutional arrangements*** further shape firms' strategies, performance and knowledge diffusion within and between industries, regions and countries via imposing constraints or incentivising firm decisions to allocate their scarce resources into different types of economic activities. The capabilities that sectors develop are also broadly shaped by regional and national institutional arrangements. As a result, the distinction between some sector-level pillars underlying ecosystems and institutional arrangements often becomes blurred. Finally, the ***relations*** component is viewed in the innovation ecosystems literature from the perspective of collaborative arrangements (complementary relations). These are characterised by the co-evolution of firms' capabilities and their cooperative engagement in supporting innovations or competitive forces underlying substituting relations (Moore, 1993; Gomes et al., 2018; Audretsch et al., 2019).

Competition could also be seen as an institutional factor affecting firms' decision to innovate via an 'escape competition' effect (Aghion et al., 2015). On the one hand, a stricter competition policy may slow growth by reducing the post-innovation rents that reward a successful innovator. On the other hand, an 'escape competition' means the firm can break away from the constraints of intense competition with a close technological rival. So, more competition raises the incremental profits that a firm earns by innovating. Consequently, intense competition in frontier industries can lead to higher innovation rates and hence faster productivity growth. According to Granstand & Holgersson (2020), with a shift from business ecosystems to innovations ecosystems, it seems a focus has also shifted from competition to collaboration, therefore overlooking the importance of the substitution effect among artefacts and resources underlying the process of creative destruction. In nutshell, the process of competition is essential to understand selection in innovative activities (Breschi and Malerba, 1997).

We focus on sectoral innovation (eco)systems. We view them as the population of firms operating within single or multiple industrial value chains engaged in value-adding activities relying not only on a set of their own resources and capabilities but also on 'sectoral platforms' defined as a combination of complementary capabilities (Breschi and Malerba, 1997; Andreoni, 2017). Sectoral innovation (eco)systems determine strategic and competitive advantages of firms via shared resources, knowledge spillovers and other types of network externalities. In this respect, firms strategies are shaped by their ecosystems and thus go well beyond stand-alone firm competitive advantage strategies (Audrestch et al., 2019). The fit between firms' capabilities and endowments and their respective sectoral ecosystems, with boundaries, often not strictly confined to the firm's primary sector of operation, are critical in shaping firms' performance and co-evolution within their ecosystem (Smith and Smith, 2015; Audretsch et al., 2019).

Building on some of the above contributions, we systemise the core components of the innovation ecosystem and suggest their operationalisation in Table 1 below. This further serves as a conceptual framework for our empirical analysis.

Table 1: Innovation ecosystem: a conceptual framework

Components of Innovation eco-systems	Operationalisation	Underlying concepts	References
Actors	Firms (distinguished by size: SMEs and Large firms)	Complex organizations engaged in generating, acquiring and disseminating new knowledge	Granstand & Holgersson, 2020; Costa et al. 2021
Firm-level capabilities	• Age (accumulated capital) • Number of employees (scaling capabilities) • A number of domestic subsidiaries (organisational capabilities) • A number of foreign subsidiaries (internationalisation capabilities) • Capital intensity (accumulated physical capital) • Labour intensity	Firms' capabilities and inputs as operationalised in column two are translated into firms' heuristics to enable firms' engagement in high-performing activities (product and process innovation, internationalisation) leading to value generation & superior performance	Costa et al. 2021; Autio (2021); Nambisan and Baron, 2013); Navaretti and Venables (2004); Estrin, Korosteleva & Mickiewicz (2020)
Sector-level capabilities[4]	• Tangible capital intensity (machinery and other equipment) • R&D capital intensity • Information & communication technologies, and intangible ICT capital (software and databases) • Human capital intensity (higher educated labour)	• Infrastructure • Sectoral innovation capabilities as measured via innovation input • Digital capabilities • Human capital capabilities All four above identified types of capabilities at a sectoral level emerge as core pillars of sectoral innovation ecosystems defining the environment conducive for different firms' clusters in driving their productivity performance (please see sections 2.2. and 2.3 of the literature review)	Autio et al. 2017; Adarov & Stehrer (2020)

[4] Sectoral capabilities identifying the pillars of innovation ecosystems at a sectoral level are largely shaped by institutional arrangements, and so boundaries between them and different types of institutions are often blurred, making it not straightforward to distinguish between the two. Given the focus on sectoral innovation ecosystems in this study, we retain our attention on sectoral capabilities underlying the pillars of sectoral ecosystems, avoiding overloading this research study with institutional indicators at a regional or national level as they are also likely to be highly correlated with the identified sectoral ecosystem pillars.

Relations[5]	• Market concentration within sectors-countries • Market concentration within sectors-EU	Competitive forces shape firms' relationships via market dynamics akin Schumpeterian creative destruction with new more efficient entrants driving out inefficient incumbent firms from the market; The indicators of competitive forces also reflect the quality of business entry and exit institutional regulatory environment, affecting firms' decision to innovate and price setting.	Gawer, 2014; Mantovani and Ruiz-Aliseda, 2016; Hannah and Eisenhardt, 2018; Aghion et al., 2015; Bruno et al. (forthcoming 2021)

Source: authors' compilation of the literature; based on Granstand & Holgersson, 2020; Radosevic & Yoruk, 2013; Autio et al., 2018; Stam & van de Ven, 2019.

In subsequent sections below, we further discuss the methodology employed in this study for identifying the above elements of innovation ecosystems using a uniquely assembled firm-industry panel dataset across EU countries over the time period of 2010-2018, and linking them further to firm performance profiles.

3. Methodology

3.1 Data description and variable definition

To construct the dataset for the analysis, we merged several databases. We started from the firm-level databases extracted from the Bureau van Dijk Amadeus database that includes information on all European companies. The data was downloaded for 25 European countries (Malta, Cyprus, Luxembourg were dropped due to unreliable information) between 2010 and 2018. The firm-level database represents the diverse and rich sample of firms across different sectors of economic activities. The analysis includes firms from different sectors of R&D intensity based on the OECD taxonomy. The list of sectors can be seen in Appendix C. The total number of observations for the firm-level database was 12.4 million. All the time-variant variables (Fixed assets, Total assets, Turnover, Cost of goods, EBITDA, Added Value, Material Cost) were transformed into the real variables using the PPI deflator for each sector at 2-digit NACE code. The real variables were retransformed into the log variables. We then trim the top and bottom 1% of the real log variables.

Also, we add to the database the concentration index, calculated as the market share of the top four firms (by turnover) for each sector (based on 4-digit and 2-digit NACE rev.2) each country and across the whole of Europe. At the same time, the original Value-added

[5] As discussed in the literature review of innovation ecosystems, relations within ecosystems consists of competition, collaboration within supply chain, interactions with customers, and other stakeholders. However, due to data constraints, we only can explore the former dimension of relations.

variable from Amadeus had a large number of missing observations (93.8%). It was replaced by the new value-added variable that was constructed as EBITDA plus cost of employment.

For the factor analysis, we use the EU KLEMS dataset that provides capital formation and labour measures at the industry level for all EU member states. The following variables were constructed using the original KLEMS data:

- Share of Computer software and databases in GFCF, volume 2010 ref.prices, NAC mn;
- Share of Computer software and databases in Capital stock net, volume 2010 ref.prices, NAC mn;
- Share of Computing Equipment in Capital stock net, volume 2010 ref.prices, NAC mn;
- Share of Computing Equipment in GFCF, volume 2010 ref.prices, NAC mn;
- Share of Hours Worked of Male with high educated;
- Share of Hours Worked of Female with high educated;
- Share of Hours Worked of Male with medium educated; Share of Hours Worked of Female with medium educated;
- Share of R&D in Capital stock net, volume 2010 ref.prices;
- Share of R&D in GFCF, volume 2010 ref.prices, NAC mn.

The descriptive statistics of these variables can be found in Appendix A.

We use a three-fold methodological approach to address the research question.

First, we employ a k-means algorithm to cluster firms into groups based on a set of firm characteristics defining its capabilities as outlined in Table 1 ‘Firm-level capabilities’ and Appendix A.

Second, using factor analysis at a sector-country level and based on cross-sector cross-country cross-time sample to identify the core pillars of the sectoral innovation ecosystems, using the framework reported in Table 1 ‘Sector-level capabilities’ and Appendix A.

Finally, we employ panel data techniques to explore performance differences across firm genotypes (capability profiles) identified in section 3.2, and the complexity of interactions between and sectoral pillars of the innovation ecosystem in further affecting productivity (section 3.3.).

3.2 Firm Clustering analysis

The firm-level database collected and checked on quality/representativeness (Bruno et al., 2020) for this paper includes an ample variety of the EU firms spanning from manufacturing to service, from South countries to technological leaders in the North[6]. We explore this heterogeneity through firm-level clustering analysis (e.g. Costa et al.., 2021). Such analysis entails a thorough consistency check across different dimensions and a clear step-by-step roadmap into a theory-based classification. These steps are unfolded below.

