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Dimitrios Exadaktylos

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The dissertation of Dimitrios Exadaktylos is approved.

PhD Program Coordinator: Prof. Rocco de Nicola, IMT School for Advanced Studies Lucca

Advisor: Prof. Massimo Riccaboni, IMT School for Advanced Studies Lucca

Co-Advisor: Prof. Armando Rungi, IMT School for Advanced Studies Lucca

The dissertation of Dimitrios Exadaktylos has been reviewed by:

Marco Grazzi, Università Cattolica del Sacro Cuore

Italo Colantone, Bocconi University

Alessandra Faggian, Gran Sasso Science Institute, L'Aquila

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Vita

May 4, 1990 Born, Athens , Greece

Education

2017- PhD in Economics. XXXIII Cycle,
IMT School for Advanced Studies Lucca, Lucca, Italy
Supervisors: Massimo Riccaboni and Armando Rungi

2017 Master's degree in Economics
Athens University of Economics and Business, Athens, Greece

2014 Degree in Economics
National and Kapodistrian University of Athens, Athens, Greece

Additional Education

2018 Summer School: "Big Data for Economics"
University of Barcelona
Barcelona, Spain

Work Experience

2021- Economist
Alma Economics
Athens, Greece

2019 Visiting PhD Student
The Vienna Institute for International Economic Studies - wiiw
Vienna, Austria
Erasmus+ Mobility Consortium for Student Rraineeships "Talent at work", 7 month grant 2018/2019.

2017 Traineeship
Joint Research Centre of the European Commision
Ispra, Italy

2014 Internship
National Bank of Greece
Athens, Greece

Publications

Working papers

1. Exadaktylos, D., Ghodsi, M., and Rungi, A. (2021). ”What do Firms Gain from Patenting? The Case of the Global ICT Industry.”. *Available at SSRN*: `https://ssrn.com/abstract=3897611`
2. Exadaktylos, D., Riccaboni, M., and Rungi, A. (2021). ”Talents from Abroad - Foreign Managers and Productivity in the United Kingdom”. *Available at SSRN*: `https://ssrn.com/abstract=3504214`

Technical reports

1. Ghodsi, M., Adarov, A., Exadaktylos, D., Stehrer, R., and Stöllinger, R. (2021). ”Production and Trade of ICT from an EU Perspective”, *wiiw Research Report No. 456*
2. Exadaktylos, D., and Ghodsi, M. (2021). ”Innovation and Company Performance in the Digital Sector”. In: *wiiw Monthly Report No. 1, January 2021*
3. Exadaktylos, D., Riccaboni, M., and Rungi, A. (2020). ”The Impact of Foreign Managers on Productivity in the United Kingdom”, In: *wiiw Monthly Report No. 3, March 2020*

Presentations

1. Exadaktylos D., Riccaboni M., Rungi A. ”Talents from Abroad: Foreign Managers and Productivity in the United Kingdom”, at *Allied Social Science Associations (ASSA) Virtual Annual Meeting 2022* (poster presentation)
2. Exadaktylos D., Ghodsi M., Rungi A. ”What do Firms Gain from Patenting? The Case of the Global ICT Industry.”, at *European Trade Study Group (ETSG)*, Ghent, Belgium, 2021
3. Exadaktylos D., Ghodsi M., Rungi A. ”Intellectual Property Rights and Competition in the Global Digital Sector. What do ICT Firms Gain from Patenting?”, at *National Documentation Centre, Athens*, 2021 (online presentation)
4. Exadaktylos D., Ghodsi M. ”How Does Innovation Stimulate Performance of Global ICT Producers in the Competitive Digital Market?”, at *IMT School Workshop on Technology and the Labour Market*, 2020 (online presentation)
5. Exadaktylos D., Riccaboni M., Rungi A. ”Talents from Abroad: Foreign Managers and Productivity in the United Kingdom”, at *The 61st Annual Conference of the Italian Economic Association*, 2020 (online presentation)
6. Exadaktylos D., Riccaboni M., Rungi A. ”Talents from Abroad: Foreign Managers and Productivity in the United Kingdom”, at *Vienna Institute for International Economic Studies*, Vienna, Austria, 2019
7. Exadaktylos D., Riccaboni M., Rungi A. ”The Impact of Foreign Managers on Productivity: Evidence from the United Kingdom”, at *European Trade Study Group (ETSG)*, Bern, Switzerland, 2019
8. Exadaktylos D., Riccaboni M., Rungi A. ”Knowledge Diffusion through Managers’ Mobility”, at *IMT Research Symposium 2019*, Lucca, Italy, 2019

Abstract

As competition becomes intense, firms seek strategies to keep afloat. Among others, they carefully choose their activity location, recruit a talented workforce, and engage in innovation. In this thesis, we shed light on these three features empirically, mainly using econometric techniques. Our contribution is in the literature of firms' competitiveness, industrial organization and economic geography.

At first, we study regional productivity disparities and their interplay with local agglomeration advantages. To do so, we apply a density-based machine learning clustering algorithm to identify firms' clusters at a fine-grained geographic scale on a sample of Italian firms. Then, we observe simultaneously the extent to which clusters explain agglomeration economies and firm selection effects. Our findings suggest that dense clusters generate agglomeration externalities that are heterogeneous across regions. In the second part of the thesis, we investigate the impact of foreign managers on firms' competitiveness on a sample of firms operating in the United Kingdom. We show that domestic firms become more efficient after recruiting foreigners to their management team due to previous industry-specific experience. In the last part, we assess the impact of patents on market share and labour productivity in the global Information and Communication Technologies (ICT) sector. Using a recent difference-in-difference approach, we find that patenting increase market share without significantly affecting labour productivity. Our evidence indicates some concerns regarding the implications of property rights from innovation on market competition.

Chapter 1

Introduction

Over the last years, the availability of detailed firm-level data has allowed researchers to investigate different drivers of competitiveness empirically. Firms may obtain a competitive advantage by adopting different strategies. Moreover, the business environment in which they operate is crucial for their performance.

The discussion around firms' strategic choices to obtain competitive advantage is an old one. In the studies by Porter (1980) and Porter (1991) provides three dimensions of firms' strategies are presented. The first one refers to strategies aiming to attain low costs. The role of management here is crucial for monitoring and maintaining cost efficiency. The second dimension is the differentiation of products and services, which reflects a firm's ability to transform the products and services provided. Among others, differentiation can be achieved through technology improvements. In fact, differentiation leads to higher competitiveness without necessarily adopting a low-cost approach while, on some occasions, may imply a larger market share. The third dimension is the so-called competitive scope (or focus) and it is about targeting activities at specific products, buyers or geographic locations to be more competitive than rivals operating in broader markets. The local environment is essential for a firm to obtain a competitive advantage as it is associated with its options regarding its resources, the amount of information that can be useful to determine its goals and the competitive pressures. Geographic concentration enhances these forces because of more interactions among firms and individuals. Teece, Pisano, and Shuen (1997) discusses a dynamic capabilities framework where firms create wealth in technologically advanced regimes when they focus on improvements in technology and management and these strategies are more efficient than actions targeted at the exclusion of competitors.

To this end, we consider that shedding light on some of the underlying mechanisms of firms' competitiveness is essential for entrepreneurs and policymakers. Therefore, in this thesis, we examine different drivers of firms' efficiency and market competition. At first, we study the role of agglomeration on the regional productivity disparities in Italy (Chapter 2). We identify firm agglomerations using an unsupervised machine learning algorithm to create arbitrarily shaped clusters of firms based on geographic density. Second, in Chapter 3, we focus on the role of management and migration by assessing the impact of foreign managers on productivity in the United Kingdom. Finally, we explore the role of property rights from innovation on productivity and competition of firms operating in the information and communication technology (ICT) sector. Our main exercise is to estimate the impact of patenting activity on market share and productivity (Chapter 4).

For our purpose, we take advantage of rich firm-level data to take into account firm heterogeneity. Analyses using detailed firm-level data are recommended when assessing firms' competitiveness as they take into account for discrepancies in firms' competitiveness (Rumelt, 1991). Our methods rely mainly on novel econometric techniques.

1.1 Agglomeration and regional disparities

The geographic location of economic activity is crucial for firms' competitiveness. Agglomeration economies refer to positive externalities arising from co-location of entities due to lower transport costs (Glaeser, 2010; Rosenthal and Strange, 2004). These externalities are usually classified into three main categories (Neffke et al., 2011). The first one is the Marshall-Arrow-Romer (MAR) externalities arising through industry specialization (Marshall, 1920). The second one is the so-called Jacobs' externalities referring to benefits from industry diversification due to the complementarity of knowledge across different sectors of activity (Jacobs, 1969). Finally, urbanization externalities appear when firms are located in large cities. Access to large markets, better institutions, and a wider pool of highly skilled employees may improve competitiveness. In addition, congestion and the high cost of labor and land may have the opposite effects (Neffke et al., 2011). [1]

Duranton and Puga (2004) update and summarize the intuitions behind three different mechanisms that drive agglomeration effects, and they are introduced by Marshall (1920): *sharing*, *matching*, and *learning*. *Sharing* is about the ability of workers and firms to maintain together the costs and benefits from the usage of intermediate goods or services, like R&D facilities or common infrastructure. *Matching* concerns the possibility of finding room for collaborations with good partners. Clearly, the bigger the agglomeration of firms or workers, the better the chances to find a good match. *Learning* entails the possibility that individuals can exchange knowledge from interactions, and hence more intense interactions ease knowledge transfer.

Large cities generate agglomeration externalities. Moreover, competition is tougher due to the larger number of firms leading to the least productive firms exiting the market. As a result, aggregated productivity increases. This notion is defined as *selection* (R. E. Baldwin and Okubo, 2006; Gaubert, 2018). Combes et al. (2012) develop a model considering agglomeration and selection effects simultaneously. The narrative is that tough selection implies weak firms to exit the market. At the same time, agglomeration externalities increase the productivity of all firms in large cities. Top performers benefit more from agglomeration externalities because workers are even more productive when working for the most productive firms. These three phenomena imply a left truncation,

[1] Urbanization externalities are often considered an identical concept to Jacobs' externalities since a diversified market structure is typical of large cities (see for instance Di Giacinto et al. (2014)).

right shift, and dilation of the productivity distribution in large cities.

Individuals' performance often depends on the region in which they operate. Inequalities are often observed between nations even when they exist under the same union. For instance, EU countries in the South and the East are lagging in terms of GDP per capita, comparing to Central and Northern countries [2]. Inequalities across regions may not only occur at the national level but also at a smaller scale, like NUTS2 or NUTS3 regions (Boldrin and Canova, 2001; Geppert and A. Stephan, 2008). Moreover they can occur within countries (Bluedorn et al., 2019; Gaubert et al., 2021). In our case, we focus on Italy, a country well-known for its geographic disparities.

Italy is characterized by a productivity slowdown having its origins in the mid-90s. Hassan and G. Ottaviano (2013) study possible causes comparing Italy with France and Germany. They find that Italy falls short in the misallocation of resources, meaning that production inputs are allocated towards less productive firms. Moreover, ICT investment has decreased compared to the other two European countries. Another potential explanation of productivity decline is poor managerial practices. The productivity slowdown is also explained by the technology gap, low-skilled human capital, inefficient management, lack of credit and investments, inadequate regulation in the labor and product market, slow judicial procedures and tax evasion (Calligaris et al., 2018; Bugamelli et al., 2018). Moreover, empirical evidence for the period 1989-2004 shows a high degree of within sector heterogeneity, inefficient selection mechanisms, a positive association between productivity, exports and patenting activity, and only a small number of firms that perform exceptionally well (namely, they are "outliers" in the distribution of firm performance indications) in terms of productivity, innovation, export and growth (Dosi, Grazzi, et al., 2012).

Geographic disparities in Italy have historical roots in the previous centuries. A study by Basile and Ciccarelli (2018) on the location patterns of manufacturing firms in Italy for the period 1871-1911 suggests a high

[2]Source: Eurostat (`https://appsso.eurostat.ec.europa.eu/nui/submitViewTableAction.do`)

concentration and specialization in the North-West as a result of a reduction in transportation costs. Furthermore, the natural characteristics and the domestic market access had a key role in the concentration. The latter prevailed at the beginning of the last century while foreign market access was a more crucial determinant of the disparities between North and South (A'Hearn and Venables, 2013). During the period 2000-2016, regional discrepancies in productivity are still increasing while the variation in terms of the unemployment rate is the largest among OECD countries (OECD, 2018). Within the country is observed considerable heterogeneity in terms of education, innovation, institutional quality and public investments, while high-skilled labor tends to migrate from the South to the North (EC, 2020). Public sector inefficiency is not only responsible for the productivity gap between Italy and the other European countries, but also for the regional discrepancies within the country (Giordano et al., 2020). Rungi and Biancalani (2019) find that market selection is more robust in the North than in the South, meaning that inefficient firms established in Northern regions are less likely to survive. Regional characteristics affect firms, but they may also contribute in regional convergence. A recent study by Castelnovo, Morretta, and Vecchi (2020) on Italian firms stresses that there are regional characteristics that affect not only firm-level productivity but also reduce the productivity disparities between North and South. More specifically, they find that bank credit, R&D expenditure, good infrastructure and high employment in cooperatives are positively correlated to regional TFP while the opposite holds in regions with low quality of public services. Interestingly, they find that regions with high technology and a large number of institutions related to arts have a positive effect on reducing the gap between northern and central/southern regions. Therefore, some spatial concentrations (for example, clusters with innovation-intensive firms) within regions may be responsible for the productivity boost (or reduction).

Agglomeration phenomena in Italy are profound. Small firms, the dominant firm size category in the national economy (Bugamelli et al., 2018), tend to form clusters in order to benefit from the exchange of knowledge through interaction. Industrial districts are a crucial characteristic of the manufacturing sector and have attracted the interest of several researchers in the past (Dei Ottati, 2018; Canello, 2016; Becattini and Coltorti, 2006; Sforzi, 2009). Di Giacinto et al. (2014) illustrate that firms are more productive when located in industrial districts or urban areas. The premium is even higher for urban areas, suggesting that diversification generates larger externalities than specialization. Furthermore, they find that small firms are more productive than medium-sized in urban areas or industrial districts. Accetturo et al. (2018) compare between agglomeration and selection effects and they find significant agglomeration effects in large cities. Selection effects appear when access to local markets improves and when cities are located in large macro-regions.

When it comes to assessing spillovers generated from agglomeration empirically, it is common to define ”dense” areas of economic activity[3]. These areas' borders are often defined using administrative boundaries, like NUTS3 regions or metropolitan areas. However, these strict definitions may neglect some agglomeration forces. For instance, Duranton and Puga (2020) stress that if a metropolitan area includes rural parts, urban density is not accurately measured. Several studies attempt to map clusters. In the case of Italy, ISTAT (2015) provides a map of industrial districts based on industry specialization in Labor Market Areas (LMAs), indicating a large concentration of industrial districts in the Central and Northern regions. [4] They do so by following the mapping algorithm developed by Sforzi (2009), which follows the socio-economic definition by Becattini et al. (1990) indicating the interconnection between population and companies in a specific region. Canello and Pavone (2016) extend Sforzi's algorithm, including more information regarding size class and classification of industrial districts.

A potential problem regarding the cases mentioned above is that the boundaries of clusters are based on administrative classification. To overcome this problem, Duranton and Overman (2005) develop a distance-based method to determine clusters of firms operating in the same in-

[3]In the literature, the concept of ”density” usually refers to population, employment or firm density.

[4]ISTAT defines Labor Market Areas as geographical areas where the majority of the human capital lives and works.

dustry. In an interesting approach by Alcácer and M. Zhao (2016), they develop an algorithm using geo-coded location information to construct clusters based on patent density. Rosenthal and Strange (2020) indicate the importance of spatial scale when assessing agglomeration externalities. They find that agglomeration mechanisms may differ depending on the scale one chooses. For instance, labor pooling appears to be more beneficial at a narrow scale since commuting costs tend to dominate as the distance increases. On the other hand, the sharp increase of information technology (IT) has reduced transport costs, facilitating agglomeration benefits at a long distance. The availability of detailed geo-coded information allows researchers to use practical tools to define regions at a detailed that ignores administrative boundaries and investigate how agglomeration mechanisms occur.

To this end, we use a machine learning clustering method developed by Ankerst et al. (1999) to define clusters of dense firms based on geo-coded information. Then we apply the econometric model by Combes et al. (2012) to introduce the following research questions:

- To what extent do firm clusters explain agglomeration and selection mechanisms?

- How do these mechanisms differ across regions?

Our findings suggest that firm clusters generate agglomeration externalities that differ across macro-regions. Specifically, these externalities are larger for the most competitive firms in the Centre and the North of Italy. This is based on the assumption that workers' productivity is higher when working for the most efficient firms and their productivity further increases due to interactions with other employees (Combes et al., 2012). To this end, we argue that this complementarity between firms' and workers' efficiency does not occur in the South and hence the most efficient Southern companies miss the chance to boost competitiveness even further.

1.2 High-skilled migration

As discussed before, thick labour markets usually generate agglomeration externalities. One mechanism through which firms and workers benefit from agglomeration, is the positive assortative matching, that is the matching between efficient employees and competitive firms. A recent study by Orefice and Peri (2020) shows that immigrant workers improve positive assortative matching. Russek (2010) sheds light on the nexus between migration and agglomeration. Specifically, he finds that immigration increases domestic firms' performance and the agglomeration incentive of self-employed workers. From a different perspective, S. P. Kerr et al. (2017) argue that high-skilled migration and agglomeration are connected in the following way: first of all, a geographic region characterised by the presence of high-skilled employees attracts even more high-skilled workers. In clusters where innovative firms operate, like Silicon Valley, competition occurs at a global scale. However, geographic proximity generate positive externalities through the interaction between entrepreneurs or scientists. Since high-skilled workers already operate there, the import of additional high-skilled labour leads to a further increase in productivity through specialization.

Economic returns from urban agglomeration may be complementary to benefits from migration in the sense that circulation of ideas brought by high-skilled migrants can be boosted in cities (Nathan, 2014). Indicatively, Gianmarco I.P. Ottaviano and Peri (2006) find a positive relationship between cultural diversity and productivity in US cities. However, immigration may not always be beneficial for regional growth. For instance, overcrowding may lead to higher costs of housing (Saiz, 2007).

A review by Nathan (2014) about the economic implications of high-skilled migration distinguishes four main channels through which skilled migrants affect the economy. The first one is innovation. Highly skilled immigrants are valuable in areas with high research activity (P. E. Stephan and Levin, 2001) while cognitive diversity within labor force improves problem-solving (Page, 2007). The second channel is the trade and foreign direct investment (FDI). Indeed Gianmarco I.P. Ottaviano, Peri, and

G. C. Wright (2018) find that immigrants in the UK increase country-specific exports due to a reduction of communication and trade costs. Moreover, migrant networks stimulate FDI from host countries to immigrants' home countries (B. S. Javorcik et al., 2011). Nathan (2014) classifies "entrepreneurship" as an additional channel. For example, the initiation of business in Silicon Valley by Chinese and Indian engineers boosted economic growth in California (Saxenian, 2002). However, trade and entrepreneurship are beyond the scope of our analysis. The channel on which we focus our attention is the production process and productivity. Indeed, immigrants may change the structure of the domestic labor force, implying some changes in domestic growth or competitiveness. At a macro level, Peri (2012) shows that immigrants increase domestic productivity because of higher task specialization. From another point of view, Parrotta, Pozzoli, and Pytlikova (2014) find a negative association between workers' diversity in ethnicity and firms' productivity, highlighting that communication and integration costs may oppose any benefits generated by immigrants (e.g. knowledge spillovers). Moreover, a study by Lewis (2011) illustrates that an increase in domestic low-to-high skill ratio due to immigration leads to a drop in capital and wages in manufacturing firms. That is because automation complements middle-skilled workers compared to low-skilled workers. Malchow-Møller, Munch, and Skaksen (2019) underline that foreign experts increase wages relative to domestic experts. A similar study by Markusen and Trofimenko (2009) suggests that domestic workers embody knowledge by foreign experts to increase labor productivity.

In Chapter 3 we focus on foreign managers, considering them as a specific case of high-skilled migrants, like employees with advanced training (Nathan, 2014). As Syverson (2011) says, "*Managers are conductors of an input orchestra. They coordinate the application of labor, capital, and intermediate inputs. Just as a poor conductor can lead to a cacophony rather than a symphony, one might expect poor management to lead to discordant production operations*". Over the last decades, detailed data on management practices allowed researchers to quantify the contribution of management to firm performance. In fact, managerial practices differ across firms and countries and they are correlated with firm performance (Bertrand and Schoar, 2003; Nicholas Bloom and Van Reenen, 2007; Nicholas Bloom and Van Reenen, 2010; Nicholas Bloom, Eifert, et al., 2013; Nicholas Bloom, Sadun, and Van Reenen, 2016; Bruhn, Karlan, and Schoar, 2018; Nicholas Bloom, Brynjolfsson, et al., 2019). The efficiency of management practices depends on various factors like market competition, regulations of management practices, family ownership, relational contracts etc. (Nicholas Bloom and Van Reenen, 2010; Gibbons and R. Henderson, 2012). However, managers' experience is also important since they can bring valuable knowledge (Mion and Opromolla, 2014; Mion, Opromolla, and Sforza, 2016; Meinen et al., 2018). Finally, recent empirical literature has stressed the complementarity between management and FDI. Cho (2018) shows that foreign affiliates bringing managers from parent firms are more productive, while Antras, Rossi-Hansberg, and Garicano (2009) illustrate that the presence of middle managers in host country eases knowledge transmission from host to home countries when communication technology in the host country is poor.

On 23 June 2016, a referendum in the United Kingdom took place asking the citizens whether they wanted to leave the European Union or not. The "leavers" won and since January 2020, the UK is officially out of the European Union. Such a decision has potential implications for the domestic economy. Consequently, several scholars try to shed light on this issue. Dhingra et al. (2017) simulate different Brexit scenarios, predicting a reduction in households' welfare and per capita income due to trade restrictions while Cappariello et al. (2020) underline that dense global value chains between the UK and the EU countries boost welfare losses. Apart from limitations in bilateral trade, Brexit implies some barriers to migration. Ortiz Valverde and Latorre (2020) estimate the effect of a reduction in migrant inflows. Their findings suggest increasing wages, but per capita GDP drops. From our side, we believe our study is helpful to understand the importance of foreigners in the production process and observe whether barriers in international mobility indirectly affect domestic competitiveness.

Eventually, the main question we introduce in Chapter 3 is the following:

- How do foreign managers affect productivity in UK firms?

Our evidence indicates that domestic firms become productive after recruiting foreigners in their management team. In particular, we find that previous industry-specific experience by foreign managers is the primary driver of productivity gains. Interestingly, we do not find any significant impact on foreign-owned firms after hiring foreign managers. A possible explanation is that productivity gains already took place after the foreign acquisition or when they became part of a multinational enterprise. Therefore, hiring talents from abroad can be a good strategy for domestic firms to compete foreign-owned enterprises.

1.3 Innovation in the ICT sector

So far, we have discussed agglomeration and foreign management as drivers for competitiveness. Another aspect we consider in this thesis is innovation. Indeed, past research stresses the complementarity between innovation and agglomeration and the existence of innovative clusters within countries (see for instance Carlino and W. R. Kerr, 2015). Moreover, innovation is a mechanism through which migrants affect domestic countries' economy. A skilled workforce may decide to relocate abroad and transfer their knowledge as they expect high future returns. Labour diversity and variation of ideas may facilitate knowledge creation. Migrant communities may diminish information and communication between origin and destination countries[5].

Innovation is one of the most critical drivers of competitiveness. P. Geroski, Machin, and Van Reenen (1993) highlight that companies engaging in innovation can accommodate the market needs, while recession effects are smooth for innovative companies. The association between R&D and productivity is an old question and it has been thor-

[5]See Nathan (2014) for a discussion about innovation as a mechanism for knowledge diffusion through high-skilled migration.

oughly studied in the past (see, for example Mansfield, 1980 and Hall and Mairesse, 1995). Syverson (2011) explicates in detail the determinant factors of productivity. Among others, he mentions the important role of IT capital and product innovation. The ability of a firm to alter its products may lead to productivity gains. Furthermore, he stresses that it is crucial to explore further the nexus between technology and productivity within industry.