Firstly, we have identified the six dimensions upon which such heterogeneity should be gauged and measured. These components or dimensions of the capability profile of individual firms are accumulated capabilities; the scale of capabilities; organisational capabilities; international organisational capabilities; accumulated physical capital or capital intensity; and labour capabilities or intensity. Each of these dimensions of capabilities is proxied by a specific (set of) variables: age for accumulated capabilities; the number of employees for the scale of capabilities; the number of subsidiaries for organisational capabilities; the number of foreign subsidiaries for international organisational capabilities; fixed to total assets ratio for accumulated physical capital or capital intensity. To measure labour capabilities or intensity, we use three measures: wage bill as a share of value-added, fixed assets and material costs. In summary, we use eight clustering variables to capture different dimensions of firms' 'capability profiles'. These variables tend to follow a log-normal distribution. Therefore, we use the standardised (mean 0, SD 1) version of their log-normal transformation (based on constant prices and the same unit of measure, thousands of Euros).

Secondly, we make the selection of the clustering procedure. Between the K-means procedure and hierarchical models, we choose K means, which is less affected by outliers and can be used for very large datasets as ours (Mooi et al., 2018). However, an exploratory "hierarchical analysis" (Ward link) does not need to pre-specify the number of clusters. Therefore, we have used the hierarchical method to choose the number of clusters for the

[6] We analyse a period in which the United Kingdom was still a member, hence it is included in the analysis.

next step with the K-means. We choose the 5 clusters solution as a fair reflection of the heterogeneity of eight clustering variables.

Third, once the clustering procedure has been selected, a measure of similarity (dissimilarity) is needed. We opt for the squared Euclidian distance (Mooi et al., 2018), one of the most reliable measures used in the literature.

Finally, we have validated and interpreted the clustering solution by checking the correspondence between the clustering variables means/median and overall distribution within their respective groupings. The whole set of results is presented in section 4.

3.3 Sectoral Factor analysis

To identify the interrelationships within the sectoral-level variables inside each pillar (see Appendix A for a list of variables used for constructing each pillar), we conducted the factor analysis. Before the analysis, the dataset was checked to meet the requirements for the factor analysis. Primary, we had to check that observations are independent and, at the same time, variables are sufficiently correlated. For that purpose, the Bartlett test and Kaiser-Meyer-Olkin Measure of Sampling Adequacy test was used. All the results pass the Bartlett test of sphericity (H0: variables are not intercorrelated is rejected) and Kaiser-Meyer-Olkin Measure of Sampling Adequacy test (a test statistic is higher than a threshold of 0.5). The results can be found in the table below.

Table 2: Summary of diagnostic tests: a factor analysis

	Pillar 1 **Digital Capabilities**	Pillar 2 **Human Capital Capabilities**	Pillar 3 **Innovation (R&D) Capabilities**	Pillar 4 **Tangible Capital Capabilities**
Bartlett test of sphericity p-value	0.000	0.000	0.000	0.000
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.551	0.650	0.665	0.529

In the next step, to identify if the factor within each pillar exists, the factor analysis is applied for each pillar. To determine the number of factors to extract, we apply the traditional Kaiser criterion to extract all factors where Eigenvalue is bigger than one. Results show that each pillar has a single factor.

The next step is to evaluate the goodness of fit of the factor solution. To check this, we examined the raw residuals of correlations. We made sure that the percentage of correlations with absolute values larger than 0.05 is less than 50% in the correlation matrix. At the same time, it was essential to check the uniqueness of the variables used for the factor analysis within each pillar. The uniqueness of the variables that determine the factor should not be higher than 0.50. Both conditions were satisfied for each sectoral level capabilities group.

After the factor analysis, the factor scores are computed for further usage in the regression model to test the impact of sectoral innovation ecosystem pillars.

3.4 Regression analysis

The exploratory analysis enables the generation of new variables, which we use in a panel regression analysis. The availability of a rich longitudinal dataset allows us to take advantage of the combination of clustering (section 3.2) and factor analysis (section 3.3) in the same analytical framework. This combination enables to test how the business environment impacts firm-level performance measures like labour productivity. The initial specification of the model is, therefore, the following (robust clustered SE):

$$VA/L_{isct}=\alpha+\beta_2(Cluster_2) +\beta_3(Cluster_3) +\beta_4(Cluster_4) +\beta_5(Cluster_5) +\phi_i+\varepsilon_{isct} \quad (1)$$

where VA/L is the natural logarithm of labour productivity in constant thousands of euros for each firm i at time t. Clusters are the respective dummies (omitted cluster 1), and $\phi_i+\varepsilon_{isct}$[7] are the random components of the longitudinal data (capturing correlation between the errors in the observation of the same firm) and the idiosyncratic error for firm i, sector s, country c at time t, respectively.

Next, we extend the model with the first component of each pillar of the factor analysis:

$$VA/L_{isct}=\alpha+\beta_2(Cluster_2) +\beta_3(Cluster_3) +\beta_4(Cluster_4) +\beta_5(Cluster_5) + \gamma_1(\text{Digital-Factor}) + \gamma_2(\text{Human-Capital Factor}) + \gamma_3(\text{R\&D-Factor}) + \gamma_4(\text{Capital-Factor}) +\phi_i+\varepsilon_{isct} \quad (2)$$

[7] A FE model cannot be estimated, due to the perfect collinearity with the clusters' variables. This is why we include a wide range of controls at the firm level and country sector and time FE.

Then we explore complementarities between factors by expanding each pair of the interaction of the four pillars above and beyond the direct effect:

VA/L_{isct}=α+β_2($Cluster_2$) +β_3($Cluster_3$) +β_4($Cluster_4$) +β_5($Cluster_5$)+ γ_1(Digital-Factor) + γ_2(Human-Capital Factor) + γ_3(R&D-Factor) + γ_4(Capital-Factor)+ γ_{12}(Digital-Factor) (Human-Capital Factor) + γ_{13} (Digital-Factor) (R&D-Factor)+ γ_{14}(Digital-Factor) (Capital-Factor) + γ_{23} (Human-Capital -Factor) (R&D-Factor)+ γ_{24} (Human-Capital -Factor) (Capital-Factor)+ γ_{34} (R&D-Factor) (Capital-Factor)+ϕ_i+ε_{isct}(3)

In the last specification, we add three groups of control variables: at the firm level $\mathbf{X_{isct}}$, at the sector level (concentration) $\mathbf{Z_{sct}}$ and **fixed effects** for country, sectors and years.

VA/L_{isct}=α+β_2($Cluster_2$) +β_3($Cluster_3$) +β_4($Cluster_4$) +β_5($Cluster_5$)+ γ_1(Digital-Factor) + γ_2(Human-Capital Factor) + γ_3(R&D-Factor) + γ_4(Capital-Factor)+ γ_{12}(Digital-Factor) (Human-Capital Factor) + γ_{13} (Digital-Factor) (R&D-Factor)+ γ_{14}(Digital-Factor) (Capital-Factor) + γ_{23} (Human-Capital -Factor) (R&D-Factor)+ γ_{24} (Human-Capital -Factor) (Capital-Factor)+ γ_{34} (R&D-Factor) (Capital-Factor) + $\mathbf{\Pi X_{isct}}$ + $\boldsymbol{\theta}$ $\mathbf{Z_{sct}}$ + $\tau_{country}$ + τ_{sector} + τ_{year} +ϕ_i+ε_{isct}(4)

$\mathbf{X_{icst}}$ group comprises age, size, the number of subsidiaries, and the number of foreign subsidiaries; $\mathbf{Z_{sct}}$ includes concentration at the country level and EU level at 2-digits sectors level.

4. Firm genotypes (capability profiles) and productivity patterns

4.1 Genotypes (capability profiles)

Cluster analysis (explained in section 3.2) gives us five clusters: Small labour-intensive firms; Small size capital Intensive firms; Medium size domestic firms; Medium size Foreign firms; and, Large Multinationals.

Table 3 shows the number of observations available in the database as firm-year pairs. This table gives us information on the robustness of the procedure, i.e., a high number of observations identifying a single cluster and the proportion of firms in each cluster. Overall, around 28% of the firm-year pairs are “small, labour-intensive firms”, 9% belong to cluster “small capital-intensive firms”, 46% are in the cluster “medium-size domestic firms”, and 13 % “medium-size foreign firms” and 4% “large MNE”.

Table 3 The number of observations used by the K-Means method to determine the cluster

Clustering	Firm-year pairs	%
Small Labour intensive	163951	28%
Small capital intensive	55533	9%
Medium Domestic	276158	46%
Medium Foreign	74670	13%
Large MNE	25051	4%
Total	595363	

Our labelling of clusters comes from the data in tables 4, 5 and 6. Table 4 reports the mean of each clustering variable in each classification. Cluster 1 is composed of relatively small and young firms of relatively low capital intensity. These are companies with a high human component and a very low capital intensity. Hence the name “small labour intensive”. Cluster 2 has larger and older firms than cluster 1, and firms are of higher capital intensity. Therefore, we define them as “small capital intensive” firms. Firms in cluster three are larger than in clusters 1 and 2 but are still domestic-oriented (on average, they have no foreign subsidiaries). This does not mean that they are not exporting, but they do not have a direct foreign market presence. These “Medium-sized Domestic firms” are much larger domestic-oriented companies, being in existence on average for 21 years. Next cluster is composed of firs of increased size compared to clusters 1,2, and 3 and have a direct international presence, though not on average substantial. We label them “Medium-sized Foreign firms”. The fifth cluster comprises the biggest companies, which are highly internationalised as they have on average 8.2 foreign subsidiaries. We label them “Large MNEs”.

Tables 5 and 6 show clusters based on the median statistic (to remove the impact of outliers) or the whole distribution (laggards 25%, 50%, 75%, frontier). These additional statistics justify the labelling of the clusters.

Table 4 Mean of Clustering variables by classified clusters

	Size	Age	Wage Ratio	Lab Fixed Ass Ratio	Lab Material Cost Ratio	Capital Intensity	# total Sub	# For Sub

Small Labour intensive	29	18	1.05	11.15	1.38	0.14	0.09	0.0
Small capital intensive	52	14	1.02	31.04	138.11	0.22	0.24	0.0
Medium Domestic	68	21	0.69	0.65	1.19	0.50	0.17	0.0
Medium Foreign	272	28	0.76	1.88	9.84	0.41	3.66	0.3
Large MNE	1153	31	0.88	2.06	46.67	0.38	15.95	8.2
Total	127	21	0.83	6.59	17.01	0.36	1.26	0.4

Table 5 Median of Clustering variables by classified clusters

	Size	Age	Wage Ratio	Lab Fixed Ass Ratio	Lab Material Cost Ratio	Capital Intensity	# total Sub	# For Sub
Small Labour intensive	17	16	0.83	3.60	0.75	0.12	0	0
Small capital intensive	21	12	0.88	6.61	34.82	0.14	0	0
Medium Domestic	28	19	0.68	0.48	0.52	0.49	0	0
Medium Foreign	66	22	0.69	0.55	0.51	0.39	2	0
Large MNE	186	25	0.71	0.64	0.51	0.36	6	3
Total	26	18	0.75	0.97	0.67	0.33	0	0

Table 6. 25% 50%(Median) and 75% of Clustering variables by Classified clusters

		Size	Age	Wage Ratio	Lab Fixed Ass Ratio	Lab Material Cost Ratio	Capital Intensity	# total Sub	# For Sub
Small Labour intensive	25%	13	8	0.69	2.00	0.37	0.06	0	0
	50%	17	16	0.83	3.60	0.75	0.12	0	0
	75%	30	25	0.92	7.69	1.61	0.20	0	0
Small capital intensive	25%	14	6	0.77	2.25	17.25	0.05	0	0
	50%	21	12	0.88	6.61	34.82	0.14	0	0
	75%	43	20	0.95	19.50	84.38	0.33	0	0
Medium Domestic	25%	15	12	0.51	0.24	0.25	0.35	0	0
	50%	28	19	0.68	0.48	0.52	0.49	0	0
	75%	63	26	0.82	0.88	1.13	0.64	0	0
Medium Foreign	25%	27	14	0.52	0.22	0.23	0.21	2	0
	50%	66	22	0.69	0.55	0.51	0.39	2	0
	75%	194	35	0.83	1.38	1.44	0.59	4	1
Large MNE	25%	66	15	0.56	0.30	0.27	0.21	3	2
	50%	186	25	0.71	0.64	0.51	0.36	6	3
	75%	576	39	0.84	1.43	1.13	0.52	11	6
Total	25%	15	10	0.57	0.37	0.30	0.15	0	0
	50%	26	18	0.75	0.97	0.67	0.33	0	0

	75%	63	26	0.88	2.92	1.90	0.54	1	0

4.2 Unconditional mapping of phenotypes

Section 4.1 gave us first insights into profiles of firms which resulted in five genotypes or capability profiles. We consider the performance of firms as their phenotype characteristics, and in this section, we report the average performance of each cluster. For this, we use four measures: Value added (constant prices), Value added per worker (constant prices), Profitability (share of EBIDTA in sales), Profit margin (share of sales cost of goods sold in sales).

The value-added of the five clusters are ranked according to their size (Table 7). As expected, value-added (VA) is disproportionally increasing from cluster 1 to cluster 5. For example, cluster 5 companies have a value-added that is 50 times the VA of cluster 1. The first three clusters are very close in terms of labour productivity, but productivity grows by 1.5 and then over 2 for clusters 4 and 5. In profitability, cluster five outperforms all others (probably due to concentration), while profit margins (less affected by financial returns) are pretty close for all five clusters. These initial insights into performance by clusters are valuable but still descriptive. The regression analysis which we report in section 6 will shed further light on the intertwined relationship between clusters, innovation ecosystems and market structure (e.g. concentration).

Table 7 Mean values of Value Added, VA/employment, Profitability and Profit Margin by Classified clusters

	Value Added (const Prices 1000 Euros)	Value added per employees (const Prices 1000 Euros)	Profitability	Profit Margin
Small Labour intensive	1340.30	43.06	0.034	0.446
Small capital intensive	2094.09	42.43	0.008	0.700
Medium size Domestic oriented	2946.32	44.33	0.048	0.732
Medium Foreign oriented	16017.16	70.65	0.009	0.741
Large MNEs	68022.36	93.82	1.355	0.541
Total	6261.48	48.81	0.081	0.682

5. Identifying sectoral ecosystem pillars

As discussed in the methodology section 3.3, we employed factor analysis to identify a latent structure behind a set of sectoral-level innovation ecosystem variables listed in Appendix A. After performing several tests, we obtained four factors underlying the four pillars of the sectoral innovation ecosystems**:**

Pillar 1 - ***Digital Capabilities*** (defined via a single factor based on intangible digital technology indicators;

Pillar 2 - ***Human Capital Capabilities*** (defined via a single factor based on the share of hours worked of both male and female with tertiary education);

Pillar 3- ***Innovation (R&D) Capabilities*** (defined via a single factor based on R&D indicators);

Pillar 4 – ***Tangible Capital Capabilities*** (defined via a single factor based on 'machinery and equipment assets' share in net capital stock).

All four pillars clearly distinguish sector-level capabilities presented in Table 1, which suggest that sector-level capabilities may be significant determinants of firm performance. Figure 1 shows the ranking of the top five sectors by factors with a cut-off point of one or greater. Appendix C describes all NACE (Rev2) sectors employed in this study, and Appendix D shows a full ranking for all the sectors.

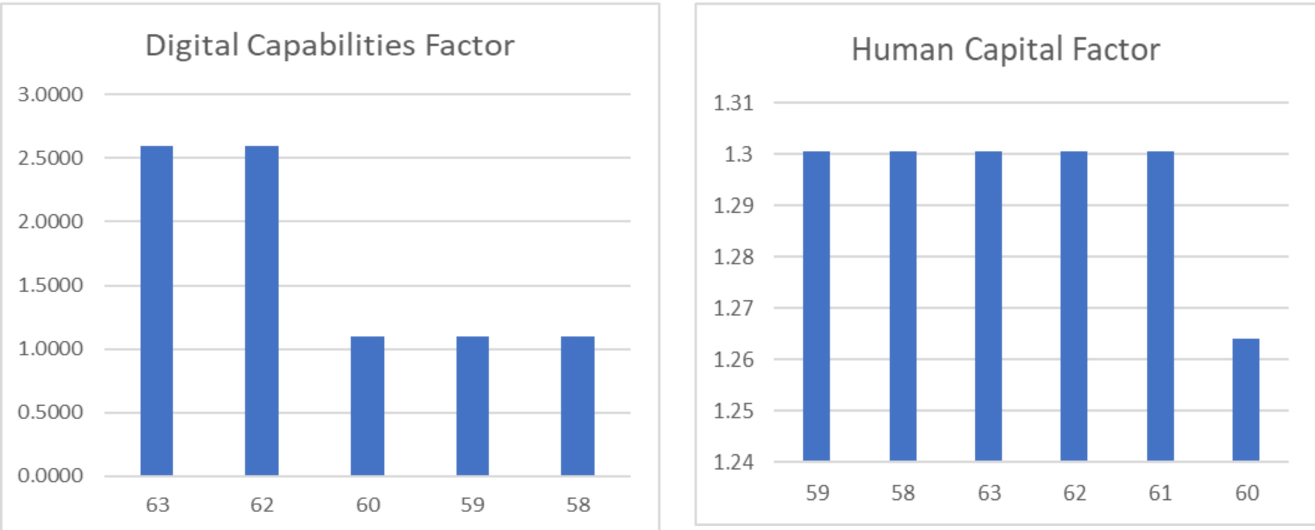
Figure 1 shows that within Pillar 1 '*Digital Capabilities'*, the 'Information and Communication' sectors (63, 62) score the highest. Similarly, ICT sectors load the highest on Pillar 2 'Human Capital Capabilities'. Pillar 3 '*Innovation (R&D) Capabilities'* primarily encompasses high-tech R&D intensity sectors, including 26 'computing manufacture'; 21 'manufacture of pharmaceutical products'; 27 'electrical equipment', and medium-high R&D intense sectors - 29 'moto vehicles', and 30 'Manufacture of other transport equipment, and 28 'Machinery'[8]. Within Pillar 4 '*Tangible capital capabilities* (Other machinery and equipment)', we primarily have medium-low or low-R&D intense manufacturing (manufacture of basic metals and metal products; wood; paper products and food manufacture).