Technological change is a crucial factor for economic growth. The theoretical framework regarding endogenous growth theory was updated and established in the early 90s (Romer, 1990; Aghion and Howitt, 1990; Grossman and Helpman, 1991), while subsequent firm-level analyses investigate in detail the nexus between innovation and growth. Del Monte and Papagni (2003) focus on the Italian case and they find that companies investing in R&D are more competitive and they have a higher growth rate than those not engaged in R&D. Interestingly, they do not find any association between R&D and profits because of rivals that copy innovative techniques. The latter is a particularly important issue for business owners. Firms engage in R&D to increase their intangible assets and benefit from new technologies. To obtain exclusive rights for an invention, they refer to responsible bodies and apply for a patent. [6] These bodies test the originality of the innovation and then decide whether to provide intellectual property rights (IPR) or not.

The role of IPR is interesting from an economic point of view. On the one hand, property rights from innovation prevent rivals from imitating their novel techniques and hence provide a competitive advantage on the owners. Indeed, while firms increase revenues through patenting, competitors may be excluded from copying and utilizing technology (Roemer-Mahler, 2013). On the other hand, this exclusion may have implications for competition. IPR restrict the free distribution of knowledge and may lead to monopoly and hence distortions in the allocation of resources (Stiglitz, 2007). From a different point of view, Acemoglu and Akcigit (2012) develop a model to show that when authorities grant

[6] For more information, see: `https://www.wipo.int/patents/en/faq_patents.html`

IPR to the best performers, less advanced firms may be motivated to increase R&D to have a higher probability of giving a patent. However, P. A. Geroski (1990) argues that monopoly does not stimulate innovative activity, expressing some doubts on whether authorities should enhance the existence of leaders in a market.

In Chapter 4 we focus on the implications of intellectual property rights on competition of a growing high-tech sector, namely ICT. Over the last decades, ICT products and services are important for firms' everyday operations, since they are used as intermediate or capital goods in the production process. The share of value-added in the ICT sector in OECD economies has risen from 7.7% in 1995 to 8.3% in 2009 (OECD, 2013). Stylized facts from Eurostat indicate that in the EU for the period 2013-2018, value-added increased by 31% for ICT manufacturing and almost 27% for ICT services[7].

The benefits of investing in ICT are anchored in the adoption of new technologies and its complementarity with either the organizational capital (Brynjolfsson and Hitt, 2003; Commander, Harrison, and Menezes-Filho, 2011; Milgrom and Roberts, 1990) or with intangible assets (Khanna and Sharma, 2018; Chen, Niebel, and Saam, 2016). Thus, policymakers and businesses tend to focus their attention on emerging digital technologies, facilitating long run-development. To this end, we investigate the role of innovation within ICT industries. A study by Koutroumpis, Leiponen, and Thomas (2020) on ICT producers shows that R&D boosts revenues. However, the rising market power of few Big-Tech companies is an ongoing discussion in the media[8]. To this end, we are interested in the effect of IPR from innovation on firms' efficiency and market competition, introducing the following research questions:

- What is the effect of patenting on market share and productivity of ICT firms?
- How do market allocation dynamics act over the years?

[7] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=ICT_sector_-_value_added,_employment_and_R%26D&oldid=521086

[8] see for instance https://www.economist.com/films/2021/05/21/why-americas-mighty-technology-companies-are-so-powerful

We find that companies increase market share after granting patents. However, even though patentees appear to be more productive, we do not observe any causal effects of patenting on productivity. Moreover, we find that production resources are allocated efficiently. Therefore, even though patenting does not provide productivity gains, productive firms are still the market leaders.

1.4 Contributions

This section presents the contribution of each chapter of the thesis.

1.4.1 Regional Disparities and Firms' Agglomerations in Italy

The contribution of Chapter 2 is twofold. At first, we apply an unsupervised machine learning clustering algorithm called OPTICS (Ankerst et al., 1999) using geo-coded information of Italian manufacturing firms to detect clusters of firms with close geographic proximity, neglecting administrative borders. Therefore, we add our work to a recently developed stream of literature that considers detailed geo-location data to study agglomeration economies. At a second stage, we explore the extent to which these clusters explain agglomeration externalities and market selection mechanisms. To do so, we apply an econometric model developed by Combes et al. (2012) and we estimate those two mechanisms simultaneously through the productivity distribution of firms inside and outside clusters.

1.4.2 Talents from Abroad: Foreign Managers and Productivity in the United Kingdom

In Chapter 3 we perform an empirical exercise to test the impact of foreign managers on firms' competitiveness. The availability of detailed data on firms' managers allows us to observe the direct effects after recruiting foreign managers. Although recent literature has stressed the role of managers' mobility on firms' export performance, there is only scant evidence regarding the impact on productivity. Therefore, we go a step back to explore whether the recruitment of foreign managers leads to efficiency gains before improving internationalization. Our identification strategy consists of a propensity score matching and a difference-in-difference technique, following similar approaches that examine the impact of foreign acquisitions on productivity (Arnold and B. S. Javorcik, 2009; Bircan, 2019; B. Javorcik and Poelhekke, 2017).

1.4.3 What do Firms Gain from Patenting? The Case of the Global ICT Industry

In Chapter 4 we shed light on the nexus between patenting, productivity and market competition between firms operating in the ICT sector. Given the emergence of digitalization and the rise of market power among the Big-Tech companies, we believe that our contribution regarding the role of property rights from innovation on market concentration and firms' efficiency is crucial. Moreover, our empirical exercise is based on an up to date difference-in-differences technique when for multiple periods and variation in the timing of the treatment (Callaway and Pedro HC Sant'Anna, 2020). Finally, we perform a descriptive analysis to observe how market share is allocated over time.

Chapter 2

Regional Disparities and Firms' Agglomerations in Italy

2.1 Introduction

The productivity gap between North and South is probably the most known and enduring feature of Italian economic geography[1]. At the same time, the North of the country also hosts a significant concentration of business activity. Therefore, this chapter checks whether Italian regional disparities are explained by an uneven distribution of economic activities in space since previous literature predicts that an average productivity advantage is expected in the presence of agglomerations of firms and workers.

The contribution of this paper can be summarised in two points: the

[1]Considerable economic discrepancies between Northern and Southern regions are observed since the reunification in 1861, when an agglomeration of manufacturing firms in a few North-Western provinces was favoured by decreasing costs and trade barriers (Basile and Ciccarelli, 2018; Rungi and Biancalani, 2019). Regional disparities existing before the reunification were magnified in the wave of the industrial revolution (A'Hearn and Venables, 2013) based on different regional comparative advantages, for example, in the endowments of water as the latter was an important source to produce hydroelectric energy for mass production.

first one is that we create clusters of geographically concentrated firms that go beyond administrative boundaries. The second point is that we study how regional productivity disparities interact with agglomeration and selection mechanisms.

We start by providing a mosaic of preliminary evidence on the geography of firm-level total factor productivity (TFP) in Italy. We show that the North-South divide underpins a substantial heterogeneity in TFP distributions. As largely expected, mean TFPs are higher in the North than in the South. Yet, notably, TFP dispersions follow an opposite pattern; they are higher in the South than in the North. Interestingly, when we look at details, we observe that the regional gap proves relatively more profound on the first quartiles of the TFP distributions. In other words, when we focus on the segments of inefficient firms only, we find the latter are relatively more inefficient in the South than in the North. On the contrary, when we look across top quartiles of TFP distributions, we do not find significant differences since most efficient firms are equally distributed throughout the country.

To get deeper into the geography of firm-level TFPs, we identify firms' agglomerations at a fine-grained scale going beyond administrative boundaries. After deriving firm-level coordinates for 401,043 manufacturing firms in the period 2007-2017, we implement an unsupervised machine learning tool, OPTICS (Ankerst et al., 1999), to capture arbitrary-shaped geographic clusters entirely based on geographical proximity. In other words, unlike past applications, we look for productivity advantages in a broader spectrum of agglomeration typologies, which can eventually encompass both large cities and specialized industrial districts. The intuition is that we just need to identify a minimum density of economic activity that should characterize an agglomeration of firms, in a way to encompass any type of agglomeration, be it an industrial district or a urban area. Therefore, we can proceed with our empirical analyses by qualifying *ex post* the type of agglomeration we are interested in, as well as the optimal scale at which we can observe agglomeration advantages.

According to our preliminary findings, firms in geographic clusters are *ceteris paribus* 4.5% more productive. Nonetheless, the advantage of being located in the North with respect to the South is far more considerable and amounts to 32% higher productivity. It immediately emerges that Italian regional disparities are preserved within firms' agglomerations, as we find an 85 percentage point difference between the most and the least productive cluster, respectively, located in the North and the South of the country.

Finally, we explore the role of market selection and agglomeration economies, as they are the longest investigated drivers of differences in the geography of productivity. The theory postulates that firms can benefit from positive agglomeration externalities because local clusters provide an easier exchange of goods, people and ideas (Glaeser, 2010). On the other hand, local market selection implies that less-productive firms cannot survive in most competitive markets. Larger markets bring about tougher selection, thus higher aggregate productivity since only more productive firms can survive to a more challenging business environment (R. E. Baldwin and Okubo, 2006; Gaubert, 2018). In a significant contribution, Combes et al. (2012) test simultaneously the presence of both agglomeration economies and firms' selection into local markets under a unique framework. Starting from firm-level productivity distributions, they provide a way to quantify the relative importance of the two distinct mechanisms. The central intuition is that these two channels work on different parameters of the distributions. Therefore, one can easily compare productivity distributions between sparser and denser areas to understand where the differences in parameters are. In the framework proposed by Combes et al. (2012), one assumes that a denser area presents a right-shifted distribution of firms' productivities. The rationale is that local interactions among firms and workers generate agglomeration externalities for all. Thus all firms in denser areas will locate relatively more to the right than in sparser areas. At the same time, according to Combes et al. (2012), one would expect a higher dilation and a higher truncation of productivity distributions in a denser area. As for the dilation, the idea is that not all firms may equally benefit from agglomeration economies, with an asymmetry over the distribution. As for truncation, one would expect that market competition is tougher in denser areas, where inefficient firms are more likely pushed out of business. For a previous application of the same empirical framework in the Italian case, see also Accetturo et al. (2018).

Against this background, we apply empirics proposed by Combes et al. (2012) in a comparison between firms located in clusters *vis á vis* sparser areas, respectively in the North, Centre, and South of the country. Usefully, we check whether right shift, dilation, and left truncation parameters are significantly different within firms' agglomerations if compared to a control group made of firms that are not in geographical proximity. Separate exercises on macro-regions allow us to investigate if agglomeration externalities and local market selection can explain the regional gap in productivity.

We find significant difference in right shift which is unequal across regions. In fact, after controlling for dilation and left truncation, productivity appears to be larger on average by 4.59% in the North, 11.03% in the Centre and 8.53% in the South. In the North and Centre, productivity distribution is also dilated, suggesting that agglomeration externalities are even larger for the most productive firms, suggesting that workers' and firms' efficiency is complementary. In other words, as it is assumed in the analysis by Combes et al. (2012), workers are more productive when they work for productive firms. In the South, the average agglomeration advantage occurs to all firms equally, since we find no evidence of dilation. Finally, we find evidence on left truncation, however not robust when we focus our analysis within regions. That indicates that our attempt to capture agglomeration *ex post* might not be suitable when one wants to proxy market selection dynamics.

Overall, our evidence suggests that clustering generates agglomeration externalities that are heterogeneous across regions. It is possible that Southern firms do not achieve a good match between the most competitive firms and the most productive workers because the latter tend to migrate to the Central or Northern regions. Accordingly, Central and Northern firms choose from a larger pool of efficient human capital. When located in dense clusters, it is easier for top performing firms to find and recruit the best talents.

Although it is beyond the scope of our chapter to understand why the beneficial effects of agglomeration are asymmetric by geography in Italy, we believe our findings are still helpful to understand that there are specific segments of firms that actually drive regional divergence in productivity, and which may require particular attention by policymakers.

The rest of the chapter is organized as follows. Section 2.2 provides related literature, while we present data in Section 2.3. In Section 2.4, we introduce the reader to the use of machine learning in firms' geography to derive local clusters. Section 2.5 discusses preliminary evidence on regional disparities and agglomeration advantages. In Section 2.6, we introduce empirical strategy and findings on agglomeration and selection forces across the country. Section 2.7 concludes.

2.2 Related Literature

Regional disparities are of serious concern in many countries. Differences across regions within countries are often more significant than between countries (Bluedorn et al., 2019). In the case of the US, Gaubert et al. (2021) show how regional incomes have been diverging since the late 1970s. In the European Union as a whole, some poorest regions that joined after the enlargement of the 2000s could catch up to continental average while others still fall behind (Crescenzi and Giua, 2020). To tackle regional divergence, the European Union designs cohesion policies through so-called structural funds, whose effectiveness is often debated (Boldrin and Canova, 2001; Fattorini, Ghodsi, and Rungi, 2020).

In this contribution, our focus is on Italy because the country is a peculiar case study where regional disparities have been most persistent (Iuzzolino, Pellegrini, and Viesti, 2013), dating back at least to the reunification of the country in 1861. After 160 years, the North-South gap remains one of the main problems on the political agenda. Studies based on empirical evidence from recent decades indicate regional discrepancies increase in the country (OECD, 2018), and they are associated with considerable heterogeneity in terms of education, innovation, institutional quality, and public investments. On top of that, labour continues to migrate from the South to the North (EC, 2020), thus reinforcing regional gaps with one-direction brain drain. Eventually, long-term institutional determinants seem to have affected historical differential growth across Italian regions (De Blasio and Nuzzo, 2010).

We start by introducing a mosaic of novel stylized facts on the geography of firms' productivity, which we believe is interesting *per se*. At first, we show that NUTS 3-digit regions geographically order average TFPs on the map. At the province level, TFPs are on average higher in the North and lower in the South. Beyond averages, we also show how TFP dispersions are fundamentally different by geography at the NUTS 3-digit level, less dispersed in the North and more in the South (in line with past evidence by Rungi and Biancalani (2019)). Such differences in different moments of the TFP distributions pave the way for a thorough investigation of the role of local agglomeration advantages.

Crucially, a connection between regional disparities and agglomeration advantages was already made by Geppert and A. Stephan (2008) at the European level. While looking at income disparities, the authors find that agglomeration forces are associated with rising income disparities within countries and between regions.

Yet, from our point of view, we argue that our link between agglomeration advantages and productivity disparities is more immediate than the link with income disparities made by Geppert and A. Stephan (2008). In this, we believe we are in line with seminal contributions that studied how densely populated areas provide firm-level productivity advantages (Duranton and Puga, 2004; Combes et al., 2012; Behrens, Duranton, and Robert-Nicoud, 2014; Gaubert, 2018). Indeed, there is a wider tradition of literature that aims at understanding whether location in an agglomerated area affects firm-level economic performance (J. Henderson, 2003; Martin, Mayer, and Mayneris, 2011) and, as a result, the economic growth of entire territories (Glaeser et al., 1992; V. Henderson, Kuncoro, and Turner, 1995; Combes, 2000). Notably, Desmet and Rossi-Hansberg (2014) generalize a model of an economy where firms' performance is in relation to space because firms can decide to innovate based on differential transport costs and technology diffusion. Hereby, we mainly follow the empirical framework proposed by Combes et al. (2012), who introduce a way of working on TFP distributions to detect simultaneous agglomeration advantages. Usefully, Combes et al. (2012) provide a method to detect advantages brought both by positive local externalities and market selection mechanisms. On top of static benefits, in our analyses, we also control for the dynamic selection induced by sorting of firms into more or less productive locations, as discussed in Gaubert (2018). According to the latter, when more promising producers choose where to establish their business, they will prefer to go where productivity advantages are already higher, thus possibly reinforcing initial spatial disparities.

In line with Arimoto, Nakajima, and Okazaki (2014), our unit of observation is the firm located (or not) in a cluster, to which we apply the empirical framework by Combes et al. (2012). In this regard, please note that Accetturo et al. (2018) perform a previous application of the same framework to Italian firms. They confirm that positive agglomeration externalities benefit firms in Italian larger cities, although market selection emerges when one considers heterogeneous trade costs. Notably, the authors show how the relative importance of agglomeration and selection effects can vary depending on the different spatial scale that the analyst considers.

Motivated by the latter evidence, we choose a fine-grained minimum geographic scale based entirely on basic firm-level latitudes and longitudes. Thus, we construct our firms' clusters feeding geographic coordinates to an unsupervised machine algorithm, OPTICS, designed by Ankerst et al. (1999). We set a minimum density of business activity for what a dense economic area should look like. Thus, our firms' clusters encompass agglomerations of different size and density firms, including industrial districts and urban areas. In this way, we can make our analyses robust to different types of agglomeration advantages *ex post*, in the course of the following investigations. A minimum density allows us to check thereafter at which scale we can retrieve productivity advantages and start becoming regional disparities.

In this, we believe we are in line with the latest arguments by Duranton and Puga (2020), who suggest that there is a need to adjust the optimal scale of analyses according to the type of agglomeration advantages one wants to capture. On the same topic, see also Rosenthal and Strange (2020), who underline that agglomeration may occur at a very close distance and the effects differ depending on the spatial scale one chooses.

2.3 Data

We source firm-level financial accounts from ORBIS[2], a commercial database compiled by the Bureau van Dijk that collects balance sheets and income statements from national public registries around the world. Usefully, ORBIS also reports postal addresses of companies that we use for georeferencing business activities, as well as the dates of a firm's entry and exit that we use to check for market dynamics. For the purpose of this study, we focus on Italian manufacturing companies with a stratified sample that includes firms that report financial accounts needed to estimate TFPs, on one hand, as well as firms that report postal addresses, on the other hand. To estimate firm-level production functions and derive TFPs, we exploit data on value added, costs of materials, and number of employees. Our preferred methodology is the one proposed by Ackerberg, Caves, and Frazer (2015), which controls for the simultaneity bias entailed by the choice of the production combination in response to productivity shocks unobserved to the statistician. As it is by now a standard in productivity studies, we offer a summary in Appendix A.1.

After a series of preparatory steps and a cleaning strategy, we end up with a sample of 401,043 firms with geographic coordinates, of which only a subset of 149,353 firms report complete financial accounts to estimate TFP for the period 2007-2017. In the following paragraphs, we first describe how we obtain firms' coordinates. Then, we report how we

[2]The Orbis database is increasingly used for firm-level studies that require comparable financial accounts across multiple regions and countries. For previous works in regional science and economic geography, see for example Cortinovis and Oort (2015) and Crescenzi, Blasio, and Giua (2020).

proxy entry and exit dynamics from firms' original information. Finally, we validate our final sample against official business demography.

2.3.1 Firm-level geographic coordinates

Our source provides complete postal addresses of sample firms. A partial and incomplete exercise of georeferencing based on postal addresses is done originally by the compilers of Orbis (54%). However, we do find that the coverage extends only over about a half of our sample. Therefore, we integrate missing coordinates using Google Maps Geolocation API (38.4%) and Open StreetMap API (7.6%). We end up with a final set of coordinates whose composition according to sources is displayed in Table 2.1.

Table 2.1: Source of firm-level coordinates and data cleaning

Source of coordinates	N. Firms	%	N. errors	%
Google Maps	172,465	38.39%	9,152	50.84%
Open StreetMap	34,386	7.65%	1,017	5.65%
Orbis	242,411	53.96%	7,833	43.51%
Total	449,262	100.00	18,002	100.00

Original postal addresses at the firm level are sourced from Orbis, by Bureau van Dijk. Compilers provide a partial geo-referencing with latitudes and longitudes. We complement missing values with information from Google Maps Geolocation API and Open StreetMap API. A cleaning strategy is implemented to take care of errors in either source, when postal addresses do not plot on maps with a correct municipality. Numbers in percentage points represent share on total.

As from the fourth column of Table 2.1, we find that coordinates are not always correct. Failures in geolocation mainly depend on typos, different punctuations or different spelling of the postal addresses. Most of these problems in disambiguation are usually solved by original sources for latitudes and longitudes. Yet, some mistakes can still remain due for example to changes in toponyms and street names since the original inclusion of the firm in the national registry, or imprecisions observed after web scraping mass geocoded information from the online sources. In order to ensure a minimum quality of the matching, we implement a procedure that spots mistakes at the municipality-level. Thus, in our routine, companies located at given coordinates are projected on a map along with the municipality they should belong to. If we find that point features fall outside the municipality perimeter, we classify them as errors and drop them from the sample. For sake of comparison, we source Italian administrative boundaries updated to 2019 from the national statistics office, ISTAT. Eventually, we find that only about 4% of the firms have unavoidable mistakes and have to be dropped from the original sample.

2.3.2 Market entry and exit

We derive entry-exit dynamics after considering the incorporation date as the moment the firm has entered a market, and the date of failure as the date it exited from the market. In Table 2.2, we report details on firm status of exiting firms as it originally appears in the database. We assume that a company has exited from the market when it is recorded as *Active (insolvency proceedings or default of payment)*, *Dissolved*, *Bankruptcy*, and *In Liquidation*. Usefully for our purpose, the majority of sample exiting firms come with a status date, when we assume that they exited from the market. Only about 0.35% of *Dissolved* companies and 22% of companies *In Liquidation* do not have a precise calendar date. In this case, we assume that the actual market exit occurred in the first year in which sales are not recorded in the database. Exiting firms in 2015 represents about 4.4% of the active companies. For the same year, Eurostat Structural Business Statistics reports a firm death rate of 5.7%.

Table 2.2: Firm exit from original data

Firm status	N. of firms	%
Active (insolvency proceedings or default of payment)	1,093	2.63%
Bankruptcy	11,990	28.88%
Dissolved	15,914	38.32%
In liquidation	13,125	31.61%
Total	41,522	100.00%

Original firm-level legal events, including legal status, are reported in Orbis, by Bureau Van Dijk. We consider firms as exited from the market if their status is any of the ones reported in the table. Status also comes with information on status date. If the latter is missing, we consider the exit date as the year when sales are not recorded for the first time.

2.3.3 Sample coverage

To validate our data, we compare with business demography reported by Eurostat Structural Business Statistics. Our firm-level sample is stratified including a larger set of firms with information on coordinates, as from the georeferencing exercise described in Section 2.3.1, and a set of firms for which we have at disposal financial accounts. The reason why the two sets do not coincide is that not all firms have an obligation to report all balance sheet information. In the Italian case, the original provider is the national registry (*Registro delle Imprese*) following national regulation, according to which there are size thresholds[3]. In Tables 2.3, 2.4, and 2.5, we report geographic, industrial and firm size coverage, respectively. We repeat the same exercise for both sample strata and compare with official census statistics. Our aim is to check whether there is any sample selection bias that we may want to address later in the analyses. Comparison is made with the latest available year as from Eurostat Structural Business Statistics.

As largely expected, Table 2.3 shows that there is a bias by firm size, which is relatively mild in the set of firms with cooordinates and more important in the case of financial accounts for TFPs. In fact, we should expect a total of about 83% of micro-firms with up to 9 employees if we look at census data. Yet, we have about 74.5% and 50.5% of them, respectively, in columns 5 and 7. Overall, we cover up to 54% of the population in the georeferenced set and up to 25% of the population in the set of financial accounts with observed coordinates.

When we look at the industry-level breakdown in Table 2.4, our sample shows relatively high correlations. Percentage shares computed on geo-referenced firms and firm with financial accounts, respectively, show a correlation of 0.96 and 0.82 with the census provided by Eurostat. Relatively small discrepancies in the subsample of financial accounts are mainly an indirect consequence of the absence of financial information

[3] According to regulations, companies must file in a complete format if two of the three following criteria are fulfilled in the first year or for two consecutive years: i) total assets bigger than $6,650,000$ Euro; ii) revenues bigger than $7,300,000$ Euro; iii) average number of employees bigger than 50. Further simplifications have been implemented since 2016.

about micro-firms, which are expected to be more present in some industries with a lower capital intensity.

A limitation of this study is that the fact that we are not able to confront with the universe of firms. This may affect the shape of our clusters. However, when looking at coverage shares by NUTS 2-digit in Table 2.5, any hint of sample selection disappears with correlations up to 0.99 and 0.98, possibly thanks to an even distribution of firms of different size across regions.

Table 2.3: Sample coverage by size-class, reference year 2015

Size Class	Eurostat SBS		Coordinates sample		TFP & coordinates sample	
	N. of firms	%	N. of firms	%	N. of firms	%
0-9 Employees	321,837	82.67%	156,251	74.47%	49,265	50.49%
10-19 Employees	39,159	10.06%	27,800	13.25%	24,029	24.62%
20-49 employees	18,771	4.82%	16,578	7.90%	15,444	15.83%
50-249 employees	8,338	2.14%	7,927	3.78%	7,630	7.82%
250 employees or more	1,212	0.31%	1,256	0.60%	1,213	1.24%
Total	389,317	100.00	209,812	100.00	97,581	100.00

Note: we report firm size coverage of the sample set with geographic coordinates only (columns 4 and 5), and with both coordinates and TFP estimated (columns 6 and 7). Firm size is measured by number of employees. Population figures come from Eurostat Structural Business Statistics in year 2015.