These sectoral associations with the identified four pillars of sectoral innovation ecosystems align well with theoretical insights and intuition. Appendix E presents factor

[8] Rankings follow the OECD taxonomy of economic activities based on R&D intensity of sectors https://inovasyon.gen.tr/images/Haberler/OECDTaxonomyofEconomicActivitiesBasedonRDIntensity2016.pdf

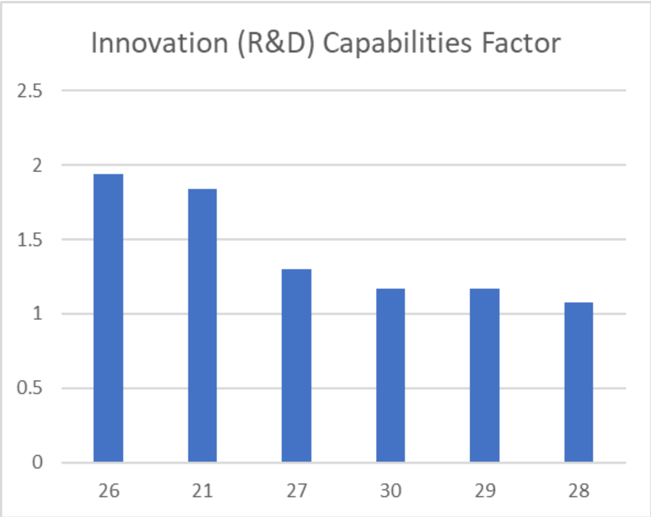
correlation scatterplots by countries, revealing leading and lagging EU economies based on their sectoral capabilities and correlation patterns. Thus, we observe a positive correlation between digital, human capital capabilities and innovation capabilities. There is a higher reliance on tangible capital (machinery and equipment) intensity where human capabilities are low. Among our sample of the EU countries, France emerges as a leading economy in digital and innovation capabilities. This may seem quite controversial given that France is ranked in the middle of the EU regarding the digital economy and society index (DESI)[9]. Also, France is not doing well regarding internet usage and broadband connection speeds. Yet, our data are confined to the business sector, where French companies are doing better when compared to the digitalisation of society. Sweden and Finland are leading in terms of R&D capabilities, but the Finnish economy remains less digitalised. Italy and Germany's economies are more capital intensive and with Germany positioning stronger in high-tech manufacturing. Finally, despite all the recent progress Estonia has made in becoming a digital economy, this seems to be more the trend in the public sector than private, which exhibits low digitalisation trends as evidenced from Appendix E[10].

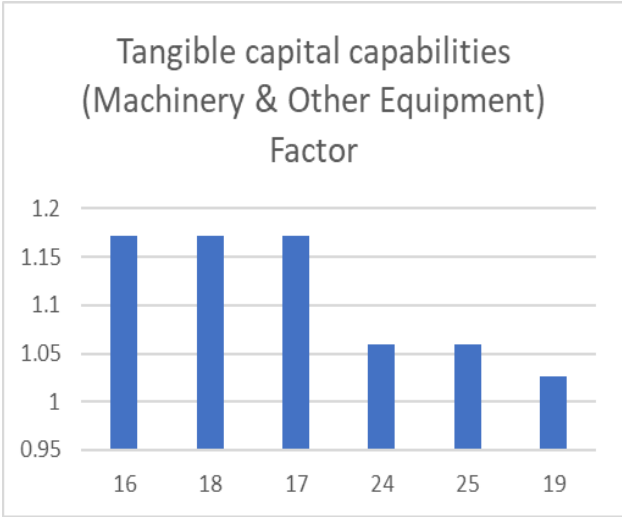
Figure 1: Factor ranking by sectors



[9] https://digital-strategy.ec.europa.eu/en/policies/desi-france

[10] For supporting evidence see also ESPON (2020) T4 – Territorial Trends in Technological Transformations, Applied Research, Final Report, EC Available at https://www.technopolis-group.com/wp-content/uploads/2021/06/ESPON_Final_Report.pdf





Source: KLEMS, 2010-2018 sector averaged

6. Productivity determinants: an empirical analysis

In this section, we report results of panel regression analysis based on different specifications, especially at how the patterns of labour productivity change for different specifications.

Table 8 shows results for the baseline random effect specification (column 1) with only clusters dummies. We then report the results of the augmented model with the "direct" effect of each of the factors (2) and with added pairs of interacted factors (dyadic complementarities effects) (3) Finally, the results with the complete set of controls for age, size, organisation, market concentration and fixed effects dummies (country, sector, and year) are reported in column 4.

6.1 Firms genotypes and productivity

The first regression explores a panel RE model where the only independent variables are the dummies for the clusters. The omitted category is cluster 1. We cannot read much into this baseline specification, given the broadly unconditional nature of such specification. However, we note a natural ranking between the first three clusters (similar to labour productivity) and the other two. Then we augment the analysis by adding different dimensions of innovation ecosystems pillars. The coefficients for three out of four clusters are significant and positive. However, coefficients are lower than in the baseline specification as the model's explanatory power has shifted to innovation ecosystems pillars, all significant and positive. As far as the clusters are concerned, the ranking in terms of labour productivity emerges as a stylised fact, even if the "superiority" of the fifth cluster is reduced when we add more controls.

Innovation ecosystems pillars are significant and positive in models with clusters and with interaction terms. Moreover, the size of coefficients for human capital and R&D are the highest in the model of interactions among pillars. However, interaction terms generate two positive, three negative and one insignificant interaction. Positive interaction between digitalisation and R&D pillar and between R&D and tangible capital investments suggest that complementary investments between these types of capabilities are essential to increased productivity. Negative signs of interactions between human capital and digitalisation, human capital and R&D, and digitalisation and tangible investments shows that this is not the right portfolio or composition of capabilities for improved productivity. This suggests that the EU faces challenges in coordinating these investments across firms, industries and countries. However, this would be misleading as we do not control for a range of firm and market-specific variables in this specification. Sectoral innovation ecosystems pillars do not operate independently but through the organisational fabric of the firm organisation and market structure.

Indeed, once we control for firm and market structure factors, the picture changes radically. Coefficients for sectoral innovation ecosystem pillars that were positive now become negative while all interaction terms become significant positive. This shows that pillars or sector level types of capabilities on their own do not impact labour productivity independently of the firm and market-specific factors. Only when we consider the firms' organizational capabilities and their market structure can we assess the impact of sector and firm-level capabilities on productivity. The main message from our most robust regression is that investment in specific types of capabilities can affect productivity only when they are complementary to other types of capabilities. Alternatively, individual types of investments on their own are never sufficient for increased productivity. However, complementarities are highly conditional on the organisational capabilities of firms and their market structure[11].

Among firm-level variables, firms' organisational capabilities are reflected in the number of local subsidiaries and their foreign presence. Also, it can be presumed that older firms have more developed organisational capabilities. Both these variables are positively associated with productivity, while size as the proxy for the capabilities scale is negatively associated with productivity. This corroborates well with the negative impact of high

[11] We are aware that market structure for many firms is not exogenous but endogenous variable. We will try to address this methodological issue in further research.

concentration in national markets on productivity. A market concentration at the EU level is not significant.