Table 2.4: Sample coverage by industry, reference year 2015

Industry (NACE 2-digits)	Eurostat SBS		Coordinates sample		TFP & coordinates sample	
	N. of firms	%	N. of firms	%	N. of firms	%
Food	53,096	13.64%	37,360	11.60%	8,408	8.62%
Beverages	3,219	0.83%	3,064	0.95%	1,100	1.13%
Tobacco	6	0.00%	44	0.01%	12	0.01%
Textiles	13,866	3.56%	10,440	3.24%	3,496	3.58%
Wearing Apparel	28,865	7.41%	29,894	9.28%	4,648	4.76%
Leather	15,235	3.91%	14,043	4.36%	3,760	3.85%
Wood	28,163	7.23%	17,774	5.52%	3,320	3.40%
Paper	3,723	0.96%	3,349	1.04%	1,679	1.72%
Printing	15,109	3.88%	11,028	3.42%	3,291	3.37%
Refined petroleum	281	0.07%	336	0.10%	186	0.19%
Chemicals	4,308	1.11%	5,041	1.57%	2,606	2.67%
Pharmaceutical	453	0.12%	744	0.23%	392	0.40%
Plastic	9,971	2.56%	8,930	2.77%	4,640	4.76%
Non-metallic Mineral	19,189	4.93%	15,777	4.90%	5,031	5.16%
Basic metals	3,407	0.88%	2,894	0.90%	1,539	1.58%
Fabricated metals	63,185	16.23%	60,291	18.72%	21,181	21.71%
Computer, electronic, optical	4,912	1.26%	7,313	2.27%	3,031	3.11%
Electrical equipement	8,363	2.15%	8,703	2.70%	3,680	3.77%
Machinery	22,761	5.85%	21,258	6.60%	11,033	11.31%
Motor vehicles	2,242	0.58%	2,695	0.84%	1,198	1.23%
Other transport	2,409	0.62%	4,277	1.33%	1,197	1.23%
Furniture	18,108	4.65%	13,637	4.23%	3,978	4.08%
Others	29,488	7.57%	22,029	6.84%	3,365	3.45%
Repair and installation	38,958	10.01%	21,140	6.56%	4,810	4.93%
Total	389,317	100.00	322,061	100.00	97,581	100.00

Note: we report industry coverage of the sample set with geographic coordinates only (columns 4 and 5), and with both coordinates and TFP estimated (columns 6 and 7). Industries are classified following NACE rev.2 2-digit categories. Population figures come from Eurostat Structural Business Statistics in year 2015.

Table 2.5: Sample coverage by geography, reference year 2015

NUTS-2 Region	Eurostat SBS		Coordinates sample		TFP & coordinates sample	
	N. of firms	%	N. of firms	%	N. of firms	%
Piemonte	30,771	7.85%	22,356	6.94%	7,032	7.21%
Valle d'Aosta	678	0.17%	392	0.12%	101	0.10%
Liguria	7,646	1.95%	5,889	1.83%	1,303	1.34%
Lombardia	78,838	20.10%	62,083	19.28%	24,893	25.51%
Abruzzo	8,938	2.28%	8,028	2.49%	1,975	2.02%
Molise	1,729	0.44%	1,418	0.44%	272	0.28%
Campania	26,162	6.67%	28,478	8.85%	5,797	5.94%
Puglia	21,074	5.37%	17,084	5.31%	4,129	4.23%
Basilicata	2,863	0.73%	2,581	0.80%	483	0.49%
Calabria	8,034	2.05%	8,364	2.60%	937	0.96%
Sicilia	20,667	5.27%	18,839	5.85%	3,049	3.12%
Sardegna	7,406	1.89%	6,328	1.97%	1,089	1.12%
Trentino Alto Adige	6,293	1.60%	4,220	1.31%	1,297	1.33%
Veneto	44,701	11.40%	33,514	10.41%	13,191	13.52%
Friuli-Venezia Giulia	7,918	2.02%	5,849	1.82%	2,298	2.35%
Emilia Romagna	36,586	9.33%	28,848	8.96%	10,712	10.98%
Toscana	38,018	9.69%	28,096	8.73%	8,407	8.62%
Umbria	6,624	1.69%	4,816	1.50%	1,449	1.48%
Marche	16,222	4.14%	12,529	3.89%	4,270	4.38%
Lazio	20,978	5.35%	22,247	6.91%	4,897	5.02%
Total	392,146	100.00	321,959	100.00	97,581	100.00

Note: we report geographic coverage of the sample set with geographic coordinates only (columns 4 and 5), and with both coordinates and TFP estimated (columns 6 and 7). Regions are classified following NUTS 2-digit categories. Population figures come from Eurostat Structural Business Statistics in year 2015.

2.4 Detecting agglomerations of firms

2.4.1 A density-based procedure

In detecting firms' agglomerations advantages, one meets with a common challenge in spatial analyses. Administrative boundaries are drawn based on political and historical determinants, less on economic patterns. Findings risk being biased because identical data points appear either sparse or clustered depending on the shape of the boundary placed around them[4]. The problem is also recently acknowledged in Duranton

[4]The modifiable areal unit problem (MAUP) is a source of statistical bias well-known to scholars since Gehlke and Biehl (1934). It emerges either in the aggregation or disaggregation of spatial phenomena into geographic units at different scales. Findings could be affected by both the shape and scale of the aggregation units. For details, see also Arbia

and Puga (2020), according to whom the increasing availability of geo-referenced data allows adapting the definition of clusters to the actual purpose of the analyses.

In this study, we are interested in capturing a broad spectrum of firms' agglomeration typologies to control at which scale (if any) one could explain regional disadvantages. Therefore, we opt for an unsupervised machine learning method that identifies arbitrary-shaped concentrations of business activity solely based on geographic information. OPTICS by Ankerst et al. (1999) is a density-based clustering algorithm that we regard as the best solution because it is not essential to fix an *a priori* number of clusters, and it complies with irregular shapes on maps. Similarly to other density-based clustering algorithms, e.g., DBSCAN (Ester et al., 1996), it works by detecting areas on maps where points are dense, thus separating them from areas where points are sparse. Yet, generally, similar algorithms find clusters according to a unique density value applied to the entire data set. Since one cannot expect a global density parameter to be always valid in space, OPTICS overcomes this limit by adopting a continuum of distance parameters, so that, given a minimum number of points, it is able to pin down clusters of variable densities. The latter is a desirable property for the scope of our research, where we want to generalize the definition of firms' agglomerations. Eventually, the algorithm requires only an upper threshold to the range of distances, $\{\epsilon_i\}$, and a minimum number of points, M, as entry parameters.

To get more into OPTICS functioning, let us introduce some more notation. We can define a ϵ_i-neighborhood of a firm-point as all the firm-points that locate at distance ϵ_i. Therefore, we can define a *core-point* a firm-point p_i if its ϵ_i-neighborhood includes at least M other firm-points. In other words, the cardinality of the set of firm-points in the ϵ_i-neighborhood is $Card(N_\epsilon(i))$, and it is $Card(N_\epsilon(p_i)) \geq M$. The latter is also referred to as the *core-point condition*.

Thus, OPTICS works following two different concepts of distance both represented in Figure 2.1a:

(1989).

1. The *core-distance* of a firm-point p_i, $c(p_i)$, is the minimum radius such that $Card(N_\epsilon(i)) \geq M$, i. e., the minimum distance required to travel from p_i to the minimum number of firm-points.

2. The *reachability distance* of a point p_j with respect to a point p_i is the maximum between $c(p_i)$ and $d(p_i, p_j)$, with the latter representing the distance between p_i and p_j.

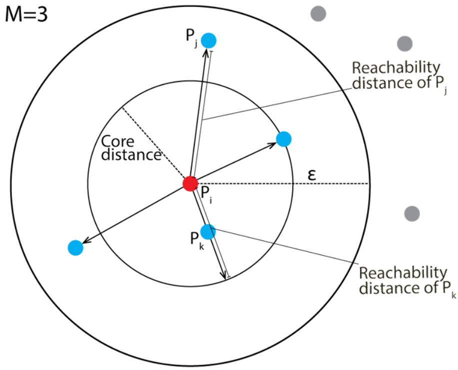
The algorithm randomly draws a firm-point, sets its *reachability distance* to undefined, and lists it in an ordered file which we here call *OrderList*. If the processed firm meets the *core-point* condition, it is subjected to the analysis of its neighborhood, otherwise a new point is randomly extracted from the database. When a *core-point* is found, all points in its ϵ-neighborhood are written in a second file, the *SeedList*, and they are sorted by their *reachability distance* from the *core-point*. The algorithm then moves the points in the *SeedList* to the *OrderList*, one by one, according to the lowest *reachability distance*, storing each time the reachability value. Importantly, when OPTICS picks the next most reachable firm from the *SeedList*, it checks whether the latter is a *core-point* itself before moving it to the *OrderList*. Every time OPTICS encounters a *core-point* while scrolling the *OrderList*, the latter is updated by adding the points found in the ϵ-neighborhood of the current *core-point* and their respective *reachability distances*. As for firm-points already enlisted in the *SeedList*, if the current *reachability distance* is smaller than the stored one, the latter is updated to the lower value. Once all firms in the *SeedList* are processed, the procedure iterates by randomly picking a point not yet processed until all the objects in the database are orderly stored in the *OrderList* with their respective *reachability distances*.

Eventually, the latter values give information on the entire clustering structure, which can be graphically represented in a so-called *reachability plot*. In Figure 2.1b, we provide a visual intuition of a *reachability plot* obtained at the end of a procedure. Reachability distances are reported on the y-axis together with firm-points on the x-axis.

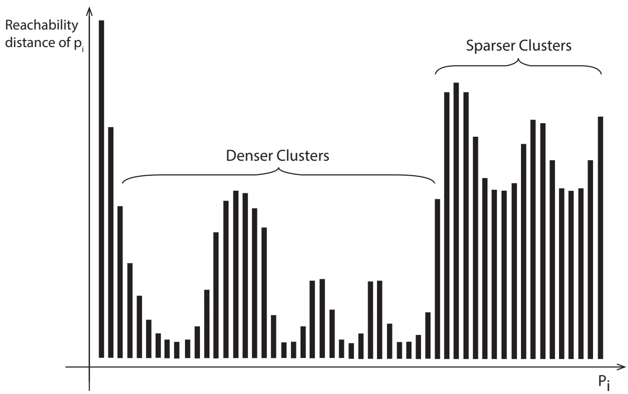
Flatter regions in the graph (in jargon, 'valleys') represent areas where firm-points are easily reachable from each other, thus possibly identifying firms' clusters. On the other hand, 'peaks' indicate that longer distances are needed to travel from one firm to another, thus possibly separating one firm agglomeration from another. Denser clusters lay lower in the graph, in correspondence of smaller values of *reachability distance*.

Figure 2.1: Graphical representation of OPTICS main features

(a) *Core distance* and *Reachability distance*



(b) *Reachability plot*



Note: (a) Given a certain value of ϵ and $M = 3$, p_i is a *core point*, and its *core distance* is the radius required to travel to the second point of its ϵ-neighborhood. Note that the *core distance* can never exceed ϵ. A *reachability distance* from p_i is defined for each point in the ϵ-neighborhood. Since the distance between p_i and p_j exceeds the *core distance*, the *reachability distance* of p_j will be equal to $d(p_i, p_j)$. Viceversa, since p_k stands at a shorter distance from p_i with respect to the *core distance*, reachability of p_k from p_i coincides with the *core distance*. (b) After the *reachability distances* are computed for the entire database, a *reachability plot* as in panel 2.1b is built. Points are reported in the processing order on the x-axis, and their respective *reachability distances* on the y-axis.

At this point, we are ready to outline the intuition behind clusters' automatic detection. The latter crucially depends on the interpretation given to the downward and upward slopes found at the starting and ending of each 'valley'. This aspect is modulated by a third fundamental parameter, ξ, which defines the steepness of the points a cluster should start and end with. In practical terms, ξ should be set as the maximum ratio between the *reachability distances* of two points:

$$\frac{r(p_i)}{r(p_{j\neq i})} \leq (1-\xi) \tag{2.1}$$

$$\frac{r(p_i)}{r(p_{j\neq i})} \leq (1-\xi)^{-1} \tag{2.2}$$

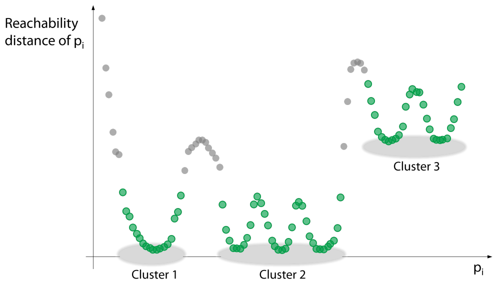
with $\xi \in [0,1]$. The first equation holds for the end of clusters and the second for the start. Based on ξ, the algorithm recognizes the areas of the *reachability plot* that accomplish the following set of conditions. A potential cluster ending (starting) area should begin and terminate with two adjacent points that meet the steepness condition in Eq. 2.1 (Eq. 2.2). Within this area, the *reachability distance* of a point p_i should never be lower (higher) than the *reachability distance* of point p_{i-1}. Finally, a cluster ending (starting) area cannot contain more than M points.

The visualization in Figure 2.2 might help to understand the meaning of ξ. For relatively small values of ξ, even slight differences in the *reachability distances* are sufficient to mark the boundaries of a cluster. As in Figure 2.2a, this results in a greater number of clusters of reduced size in terms of points. As the value of ξ approaches 1, the steepness condition imposed on downstream and upstream areas becomes stricter. As a consequence, OPTICS will recognize an ever smaller number of increasingly larger clusters (see Figure 2.2b and 2.2c).

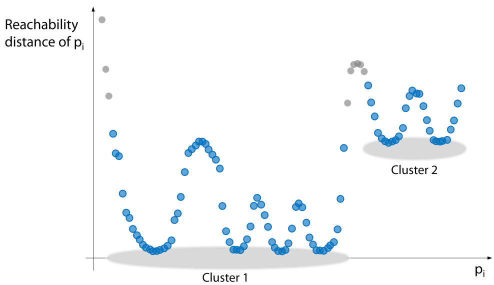
Figure 2.2: Effect of ξ setting

(a) Low ξ

(b) Medium ξ



(c) High ξ



Note: We simulate a *reachability plot* to show how ξ setting affects cluster detection. We assume three levels for the ξ parameter. Very small values of ξ (2.2a) imply that virtually every 'valley' in the plot is considered a cluster. As ξ switches to a medium level (2.2b), the number of clusters decreases. Clusters 2, 3, and 4 from panel a) are merged into a larger one, as the 'peaks' separating them are no longer steep enough. Finally, only two large clusters are found at very high levels of ξ (2.2c).

In this context, several solutions of ξ can make sense depending on the granularity scope of the analysis, as originally remarked by Ankerst et al. (1999).

2.4.2 Our application

We run OPTICS on the set of firm-level coordinates obtained as from Section 2.3.1. Since no distance is specified, a default ϵ equal to the highest *core distance* found in the sample is automatically set[5], thus, a manual setting is required for two parameters only, M and ξ. These are defined as the result of a fine-tuning based on our prior albeit limited knowledge about the existence of firms' agglomerations in Italy.

Briefly, we pick as entry parameters those values that return the most realistic picture of what happens in selected areas, where some agglomerations had been already mapped. Then, we extend parameters from those limited areas to the entire Italian territory.

At first, we evaluate a variety of sources, including the list of industrial districts issued by official statistics offices (ISTAT, 2015), the regional law in Lombardy addressed to industrial districts (Decision of the Lombardy Regional Council No 7/3839 of 16 March 2001, complying with Regional Law No 1/2000), as well as the industrial areas monitored by a commercial bank (Intesa San Paolo, 2015) and by an *ad-hoc* observatory, (Osservatorio Nazionale dei Distretti Italiani, 2015). More than often, sources are contradictory as how many clusters there are. Most sources do not report precise information on the actual geographic boundary of firms' clusters, as they loosely relate to the wider region on which they could be found.

Please note that our scope is to encompass different types of agglomerations, which may include also industrial districts as a special category.[6]

[5]Using the maximum *core distance* better ensures an accurate reproduction of the natural grouping structure of the database in the *reachability plot* (Ankerst et al., 1999).

[6]Please note a disconnection between studies that empirically observe the evolution of industrial districts and the ones that model the more general impact of agglomeration economies. Industrial districts in the original definition of Marshall (1920) are viewed as places where workers and firms co-locate and specialise in a main industry. Yet, agglom-

Yet, previous experience in mapping industrial districts is extremely valuable to us. We take it as a departing point to fine-tune our algorithm and identify the optimal value of ξ, and the number of minimum firm-points, M, which we expect in a firms' agglomeration. For our approximation, we decide to pick baseline parameters $\xi = 0.45$ and $M = 350$.

Based on previously identified baseline parameters, we are able to draw 184 clusters of firms in Figure 2.3. Furthermore, we visualise the way in which our OPTICS polygons overlap with NUTS 3 regions (Figure 2.4). *Prima facie*, we observe that they are homogeneously distributed along the entire Italian territory. There is no specific pattern that we can observe making a difference between the North and the South of the country. This is in line with what we know of the country's manufacturing system, which is traditionally not concentrated in a few geographic areas. Denser areas inside clusters collect about 76% of total sample firms. Looking at clusters up close, we note that they capture different types of agglomerations including both urban areas and industrial districts . However, please note that clusters tend to spread on a wider geographic area in the South, while they are smaller and more compact in the North.

eration advantages are mainly studied as originated within 'cities', where the latter are usually proxied by administrative boundaries. See also Combes (2000) and Gaubert (2018). Our general definition based exclusively on firms' densities allows us encompassing both, provided that a minimum density of business activities is retrieved.

Figure 2.3: Italian manufacturing clusters, 2007-2017

Note: OPTICS clustering on ORBIS data with $\xi = 0.45$ and $M = 350$. Note that colours do not uniquely identify clusters. Companies that are not assigned to any cluster are marked in grey.

Figure 2.4: Firms' clusters vs. NUTS 3-digit administrative boundaries

Note: Green polygons represent firms clusters, often overlapping across NUTS 3-digit regions framed in black. NUTS3 regions striped on the inside correspond to *Predominantly Urban areas*, as defined by Eurostat (provinces where the share of population living in rural areas is below 20), and *Metropolitan regions* as defined by OECD (combinations of NUTS3 populated by at least 250,000 inhabitants).

2.5 Stylized facts

In this section, we provide novel stylized facts on the North-South productivity gap and on the benefits from firms' agglomerations. For our purpose, we rely on estimates of Total Factor Productivity (TFP) at the firm-level following the methodology by Ackerberg, Caves, and Frazer (2015). Preliminary evidence reported here will thus pave the way for an informed discussion of empirical findings in the following sections.

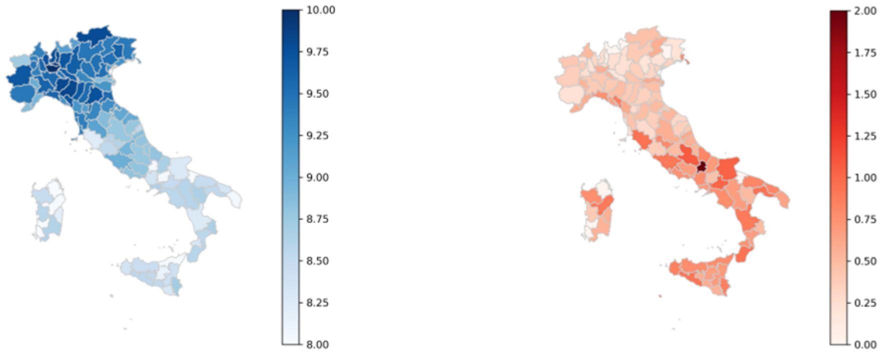
2.5.1 North-South productivity gap

The first stylized fact we provide is illustrated by Figure 2.5, where we show averages and standard deviations of (log) TFP, respectively, for each NUTS 3-digit region in Italy in the reference year 2015. As largely expected, average (log) TFPs are bigger in Northern regions and they drop as we move along the map to the South (blue map). Yet, an opposite pattern is detected in the case of standard deviations, since we observe firm-level TFPs are more dispersed in the South of the country (red map). This is an interesting insight into the heterogeneity of firm-level TFP distributions by geography[7]. Geographic patterns are similar for every year we consider from our albeit short timeline at disposal.

We believe the latter evidence specifically pinpoints to an appraisal of differences in TFP distributions as due to different local mechanisms of agglomeration and market selection that are worth further investigations. As from previous literature (Combes et al., 2012), we know that TFP firm-level distributions contain non-trivial information on how firms are actually benefiting (or not) from agglomeration economies.

[7] For a previous reference on a similar finding, see Rungi and Biancalani (2019).

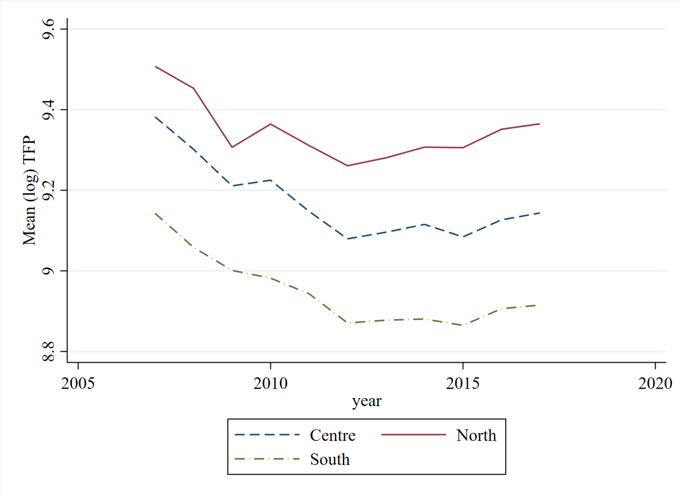
Figure 2.5: Mean and standard deviation of (log) TFP in NUTS 3-digit regions, year 2015



However, when we look at aggregate trends, production dynamics keep diverging at a regional level[8]. In Figure 2.6, we register a general downfall in mean TFP in the country after the financial crisis in 2007-2008, which is particularly harsher in the South. The difference in recovery speeds since 2011 has contributed to widening the gap because the Centre diverges towards Southern flatter growth rates.

[8]From now on, we define the unique aggregate of NUTS1 regions ”NorthEast” and ”NorthWest” Italy as ”North” and the unique aggregate of the NUTS1 regions ”South” and ”Islands” as ”South”. ”Centre” remains the same as the NUTS1 definition.

Figure 2.6: Mean (log) TFP by macro-region, trend 2007-2017

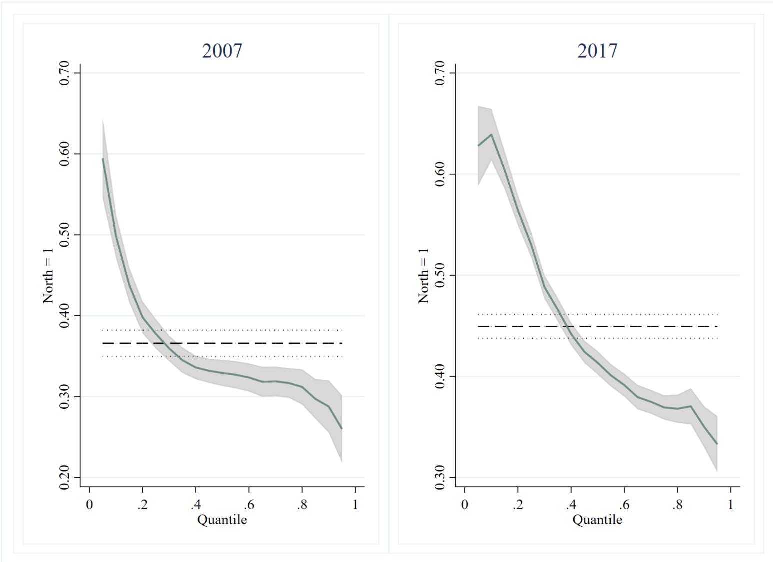


Note: Regions are defined following NUTS 1-digit classification. North West and North East as well as South and Islands are reported as unique aggregates (called "North" and "South" respectively).