Table 8 Longitudinal data regression on clusters and factors: accounting for complementarities in innovation ecosystems

VARIABLES	(1) Baseline	(2) Factors	(3) Complementarities	(4) Complementarities (with Controls)
2 Small Capital Intensive	-0.042***	0.004	0.020**	0.073***
	(0.009)	(0.008)	(0.008)	(0.008)
3 Medium Domestic	-0.023***	0.161***	0.174***	0.177***
	(0.007)	(0.007)	(0.007)	(0.007)
4 Medium Foreign	0.605***	0.475***	0.465***	0.245***
	(0.010)	(0.009)	(0.009)	(0.013)
5 Large MNE	0.922***	0.530***	0.525***	0.243***
	(0.013)	(0.014)	(0.013)	(0.029)
Digital		0.041*	0.621***	-0.667***
		(0.025)	(0.050)	(0.077)
Human Capital		1.086***	2.099***	-0.363***
		(0.024)	(0.083)	(0.113)
R&D		0.750***	1.100***	-0.351***
		(0.022)	(0.062)	(0.077)
Tangible Capital		0.221***	0.266***	-0.068
		(0.020)	(0.038)	(0.047)
Digital # Human Capital			-1.547***	0.328***
			(0.092)	(0.106)
Digital # R&D			2.067***	0.545***
			(0.138)	(0.165)
Digital # Tangible Capital			-0.666***	0.756***
			(0.101)	(0.117)
Human Capital # R&D			-3.369***	0.672***
			(0.153)	(0.183)
Human Capital # Tangible Capital			0.085	0.060
			(0.116)	(0.134)
R&D # Tangible Capital			0.876***	-0.236***
			(0.072)	(0.086)
LN Size				-0.159***
				(0.005)
LN # foreign sub				0.082***
				(0.015)
LN # total subsidiaries				0.153***
				(0.008)
LN Age				0.184***
				(0.004)
Concentration index 2dig				-0.082***
				(0.018)
Concentration index EU 2dig				0.027
				(0.041)
Constant	3.355***	3.137***	2.836***	4.194***
	(0.005)	(0.021)	(0.032)	(0.054)
Observations	516,292	244,566	244,566	244,566
Number of id	94,532	49,285	49,285	49,285
Country FE	NO	NO	NO	YES
Sector FE	NO	NO	NO	YES
Year FE	NO	NO	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.2 Pillars of sectoral innovation ecosystems: direct and interaction effects

We find a positive and significant direct effect of all four sector innovation ecosystem pillars on firms' productivity (Table 8, column 2). However, unlike with the other three pillars, this effect is marginal in digital capabilities. Also, the interaction effects between pillars (except digitalisation and R&D which remain positive) turns from negative into positive once we control for firm and market variables. The interaction is quite a significant and policy-relevant result of the analysis, which we further explore (Appendix G).

Among the most relevant insights, we note the following. First, the interaction between human capital and digital capabilities shows that human capital enhances the impact of digital capabilities (DCs) on productivity but only up to the 50th centile of DCs' distribution. At the same time, lack of human capital reduces the effect of DCs on productivity. These results point to a non-linear and uni- or bi-directional relationship between different types of investments. It suggests that the highly educated labour force coupled with DCs has a labour productivity-enhancing effect up to some level of DCs (Figure G1). On the other hand, DCs do not seem to be a pre-condition for human capital to drive productivity, as evidenced in Figure G2. Alternatively, a specific level of human capital is the precondition for increased labour productivity.

Second, DCs coupled with R&D investments are essential to productivity growth, but this effect takes place only at a higher level of R&D distribution (above 50th centile) (Figure G4). This indicates the importance of digital capabilities in R&D intense environments, which, following our analysis presented in section 5, are primarily high-tech intense manufacturing sectors, including computing, pharmaceuticals and electronic products. This also suggests that the impact of DCs or R&D on their own may be quite limited. The strong effect emerges when both levels of investments are high in relative terms.

Third, the strongest complementarities are between digital capabilities and investment into tangible capital, which is likely to be associated with Information and Communication Technologies needed for digital capabilities, measured as software and databases (i.e. intangibles) to influence productivity (Figure G5) positively. This complementarity effect is reciprocal, given the crucial supporting role DCs play in enhancing the impact of tangible capital on growth (Figure G6). However, this effect is the strongest at either lower or higher levels of tangible capital distribution, suggesting that DCs work as essential bedding for tangible capital to sprout or reinforce its effect on productivity in fixed assets intense industries (Figure G6).

Fourth, we observe a substituting effect between innovation (R&D) and human capital (Figures, G7-8). Human capital is measured as the share of hours worked by males and females with higher education. A substituting effect suggests that in R&D intense environments, we observe a possible replacement of highly-qualified labour with machines and automated processes. This trend was previously observed primarily among blue-collar workers, but based on these results, it appears to be the case among white-collar workers too.

Fifth, there is a substituting effect between tangible capital investment and innovation capabilities (Figure G10) which is in line with our earlier research on disjoined face of disembodied and embedded R&D (Bruno et al., 2021).

Sixth, we find some complementarity between human capital capabilities and tangible capital capabilities, with the former supporting the latter for increasing productivity.

7. Conclusions

This working paper builds on our earlier work on sectoral patterns of innovation and productivity between SMEs and larger firms. In this study, we explore how the external environment (broadly defined by the innovation ecosystem surrounding a company) influences firm performance, depending on their size and age and, more importantly, on their resources, scaling, and organisational capabilities. To answer this research question, we construct a sizeable firm-sector-country panel data for 2010-2018, using Amadeus and KLEMS datasets.

The literature suggests that firms' behaviour and performance are influenced by a combination of factors that work individually and interactively in shaping firms' strategies and decision-making on allocating scarce resources (Lafuente et al. 2019). Respectively, we ground our analysis of firm performance within the innovation systems framework. We see firms as key actors of this system. Using a clustering approach, we group them further by common features based on their use of labour and capital resources, scaling capabilities, and scope for their market operation. Altogether we identify five clusters of firms that share not only common capabilities but also performance profiles. By embedding our analysis further into sectoral innovation ecosystems, we study the importance of the direct effects of core pillars of sectoral innovation on firm productivity and the interplay between these pillars.

Our findings suggest that small labour or capital-intensive firms are least productive and that productivity gain increases with a rise in firms' scalability and resource capabilities. When we control for fixed effects at sector, country and year levels, the differences between top and middle clusters (categories 3-5) are reduced. Second, each of the four pillars of sector-level innovation ecosystem ((i) digital capabilities; (ii) human capabilities; (iii) innovation capabilities, and (iv) tangible capital capabilities) has a positive and significant effect on firm performance. However, the direct effect of digital capabilities is weaker compared to the effect of other capabilities. This confirms intuition and results from the literature that digital investments without complementary investments are not a solution to increased productivity. By analysing pairwise interactions between these four pillars, we discover some critical complementarities.

Our results suggest strong complementarities between digital capabilities (software and databases) and investment in fixed capital (tangibles) in enhancing productivity, with the latter being instrumental specifically for DCs affecting growth. This suggests that having ICT and other physical investments is essential for DCs to increase productivity. This is interesting when interpreted jointly with the direct effect of digital capabilities, which was only marginally statistically significant. Also, DCs are a pre-condition/or accelerator for tangible capital to enhance productivity. This is the case in industries with low tangible capital intensity (e.g. services sector) and high tangible capital intensity (wood, paper, food and metal manufacturing).

We also find some crucial complementarities between digital capabilities and human capital, although only up to the median point of human capital capabilities distribution, so in less-intense HC industries, and the beneficial effect of digital capabilities in high-tech intense industries. The latter emphasizes the earlier argument by Berlingieri, 2020, of observing the breakdown of the innovation diffusion machine across the EU economies. The benefits of digital capabilities may not accrue equally to all sectors despite the widely encompassing trend towards digitalisation across the EU. It is essential also to put some ICT infrastructure in place for other industries to also reap the benefits from digitalisation.

Among some limitations of our study, it is worth highlighting the following. Industrial ecosystems continuously evolve due to the emergence of new processes, decline of mature industries or their transformation – the processes driven primarily by market dynamics. A longer period is needed to study such dynamics. The transformation process involves different types of structural traverses underlined by complex and dynamic interdependencies

(Andreoni, 2017). Still, these are best captured at a product level and firm linkages within the value chain, which are not observable in the accounting data.