Yet, previous aggregate trends may hide different patterns when we specifically consider firm-level heterogeneity. To check for the latter, we run a quantile regression at the beginning and the end of our period, respectively in 2007 and 2017, whose dependent variable is firm-level (log of) TFP and whose only regressor is a binary indicator equal to 1 if a firm operates in the North, and 0 if the firm is located in the South. Firms located at the Centre are excluded here. For the sake of reference, we plot results against a simple least-squares estimate in Figure 2.7.

What we observe is that the productivity gap develops along the entire distribution, although unevenly. It gradually decreases as we move from the bottom to the top of the distribution. The latter feature persists throughout the decade, while, over time, the divide has increased in each productivity class and has become even more heterogeneous. Nonetheless, the most considerable gap is present on the left tail. It implies that firms with the lowest levels of TFP play a major role in dragging down the aggregate productivity trend of the South with respect to the North, as we observe in Figure 2.6.

Figure 2.7: TFP distributions and regional disparities - Quantile regressions



Note: We illustrate the findings of quantile regressions whose outcome is (log of) TFP by including as a regressor a dummy variable equal to 1 for companies operating in the North, and 0 for companies operating in the South. Firms operating in the Centre are excluded. No firm controls are included and we control for robust standard errors. We report 95% confidence intervals. As a reference point, we plot OLS estimate on the horizontal line. First and last year are reported.

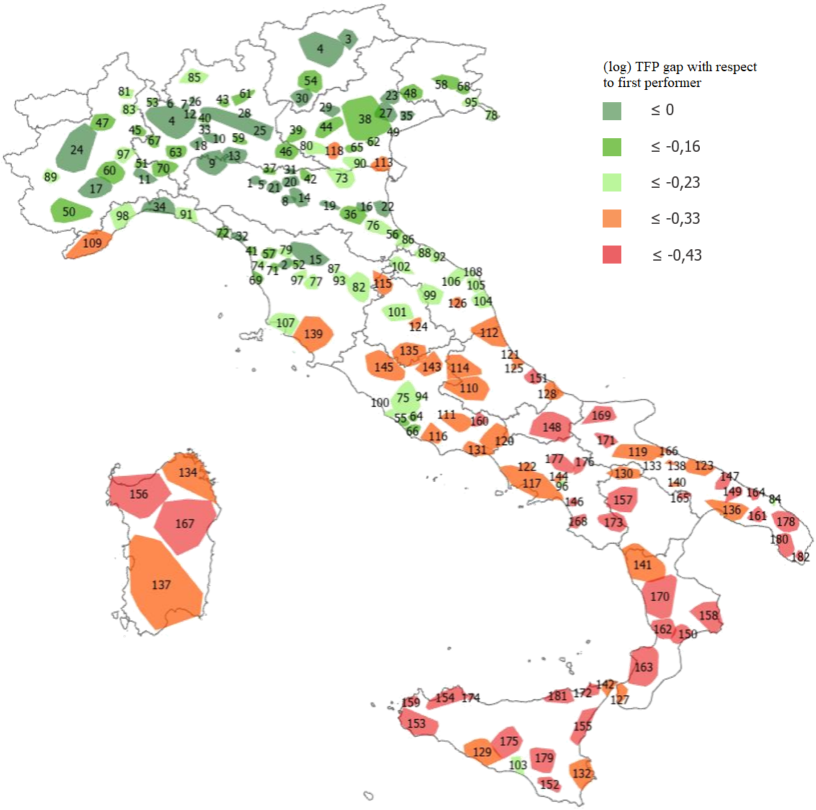
2.5.2 Ranking clusters by productivity

We now evaluate how the productive dichotomy between North and South appears when we observe it through the lens of our firm clusters. Is the regional gap still so sharp when denser areas only are considered? Do we find any interesting exception among business agglomerations? To address these questions, we qualify each cluster by the average productivity difference with respect to the best performer and rank accordingly. We regress firm-level TFP (in logs) on cluster-id indicators according to the following specification

$$logTFP_{icjt} = \alpha + \beta\, clusterID_c + \delta\, X_{icjt} + \gamma_t \times \eta_j + \epsilon_{icjt} \qquad (2.3)$$

where X_{icjt} is a set of firm-level controls including age, employment and capital intensity for each firm i in cluster c, in industry j at time t; γ_t and η_j are respectively time and 2-digit industry fixed effects and consider β coefficients in an orderly fashion. The internal ranking thus obtained can be observed in Figure 2.8. The most productive firm agglomeration extends over the urban area of Parma in North Italy. With some exceptions, the map reveals a straightforward pattern wherein most productive clusters (in dark green) are in the North, least productive (in red) in the South. The Center is a transition zone where some very virtuous agglomerations (see Tuscany) coexist with others that become gradually less efficient when descending towards the South. A more detailed analysis is facilitated by Table 2.6, where coefficients of the cluster fixed effects *clusterID*$_c$ for top and bottom performers are reported. There is a high productivity dispersion across clusters located in different areas, up to a maximum of 85 percentage points (log units 0.614) difference between the best performer and the very last one, respectively located in the North and South. The top ten performers are in Lombardy, Emilia Romagna, Alto Adige and Tuscany, and are quite heterogeneous by type. Indeed, among the most productive clusters, there are some overlaid onto cities (Parma, Bolzano, Sassuolo, Piacenza, Crema), and others coinciding with well-known industrial districts. For example, the second best is in Tuscany and corresponds to the industrial district of Santa Croce sull'Arno, which is specialized in leather and footwear production.

Figure 2.8: Ranking clusters by productivity gains



Note: OPTICS clusters are ordered according to their average (log) TFP difference with respect to the top performer. Each polygon is labeled by its position in the ranking. Quantiles of the internal percentage gap distribution are reported in graduated colors.

Table 2.6: Internal productivity ranking of firm clusters: top and bottom performers

Top 10 Performers		**Bottom 10 Performers**	
Ranking	$\hat{\beta}$	Ranking	$\hat{\beta}$
2	-0.042***	182	-0.614***
3	-0.046	181	-0.574***
4	-0.065***	180	-0.553***
4	-0.065***	179	-0.552***
5	-0.067**	178	-0.544***
6	-0.070***	177	-0.534***
7	-0.076***	176	-0.531***
8	-0.084***	175	-0.523***
9	-0.085***	174	-0.514***
10	-0.096***	173	-0.508***

Note: Each coefficient measures the difference in productivity between each cluster and the cluster with the highest productivity level. The latter extends over the urban area of Parma. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

Overall, the regional divide is confirmed, and we find no relevant exceptions among firm agglomerations such that the North-South hierarchy is upturned.

2.5.3 Regional gaps and firms' agglomerations

At this point, we still have to clarify the effect of the spatial concentration of manufacturing activity in terms of productivity. Based on akin literature and previous findings, we expect our clusters to enclose an average productivity boost, as they arise at locally significant firm density[9].

We adopt the same base model as in Eq. 2.3 and replace the categorical of interest with a dummy variable indicating whether or not a company belongs to a cluster. We also consider a regional categorical

[9]Theoretical literature predicts agglomeration forces to trigger productivity improvements. Yet, the empirical results brought in support of this thesis are usually found either within large cities (defined according to population), or within specialized industrial districts (defined according to specialization indices). In this chapter, agglomeration is measured in terms of the sole firm density criterion. Thus, we ignore sector-specificity, as well as city size.

and specify the North as reference. Moreover, we add a categorical variable for the macro regions and we cluster standard errors. According to the outcome reported in Table 2.7, the first two specifications reveal that being part of an agglomeration of companies positively affects productivity, although the macro-region advantage is far larger. Indeed, a company located in the North is on average more efficient by almost 32 percentage points ($e^{0.2787} - 1 \simeq 0.321$) than one located in the South, whereas a company located in a cluster is on average more productive by 4.5 ($e^{0.0442} - 1 \simeq 0.452$) percentage points than one located in a sparse area.

Table 2.7: The relationship between firm agglomeration and firm-level productivity

(log) TFP	(1)	(2)	(3)
Inside clusters		0.0442***	
		(0.0116)	
Centre	-0.1083***	-0.1118***	
	(0.0164)	(0.0262)	
South	-0.2750***	-0.2787***	
	(0.0088)	(0.0209)	
Inside clusters x Centre			-0.0998***
			(0.0308)
Inside clusters x South			-0.2701***
			(0.0246)
Outside clusters x North			-0.0330**
			(0.0155)
Outside clusters x Centre			-0.1783***
			(0.0169)
Outside clusters x South			-0.3353***
			(0.0169)
Observations	874,855	874,855	874,855
R^2	0.2646	0.2652	0.2654
Firm controls	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes

Note: Firm-level controls include age, employment and capital intensity (in logs). Errors are clustered at 2-digit industry level in column (1). Two-way clustering of standard errors at cluster and 2-digit industry level in columns (2) and (3). *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

In the third column, we consider the interaction between macro region and cluster membership. We compare each coefficient with the category *Inside clusters* $\times$ *North*. We observe that firms based in a Northern cluster are on average more productive than those located in the Centre by 10.5% ($e^{0.0998} - 1 \simeq 0.105$) when they fall into an industrial agglomeration, otherwise, the TFP differential increases to 19.5% ($e^{0.1783} - 1 \simeq 0.195$). The TFP gap is even larger in the South. Specifically, firms located in Northern clusters are more productive by 31% ($e^{0.2701} - 1 \simeq 0.310$)

when Southern firms are inside clusters and 39.8% ($e^{0.3353} - 1 \simeq 0.398$) when outside. Overall, inside areas where the manufacturing activity is dense, the regional productivity gap is slightly dampened.

2.6 Empirical strategy and results

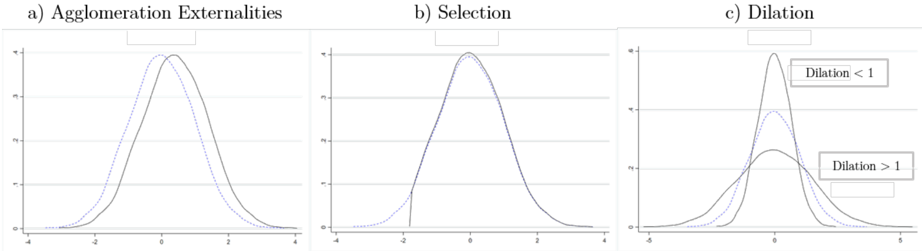
Our preliminary exercise indicates some productivity premia for companies located inside clusters. In our main analysis we examine whether this productivity advantage is related to agglomeration and selection mechanisms. Furthermore, we investigate whether the relative importance of these two drivers differ according to the geographical area. In that way, we provide some insight into the role of agglomeration on regional disparities.

We apply the empirical framework by Combes et al. (2012) using our scope of firm clustering (Section 2.6.1)[10]. As Arimoto, Nakajima, and Okazaki (2014) show, the model can be applied for cases where we consider regions based on firm density. Therefore, we estimate the relative agglomeration externalities simultaneously with firm selection for companies inside clusters. To do so, we compare the productivity distribution between companies in dense and non-dense areas by estimating three parameters to quantify the relative right shift, dilation and left truncation. A distribution is right-shifted when all firms' productivity in dense areas is larger because of interactions among contiguous companies. Hence, the right shift parameter is a proxy for agglomeration externalities. The dilation parameter indicates how dispersed a productivity distribution is, suggesting productivity advantages are not equal in each distribution tail. When dilation is combined with right shift, productivity advantages in large cities are even larger for the most productive companies, due to the assumption that a worker is more productive when working at a more efficient company. Left truncation occurs when inefficient companies are not able to survive due to fierce competition. Hence it is a proxy for market selection.

[10]The model has been also reproduced by Accetturo et al. (2018) for the case of Italian cities

Figure 2.9 illustrates a visual representation of what each parameter represents. In each panel, the dashed line depicts a hypothetical distribution of log TFP for companies that are outside clusters while the solid curves concern distribution of firms inside clusters. We hypothesize a right shift due to agglomeration externalities (panel (a)), a left truncation due to market selection (panel (b)) and a relative higher (> 1) or lower (< 1) dilation in the distribution of firms inside clusters (panel (c)).

Figure 2.9: Three potential transformations of the log productivity distribution due to geographical agglomeration



Note: The above distributions are simulated for illustrative purposes only. The dashed blue line hypothetically corresponds to sparse areas. The black solid line hypothetically corresponds to dense areas. In panel *a*, a right shift of the distribution is simulated as consequence of agglomeration economies. Panel *b* shows the left truncation brought on by the selection mechanism. Panel *c* depicts the dilation effect. A dilation coefficient higher than one means that, inside denser areas, the distribution is more dispersed. The opposite is observed when the coefficient is lower than one.

2.6.1 Econometric approach

The model starts with the definition of two distributions with cumulative density functions F_i and F_j, where i are firms located inside clusters and j are firms located outside clusters, and an underlying distribution with cumulative density function $\tilde{F}$. The main assumption is that, to obtain the function F_i of log TFP (ϕ) for firms located inside clusters, one should (i) right-shift by A_i, (ii) dilate by D_i the underlying distribution with cumulative density function $\tilde{F}$, and (iii) and left-truncate its values by $S_i \in (0, 1)$. In a similar way, the density function F_j of ϕ for firms located outside clusters can be derived by the right shift, dilation and left truncation parameters A_j, D_j and $S_j \in (0,1)$ respectively. As mentioned in the previous section, these parameters denote the relative agglomeration externalities and selection effects between companies inside and outside clusters.

The cumulative distributions of the firms inside clusters i and outside clusters j are defined as follows:

$$F_i = \max\left\{0, \frac{F_j\left(\frac{\phi - A}{D}\right) - S}{1 - S}\right\}, \quad \text{if} \quad S_i > S_j \tag{2.4}$$

$$F_j = \max\left\{0, \frac{F_i(D\phi + A) - \frac{-S}{1-S}}{1 - \frac{-S}{1-S}}\right\} \quad \text{if} \quad S_j > S_i \tag{2.5}$$

where $D = \frac{D_i}{D_j}$, $A = A_i - DA_j$ and $S = \frac{S_i - S_j}{1 - S_j}$. Parameters A, D and S indicate the relative right shift, dilation and left truncation between firms i and j.

Following the quantile specification of the model and after a change in variables, we end up to the following equation:

$$\lambda_i(r_s(u)) = D\lambda_j(S + (1 - S)r_s(u)) + A \quad \text{for} \quad u \in [0,1] \tag{2.6}$$

where $\lambda_i(u) = F_i(u)^{-1}$ is the uth quantile of F_i and $\lambda_j(u) = F_j(u)^{-1}$ is the uth quantile of F_j, $r_s(u) = \max(0, \frac{-S}{1-S}) + \left[1 - \max(0, \frac{-S}{1-S})\right] u$.

Eq. 2.6 indicates the association between the quantiles of the log productivity distribution of firms inside clusters i and firms outside clusters j through the parameters of relative shift A, relative dilation D and relative truncation S. The estimates for A, D and S are derived from the following relationship:

$$m_\theta(u) = \lambda_i(r_s(u)) - D\lambda_j(S + (1 - S)r_s(u)) - A \tag{2.7}$$

The estimator for $\theta = (A, D, S)$ is defined as:

$$\hat{\theta} = argmin_\theta \left[\int_0^1 [\hat{m}_\theta(u)]^2 du + \int_0^1 [\hat{\tilde{m}}_\theta(u)]^2 du\right] \tag{2.8}$$

where $\hat{m}_\theta$ is the estimate of m_θ and $\hat{\hat{m}}_\theta$ is the estimate of the following relationship:

$$\tilde{m}_\theta(u) = \lambda_j(\tilde{r}_s(u)) - \frac{1}{D}\lambda_i\left(\frac{\tilde{r}_s(u) - S}{1 - S}\right) + \frac{A}{D} \tag{2.9}$$

where $\tilde{r}_s(u) = \max(0, S) + [1 - \max(0, S)]u$. The goodness of fit is $R^2 = 1 - \frac{M(\hat{A},\hat{D},\hat{S})}{M(0,1,0)}$.[11]

Finally, for each firm we consider the mean (log) TFP across our period of analysis:

$$\hat{\phi} = \frac{1}{T}\sum_{t=1}^{T}\hat{\phi}_t \tag{2.10}$$

where T is the number of years.

2.6.2 Results

This section illustrates the results of our baseline analysis. We compare firm-level productivity distributions inside and outside OPTICS clusters. Table 2.8 reports the estimates for $\hat{A}$, $\hat{D}$ and $\hat{S}$ for the whole sample and by macro-region[12].

Considering the whole sample, we observe a significant right shift coefficient indicating positive agglomeration externalities for firms operating in dense clusters (column 1). According to Combes et al. (2012), agglomeration economies involve and benefit all companies, although often unevenly. Adopting the authors' point of view, we suppose that high firm density implies that a larger pool of workers will exchange knowledge. The productivity increase triggered by interactions is then passed on from the employees to the companies for which they work. In fact, $\hat{A} = 0.0327$ meaning that firms located inside clusters are on average more productive by $e^{0.0327} - 1 = 3.32\%$. Right shift is observed in

[11] For more details about the analytical solution, see Combes et al. (2012). To estimate the model we use the *estquant* command in Stata (Kondo, 2017).

[12] In line with Combes et al. (2012), we normalize our value of log TFP so the conditional mean of log TFP for firms outside clusters to be zero. Moreover, we remove outliers at 1 percent in each tail of the TFP distribution.

each region as well. Firms are on average more productive by 4.59% in the North, 11.03% in the Centre, and 8.53% in the South.

The coefficient for dilation is larger and significantly different from 1. When we consider the whole country in our analysis, we find that $\hat{D} = 1.0622$ (column 2). Productivity distribution is more dilated inside clusters. When we focus on each region separately, we observe that dilation occurs only in the North and Centre. The third Panel of Figure 2.9 might help to gain a better understanding. In the North and in the Center, where $\hat{D} > 1$, productivity is more dispersed inside firm agglomerations. In the South, we observe an insignificant coefficient, hence dilation does not occur.

As Combes et al. (2012) suggest, when right shift is combined with dilation or when $\hat{A} > 0$ and $\hat{D} > 1$ simultaneously, productivity gains from agglomeration externalities are greater for the most productive firms. Here, right shift and dilation occur when we consider the country as a whole and focus on the North and the Centre. The intuition is that workers are more productive when working for more efficient companies. However, this does not happen in the South. Productivity distribution is right-shifted for firms inside clusters, but dilation is absent, meaning that agglomeration externalities equally benefit all firms. This is indicative of the best performers' incapability to complement their production techniques with human capital to boost competitiveness further. Overall, we find that our clusters indeed capture agglomeration externalities, and they appear to be heterogeneous across regions.

Left truncation is significant when we run the regression at a national scale (Column 3) with a coefficient of $\hat{S} = 0.0033$. However, at a regional scale significance disappears, casting some doubts on the robustness of our results and on the ability of our clustering approach to capture selection mechanisms. As illustrated in Figure 2.9, left truncation implies an entire range of productivity values to disappear from the distribution of the companies located inside agglomerations. For this to be achieved, the selection effect should operate before companies enter the market. Indeed, the selection we observe through Combes et al. (2012) methodology entails that inefficient companies do not even enter highly competitive markets. The direct consequence is that extremely low values of productivity will not even show up in the distribution. Therefore, our evidence regarding selection mechanisms directly affecting a company's entry choice is relatively weak.

Table 2.8: Relative agglomeration and selection between firms located inside and outside clusters

	$\hat{A}$	$\hat{D}$	$\hat{S}$	Pseudo R^2	Observations
Inside vs Outside	0.0327***	1.0622***	0.0033***	0.9323	146,364
	(0.0041)	(0.0071)	(0.0010)		
Inside vs Outside (North)	0.0449***	1.0700***	0.0009	0.9799	86,317
	(.0050)	(.0082)	(0.0013)		
Inside vs Outside (Centre)	0.1046***	1.0542***	0.0011	0.9705	29,942
	(0.0088)	(0.0140)	(0.0016)		
Inside vs Outside (South)	0.0819***	0.9872	-0.0010	0.9274	30,105
	(0.0106)	(0.0159)	(0.0020)		

Note: The table provides estimates for relative right shift, dilation and left truncation between firms located inside and outside clusters. Bootstrapped standard errors with 100 bootstrap replications are in parentheses. In all regressions the bootstrap sampling is done in the whole sample, considering all observed firms across the country. *, ** and *** denote that $\hat{A}$ and $\hat{S}$ are different than 0 and $\hat{D}$ different than 1 at 10%, 5% and 1%, respectively.

2.7 Conclusions

Productivity disparities across regions are typical in Italy, with the North being consistently ahead of the South. Moreover, firms tend to co-locate and benefit from agglomeration externalities. In our study, we capture agglomeration using a machine learning density-based clustering algorithm, developed by Ankerst et al. (1999) and applied to geocoded information of firms. Our preliminary evidence confirms regional inequalities. Companies in the Northern regions are the most productive. Furthermore, we observe a large productivity dispersion in the South.

To consider agglomeration and selection effects simultaneously and see how the estimates differ by region, we use the econometric approach by Combes et al. (2012) to compare the distribution of firms' productivity inside and outside clusters in Italy as a whole and within macro-regions, using data on manufacturing companies for the years 2007-2017. Our findings suggest agglomeration externalities generated for firms inside clusters. Geographic proximity facilitates productivity gains through interactions among firms.

Productivity distribution is right-shifted and dilated inside clusters in the North and Centre. Based on the theoretical assumption by Combes et al. (2012) about the complementarity of productivity between firms and workers, the existence of a simultaneous right shift and dilation in productivity distributions for firms inside clusters indicates that agglomeration externalities are even stronger for top producers. The same effect does not appear in the South since we only observe a right shift in the productivity distribution. Our evidence sheds light on regional disparities within Italy, indicating that top producers in the South are not as capable as those in the North and Centre to take advantage of agglomeration mechanisms to boost competitiveness even further. A possible explanation could be that migrating efficient human capital from the South to the North leads to better matching between the most productive employees and the most competitive companies. That matching is facilitated in areas with high firm density where recruiters may spot the best talents. The brain drain in the South (EC, 2020) does not allow similar mechanisms to occur.

Our results regarding selection effects are significant when we perform our analysis in the whole country, but significance vanishes when we investigate each region separately. Therefore, we have only weak evidence, and we cannot confidently argue that our clustering technique facilitates selection mechanisms. Market competition may exist at a different spatial scale than clusters' boundaries since the latter are only based on firm density.

Chapter 3

Talents from Abroad: Foreign Managers and Productivity in the United Kingdom

3.1 Introduction

Over the last decades, workers' mobility has increased dramatically. There are already about 164 million migrant workers around the world (ILO, 2018) and, according to R. Baldwin (2016) and R. Baldwin (2019), we should expect an ever-increasing global mobility of workers in the future years after the adoption of new information technologies and further reduction in travel costs. Foreign employment in the UK has risen from 3.54% to 11.33% in the period 1997-2019 (ONS, 2019)[1]. Indeed, the United Kingdom has been a desirable destination in the last decades, and a boost in immigration rates has been at the core of the referendum campaign that supported exit from the European Union. Crucially, workers' international mobility facilitates transfer of knowledge among firms (Bahar

[1] Data until the first quarter of 2019.

and Rapoport, 2018), possibly reducing transaction costs after they bring valuable information on their origin countries (Gould, 1994; Parsons and Vézina, 2018). The diversity brought by migrant workers can contribute to firms' relational capital and ability to market products internationally (Parrotta, Pozzoli, and Pytlikova, 2014). In the long run, host countries are better off thanks to greater product variety available in consumption and intermediate inputs (Giovanni, Levchenko, and Ortega, 2015). Nationality diversity among managers has also shown to be positively associated with firm performance (B. B. Nielsen and S. Nielsen, 2013).

In this study, we specifically test how firms' competitiveness is affected by the mobility of a peculiar category of high-skilled workers, the managers, as vital contributors to any firm's organization. From our point of view, a (domestic or foreign) manager's ability to transfer knowledge from previous positions is revealed when she implements better managerial practices[2] that determine the way other workers organize their productive activities. Yet, scholars have been rather silent on the relationship between foreign management and productivity while prioritizing the impact on export performance (Meinen et al., 2018; Mion, Opromolla, and Sforza, 2016; Mion and Opromolla, 2014). From our perspective, the nexus between organization and productivity is of primary order: foreign managers can have an impact (or not) on firms' productive capabilities, which in turn may lead (or not) to better export performance. Eventually, talents from abroad may bring tacit knowledge that is beneficial to a firm whatever its strategy on domestic or foreign markets.