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Appendix A: Descriptive statistics and definitions of explanatory factor/cluster variables, controls and dependent variables

Variable	Definition	Mean	S.D.
Sector-level structure component variables and factors			
sh_iq_comp_soft_db	Share of Computer software and databases in GFCF, volume 2010 ref.prices, NAC mn (Source: KLEMS)	0.13	0.16
sh_kq_comp_soft_db	Share of Computer software and databases in Capital stock net, volume 2010 ref.prices, NAC m (Source: KLEMS)	0.06	0.011
sh_kq_comput_equip	Share of Computing Equipment in Capital stock net, volume 2010 ref.prices, NAC m (Source: KLEMS)	0.01	0.02
sh_iq_comput_equip	Share of Computing Equipment in GFCF, volume 2010 ref.prices, NAC mn (Source: KLEMS)	0.04	0.09
sh_hrs_male_uni_edu	Share of Hours Worked of Male with high educated (Source: KLEMS)	16.81	10.80
sh_hrs_female_uni_edu	Share of Hours Worked of Female with high educated (Source: KLEMS)	9.22	6.57
sh_hrs_male_interm_edu	Share of Hours Worked of Male with medium educated (Source: KLEMS)	34.72	13.09
sh_hrs_female_interm_edu	Share of Hours Worked of Female with medium educated (Source: KLEMS)	16.47	8.08
sh_kq_rnd	Share of Research and development in Capital stock net, volume 2010 ref.prices, (Source: KLEMS)	0.12	0.13
sh_iq_rnd	Share of Research and development in GFCF, volume 2010 ref.prices, NAC mn (Source: KLEMS)	0.16	0.15
sector_rd_as_perc_total_assets	R&D as % of Total Assets (Source: Eurostat)	0.17	0.14

sh_kq_other_equip	Share of Other Machinery and Equipment in Capital stock net, volume 2010 ref.pri	0.38	0.19
sh_iq_other_equip	Share of Other Machinery and Equipment in GFCF, volume 2010 ref.prices, NAC mn	0.39	0.21
Control variables			
numberofemployees	Number of Employees	122.91	1387.16
subsid	Number of Firm's Subsidiaries.	1.15	15.69
for_subs	Number of Foreign Subsidiaries	0.34	5.18
age		20.83	17.53
concentration_index_2dig	Sector Country Year concentration_index_2dig	0.32	0.20
concentration_index_EU_2dig		0.14	0.05
Dependent variables			
r_ValueAdded_Emp	Labour Productivity as EBITDA plus costs employment on number of employees (PPI Adjusted)	48.81	216.72

Appendix B: Correlation Matrix

	Log of real Value Added on number of employees	Score for Digital Capabilities factor	Score for Human Capital factor	Score for Innovation (R&D) capabilities factor	Score for Tangible capital capabilities : Machinery and other equipment	Cluster Catergory	Log of number of employees	Log of number of foreing subsidiaries	Log of numbr of subsidiaries	Log of age of the firm	Concentration index	Concentration index EU
Log of real Value Added on number of employees	1											
Score for Digital Capabilities factor	0.0713	1										
Score for Human Capital factor	0.2522	0.5988	1									
Score for Innovation (R&D)	0.1726	0.0702	0.2323	1								
Score for Tangible capital	-0.0994	-0.6633	-0.5961	-0.47	1							
Cluster Catergory	0.213	-0.0949	-0.0721	-0.0331	0.0398	1						
Log of number of employees	0.1562	-0.0864	-0.0205	0.1871	-0.0737	0.4682	1					
Log of number of foreing	0.1586	0.0105	0.0257	0.1296	-0.059	0.5441	0.4235	1				
Log of numbr of subsidiaries	0.2484	0.0082	0.0365	0.0089	-0.0461	0.6661	0.4564	0.6834	1			
Log of age of the firm	0.2402	-0.0682	0.0061	0.0957	0.0449	0.2242	0.2109	0.1112	0.1827	1		
Concentration index	0.0945	0.1605	0.1701	0.3057	-0.4502	0.0966	0.1812	0.0744	0.0966	-0.0297	1	
Concentration index EU	0.0772	0.3055	0.2095	0.3151	-0.4395	0.0536	0.1287	0.056	0.0776	-0.0346	0.611	1

Appendix C Description of NACE 2 revision sectors used in this study

Intermediate SNA/ISIC aggregation A*38	Sector Code (2-digit Nace Rev.2 code)	Label	R&D Intensity
Manufacturing (C)			
CA	10	Manufacture of food products	Low
	11	Manufacture of beverages	
	12	Manufacture of tobacco products	
CB	13	Manufacture of textiles	Low
	14	Manufacture of wearing apparel	
	15	Manufacture of leather and related products	
CC	16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	Low
	17	Manufacture of paper and paper products	
	18	Printing and reproduction of recorded media	
CE	20	Manufacture of chemicals and chemical products	Medium-High
CF	21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	High
CG	22	Manufacture of rubber and plastic products	Medium-Low
	23	Manufacture of other non-metallic mineral products	
CH	24	Manufacture of basic metals	Medium-Low
	25	Manufacture of fabricated metal products, except machinery and equipment	
CI	26	Manufacture of computer, electronic and optical products	High
CJ	27	Manufacture of electrical equipment	Medium-High
CK	28	Manufacture of machinery and equipment n.e.c.	Medium-High
CL	29	Manufacture of motor vehicles, trailers and semi-trailers	Medium-High
	30	Manufacture of other transport equipment	
Utilities Industries (D + E)			
D	35	Electricity, gas, steam and air conditioning supply	Low
E	36	Water collection, treatment and supply	Low
	37	Sewerage	
	38	Waste collection, treatment and disposal activities; materials recovery	
	39	Remediation activities and other waste management services	
ICT Services (J)			
JA	58	Publishing activities	Medium-Low

<table>
<tr><td rowspan="2"></td><td>59</td><td>Motion picture, video and television programme production and sound recording</td><td rowspan="2"></td></tr>
<tr><td>60</td><td>Programming and broadcasting activities</td></tr>
<tr><td>JB</td><td>61</td><td>Telecommunications</td><td>Medium-Low</td></tr>
<tr><td rowspan="2">JC</td><td>62</td><td>Computer programming, consultancy and related activities</td><td rowspan="2">Medium-High</td></tr>
<tr><td>63</td><td>Information service activities</td></tr>
<tr><td colspan="4">Professional, Scientific and technical activities (M)</td></tr>
<tr><td rowspan="3">MA</td><td>69</td><td>Legal and accounting activities</td><td rowspan="3">Medium-low</td></tr>
<tr><td>70</td><td>Activities of head offices; management consultancy activities</td></tr>
<tr><td>71</td><td>Architectural and engineering activities; technical testing and analysis</td></tr>
<tr><td>MC</td><td>72</td><td>Scientific research and development</td><td>High</td></tr>
<tr><td rowspan="3">MC</td><td>73</td><td>Advertising and market research</td><td rowspan="3">Medium-Low</td></tr>
<tr><td>74</td><td>Other professional, scientific and technical activities</td></tr>
<tr><td>75</td><td>Veterinary activities</td></tr>
</table>

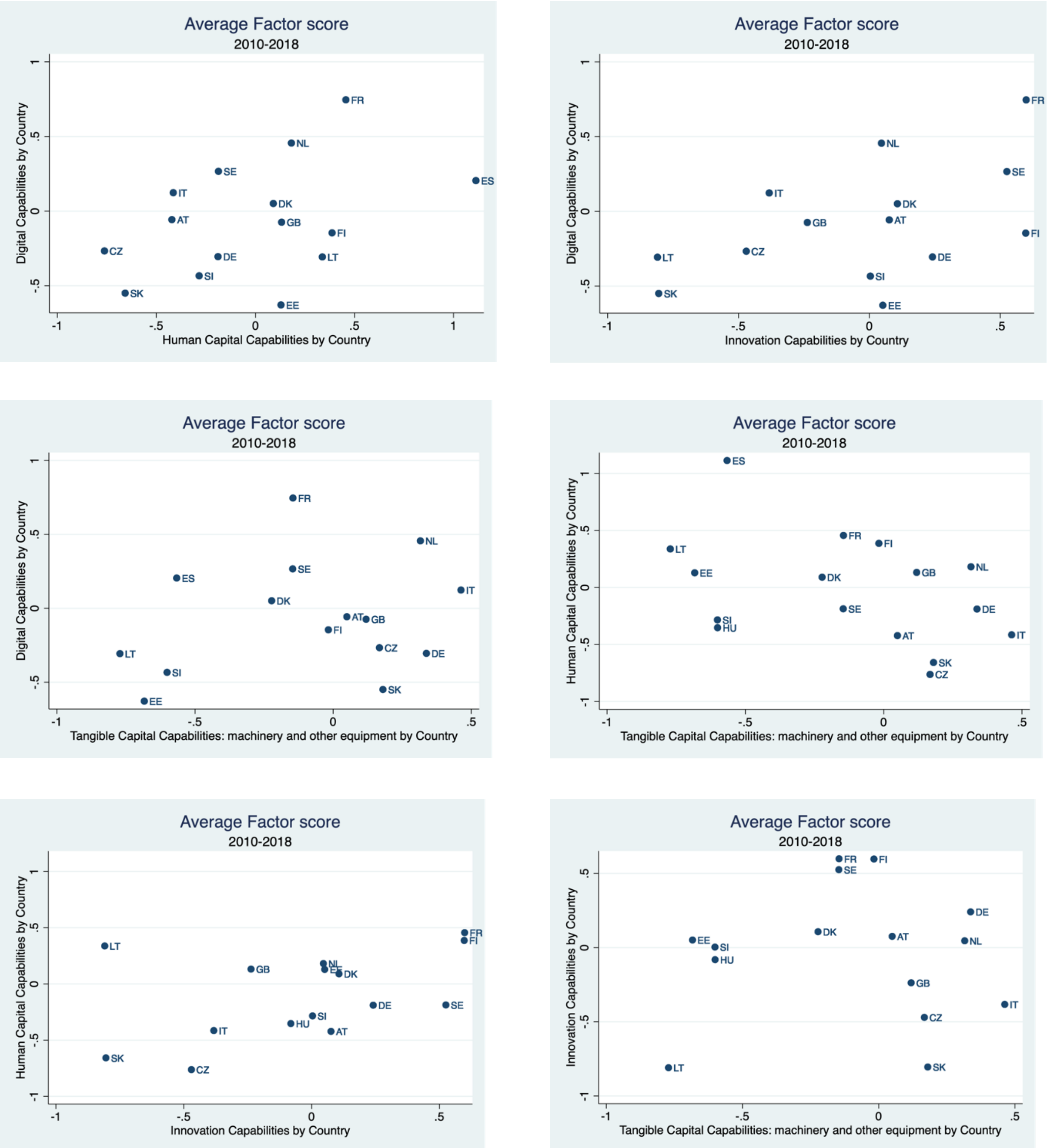
Appendix D Factor rankings by sectors (full listing)