We find that the recruitment of foreign managers has a positive and significant impact (4.9%) on the Total Factor Productivity (TFP) of domestic firms. In contrast, we detect no statistically significant impact of foreign managers' recruitment on foreign-owned companies' productivity, possibly because alignments on managerial practices already oc-

[2]Our reference is to seminal works that show how good managerial practices explain differences in productivities across firms and countries (Nicholas Bloom, Sadun, and Van Reenen, 2016; Nicholas Bloom, Lemos, et al., 2014; Nicholas Bloom and Van Reenen, 2010; Nicholas Bloom and Van Reenen, 2007; Bertrand and Schoar, 2003). See more details in Section 3.2.

curred at the moment of a takeover by foreign headquarters. We find that productivity gains in domestic firms are mostly due to industry-specific experience gathered by foreign managers in previous positions. We argue that market-specific knowledge allows recruiting firms to increase both efficiency and volume of activity since we observe *ex-post* increases in revenues, usage of intermediate inputs, and investment in fixed assets.

For our analyses, we take advantage of a novel dataset that matches the individual careers of 115,505 managers and the financial accounts of 10,238 firms in the United Kingdom in the period 2009-2017. From our perspective, the UK is a compelling case study of a country that is revising migration policies after exiting from the European Union. We assess firms' competitiveness by estimating Total Factor Productivity (TFP) *à la* Ackerberg, Caves, and Frazer (2015), and we make our findings robust to alternative methods by Wooldridge (2009) and Levinsohn and Petrin (2003). Our identification strategy encompasses difference-in-difference estimates controlling for pre-recruitment trends after implementing a propensity score matching that matches treated firms with nearest untreated neighbors along with different firm-level characteristics (Abadie and G. W. Imbens, 2006; G. Imbens et al., 2004; Donald B. Rubin, 2001). In our empirical setup, we build on previous scholars' experience that tested productivity gains as a consequence of foreign acquisitions (Bircan, 2019; Arnold and B. S. Javorcik, 2009; B. Javorcik and Poelhekke, 2017). Our findings are robust to challenges on reverse causality, sample composition effects, and alternative TFP methodologies.

The remainder of the chapter is organized as follows. Section 3.2 discusses our framework by nesting in previous literature. Section 3.3 describes the data set and draws attention to preliminary evidence. Section 3.4 introduces results on the relationship between foreign management, market experience, and firms' competitiveness. Section 3.5 discusses sensitivity and robustness checks. Section 3.6 concludes.

3.2 Related literature

The fundamental idea that good management correlates with efficient usage of inputs is an old one that we date back to Walker (1887). However, empirical studies had to wait for good microdata on managers and managerial practices (Syverson, 2011). In the last decade, a fruitful research line highlights how different managerial practices can explain part of the productivity gap across both firms and countries (Nicholas Bloom, Brynjolfsson, et al., 2019; Bruhn, Karlan, and Schoar, 2018; Nicholas Bloom, Sadun, and Van Reenen, 2016; Nicholas Bloom, Eifert, et al., 2013; Nicholas Bloom and Van Reenen, 2010; Nicholas Bloom and Van Reenen, 2007; Bertrand and Schoar, 2003). Recently, a study by Giorcelli (2019) shows how specific management training can have an enduring impact on firms' performances, up to fifteen years after the end of the program.

We relate to the above strand of research because we look at the role of foreign talents after we assume that the main channel through which any (domestic or foreign) manager can impact productivity is by setting good managerial practices. Our primary intuition is that foreign managers are a peculiar category of high-skilled migrants like engineers, researchers, and other professionals (Nathan, 2014), whose occupation often requires a combination of advanced training and soft skills. Since we already know from previous works that migrant workers increase the TFP of firms in a region or a country (Beerli et al., 2018; Mitaritonna, Orefice, and Peri, 2017), we reasonably expect that foreign managers have no lesser impact given their crucial role in any firm's organization. In a general equilibrium model, Fadinger and Mayr (2014) show how an increase in the share of skilled migrants can reduce unemployment rates and brain drain in a country, with a magnitude that depends on the elasticity of substitution between skilled and unskilled workers. In the end, the international geography of skills can have aggregate and distributional impacts with significant consequences from a global perspective (Burzynski, Deuster, and Docquier, 2020).

Our contribution also relates to previous works that test the causality direction from recruitment managers to better export performance

(Meinen et al., 2018; Mion, Opromolla, and Sforza, 2016; Mion and Opromolla, 2014). From our viewpoint, we argue that the study of the impact on productivity is of primary importance. An evaluation of firms' productivity gains should logically precede any increase in exporting activity. Indeed, recruited talents can be beneficial to firms whatever their strategies on foreign markets. Thus, a company can benefit (or not) from changes in managerial practices implemented by recruits, first improve competitiveness, and then propose better on international markets. We believe our approach is in line with previous scholarly efforts to predict firms' self-selection by productivity into an international status when trade is costly (Melitz, 2003; Helpman, Melitz, and Yeaple, 2004; Melitz and G. I. P. Ottaviano, 2008; Conconi, Sapir, and Zanardi, 2016). Against this background, our stand is not in contradiction with the possibility that some workers, including managers, are indeed poached to reduce transaction costs and trade with specific destinations (Gould, 1994; Parsons and Vézina, 2018). In this case, one would still observe an improvement in productivity due to lower trade costs, and then a boost in either imports or exports, as demonstrated in the case of foreign workers in UK services firms by Gianmarco I.P. Ottaviano, Peri, and G. C. Wright (2018).

Interestingly, in our contribution, we find that foreign managers' recruitment has a significant impact on domestic firms' productivity, thanks to the experience that recruits previously gathered in the same sector of the recruiting firms. Thus, our findings could not exclude that firms poach managers to reduce transaction costs on foreign markets. We find that recruiting events pave the way for a rise in domestic firms' activity (i.e., higher revenues, expenses on intermediate inputs, and investment in fixed assets) and increased domestic firms' capital intensity

Please note, however, that we do not find any significant productivity gains by foreign-owned firms after recruiting foreign managers. Nor do they increase their volumes of activity after recruiting events. In this case, we argue that earlier alignment of managerial practices with foreign headquarters could have already occurred at the moment of the ownership takeover [3].

[3] Please note that in our context we do not control for firms' exporting status due to

For our identification strategy, we build on previous scholars' experience on testing the relationship between productivity and foreign acquisitions (Bircan, 2019; Arnold and B. S. Javorcik, 2009; B. Javorcik and Poelhekke, 2017). As in the case of foreign takeovers, we aim to challenge reverse causality. Best (domestic or foreign) managers are attracted by firms, locations, and industries with a higher potential. Thus, following previous literature, we explicitly check for firms' pre-recruiting trends and managers' cherry-picking firms and regions. In particular, regional heterogeneous attractivity is a crucial confounding element once we acknowledge that most productive firms locate in denser and urban areas (Combes et al., 2012). Against previous evidence, we recognize that supply-driven changes in immigrant workers' endowments can increase local benefits from assortative matching (Orefice and Peri, 2020; Dauth et al., 2018), hence having an indirect impact on firm-level productivities.

Eventually, we provide evidence that domestic manufacturing firms with foreign managers in their team are not significantly different in productivity from foreign-owned firms with or without foreign managers. We argue that the recruitment of talents from abroad is a strategy that may allow domestic firms to catch-up with foreign competitors. In this respect, we believe that the workforce's international composition is a further dimension that deserves more room by scholars interested in firms' global outreach, for example, in Bernard et al. (2018).

Finally, we relate our work to recent literature that explores the impact of the Brexit event (Ortiz Valverde and Latorre, 2020; Cappariello et al., 2020; Dhingra et al., 2017), as our results imply that any upcoming limit to the mobility of global talents depress domestic productivity, on top of losses from new frictions in international markets for inputs and outputs.

data limitation. Indeed, domestic exporters may tend to perform better than non-exporters (Mayer and Gianmarco IP Ottaviano, 2008).

3.3 Data and preliminary evidence

3.3.1 Managers and firms

We source data on managers' careers and firms' financial accounts in the United Kingdom from Orbis, a commercial database compiled by the Bureau Van Dijk[4], which is a consultancy firm controlled by Moody's Analytics. The database collects original information on management based on individual companies' filings, including their roles, dates of recruitment, nationality, gender, and age. Unfortunately, only scant information is present about managers' education and wages.

Interestingly, the UK has good coverage of management information thanks to specific filing requirements asked by compilers of the UK national registry, the Companies House, following the Companies Act in 2006[5].

In this context, we consider a manager as any individual that participates in a company's board, committee, or executive department. Therefore, we exclude from our analysis advisors and shareholders as they do not participate in the daily administration of the company. Our sample consists of 10,238 firms with unconsolidated financial accounts and strictly positive values on turnover, costs of goods sold, fixed assets and the number of employees for at least one year during the period 2009-2017. These firms are matched with a sample of 115,505 managers. Please note, however, that any manager in our sample can cover more than one role in the same company, or she can participate in the management of more than one company at the same time. Since we have recruitment dates differentiated by both role and company for each manager, we can

[4]The Orbis database collects and standardizes firms' financial statements from around the globe. Orbis data are increasingly used for firm-level studies on multinational enterprises. See for example Alviarez, Cravino, and Levchenko (2017), Cravino and Levchenko (2016), and Del Prete and Rungi (2017).

[5]In particular, the primary legal concern is that a company cannot appoint managers that are undischarged bankrupts or that were previously disqualified by the court from acting as company directors. In recent past, risk and compliance companies systematically scrutinized the ensemble of directors from the Companies House registry to unearth how many were included on international watchlists of individuals considered at high risk of crime. See, for example, O'Neill (2008).

follow a manager's career within and across companies and we can retain information on her/his previous workplaces. In Appendix Table B.1, we present a snapshot of managers' levels of responsibility as included in our sample. In the following analyses, we consider the date of recruitment the earliest date a manager covered any role in that company. In the end, the nationality of managers is a crucial variable in our analysis. In our sample, we find that 13.30 % of managers have a foreign nationality.

Table 3.1: Top 10 nationalities of foreign managers

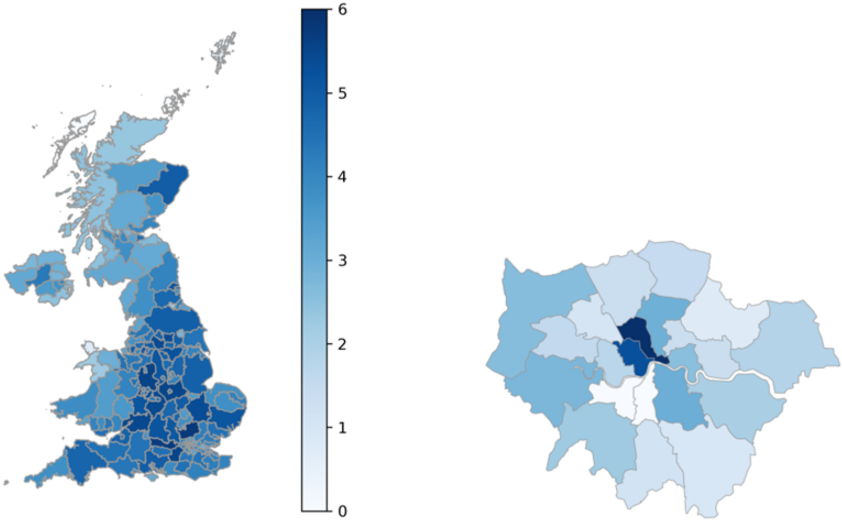
Nationality	No. of managers *-per-* nationality
United States	4,030
Germany	1,800
France	1,370
Japan	1,347
Ireland	975
South Africa	751
Netherlands	712
Italy	646
Sweden	555
Belgium	474
Others	4,699

Note: A foreign manager is a manager with a nationality different from UK. In case of multiple nationalities, including UK, the individual is considered a domestic manager. Please note that we count for each country including foreign managers with multiple nationalities. For instance, a manager with passport from the US and Germany is counted in the row "United States" and in the row "Germany".

Table 3.1 presents the top 10 most common nationalities we detect in our sample. Please note how we adopt here a conservative definition of a foreign manager. For instance, a manager that has dual citizenship, including the UK's, is still considered domestic. In this case, we want to exclude as much as possible from the set of foreign managers individuals that are UK citizens raised by foreign individuals that migrated relatively earlier in their age. As largely expected, managers landing in UK companies come from around the globe. We find in our sample 15,353 foreign managers with 102 different foreign nationalities. Out of them, 1,690 are citizens with multiple passports different from UK's. The most represented country is the US, followed by Germany, France, and Japan. Overall, we find that 50.14% of foreign managers are citizens of the European Union, and they represent about 6.67% of the total managers.

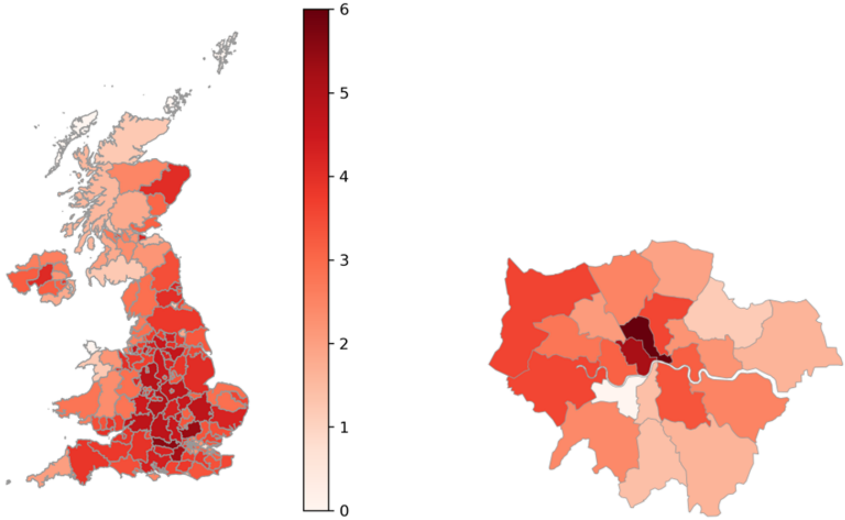
In Figures 3.1 and 3.2, we report the geographic coverage by NUTS 3-digit regions of our sample firms with at least one manager and firms that have at least one foreign manager, respectively. *Prima facie*, we do not observe any specific pattern of geographic selection in our data, as we can spot foreign teams of managers on the entire UK territory. In general, we find that most populated urban regions are also denser in terms of manufacturing activities, with the exclusion of London, where we expect a specialization in services. About 12.5% of companies with foreign managers locate in the Greater London area, where the share of foreign managers on the total is about 19%. Notably, we observe how the recruitment of talents from abroad seems to be a widespread practice of many firms across all UK regions.

Figure 3.1: Geographic coverage: all firms



Note: The total number of sample firms in the UK (on the left) and a focus on London (on the right) are reported in logarithmic scale.

Figure 3.2: Geographic coverage: firms with foreign managers



Note: The number of sample firms with at least one foreign manager (on the left) and a focus on London (on the right) are reported in logarithmic scale.

For the sake of completeness, in Appendix Table B.2, we show the top 10 origin countries of foreign-owned firms. The identification of foreign-owned companies follows international standards (OECD, 2005; UNCTAD, 2009; UNCTAD, 2016), according to which a subsidiary is controlled after a (direct or indirect) concentration of voting rights (> 50%). We observe that a majority of foreign-owned subsidiaries (1,201) is controlled by US parent companies, whereas the second origin country is

Germany (357), followed by Japan (264) and France (241). If we cumulate foreign subsidiaries held by parent companies located in EU members, we find they represent that the latter represent 39.8% (1,497) of the total number of foreign subsidiaries (3,757).

3.3.2 Productivity, foreign managers, and ownership

For our baseline analyses, we estimate firm-level total factor productivities (TFPs) following the technique by Ackerberg, Caves, and Frazer (2015). TFP is traditionally interpreted as the portion of output growth not explained by growth in observed inputs. The major identification problem in estimating a firm-level production function is that input choices can depend on shocks unobserved by the econometrician at the end of the period, when firms' financial accounts typically become available. Therefore, an endogeneity problem can arise such that the observed combination of production factors is simultaneous to the possibly unobserved shocks, hence OLS estimates are inconsistent. In this context, Ackerberg, Caves, and Frazer (2015) improve on previous efforts by Levinsohn and Petrin (2003), and Wooldridge (2009), which we however include as alternative estimators for robustness checks. To estimate TFPs, we source data on operating revenues, costs of goods sold, number of employees, and fixed assets. We further control for firm age. All variables are properly deflated using producer price indices that are specific for each 2-digit manufacturing industry for turnover while for capital stock and intermediate inputs are provided at aggregate level (sourced by Eurostat).

For the rest of the analysis, we keep in our panel only managers with full information on the dates of appointment and resignation, to track the whole tenure in their company. At this stage we can present preliminary evidence on the difference in mean TFP between different categories. As largely expected, foreign firms are on average more productive than domestic firms (last line, Table 3.2). More interesting, we detect a slightly smaller difference for firms that have foreign managers in their team (first line, Table 3.2). The latter is a novelty of our study. The advantage is particularly evident in the case of domestic firms (second line).

Even more interestingly, we do not find a significant difference in competitiveness when we compare domestic firms with foreign managers and foreign-owned firms (line 4).

Table 3.2: Productivity premia, foreign managers, and ownership

	Mean difference in (log) TFP	N. obs.
Firms with vs. without foreign managers	.175*** (.016)	50,869
Domestic-owned with vs. without foreign managers	.225*** (.029)	29,254
Foreign-owned with vs. without foreign managers	-.039 (.032)	19,687
Foreign- vs. domestic-owned with foreign managers	.014 (.032)	23,615
Foreign- vs. domestic-owned firms	.181*** (.016)	48,491

Note: The table reports t-tests on the difference in TFP across different categories of firms. Standard errors are reported in parentheses. *** denotes significance at 1%.

Previous preliminary evidence motivates our following analyses, where we will explicitly challenge the hypothesis that foreign managers can transfer knowledge to a domestic firm in the form of generic or specific skills in production and, thus, allow them to catch up with foreign or domestic competitors. To this end, we want to rule out any phenomenon of cherry-picking, such that more productive firms are also the ones that are more likely to hire better talents and pay their expensive bills.

3.4 Empirical strategy and results

We assess the impact of hiring foreign managers on the productivity of a firm. We consider firms as receiving treatment when they recruit a foreign manager in the period 2009-2017. Clearly, we need to control the endogenous choice of a manager that accepts a position in any workplace, industry, and geographic region that allows changing her career for the better. To this end, we proceed in four stages.

In Section 3.4.1, we perform an exercise to determine the average benefit of a firm that hires a foreign manager (Average Treatment Effects on the Treated - ATT) while controlling as much as possible for endogenous firms' characteristics and pre-recruitment trends. The event studies reported in Figures 3.3 and 3.4 for domestic and foreign firms, respectively, will show the evolution of TFP benefits along the timeline we observe.

Then, in Section 3.4.2, we control for the selection of more productive firms into treatment, i.e., the endogenous better ability of actual recruiters to participate in the international market for talents if compared with non-recruiters. To this end, we put together a control group made of firms that never hired foreign managers after a propensity score matching exercise. In this case, we challenge our identification strategy to simulate a counterfactual with firms that are otherwise similar along with all the characteristics that make them an attractive destination for a talented worker, including their observed productivity, except for their recruiting strategy in the observed period.

After that, in Section 3.4.3, we check that foreign talents' previous industry experience is the primary channel through which domestic firms can reap productivity gains.

Eventually, in Section 3.4.4, we provide additional results that qualify the impact of foreign managers when we look at alternative firm-level indicators, including sales, usage of inputs, capital intensity, and investment.

Robustness and sensitivity exercises are offered in Section 3.5, where we check for: i) a placebo test after treating firms with local managers; ii) different TFP estimators; iii) sample composition in terms of both firms' locations and managers' passports.

3.4.1 Foreign managers and recruiting firms

We start by estimating the following equation considering exclusively the group of companies that hired foreign managers for the first time in our period of analysis:

$$(log)TFP_{ijrt} = \beta_0 + \beta_1 T_{ijr} \times Post_t + \beta_2 X_{ijrt} + \gamma_j + \delta_t + \zeta_r + \sum_k \eta_k \times \delta_t + \varepsilon_{ijrt} \tag{3.1}$$

where the dependent variable TFP_{ijrt} is the Total Factor Productivity of a firm i active in a sector j and region r at time t. TFP is calculated following the semiparametric methodology by Ackerberg, Caves, and Frazer (2015). T_{ijr} is the treatment, i.e., it indicates that a firm recruited the first foreign manager, whereas $Post_t$ is a binary variable equal to one for observations following the recruitment. In this case, $(1 - e^{\beta_1})$ is our main quantity of interest and it catches the average productivity gains by recruiting firms expressed in percentage units. X_{ijrt} includes firm-level controls (size, age, capital intensity, wage bill, the ratio of managers over employees, foreign ownership) and regional employment (defined as the share of NUTS 2 regional over national employment) as a proxy of local attractiveness. Additionally, we include γ_j, δ_t and ζ_r as 2-digit industry, year, and NUTS-3 regional fixed effects, respectively. Crucially, at this stage, we control for self-selection of talented managers into companies and industries with better prospects. In a similar way with Bircan (2019) we include a set of trends to reflect the industry and the characteristics of the firm before treatment. Hence, the term $\sum_k \eta_k \times \delta_t$ represents a full set of pre-recruitment features[6] (age, size and 2-digit industry) interacted with a time trend δ_t. We repeat the same exercise first for all firms, and then for domestic and foreign-owned firms, separately.

In columns 1-3, Panel B of Table 3.3, we find a significant increase in TFP for domestic firms ranging in an interval from 4.39% to 7.36% (log units: from .043 to .071) after they hire foreign managers. Interestingly, the impact is relatively higher when we control for pre-treatment trends in column 3. Apparently, domestic firms entirely explain the significance of coefficients in Panel A, when we do not separate firms by ownership status.

[6] We categorize firm age in the following classes: $[0, 4]$, $[5, 9]$, $[10, 14]$, and $15+$ years. We categorize firm size in the following classes: $[0, 9]$, $[10, 19]$, $[20, 49]$, $[50, 249]$, and $250+$ employees.

When we look at foreign-owned firms in Panel C of Table 3.3, we never find any statistically significant impact on TFP after hiring foreign managers. As far as we know, there is no previous record of a similar finding in previous literature. Our guess is that foreign headquarters already had the opportunity to realign managerial practices in subsidiaries at the time of the takeovers. Previous findings seem to be systematic in the following analyses.

Eventually, the albeit weakly positive and significant results for all firms reported on columns 1-3 of Panel A are entirely driven by the impact that foreign managers have on domestic firms.

In Figures 3.3 and 3.4, we also visualize the coefficients on separate event studies performed for domestic and foreign firms, respectively. We follow the trend of (log of) TFP in the three years following the recruitment of foreign managers while controlling for what happened two years before. In a nutshell, the plots represent the coefficients of a modified version of Eq. 3.1, where the productivity trends are visualized over an interval of six years centered around the moment that any recruiting firms decided to hire a foreign manager.