Sector Code	Digital Capabilities Factor Score	Rank	Sector Code	Human Capital Factor Score (Klems data on Labour is aggregated on a NACE 2 dig Macro Level	Rank	Sector Code	Innovation (R&D) Capabilities Factor Score	Rank	Sector Code	Tangible capital capabilities (Machinery) Factor Score	Rank
63	2.595985	1	59	1.300619	1	26	1.937414	1	16	1.172452	1
62	2.595985	2	58	1.300619	2	21	1.838439	2	18	1.172452	2
60	1.094923	3	63	1.300619	3	27	1.296576	3	17	1.172452	3
59	1.094923	4	62	1.300619	4	30	1.172606	4	24	1.05932	4
58	1.094923	5	61	1.300619	5	29	1.172606	5	25	1.05932	5
61	0.2991337	6	60	1.264005	6	28	1.07738	6	19	1.026544	6
26	0.0766545	7	70	0.7532236	7	20	0.4643651	7	10	0.8756415	7
75	-0.0483257	8	75	0.7532236	8	69	0.2918927	8	11	0.8756415	8
73	-0.0483257	9	73	0.7532236	9	71	0.2918927	9	12	0.8756415	9
72	-0.0483257	10	71	0.7532236	10	73	0.2918927	10	23	0.8547464	10
69	-0.0483257	11	69	0.7532236	11	74	0.2918927	11	22	0.8547464	11
71	-0.0483257	12	72	0.7532236	12	75	0.2918927	12	20	0.7495772	12
70	-0.0483257	13	74	0.7532236	13	70	0.2918927	13	15	0.5350245	13
74	-0.0483257	14	35	0.1404122	14	72	0.2918927	14	14	0.5350245	14
28	-0.0806609	15	15	-0.523516	15	62	0.0252951	15	13	0.5350245	15
27	-0.0968092	16	21	-0.523516	16	63	0.0252951	16	30	0.1777942	16
13	-0.1162148	17	12	-0.523516	17	22	-0.0389638	17	29	0.1777942	17
15	-0.1162148	18	13	-0.523516	18	23	-0.0389638	18	35	0.0903991	18
14	-0.1162148	19	24	-0.523516	19	15	-0.181497	19	27	0.0382984	19
30	-0.1824771	20	27	-0.523516	20	13	-0.181497	20	28	0.0146105	20
29	-0.1824771	21	14	-0.523516	21	14	-0.181497	21	21	-0.2466186	21
16	-0.2899933	22	25	-0.523516	22	24	-0.2384844	22	26	-0.4381282	22
18	-0.2899933	23	30	-0.523516	23	25	-0.2384844	23	74	-0.5233256	23
17	-0.2899933	24	17	-0.523516	24	19	-0.3640266	24	71	-0.5233256	24
25	-0.3577537	25	29	-0.523516	25	10	-0.4388875	25	69	-0.5233256	25
24	-0.3577537	26	16	-0.523516	26	11	-0.4388875	26	75	-0.5233256	26
23	-0.3634856	27	22	-0.523516	27	12	-0.4388875	27	73	-0.5233256	27
22	-0.3634856	28	18	-0.523516	28	60	-0.4454366	28	70	-0.5233256	28
10	-0.3653772	29	28	-0.523516	29	58	-0.4454366	29	72	-0.5233256	29
11	-0.3653772	30	23	-0.523516	30	59	-0.4454366	30	39	-0.5606784	30
12	-0.3653772	31	19	-0.523516	31	17	-0.4682482	31	37	-0.5942598	31
21	-0.3911182	32	26	-0.523516	32	18	-0.4682482	32	38	-0.5942598	32
20	-0.4245156	33	20	-0.523516	33	16	-0.4682482	33	36	-0.5942598	33
19	-0.4511025	34	11	-0.523516	34	61	-0.5674574	34	61	-0.8215625	34
35	-0.532764	35	10	-0.523516	35	39	-0.8258737	35	63	-0.8982111	35
39	-0.5460777	36	36	-0.54208	36	38	-0.8261437	36	62	-0.8982111	36
36	-0.5531066	37	37	-0.54208	37	36	-0.8261437	37	58	-0.9799197	37
38	-0.5531066	38	38	-0.54208	38	37	-0.8261437	38	60	-0.9799197	38
37	-0.5531066	39	39	-0.553458	39	35	-0.8296819	39	59	-0.9799197	39

Source: Authors' calculations based on sectoral level KLEMS data[12].

[12] https://euklems.eu/download/

Appendix E: Factor correlation scatterplots by countries



Source: Authors' calculations based on KLEMS data[13].

[13] https://euklems.eu/download/

Appendix G: Interaction effects: a graphical presentation

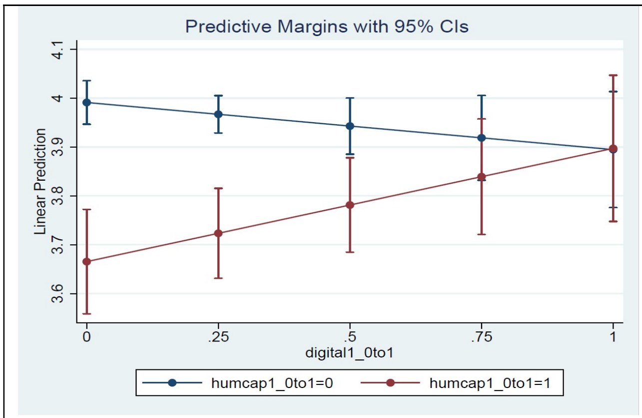


Figure G1: The impact of digital capabilities on productivity conditional on human capital capabilities

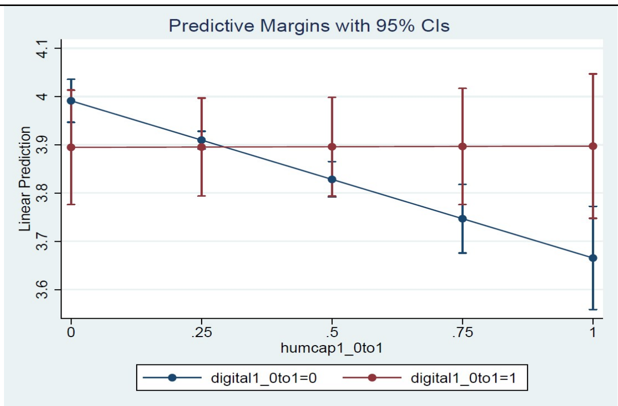


Figure G2: The impact of human capital capabilities on productivity conditional on digital capabilities

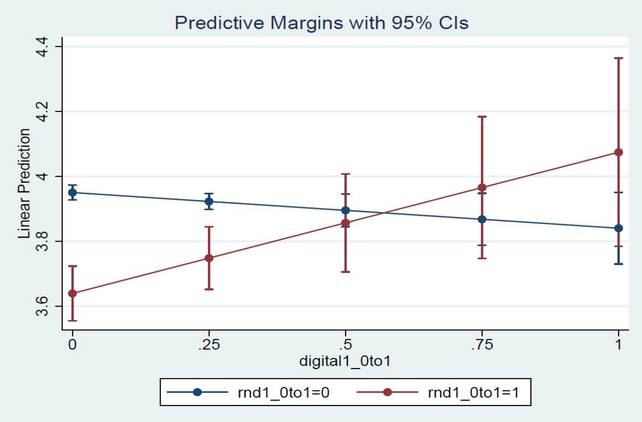


Figure G3: The impact of digital capabilities on productivity conditional on innovation capabilities

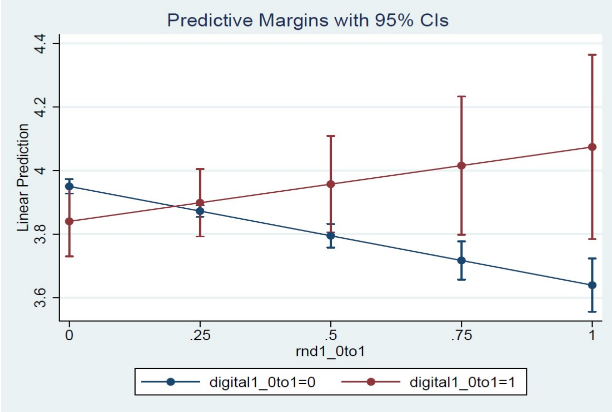


Figure G4: The impact of innovation capabilities on productivity conditional on digital capabilities