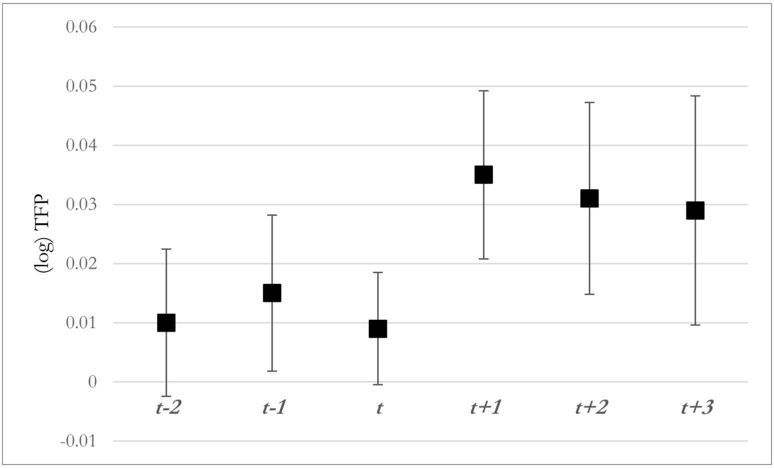
Table 3.3: TFP and foreign managers - ATT

	(1)	(2)	(3)
Dep. variable:	(log) TFP	(log) TFP	(log) TFP
Panel A: All firms			
Hired × Post-recruitment	.023*	.022*	.021*
	(.012)	(.012)	(.011)
R^2	.935	.936	.946
No. of obs.	23,932	23,932	23,932
Panel B: Domestic firms			
Hired × Post-recruitment	.043***	.050***	.071***
	(.011)	(.012)	(.025)
R^2	.925	.928	.943
No. of obs.	4,562	4,562	4,562
Panel C: Foreign firms			
Hired × Post-recruitment	.011	.010	.009
	(.013)	(.014)	(.013)
R^2	.942	.943	.954
No. of obs.	19,370	19,370	19,370
Panels A, B and C:			
Firm controls	Yes	Yes	Yes
Industry effects	Yes		
Year effects	Yes		
Region effects	Yes	Yes	Yes
Industry × Year effects		Yes	Yes
2-digit Industry & age & size trends			Yes

Note: The table reports the average treatment effect on the treated firms (ATT) after controlling for confounders. Coefficients are in log units. Errors are clustered by 2-digit industries in parentheses. Controls include firm size, firm age, capital intensity, average wage bill, the share of managers on total employees, regional share of employment and, for Panel A, foreign subsidiary status. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

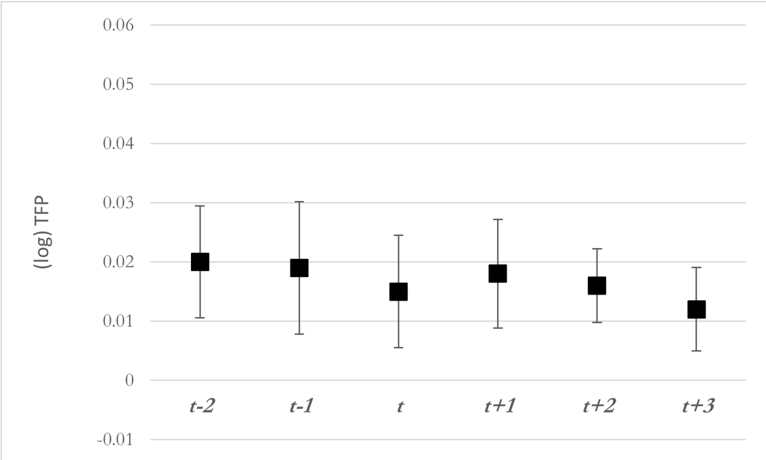
Interestingly enough, the positive productivity gains by domestic firms (Figure 3.3) already occur the first year after the foreign talent arrives and stay there for the following three years, whereas no significant benefits are registered by foreign-owned firms (Figure 3.4) where a slightly albeit non-significant negative trend in productivity shows up.

Figure 3.3: TFP, foreign managers and domestic firms



Note: Event study for the productivity impact of recruiting foreign managers at time *t* by domestic-owned firms. Markers show the magnitude of coefficients and bars indicate a 95% confidence interval of a modified version of Eq. 3.1. Errors are clustered by 2-digit industries. Industry-time fixed effects, region fixed effects, firm-level characteristics, and pre-recruiting trends are controlled for.

Figure 3.4: TFP, foreign managers and foreign firms



Note: Event study for the productivity impact of recruiting foreign managers at time t by foreign-owned firms. Markers show the magnitude of coefficients and bars indicate a 95% confidence interval of a modified version of Eq. 3.1. Errors are clustered by 2-digit industries. Industry-time fixed effects, region fixed effects, firm-level characteristics, and pre-recruiting trends are controlled for.

3.4.2 Recruiting and non-recruiting firms

In this Section, we specifically challenge the selection of some firms into treatment, i.e., the endogenous ability of firms that actually recruited foreign managers in our period of analysis to attract the best (domestic or foreign) talents. Our guess is that part of the productivity premia on domestic firms we observe in Table 3.3 is explained by an inherently higher potential of the firms that have the ability to go onto international job markets, while proposing better salaries and better prospects for managers' careers. For our purpose, we apply a matching procedure to select a control group made of firms that never hired foreign managers in our period of analysis, although they mirror the characteristics of observed recruiters.

Table 3.4: Probit estimates for a propensity score matching

Dep variable: Recruiting foreign manager(s) = 1	
(log) TFP_{t-1}	.0337**
	(.0150)
(log) Firm size$_{t-1}$	.0328***
	(.0080)
(log) Average wage$_{t-1}$	.1083***
	(.0168)
(log) Capital Intensity$_{t-1}$	.0171***
	(.005)
(log) Age$_{t-1}$	-.0457***
	(.0079)
Skill Intensity$_{t-1}$	.0580*
	(.0313)
(log) Number of Managers$_{t-1}$	.195***
	(.0152)
Regional Employment$_{t-1}$	2.5174***
	(.6014)
Foreign ownership	.6074***
	(.0106)
Pseudo R^2	0.364
No. of obs.	47,717
Year and 2-digit industry FE	Yes
Errors clustered by firm	Yes

Note: The table reports estimates of a probit model. The dependent variable is equal to one if a firm recruited a foreign manager. Errors are clustered by firm in parentheses. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

We run a five-nearest neighbor matching algorithm (Abadie and G. W. Imbens, 2006; G. Imbens et al., 2004; Donald B. Rubin, 2001) that searches for peers within any 2-digit industry-*per*-year cell in which we find treated firms in the UK, to make sure that differences in performance coming from different market conditions do not exert influence on our estimated effects. All time-variant explanatory variables are lagged one year to reflect pre-treatment performances. We choose a set of predictors for treatment borrowing from previous literature that studies the impact of foreign ownership (Bircan, 2019; Arnold and B. S. Javorcik, 2009; B. Javorcik and Poelhekke, 2017). In fact, we assume that the recruitment of foreign managers is endogenous to a similar set of observable characteristics that make a company desirable as a target by a foreign company, including technology, firm age, firm size, the average composition of employment, capital intensity. In addition, we include three specific controls that can make a new position in a company desirable for talented newcomers: the share of managers on total employees, as a proxy for the skill composition of the workforce, the total number of managers, and the regional employment. The latter is particularly useful since we acknowledge that local assortative matching between workers and firms exert an indirect impact on firm-level productivity, as acknowledged by Orefice and Peri (2020) and Dauth et al. (2018).

Table 3.4 presents estimates of the first-stage probit model. Notably, all main predictors correlate with selection into treatment as expected. Firms that are more productive, bigger, and offering a higher wage are more likely to recruit foreign managers in our sample. Relatively younger firms, with an already high number of managers and higher skill intensity attract foreign recruits. The firm is also relatively more attractive for a foreign talent when it is foreign-owned and locates in a populated region. In Table 3.5, we also evaluate the quality of the matching procedure by implementing a balancing test. There, we compare the sample averages of all covariates of both the treatment and the control groups. Eventually, we find that there is no *ex-post* statistically significant difference along the set of variables that we include for the matching, because null hypotheses of equal mean are always rejected in the matched sample. In the last column of Table 3.5, we report the variance ratio, $V_e(T)/V_e(C)$, of the residuals of the covariates of the treated over the control group. Following Donald B. Rubin (2001), a perfect match implies a ratio equal to one, whereas a ratio between 0.5 and 2 indicates an acceptable quality. In our case, we do have many variance ratios that fall in a range close to one. Moreover, the standardized biases we report in column 5 of Table 3.5 are less than 10% in absolute value for all variables after matching.

Table 3.5: Balancing test on the nearest-neighbour matching procedure

Variable	Sample	Average treated	Average untreated	% Bias	t-test	p-value	$V_e(T)/V_e(C)$
(log) TFP$_{t-1}$	Unmatched	2.66	2.45	11.3	13.28	0.001	1.16
	Matched	2.67	2.66	0.50	0.52	0.601	1.05
(log) Size$_{t-1}$	Unmatched	4.49	3.97	36.7	44.80	0.001	1.40
	Matched	4.64	4.62	1.3	1.48	0.138	1.15
(log) Avg wage$_{t-1}$	Unmatched	5.98	5.73	52.7	61.97	0.001	1.02
	Matched	5.98	5.95	6.5	7.56	0.001	0.99
(log) Age$_{t-1}$	Unmatched	8.83	8.75	8.4	12.15	0.001	1.16
	Matched	9.03	9.01	1.6	1.95	0.051	1.05
(log) N. Managers $_{t-1}$	Unmatched	1.51	1.24	55.5	74.90	0.001	0.90
	Matched	1.57	1.53	9.5	10.82	0.001	0.96
(log) Capital intensity$_{t-1}$	Unmatched	5.55	4.98	35.8	42.94	0.001	1.25
	Matched	5.56	5.50	3.6	3.78	0.001	1.11
Skill intensity$_{t-1}$	Unmatched	0.15	0.12	6.8	8.37	0.001	0.80
	Matched	0.10	0.10	1.9	2.71	0.007	0.72
Regional employment$_{t-1}$	Unmatched	0.03	0.03	13.0	19.44	0.001	1.23
	Matched	0.03	.03	5.7	5.77	0.001	1.11
Foreign subsidiary	Unmatched	0.78	0.13	172.4	277.76	0.001	1.11
	Matched	0.81	0.81	1.7	1.61	0.107	0.96

Note: The table reports sample averages and t-tests for the original unmatched sample and after the application of a nearest-neighbor matching technique. See Donald B. Rubin (2001), P. R. Rosenbaum and D. B. Rubin (1983), and Paul R. Rosenbaum and Donald B. Rubin (1985) for more details.

Having ensured that there is a good match among the matched groups of observations, we proceed with diff-in-diff estimates proposed in Eq.3.1, and we report nested results in Table 3.6. Interestingly, TFP premia on domestic firms become slightly lower after implementing the matching procedure, if we compare with Table 3.3. Our baseline results are on column 3, where we report the most challenging specification, complete with firm controls, region effects, industry-*per*-year fixed effects, and a term that catches previous trends possibly making a firm or an industry already desirable as a successful destination to pursue a career before a talent is hired. In this case, a foreign recruit makes on average a domestic firm about 4.9% more productive (log units 0.048, $e^{0.048} \simeq 1.049$). As in previous results of Table 3.3, we confirm that there are no statistically significant productivity gains among foreign-owned firms.

Table 3.6: TFP and foreign managers - ATE

	(1)	(2)	(3)
Dep. variable:	(log) TFP	(log) TFP	(log) TFP
Panel A: Domestic firms			
Hired × Post-recruitment	.047***	.048***	.048**
	(.012)	(.013)	(.023)
R^2	.950	.951	.950
No. of obs.	16,696	16,696	16,696
Panel B: Foreign firms			
Hired × Post-recruitment	.008	.010	.009
	(.019)	(.019)	(.019)
R^2	.967	.968	.968
No. of obs.	8,060	8,060	8,060
Panels A, and B:			
Firm controls	Yes	Yes	Yes
Industry effects	Yes		
Year effects	Yes		
Region effects	Yes	Yes	Yes
Industry × Year effects		Yes	Yes
4-digit Industry & age & size trends			Yes

Note: The table reports estimates for a sample matched after a propensity score. Errors are clustered by 2-digit industries in parentheses. Coefficients are in log units. Firm-level controls include age, employment, capital intensity, average wage bill, skill intensity and regional employment. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

3.4.3 The role of industry experience

In general, there are many potential skills that foreign talented workers can provide to increase the productivity when in a new management team. They can train native workers and show techniques that the latter could otherwise find difficult to learn by themselves (Markusen and Trofimenko, 2009), or they can bring skills that help reducing transaction costs once they bring valuable information on their native countries (Gould, 1994; Parsons and Vézina, 2018). In general, the cultural diversity brought by workers of different origins can contribute to firms' relational capital and their ability to market products internationally (Parrotta, Pozzoli, and Pytlikova, 2014).

In the specific case of foreign managers, we argue that all the previous skills or knowledge imply that (domestic or foreign) managers can intervene to change managerial practices. See also the framework we sketch from related literature in Section 3.2. The tacit knowledge that managers bring in the new company is usefully transferred into the implementation of better management. Unfortunately, we are not able in our data to track whether managerial practices actually change after recruitment. Neither we have much to tell about the intangible skills of newly-hired manager from our data. What we can do is to understand from previous stages of their career what recruits did, as we have information on the companies where managers worked before taking the new UK positions.

Briefly, in this Section, we explicitly challenge the hypothesis that market-specific experience can explain productivity gains in domestic firms observed in previous paragraphs. For our purpose, we repeat the baseline exercise of Eq. 3.1, this time controlling for firms recruiting foreign managers that previously worked in a company outside the UK and have the same core economic activity (NACE 2-digit) with the latest recruiting firm in the UK.

As in latest results, we rely on a control group that is derived after a propensity score matching exercise described and validated in Section 3.4.2. We report results for domestic and foreign firms, separately, in Table 3.7.

Interestingly, we do find that TFP gains in domestic firms are mainly explained by previous market-specific experience, and the related coefficient is relatively higher than previous estimates (8.3%; log units: 0.080), although on average also managers with no market-specific experience have a positive albeit weakly significant impact (2.1%; log units: 0.021). In column 2 of Table 3.7, we still do not find a significant impact on the productivity of foreign-owned firms.

In the case of domestic firms, we argue, we are able to catch the nature of the managerial knowledge that is passed to the firm. Previous market experience entails an on-field training that may be particularly appealing to recruiters. We think our findings relate to earlier works testing the impact of recruitment events on export performance (Mion and Opromolla, 2014; Mion, Opromolla, and Sforza, 2016). There, as well, a market-specific experience is most beneficial for firms that poach managers to have better access to foreign markets, hence reducing the beachhead costs. Given our data, we cannot exclude that firms can also take advantage from reducing frictions when proposing on export destinations. In fact, checks on alternative outcomes reported in the following paragraphs allow us showing how foreign managers pave the way for a generalized increase in the volume of activity by domestic firms that could be associated (or not) to rising export shares.

Table 3.7: TFP, foreign managers, and market experience - ATE

	Domestic	Foreign
Dep. variable:	(log) TFP	(log) TFP
Hired × Post	.021*	.004
	(.010)	(.023)
Hired × Market × Post	.080***	.021
	(.034)	(.023)
R^2	.951	.968
No. of obs.	16,696	8,060
Firm controls	Yes	Yes
Region effects	Yes	Yes
Industry × Year effects	Yes	Yes
Industry & age & size trends	Yes	Yes

Note: The table reports estimates on a matched sample when the treatment is split considering companies that recruited foreign managers with and without specific market experience. Coefficients are in log units. Errors are clustered by 2-digit industries in parentheses. Firm-level controls include age, employment, capital intensity, average wage bill, skill intensity and regional employment. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

3.4.4 Alternative outcomes

In this Section, we go beyond TFP to check which other dimensions of the production process are mainly affected by the recruitment of foreign managers. Firm-level TFP is a much useful measure that catches technology and efficiency as the portion of output growth of a firm that is not explained by growth in inputs (Syverson, 2011). It helps to reconcile firms' microeconomic performance with aggregate welfare since higher aggregate productivity is a source of economic growth. Yet, we believe that looking at other indicators of firm-level productive performance can help complete our picture of the changes induced by recruits.

In Table 3.8, we focus on alternative outcomes including firms' revenues, costs of goods sold (COGS), number of employees, fixed assets, and capital intensity. The exercise we perform is similar to the one proposed in Table 3.6 with a control group build after a propensity score matching, while keeping the most challenging specification with firm controls, region effects, industry-time effects, and pre-recruitment trends as from Eq. 3.1.

Interestingly, we observe that domestic firms start having a higher volume of activity after recruiting foreign managers. On average, they sell about 19.6% (log units: .179) more of their products, and they consume about 23% more intermediate inputs, thus pointing to expansion plans that entail also additional investment. Our hypothesis seems corroborated by an albeit weakly significant average increase in the amount of fixed assets (21.2%; log units: .192), which implies a higher capital intensity (23.4%; log units: .210). Notably, no significant change is observed in number of employees by domestic firms.

In line with previous results on TFP, foreign-owned firms do not register any significant change in either of the alternative firm-level outcomes that we test in Table 3.8. We believe latter results strengthen our previous guess that foreign-owned firms do not see foreign managers as crucial for their productive strategy since any alignment in managerial practices or expansion plans may have occurred as a consequence of the takeover by foreign headquarters.

Table 3.8: Alternative outcomes - ATE

	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
Dep. variable:	(log) Sales	(log) Sales	(log) COGS	(log) COGS	(log) Employees	(log) Employees	(log) Fixed Assets	(log) Fixed Assets	(log) Capital Intensity	(log) Capital Intensity
Hired × Post	.179***	.039	.207***	.018	-.011	.002	.192*	-.007	.210***	-.019
	(.072)	(.074)	(.075)	(.079)	(.063)	(.070)	(-.105)	(.120)	(.074)	(.081)
R^2	.167	.220	.180	.230	.152	.247	.198	.233	.190	.230
No. of obs.	17,215	8,258	17,215	8,258	17,215	8,258	17,215	8,258	17,215	8,258
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry & age & size trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports estimates after a propensity score matching. The treatment is split considering companies that recruited foreign managers with and without specific industry experience. Coefficients are in log units. Errors are clustered by 2-digit industries in parentheses. Firm-level controls include age, employment, capital intensity, average wage bill, skill intensity and regional employment. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

3.5 Sensitivity and robustness checks

In this Section, we introduce four primary checks on the robustness and sensitivity of our results. Our first concern is that a specific TFP methodology does not drive our findings. In Table 3.9, we report results after following three alternatives from related literature: i) the Levinsohn and Petrin (2003) algorithm was the first to propose intermediate inputs in a two-stage procedure that proxies unobserved shocks that possibly introduce a simultaneity bias due to unobserved adjustments in the combination of factors of production; ii) Wooldridge (2009) proposed to solve the same simultaneity bias by implementing a generalized method of moments (GMM) procedure; iii) Ackerberg, Caves, and Frazer (2015) suggest another variant of our baseline, where we switch from a Cobb-Douglas to a trans-logarithmic production equation to catch different functional forms. Our central tenets are robust across different TFP methodologies. However, magnitudes can vary depending on underlying dispersions. TFP premia are smaller than previous baseline estimates in Levinsohn and Petrin (2003), and bigger in Wooldridge (2009).

Table 3.9: Alternative TFP methods - Average Treatment Effects

	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
Dep. variable:	(log) TFP	(log) TFP	(log) TFP	(log) TFP	(log) TFP	(log) TFP
Hired × Post	.025***	.011	.043***	.017	.098***	-.002
	(.005)	(.008)	(.007)	(.019)	(.023)	(.190)
R^2	.945	.851	.953	.887	.956	.821
No. of obs.	16,696	8,060	16,696	8,060	16,696	8,060
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Region effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry & age & size trends	Yes	Yes	Yes	Yes	Yes	Yes
Method	LevPet	LevPet	WRDG	WRDG	ACF-T	ACF-T

Note: The table reports estimates on a matched sample for alternative measures of TFP: Levinsohn and Petrin (2003) (LevPet); Wooldridge (2009) (WRDG); a translog variant of Ackerberg, Caves, and Frazer (2015) (ACF-T). Coefficients are in log units. Errors are clustered by 2-digit industries in parentheses. Firm-level controls include age, employment, capital intensity, average wage bill, skill intensity, and regional employment. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

In a second check, our concern is that our previous findings could catch productivity gains by firms that are just more active on labor markets and hire the best managers, whatever their nationality. As a matter of fact, there is a majority of firms in our sample that hire both foreign and domestic managers in our period of analysis. As we can assume that a higher managerial mobility allows some proactive firms to a faster reallocation of productive resources, we challenge our findings by proposing a specific placebo test in Table 3.10. In this case, we consider as treated those firms that recruited British managers only. Thus, we reset our control group by performing a propensity score matching that looks for nearest neighbors in the set of firms that did not recruit any manager in our period of analysis. Results in Table 3.10 show that there is a weakly significant impact on domestic firms, which is however three times smaller than previous baseline estimates.

Table 3.10: A placebo test: TFP and British managers

	Domestic	Foreign
Dep. variable:	(log) TFP	(log) TFP
Hired × Post	.014*	.004
	(.008)	(.023)
R^2	.914	.868
No. of obs.	1,586	987
Firm controls	Yes	Yes
Region effects	Yes	Yes
Industry × Year effects	Yes	Yes
Industry & age & size trends	Yes	Yes

Note: The table reports placebo estimates after treating firms with British managers only. The control group is made by firms that never hired any manager in the period of analysis. Coefficients are in log units. Errors are clustered by 2-digit industries in parentheses. Firm-level controls include age, employment, capital intensity, average wage bill and the share of managers on employees. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

A third check that we perform pertains to firms' locations. Please note how we previously controlled for idiosyncratic local shocks after including regional fixed effects in baseline estimates. We also checked how regions could be differently attractive for talents, as proxied by local employment, when matching recruiting firms with peers in the propensity score exercise in Section 3.4.2. Yet, we still may find that estimates are sensitive to recruiting events' heterogeneous distribution across different regions. For this reason, in Table 3.11, we first show estimates considering the entire sample excluding Greater London, and then separating urban and non-urban areas. The classification in urban and non-urban NUTS-3 regions follows Eurostat definitions based on relative employment densities. Findings are still significant on domestic firms, although magnitudes vary. Excluding London from the sample raises the TFP gains by domestic firms. Eventually, recruiters in non-urban areas register higher productivity gains, whereas urban areas report a relatively lower magnitude of coefficients. Following latter evidence, we argue that the magnitude of TFP gains by domestic firms is higher at the margin where productivity is *ex ante* on average lower. Indeed, as largely expected, TFP levels in our sample are significantly correlated with the regional employment (coefficient .715), even after controlling for local industrial specialization (defined as the share of firms within the same industry and region) and different firm characteristics.

Table 3.11: Robustness checks: firms' locations - ATE

	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
Dep. variable:	(log) TFP	(log) TFP	(log) TFP	(log) TFP	(log) TFP	(log) TFP
Hired × Post	.066***	.019	.127***	-.001	.022**	.014
	(.025)	(.019)	(.056)	(.033)	(.012)	(.023)
R^2	.955	.971	.954	.921	.949	.967
No. of obs.	15,146	7,364	4,709	2,347	11,395	5,552
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Region effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry & age & size trends	Yes	Yes	Yes	Yes	Yes	Yes
Firms' locations	w/o London	w/o London	Non-urban	Non-urban	Urban	Urban

Note: The table reports estimates on a matched sample to check for sample composition by firms' locations. Coefficients are in log units. Errors are clustered by 2-digit industries in parentheses. Firm-level controls include age, employment, capital intensity, average wage bill, skill intensity, and regional employment. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

Finally, in Table 3.12, we check that our results are valid after recruiting either a foreign manager with a passport from the United States or from any other country in the world. We believe it is important to link this sensitivity check to our preliminary evidence reported in Section 3.3.1, where we show that the most represented nationality among foreign managers is American. We want to check that our results are not driven by some lower frictions among managers that share English as mother tongue. The impact on TFP is indeed relatively higher after recruiting American managers in domestic firms, whereas we confirm no significant impact on foreign-owned firms in either case.

Table 3.12: Robustness checks: managers' passports - ATE

	Domestic	Foreign	Domestic	Foreign
Dep. variable:	(log) TFP	(log) TFP	(log) TFP	(log) TFP
Hired × Post	.072***	.020	.039***	.014
	(.034)	(.084)	(.015)	(.024)
R^2	.978	.961	.954	.919
No. of obs.	1,601	977	15,719	6,459
Firm controls	Yes	Yes	Yes	Yes
Region effects	Yes	Yes	Yes	Yes
Industry × Year effects	Yes	Yes	Yes	Yes
Industry & age & size trends	Yes	Yes	Yes	Yes
Foreign manager's passport	US	US	non-US	non-US

Note: The table reports estimates on a matched sample to check for sample composition by managers' passports. Coefficients are in log units. Errors are clustered by 2-digit industries in parentheses. Firm-level controls include age, employment, capital intensity, average wage bill, skill intensity, and regional employment. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

3.6 Conclusion

As far as we know, no previous work has addressed the primary relationship between foreign management and firm-level productivity. From our perspective, foreign managers are highly skilled migrants that contribute to the transmission of knowledge across national borders. Their role in a firm's organisation is peculiar, as they make a combination of specific training experiences and soft skills. They transfer knowledge acquired from previous positions to set the most suitable managerial practices that allow other workers to make the best contribution to the company's mission.

In this contribution, we find that domestic manufacturing firms primarily benefit from hiring foreign managers. We find that their Total Factor Productivity (TFP) increases, on average, 4.9% after recruiting foreign talents. In general, recruiting highly-skilled workers allows firms to have access to a broader pool of skills than those available on the domestic market. In the case of foreign managers, we find that previous industry experience abroad qualifies their contribution to recruiting companies' competitiveness. Interestingly, beyond TFP, we observe that foreign managers' recruiting anticipates an increase in the volume of activity (sales and intermediate inputs) and higher investment in fixed assets, possibly due to newcomers' expansion plans, which increase a domestic firm's capital intensity.

On the other hand, we detect no significant TFP gains by foreign-owned firms after hiring foreign managers. In this case, we argue that productivity spillovers could have occurred already at the moment of takeovers by foreign headquarters when subsidiaries became part of a multinational enterprise. Different specifications confirm the lack of a significant impact on foreign firms throughout our chapter. Interestingly, we show no statistical difference in productivity levels between domestic firms with foreign managers and foreign-owned firms.

Our identification strategy encompasses propensity score matching, diff-in-diff analyses, and the inclusion of pre-recruitment trends to challenge reverse causality and the hypothesis of parallel trends. Results are robust to several checks, including a placebo test with local managers, the adoption of different TFP estimators, controls for sample compositions in firms' locations and managers' countries of origin.

Eventually, we support the idea that the international composition of management teams is a dimension that deserves more attention from scholars that study the global outreach of modern firms. From this perspective, we argue that upcoming barriers to the circulation of highly skilled workers, including managerial talents, resulting from the Brexit event and the latest pandemic crisis hampers domestic manufacturing industries' competitiveness.

Chapter 4

What do Firms Gain from Patenting? The Case of the Global ICT Industry

4.1 Introduction

Over the past decades, digitalization has played a significant role in the transformation of many production processes. Firms in Information and Communication Technologies (ICT) have become major players globally while the so-called digital sector has rapidly grown. The industry contributes innovative goods and services destined to consumers and technological inputs destined to firms across many other industries. The benefits of investing in ICT are evident because many firms can potentially gain in terms of efficiency (Brynjolfsson and Hitt, 2003) through a reshaping of innovation strategies (Nambisan, M. Wright, and Feldman, 2019). Thus, policymakers tend to attribute a high value to the ICT industry as an engine of economic growth. However, concerns have been raised about a fast market concentration among few Big-Tech global players; thus, antitrust authorities in the US and the European Union started their probes to check for abuses.

Against the previous background, we aim to investigate the relationship between patenting activity and firm-level outcomes in the global ICT sector in 2009-2017 using a panel of 179,660 firms in 39 countries. Motivated by preliminary evidence on positive correlations between the stock of patents held by companies and main firm-level outcomes, including market shares, productivity, and firm size, we investigate the direction of causality by employing a most recent diff-in-diff strategy for panel data proposed by Callaway and Pedro HC Sant'Anna (2020), which is useful when we have many time periods, when units are treated at different points in time, and when the assumption of parallel trends is conditional on observables. Having complete information on the timing of patents' registration processes, we consider a firm treated when publish a new patent with granted property rights in our period of analyses. Thus, we find a robust 11% increase in market shares after companies benefit from the protection of Intellectual Property Rights (IPR). Firm size and capital intensity follow with 12% and 10% growth rates, respectively. Interestingly, we find no significant evidence that companies become more productive after patenting once we challenge correlations for reverse causality.

In this context, we comment that our findings provide evidence that more productive companies can sustain the fixed costs of R&D, thus coming to the successful registration of Intellectual Property Rights. Yet, IPR does not provide *ex-post* productivity gains to ICT firms while granting them market power over competitors.

Our results are robust when we control for ownership structures of domestic and multinational companies. In fact, we do know that benefits from R&D efforts may accrue to smaller segments of activities within the corporate perimeter. We separate patents granted to parent companies from the ones held by their subsidiaries. In this case, our main tenets are confirmed, although we find a slightly larger impact coming from subsidiaries' patenting activities, possibly due to a specialization of R&D labs within more prominent corporate structures.

Finally, we complement our exercise on causality with an analysis of the market allocation of productive resources based on the methodology proposed by Olley and Pakes (1996). In general, we observe that more productive firms see their market shares grow relatively more. That is, we do not observe significant problems in an efficient allocation of resources in the global digital market, although companies gain higher market power through IPRs. In this case, we consider the ICT sector as a peculiar case of a dynamic industry that has not reached a maturity stage yet, thus showing room for more efficient players to emerge. Still, we argue that policymakers should be better aware of the trade-off between conceding IPR protection and obtaining a higher market concentration. If one believes our findings, IPRs *per se* are not leading to productivity gains to the ones that make the efforts. Future studies could eventually ascertain the empirical association between market power by innovators and productivity gains by purchasers of innovative goods and services, as in the case of ICT inputs that are sourced by downstream producers across various industries.

To grasp the relevance of patenting activity in the ICT global industry, in Table 4.1, we report a match of the top ICT global firms according to Fortune Global 500 in the reference year 2020 with the stock of patents they have accumulated over years, as from our patent data. The Fortune's ranking is originally based on global revenues and, consistently, we match in the last column with information on all the patents in portfolio that are held by either a parent company in the origin country or its subsidiaries located wherever in the rest of the world. Notably, we have an average stock of 160 thousands by top ICT firms; the most historically active assignee has been Samsung Electronics in South Korea with up to 641,743 granted patents around the world. Foxconn in Taiwan is the one relying relatively less on patenting activity with an albeit non-negligible stock of 2,266 patents. In the following analysis, we will include both bigger and smaller companies to check how heterogeneous patenting activity can be in the entire industry, in a relationship with both firm-level productivity and market concentration.

Table 4.1: Top ICT global firms and stocks of patents

Fortune's 500 Global rank	Company	Country	Revenues (bln USD)	N. employees	N. granted patents
1	Apple	United States	260,174	137,000	54,536
2	Samsung Electronics	South Korea	197,705	287,439	641,743
3	Foxconn	Taiwan	178,860	757,404	2,266
4	Alphabet	United States	161,857	118,899	60,049
5	Microsoft	United States	125,843	144,000	89,635
6	Huawei	China	124,316	194,000	98,880
7	Dell Technologies	United States	92,154	165,000	11,509
8	Hitachi	Japan	80,639	301,056	268,598
9	IBM	United States	77,147	383,056	216,837
10	Sony	Japan	75,972	111,700	219,092
11	Intel	United States	71,965	110,800	91,214
12	Facebook	United States	70,697	44,942	12,381
13	Panasonic	Japan	68,897	259,835	384,817
14	HP Inc.	United States	58,756	44,942	61,715
15	Tencent	China	54,613	62,885	18,552
16	LG Electronics	South Korea	53,464	74,000	315,038
17	Cisco	United States	51,904	75,900	17,997
18	Lenovo	China	50,716	63,000	27,716

Note: The table indicates the list of top ICT global firms in year 2020, according to the Fortune Global 500 ranking, and the total number of patents that have been granted at any time in their business history, as reported by the Orbis Intellectual Property database. Please note how the same invention can be published (granted) as a patent more than once at (by) different country offices, i.e., we have a so-called family of patents that identifies a unique invention.

The rest of the chapter is organized as follows. Section 4.2 summarizes related literature. Section 4.3 introduces data and provides preliminary evidence. Section 4.4 discusses our identification strategy and results. In Section 4.5 we provide a further analysis, investigating the market allocation dynamics of the ICT industry. Section 4.6 concludes.

4.2 Related literature

We relate our contribution to the strand of literature that points to drawbacks in IPR protection. The latter is usually justified as a way to introduce artificial scarcity and amend non-rivalry and non-excludability in the consumption of knowledge. In fact, early positive externalities reduce the incentives for knowledge producers who may find it non-profitable and, thus, underinvest in an industry that greatly contributes to social welfare and economic growth. In this context, patents are supposed to be a way to counterbalance market imperfections. They generate a temporary legally enforced monopoly to guarantee producers that want to gain from knowledge generation.

Over the last years, however, several scholars have raised concerns about the contradictory behaviour of IPR practices. In their seminal works, Dosi, Marengo, and Pasquali (2006) and Boldrin and Levine (2008) build cases against intellectual monopolies discussing evidence that IPR regimes have at best no impact or, in some cases, even a negative impact on innovation rates. They favour rent-seeking behaviour by firms that benefit from a monopolistic power granted to them on the knowledge they generate, while reducing positive externalities and social welfare. Interestingly for our case, Boldrin and Levine (2013) point out how there seems to be no positive relationship between patenting activity and productivity. Specifically, the authors point to an inconsistency between the partial equilibrium, where patents stimulate innovation, and the general equilibrium, where instead protection reduces aggregate innovation rates.

Looking into specific domains, Henry and Stiglitz (2010) discuss the case of climate change and environmental protection, where patenting is problematic. In particular, they sketch the case of research in genetically modified organisms, where a different regime has brought wider social benefits. Interestingly, Moser (2013) and Gompel (2019) review other cases in economic history when, in the absence of modern IPR regimes, different forms of protection or even knowledge sharing were also able to accompany waves of important innovations. Eventually, Cimoli et al. (2014) discuss how modern IPR regimes could represent an obstacle to knowledge diffusion in developing countries, which may specifically need imitating successful developed countries to boost economic growth. Yet, on the other front of the controversy, other scholars stress that IPR protection should be even more important in modern times if one considers the strategic role that intangible assets play for the economic potential of regions and countries (Ziedonis, 2008; Haskel and Westlake, 2018).

Against the previous background, our primary concern is to investigate the nexus between innovation and market competition at the firm level, thus providing evidence on the relationship between firm-level market shares, productivity, and patenting activity. We choose to investigate the case of the global ICT firms as a typical example of an innovative segment of modern economic activities, which contributes to economic growth thanks to the widespread adoption of technologies that enhance the productivity of both private and public activities[1]. Firms in ICT have unique business models and require technological platforms that engage many downstream producers (Teece, 2018). Given the relevance of innovations coming from the ICT industry, producers seem particularly keen on claiming IPR protection through court proceedings (Graham and Vishnubhakat, 2013) and thus keep their market advantages.

This contribution finds a spurious correlation between the stock of patents and firm-level productivity that is not robust to reverse causality. While we observe how more productive firms certainly are able to register more patents, then we check that they do not reap productivity gains *ex post*, after IPRs are protected. Then, what do ICT producers gain from IPR protection? We find that they obtain an increase in market shares that is, instead, robust to challenges on the direction of causality. We believe our results are in line to a certain extent with previous evidence from the US published by Balasubramanian and Sivadasan (2011), according to which patent stocks are positively correlated with firm size, scope, skill intensity, and capital intensity. Please note, however, how the authors do not test the impact on market shares, thus leaving the reader agnostic about the consequences of IPR on market structures.

[1] Please note, however, the existence of a strand of research that questions the actual contribution of modern ICTs to aggregate productivity as unsatisfactory if measured against initial expectations. The argument follows that one should expect much more productivity from adopting new technologies than what is actually measured, hence a so-called productivity paradox. Among others, see Acemoglu, Autor, et al. (2014).

Our empirical strategy relies on a most recent econometric framework, Callaway and Pedro HC Sant'Anna (2020), which allows us introducing a panel dimension in a difference-in-difference setup when units are treated in different moments on the timeline. In fact, a recent stream of econometric literature has underlined how traditional diff-in-diff setups are biased in similar contexts, while sometimes possibly showing an opposite different sign on the underlying true population relationship[2].

Of course, we are not the first to investigate the relationship between firm-level innovation and market outcomes. Among the many, Acs and Audretsch (1988) and P. A. Geroski and Pomroy (1990) underline how innovation is negatively associated with market concentration. Aghion, Nick Bloom, et al. (2005) suggest that firms have a market advantage when they innovate in industries that suffer from lower competition. Otherwise, when competition is high, market followers have lower incentives to innovate than the leaders. On the same line, Blundell, Griffith, and Van Reenen (1999) also challenge the association between market share and innovation. After exploiting dynamic count data models, their findings suggest a positive impact of market share on patent stocks. However, a high product market competition within industry increases innovative activity.

More controversial is the relationship between patenting and productivity. In the US, Balasubramanian and Sivadasan (2011) find only a weak significance of the nexus after using data similar to ours matched at the firm-patent level. Unfortunately, we can only loosely relate to previous studies using R&D expenses and other category indicators from *ad hoc* surveys as a proxy for innovation activity (Griffith et al., 2006; Mairesse and Robin, 2009; Mohnen and Hall, 2013; Crespi and Zuniga, 2012). In these cases, we would not measure the monopoly power granted through IPR, as not all R&D efforts are finally granted protection. We can instead also relate to the work by Nicholas Bloom and Van Reenen (2002), who find that patents increase productivity in the long run, once inventions

[2]For further insights on this recent albeit fruitful strand of econometric research, see also Chaisemartin and D'Haultfœuille (2020), Goodman-Bacon (2021), Sun and Abraham (2020), Athey and G. W. Imbens (2021), Borusyak and Jaravel (2017).

are incorporated in the production process and efforts have been made to promote new products or production processes. However, from our viewpoint, the empirical evidence provided by Nicholas Bloom and Van Reenen (2002) is not entirely convincing. We argue that the authors test their hypotheses on a highly self-selected sample of only about 200 firms that could stay quoted at the stock exchange throughout the entire period of analyses, thus not representative of the underlying business population.

Eventually, please note that we always make our analyses robust to different definitions of the corporate perimeter, thus encompassing patents that are either granted to parent companies or their subsidiaries. In this way, we can control for optimal strategies by multinational enterprises that can, for example, locate part of their R&D activities in countries where IPR regimes are more favourable or where taxation is relatively lower (Skeie et al., 2017) on R&D activities. It is the case of IPR regimes where patent boxes are allowed; thus, revenues from granted patents are exempted from taxes to benefit from higher profits from international activities (Bösenberg and Egger, 2017; Alstadsæter et al., 2018; Davies, Kogler, and Hynes, 2020). More in general, there is ample evidence that multinational enterprises in any sector, not only ICT, can take advantage also from technology developed across different geographic regions, thus exploiting local subsidiaries for reverse knowledge transfer (Driffield, Love, and Yang, 2016). Therefore, a focus on parent companies only would exclude an essential share of companies' innovation efforts.

4.3 Data and preliminary evidence

4.3.1 Data on firms and patents

For our purpose, we exploit a matched dataset of firms and registered patents in the period 2009-2017 sourced from the ORBIS database[3], com-

[3]The ORBIS database has become a standard source for global financial accounts. See for example Gopinath et al. (2017), Cravino and Levchenko (2016), Del Prete and Rungi (2017), and Fattorini, Ghodsi, and Rungi (2020). The coverage of smaller firms and details about financial accounts may vary among countries depending on the requirements by national

piled by the Bureau Van Dijk. In particular, the module on Intellectual Property links companies and other entities (i.e., assignees of IPR) to their original patent filings collected from PATSTAT, the global database maintained by the European Patent Office. Usefully for our scope, the IP module by Orbis follows: i) the evolution of each patent filing, from the publication to the moment the property right is granted; ii) the changes in property rights from one assignee to another, e.g., in case of companies' mergers and acquisitions. Previous users of the same database include Noailly and Smeets (2015), who study the effect of technological change on environmental performance, and Alstadsæter et al. (2018), who investigate the determinants of patent registration. Andrews, Criscuolo, and Menon (2014) also use a similar matched patent-firm dataset to identify the impact of first patenting on firm performance across industries and countries [4].

We deflate financial accounts to express them in constant 2015 US dollars, however the market share is expressed as the share of revenues in nominal terms. Exchange rates from national currencies are originally provided by the Bureau Van Dijk, while deflators are primarily sourced from either the OECD STAN Database (*deflators*) or Eurostat (producer price indeces) for gross output, intermediate, and capital goods by country and sector of activity, respectively[5]. Although in principle the IP module by Orbis includes patents and firms from all over the world, we keep in the following analyses only patents held by firms that report basic financial information we need for testing our hypotheses.

Eventually, we end up with a sample of $179,660$ firms active in 39 countries and operating in the ICT industry[6]. Our definition of the ICT

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business registries, as observed in Kalemli-Ozcan et al. (2015).

[4]Please notice that the same technology may be patented across multiple countries. However, in our context we expect that multiple patenting should not affect our analysis, as it actually implies stronger protection.

[5]In cases where deflators are not available at two-digit or more aggregate sector level, we use the GDP deflator at country level. Deflators for Taiwan do not appear in the OECD or Eurostat, hence they are sourced by national statistics.

[6]We keep only countries that report at least one patent. Moreover, we exclude countries where deflators where not found in the OECD or Eurostat. The only exception is Taiwan because of its high patenting activity. Finally, we drop firms operating in China with less than 10 employees. The reason is that the vast majority of these observations are problem-

perimeter encompasses both manufacturing and services, and it is based on the work made by Benages et al. (2018), who compiled the 2018 PREDICT database for the European Commission. In Appendix Tables C.2 and C.1, we enlist countries and NACE 2-digit industries, respectively, included in the following analyses [7].

4.3.2 Preliminary evidence

First of all, we provide a snapshot of the evolution of market concentration in the ICT industry, as from our data. To this end, we compute the value of the Herfindahl–Hirschman Index (HHI) calculated as the sum of squared market shares of all firms in our database. Thus, we report growth rates in the period of analyses. Each firm's market share is computed as the share of nominal turnover over the total ICT industry as defined by Benages et al. (2018)[8]. In Figure 4.1, the solid line reports its evolution over time, starting from the percentage change from 2010 to 2011. Clearly, the trend on HHI suggests some volatility in the industry, but with a tendency to become relatively less concentrated in our period of analyses. As from our data, the tendency to a lower concentration comes from the entry of new ICT producers in the market over the last decade. On the other hand, when we juxtapose the growth rate of newly granted patents by ICT firms, Figure 4.1 shows a positive trend in the same period. Apparently, we look at a rather dynamic industry that is generating new knowledge encoded in IPR, while newcomers participate to the profitable opportunities from a rising market.

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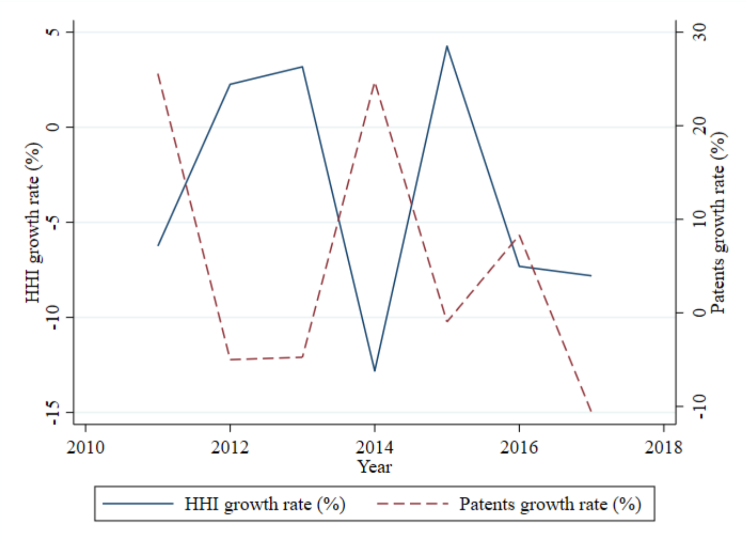
atic in the sense that they refer to medium or large firms but they reported a very small number of employees.

[7]A descriptive analysis on a similar sample by ORBIS has been used in Ghodsi et al. (2021)

[8]Please note that we do not define market shares within the narrow core industry according to standard NACE rev. 2 classification, because we consider that all ICT firms compete in the same broader sector. As underlined by Patel and Pavitt (1997), firms tend to produce technology in different fields.

Figure 4.1: Market concentration and IPR in the ICT industry



Note: The figure illustrates the growth rates of Herfindahl-Hirschman Index (HHI) (blue solid line) computed from firm-level market shares in the ICT industry, juxtaposed to the trend of the growth rates of patents granted to ICT companies in the same period of analyses (red dashed line).

Notably, however, patents are concentrated among a few patentees, while many firms in the ICT industry do not patent at all in the period we investigate. Therefore, in Table 4.2, we provide preliminary evidence on the differences in market shares and labor productivity between patentees and non-patentees. Market shares are computed considering firm-level revenues on the total sample each year. Labor productivity measures revenues per worker. Thus, we check whether t-tests indicate a statistical significance in the distributions of firm-level outcomes of interest considering any firm-year observation. We register that patentees have on average a much higher market share than non-patentees. When we look at labor productivity, the difference is still significant, albeit in logs. The average patentee generates about $217,000$ dollars per worker in a year, whereas an average non-patentee registers about $68,000$ dollars per worker in a year. Patentees are also larger on average in terms of revenues, as they generate about 7.5 million dollars while annual revenues are about 0.5 million dollars when they do not own a granted patent. Finally, patentees are clearly more capital intensive on average.

The difference in means persists when we consider ICT manufacturing and ICT services separately and, for all outcomes, is higher for ICT services. However, it is worth mentioning that patenting activity appears to be higher in the case of ICT manufacturing sectors (the share of firm-year observations with at least a patent is around 13.5% in the case of ICT manufacturing against around 0.5% in the case of ICT services). The latter is expected as observed in past studies (see for instance Andrews, Criscuolo, and Menon (2014)). Therefore, the discrepancies in mean difference could be possibly related to the different variation between the two subsamples.

Table 4.2: Firm-level outcomes of patentees and non-patentees

	% Market share	(log) Labour productivity	(log) Size	(log) Capital intensity	N. obs.
Patentees	0.0271	12.2857	18.1386	11.5203	21,097
	(0.0011)	(0.0076)	(.01651)	(.0115)	
Non-patentees	0.0004	11.1316	13.1754	8.8694	910,516
	(0.0000)	(0.0014)	(.0024)	(.0023)	
Difference	0.0268***	1.1541***	4.9632***	2.6509***	
	(0.0001)	(0.0093)	(.01604)	(.0154)	

Note: The table reports t-tests on the differences in market share, (log) labour productivity, (log) size and (log) capital intensity for companies having at least one patent *vis á vis* companies without patents. The unit of observation is firm-year level. Standard errors in parentheses. *** denotes significance at 1%.

Eventually, to check how our main outcomes of interest correlate with patenting activity, we perform basic least-squares regression as follows:

$$y_{ict} = \beta_0 + \beta_1 Pat_{ict} + \beta_2 X_{ict} + \gamma_i + \delta_{ct} + \epsilon_{ict} \tag{4.1}$$

where y_{ict} is the logarithm of the ith firm's outcome observed in country c at time t. The main coefficient of interest to us is the one on the flows of granted patents, which we indicate with Pat_{ict}[9]. As we have a large

[9]Please note that here, as indicated in Section 4.3, we consider patents as belonging to

number of firms without any patent, and the distribution of the number of patents is highly skewed, we rescale the latter using the inverse an hyperbolic sine transformation ($ln(x + \sqrt{x^2 + 1})$), which is an approximation of the logarithmic value of the same variable that does not drop zeros (Bellemare and Wichman, 2020). X_{ict} is a vector of firm-level controls, including (logs of) number of employees, capital intensity, and the age of the company. γ_i indicates a full set of firm fixed-effects; δ_{ct} are country-per-year fixed effects controlling for institutional characteristics and unsynchronized business cycles.

Results show that a higher degree of patenting activity is always associated to positive firm-level outcomes. Firms being granted more patents have a relatively higher market share; they are more productive, bigger, and more capital intensive.

Table 4.3: Firm-level outcomes and patenting activity. Correlations.

Variable	Coeff.	s. e.	N. obs.
(log) Market share	.028***	(.006)	931,613
(log) Labor productivity	.029***	(.006)	931,613
(log) Firm size	.059***	(.007)	931,613
(log) Capital intensity	.053***	(.006)	931,613

Note: Each coefficient is the result of a least-square regression of the (log) firm-level outcome (by row) *vis á vis* the number of patents granted each year to the company standardized with the inverse of an inverse hyperbolic sine transformation ($ln(x + \sqrt{x^2 + 1})$) to approximate the natural logarithm while retaining zeros, as suggested by (Bellemare and Wichman, 2020). Firm-level controls, firm-level fixed effects, and country-year fixed effects are included. Firm-level clustered standard errors are reported.

Clearly, positive correlations in Table 4.3 do not say whether, for example, bigger and more productive firms are also the ones that are more able to generate patents, as this is our hypothesis. At this stage, it may

the company directly or through one of its subsidiaries. For robustness checks on this point, see Section 4.4.3

still be valid the opposite and firms become bigger and more productive because they can register more patents. The following paragraphs will fundamentally check for reverse causality. Therefore, preliminary evidence in Table 4.3 motivates the following analyses on the direction of causality. In particular, we are interested in analyzing whether the intellectual property right granted by a patent impacts market shares and labour productivity as primary indicators of the firms' position in the market and its efficiency. Firm size and capital intensity are secondary to our arguments on changing competitive scenarios, yet they indicate how the firm responds to IPR protection.