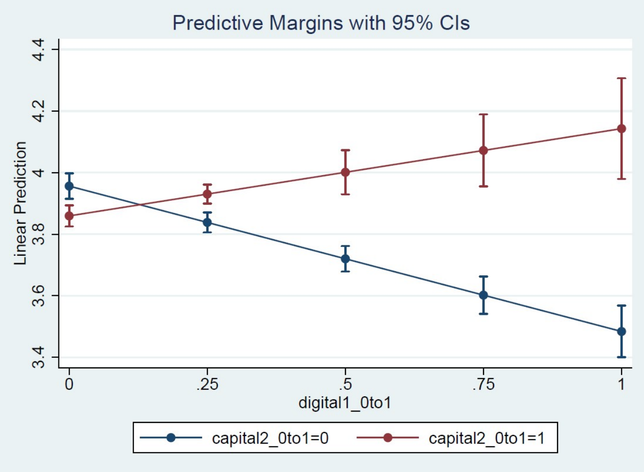


Figure G5: The impact of digital capabilities on productivity conditional on tangible capital

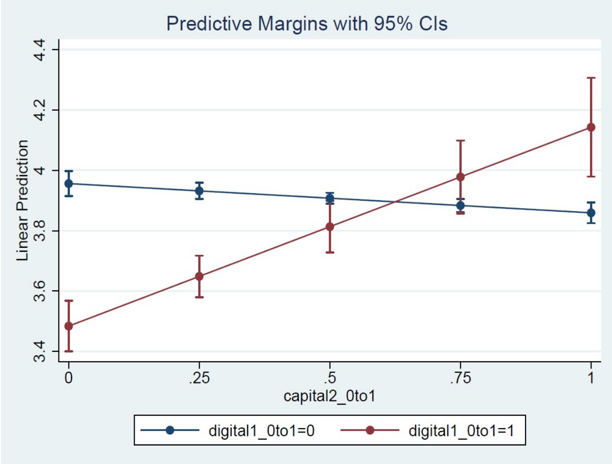


Figure G6: The impact of tangible capital on productivity conditional on digital capabilities

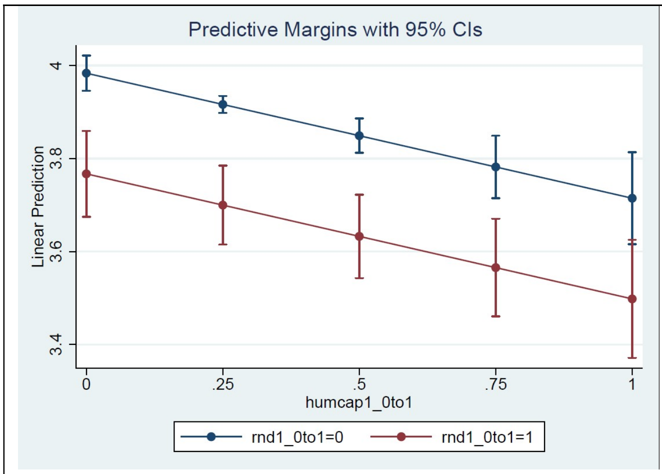


Figure G7: The impact of human capital capabilities on productivity conditional on innovation capabilities

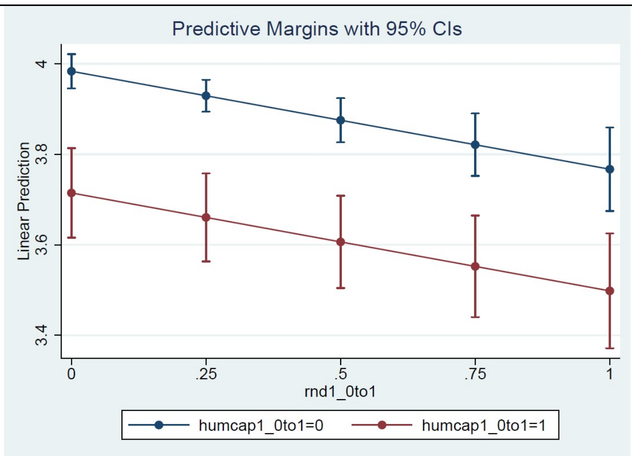


Figure G8: The impact of innovation capabilities on productivity conditional on human capital capabilities

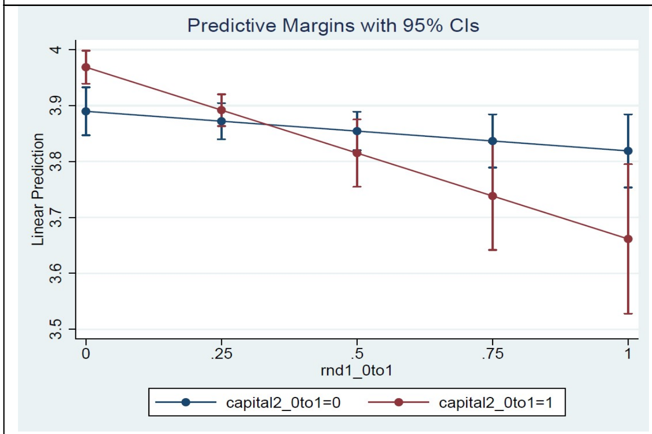


Figure G9: The impact of innovation capabilities on productivity conditional on tangible capital capabilities

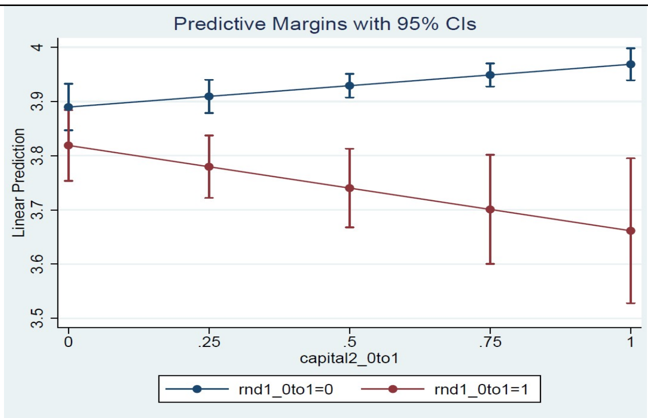


Figure G10: The impact of innovation capabilities on productivity conditional on tangible capital capabilities

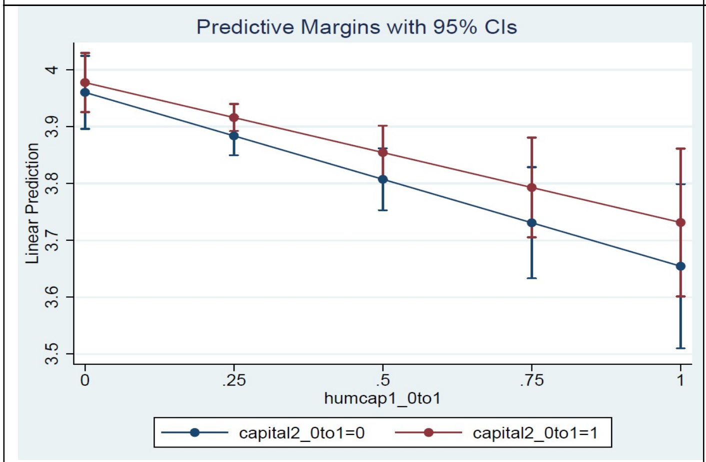


Figure G11: The impact of human capital capabilities on productivity conditional on tangible capital capabilities

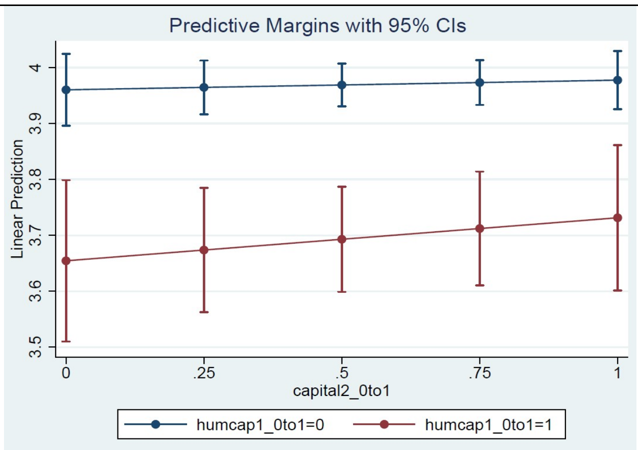


Figure G12: The impact of tangible capital capabilities on productivity conditional on human capital capabilities.