4.4 Empirical strategy and results

Our objective is to assess the impact of patenting on firm-level outcomes that return us with useful information on the evolution of the ICT industry. A firm's market share is a basic and straight indicator of market power, whereas productivity is often a target for competition-oriented policies. One assumes that if markets function properly, then consumers can benefit from the efficiency and productivity of firms. For our purpose, we adopt a novel empirical setup for a difference-in-difference strategy introduced by Callaway and Pedro HC Sant'Anna (2020), which allows treatment to occur at different moments on the timeline. Basically, the authors show that previous two-way fixed effects estimators are biased in presence of a panel dimension. The intuition is that a bias occurs when newly treated units in one period are compared to units that had been already treated in a previous period. In the following paragraphs, we introduce notation to clarify how the identification strategy works, and then we report main findings.

4.4.1 Empirical strategy

Following Callaway and Pedro HC Sant'Anna (2020), our first aim is to identify the average treatment effect on the treated (ATT) for any group of firms g that have published at least a granted patent at a specific time

t, as follows:

$$ATT(g,t) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{p_g(X)C}{1-p_g(X)}}{\mathbb{E}\left[\frac{p_g(X)C}{1-p_g(X)}\right]}\right)(Y_t - Y_{g-1} - m_{g,t}(X))\right] \quad (4.2)$$

where G_g is a binary variable equal to one if a firm belongs to the group g; C is a binary equal to one for firms that have never been granted a patent at any time period; Y_t is the firms' outcome at time t, i.e., market share, labour productivity, firm size or capital intensity. Then, $p_g(X) = P(G_g = 1|X, G_g + C = 1)$ is the probability of publishing a granted patents at time g conditional on pre-treatment covariates X and: i) either belonging in group g; ii) or not being granted any patent at any time during the period. Then, $m_{g,t}(X) = \mathbb{E}[Y_t - Y_{g-1}|X, C = 1]$ is the population outcome regression for the control group made by firms that have never been granted a patent in our period of analyses[10].

Few additional words are worth spending to define what we mean with treatment and control groups in the case of intellectual property rights. In our baseline specification, we define the timing of treatment as the moment a company has published a granted patent, including in the corporate perimeter both headquarters and subsidiaries. As discussed in related literature, the main idea is that multinational companies can control important portfolios of patents and manage them through subsidiaries located in many countries. In bigger groups, considerations about fiscal optimization and local knowledge advantages can combine and bring highly specialized delocalized R&D labs to focus on intellectual property rights (Bösenberg and Egger, 2017; Alstadsæter et al., 2018; Davies, Kogler, and Hynes, 2020). Coherently, the control group encompasses ICT companies that have not been granted patents either at the headquarter or subsidiary levels, at any point in our period of analysis. Robustness checks are provided in Section 4.4.3, where we separate

[10]Please note that Callaway and Pedro HC Sant'Anna (2020) provide alternative specifications to estimate group-time average treatment effects. In this application, we adopt the doubly robust estimator first proposed by Pedro H.C. Sant'Anna and J. Zhao (2020) because it is claimed to be more robust than the other alternatives.

headquarters' and subsidiaries' patents.

Importantly, we always check that the assumption of parallel trends is made conditional on companies' characteristics before treatment. Specifically, we control for capital intensity, number of employees, firm age, 2-digit NACE rev. 2 industry-level dummies, and three fixed effects for companies with headquarters located in the European Union, , the United States, and the rest of the world. For this exercise to work, we must consider a balanced panel with complete information on labour productivity, employment, capital intensity and age. Then, we have to exclude companies that are treated in 2009 because we do not have the chance to check for what happens before the treatment, i.e., before a patent is granted. Please note that a limitation of our study is that we can only consider cases of first patents granted within our period of analysis. That is, we cannot observe the moment a patent has been granted before 2009, which is the first year for which we have reliable matched data between firms and granted patents. Eventually, we end up with a reduced sample of $25,052$ firms of which 546 companies have been treated at some point in 2010-2017, and $24,506$ have never been granted any patents in the same period.

At this point, to estimate the overall impact of patenting on firm-level outcomes, we shall consider a weighted average of previously defined $ATT(g,t)$, in the following way:

$$\theta_s^O = \sum_{g=2}^{T} \theta_s(g) P(G = g) \tag{4.3}$$

where,

$$\theta_s(g) = \frac{1}{T - g + 1} \sum_{g=2}^{T} \mathbf{1}\{g \leq t\} ATT(g,t)$$

and T denotes the number of years. In other words, even if we work on a panel dataset, where firms can be granted patents at different moments on the timeline, we can still obtain a unique parameter, θ_s^O, which tells us whether patents do have an impact or not on firm-level outcomes. That parameter is finally a weighted average of time-specific parameters, as the latter are obtained considering groups of firms that have been treated in any observed period. The group-specific weights, $P(G = g)$'s, are obtained considering the relevance of each group over the total sample.

Finally, we can test the persistence of the effect thanks to a classical event study analysis, for which we need to compute "the length of exposure to the treatment", e. The latter is another form of aggregation of the group-time specific effect, which we can define as:

$$\theta_{es}(e) = \sum_{g=2}^{T} \mathbf{1}\{g + e \leq T\} P(G = g | G + e \leq T) ATT(g, g + e) \qquad (4.4)$$

In plain words, Eq. 4.4 returns the average impact on firm-level outcomes after e periods from being granted a patent.

4.4.2 Results

In Table 4.4, we report estimates of the impact of patenting activity on firm-level outcomes. According to our findings, companies being granted patents published in the period 2010-2017 benefit from an increase in market share by 11.07% (log units: 0.105). In the case of productivity, we find only a weakly significant impact that is however much smaller in magnitude (3.67%; log units: 0.036). On the other hand, results are clearer on revenues (12.08%; log units: 0.114), and capital intensity (10.3%; log units: 0.098). Please note the important difference in magnitudes between the previous coefficients and the ones reported in Table 4.3. Once we control for reverse causality, we understand that much of that difference indicates a self-selection of bigger and more productive firms into IPR protection.

Table 4.4: Patenting and firm-level outcomes - ATT

Variable	θ_s^O	s. e.	No. of treated firms	No. of untreated firms
(log) Market share	.105***	(.027)	546	24,506
(log) Labor productivity	.036*	(.020)	546	24,506
(log) Firm size	.114***	(.028)	546	24,506
(log) Capital intensity	.098***	(.034)	546	24,506

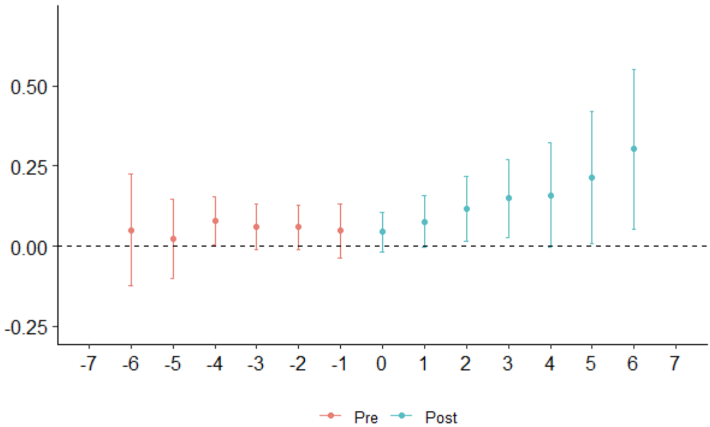
Note: The table illustrates aggregate treatment effects (parameter θ_s^O, as from Eq. 4.3) under the assumption of parallel trends made conditional on firms' characteristics, industry affiliation, and location dummies. Standard errors are clustered at the firm level. *, ** and *** denotes significance at 10%, 5% and 1%, respectively.

As for the weakly significant impact on productivity, please note how robustness checks reported in Section 4.4.3 do not confirm statistical significance. When we control where in the corporate perimeter productivity gains actually occur, either at the level of headquarters or of subsidiaries, then we do not find any statistical significance. Similar non-significant results are obtained when we check for the specific nature of the industrial activity, whether it is in line with the headquarters' or the one indicated by subsidiaries. Therefore, at the end of the study, we will conclude that there is no significant impact of IPR protection on productivity gains. Yet, please note that our findings are somewhat coherent with cross-country general evidence on companies beyond the ICT industry, as in Andrews, Criscuolo, and Menon (2014), where a similar relationship, between patent stock and TFP is non-significant in their baseline estimates. However, some significance appears only when they check for long-run effects which are smaller in magnitude than effects on firm size. Balasubramanian and Sivadasan (2011) find a significant effect on productivity in US firms, but again relatively smaller if compared to the impact on firm size.

Further investigations may be needed to get deeper into the relationship between patenting activity and productivity. Yet, according to us, the ICT industry has some peculiarities that are worth further considerations at this stage. Patents by ICT firms are mainly devoted to the protection of product innovations, relatively less to process innovations. Firms ask for protection of new technological advancements that improve the products they professionally sell for the benefits of consumers. In this case, it makes sense that we detect an impact on market shares and firm size, thanks to higher revenues after IPR. In this context, the impact on the same firms' productivity can be marginal as product innovations do not have a direct impact on the way production factors are organized.

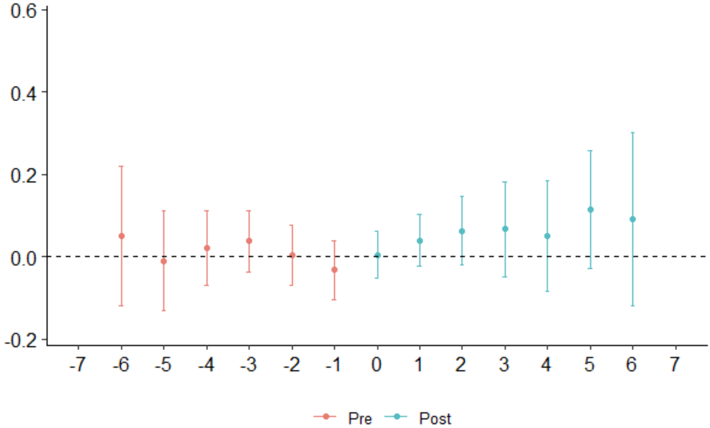
Eventually, we report event studies following the procedure described in Eq. 4.4 in the following Figures 4.2, 4.3, 4.4, and 4.5. We aim to check how our main firm-level outcomes of interest are affected by treatment, i.e., how IPR protection has an impact as time passes from when the representative company has been granted a patent. As in any classical event study, we align events on a reference period, $e = 0$, which is the first year a firm has been granted a patent in our sample, $e = 0$. Therefore, following Eq. 4.4, we are able to plot the impact on the outcome of the representative company at any following period, thereby checking that previous trends are conditional on firm-level characteristics, industry affiliations, and firm's location choices. Evidently, in any of the following figures, we do not visualize any statistically significant trend before treatment, i.e., companies are not systematically showing that they were becoming bigger, more productive, or capital intensive before obtaining IPR in $e = 0$.

Figure 4.2: Event study: patents and market shares.



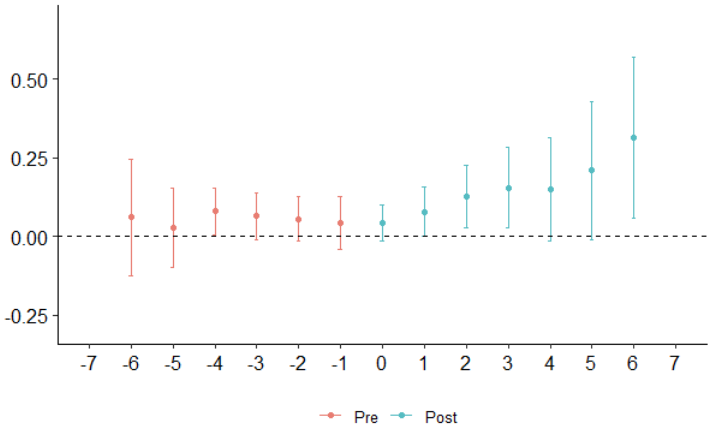
Note: Event study on the impact of first patenting when it takes place either at a parent firm or at a subsidiary. Parameters are estimated under parallel trend assumptions conditional on the number of employees, capital intensity, age (in logs), 2-digit sector and regional dummies. Blue lines denote point estimates and simultaneous 99% confidence bands for the effect of the treatment.

Figure 4.3: Event study: patents and productivity.



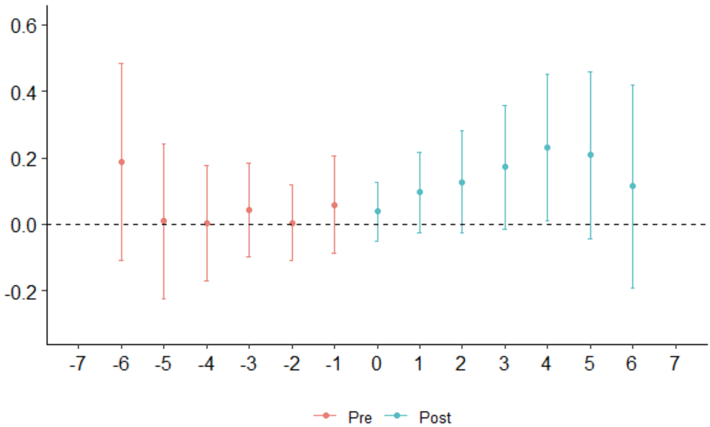
Note: Event study on the impact of first patenting when it takes place either at a parent firm or at a subsidiary. Parameters are estimated under parallel trend assumptions conditional on the number of employees, capital intensity, age (in logs), 2-digit sector and regional dummies. Blue lines denote point estimates and simultaneous 99% confidence bands for the effect of the treatment.

Figure 4.4: Event study: patents and firm size.



Note: Event study for the impact of first patenting when it takes place either at a parent firm or at a subsidiary. Parameters are estimated under parallel trend assumptions conditional on capital intensity and age (in logs), 2-digit sector and regional dummies. Blue lines denote point estimates and simultaneous 99% confidence bands for the effect of the treatment.

Figure 4.5: Event study: patents and capital intensity.



Note: Event study for the impact of first patenting when it takes place either at a parent firm or at a subsidiary. Parameters are estimated under parallel trend assumptions conditional on the number of employees and age (in logs), 2-digit sector and regional dummies. Blue lines denote point estimates and simultaneous 99% confidence bands for the effect of the treatment.

In the case of market shares (Figure 4.2), we do observe a significant increase in the following periods, up to six years after the patents have been granted. We spot similar significant patterns when we test for firm size, as measured in terms of revenues, and for capital intensity. Altogether, as expected, the pattern of productivity is not statistically significant, in line with results shown in Table 4.4.

4.4.3 Robustness checks

We perform two different robustness checks. Results are reported in Appendix C.

First, we check whether the corporate perimeter matters for the magnitude and the significance of the impact of the patenting activity. We separately test the impact of patents held by parent companies and parents held by subsidiaries, based on prior knowledge that most ICT companies are multinational enterprises that can locate R&D labs across national borders, while exploiting locally competitive advantages and different opportunities for optimal intra-firm tax strategies. Appendix Tables C.6 and C.7 show that main tenets on market shares and firm size are confirmed, even if we have to work with smaller subsets if compared to previous baseline analyses. However, the coefficient for the impact of capital intensity (Table C.6) does not keep statistical significance in the case of headquarters. Notably, we can never observe a significant change in productivity, neither in the case of headquarters nor in the case of subsidiaries.

A second concern we have is that we can find several activities unrelated to the core activity within the same perimeter together with headquarters, as for example in the case of bigger business groups that differentiate their exposure across different markets. In this case, we perform separate tests on: i) subsidiaries that are active in the same 2-digit sector of the parent company, and ii) subsidiaries whose main activity is different from the parent. Interestingly, only ICT subsidiaries in the same 2-digit sector of the parent show an impact according to our expectations on market shares and firm size (Appendix Table C.8). There is no significant impact on the latter outcomes when a subsidiary operates outside the core industry of the parent company. An exception is the case of capital intensity, in Appendix Table C.9, possibly due to an increase in tangible assets that any investment undertaken by a subsidiary entails whatever the industry.

Third, we check for alternative specifications of the empirical strategy as already provided by Callaway and Pedro HC Sant'Anna (2020). Specifically, we consider an alternative $ATT(g,t)$ estimator defined Outcome Regression (OR). The approach is similar to the doubly robust approach we adopted in the baseline. The difference is that it does not rely on the conditional probability of being treated. In practice, the term $p_g(X)$ is omitted from Eq. 4.2. From an econometric point of view, it does not control for the characteristics that make treated companies (i.e., firms being granted a patent) different from the ones that are not (i.e., firms that never obtain a granted patent in our analyses). Results are reported in Appendix Table C.10. Also in this case, all previous results are confirmed, although the coefficient on capital intensity loses some statistical significance.

4.5 Productivity and misallocation

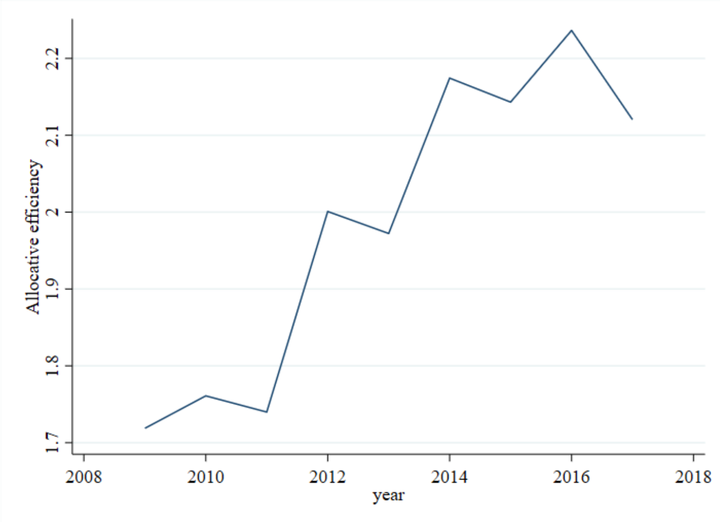
We have already provided evidence that patenting allows companies to obtain larger market shares, whereas we did not find any significant impact on labor productivity. In this Section, we want to check how market shares and productivity co-move in the same period of analysis, as the latter is an information that is useful to quantify allocative efficiencies in the ICT industry. The intuition is that markets are inefficiently allocating productive resources when less productive firms are obtaining market shares at the expense of more productive firms. In this respect, we rely on (Olley and Pakes, 1996) who provide a simple decomposition of the level of aggregate labor productivity into an unweigthed firm-level average and a covariance term, as follows:

$$\sum_{i=1}^{N} \Delta s_{it} \Delta p_{it} = \sum_{i=1}^{N} s_{it} p_{it} - \bar{p}_t \tag{4.5}$$

where s_{it} is the market share of firm i at time t and p_{it} denotes the logarithmic terms of labour productivity. In Figure 4.6, we sketch the trend of the covariance term after using all available information about global ICT firms in our dataset. Interestingly, the covariance between market shares and productivity is always positive and overall rising in the period we investigate. We comment that the ICT global industry is a dynamic and rising sector, where there is still room for market gains by competitive companies. As demonstrated by preliminary evidence in Table 4.2, firms that obtain patents are considerably more productive than non-patentees.

Obviously, the IPR regime did not prevent the market from revealing productivity gains and allocate resources efficiently among most efficient firms. Yet, what we can conclude from our findings are that those productivity gains have been obtained not because of the IPR protection they obtained.

Figure 4.6: Productivity and efficient allocation



Note: The figure illustrates the allocative efficiency of market shares with respect to labour productivity, as from the methodology proposed by Olley and Pakes, 1996. A rising covariance term between market shares and productivity indicates that more productive firms are gaining market shares.

4.6 Conclusion

The global ICT industry is a fundamental source of growth in modern economies. Its products and services are not only purchased by final consumers that want to upgrade and update on newest technologies; they are also important inputs in the production processes of many other sectors. Comprehensibly, the sector attracts the attention of policy makers and commentators. Most recently, serious doubts have been raised about a too fast market concentration among few Big-Tech global players. Antitrust authorities both in the US and the European Union started to investigate whether there is evidence of detrimental effects to social welfare.

Against this background, we believe the industry is a peculiar case where we can study the impact of IPR protection on firm-level outcomes. In fact, the ICT industry is also the one from where major innovation efforts have been granted patents in latest years. One should pay more attention to the link between IPR protection and market concentration, as there is by now an important strand of literature that underlines important drawbacks of actual IPR regimes.

In this contribution, we provide a test on the direction of causality running from patenting activity to firm-level outcomes, namely market shares, productivity, firm size, and capital intensity. We adopt a novel unbiased approach for a difference-in-difference setup, where treatment can occur at different moments on the timeline. We show how firms that are granted patents can benefit from a rise in market share, firm size, and capital intensity.

Interestingly, labor productivity does not significantly change after IPR protection. Yet, stylized facts show how patentees are on average much more productive than non-patentees. Therefore, we comment that more productive firms are the ones that are able to sustain the fixed costs of innovation. In the case of ICT industry, innovation take place mostly in terms of new products to be sold on the market. Thereafter, they can use IPR regimes to obtain market power and consolidate their position against competitors, therefore contributing to the rise of superstar firms.

In our view, there are important avenues of studies that could help understanding better the relationship between IPR protection and market structures. Among others, one limitation of our study is that we do not have a counterfactual for what could have been the performance of the entire industry if the IPR regime had been different. When we perform a productivity decomposition á la Olley and Pakes (1996), we observe that more productive firms on average have gained higher market shares in the period of analysis. Thus, there has been an allocation of productive resources towards more efficient firms. Yet, one would like to know whether there could have been even more efficiency gains with a different regulation of IPR. From another point of view, one could be interested in studying the impact of patenting activity on the actual purchasers of ICTs, including firms that take ICTs as inputs to improve the quality of products and services across sectors different from ICT.

The literature on market competition still has some open challenges that need to be considered. Berry, Gaynor, and Scott Morton (2019) highlight that empirical studies focusing on firms' market power suffer from limitations. For instance, the market structure and key outcomes of market power are not usually observed from the data and they need to be estimated or calculated, leading to possible imprecisions. Furthermore, endogeneity problems arise when considering the relationship between markups, market share and industry concentration. Another important issue is that the drivers of market power have changed over the last decades and information technology has a crucial role in it. For example, considering the production side, information technology may lead to higher markups as it is usually a part of firms' fixed costs. From the demand side, network effects between consumers on online platforms may affect competition.

Moreover, the literature highlights that antitrust enforcement has been loosed. As a result, the domination of the markets by one or a few firms has been facilitated (Berry, Gaynor, and Scott Morton, 2019; Shapiro, 2019). The US and the global market need to redirect the antitrust policy to enhance competition, highlighting the necessity to reconsider and carefully evaluate cases of mergers and firm strategies aiming to exclude dominated firms or to enable anti-competitive practices in the labor market.

Recent evidence on patents, market structure and firm performance, indicates that future research needs to further investigate the factors related to intellectual property rights that drive competition. The geographic concentration of IT patenting brings about the need to study its effect on competition, firms' competitiveness or any further implications, like the development of innovative cities (Forman and Goldfarb, 2020). Finally, due to the absence of information on firms' exports, our study remains silent on the implications of patenting on trade. Studies like De Rassenfosse et al. (2020) that show the positive effects of patent protection on exports, may motivate future research to focus on the nexus between market power, trade and patents.

Chapter 5

Conclusion

In this thesis, we looked into different drivers of firms' competitiveness and market competition.

At first we considered the interaction between regional disparities and agglomeration economies taking advantage of detailed spatial information of firms. Then, we assessed the impact of foreign managers on firms' competitiveness. Finally, we shed light on the nexus between property rights from innovation, productivity and market competition in the ICT sector.

In the following section, we summarize the most crucial contributions and findings.

5.1 Summary

In Chapter 2 we applied a machine learning algorithm to cluster firms at a fine-grained scale. In particular, we applied a density-based clustering algorithm, the OPTICS (Ankerst et al., 1999) to examine the extent to which agglomeration economies explain regional disparities within Italy. After confirming the well-known productivity inequalities between North and South, we found that firms are more productive on average within clusters. To go deep into the role of agglomeration economies and selection mechanisms, we performed the econometric approach developed by Combes et al. (2012). Our findings suggest that dense clusters of firms generate agglomeration externalities that remain significant within macro-region. Interestingly, we observe that productive firms in the North and the Centre benefit more from these externalities, indicating that competitive firms are more efficient when taking advantage of their production inputs. Our evidence regarding market selection effects is not confirmed when performing the analysis within each region. To this end, we argue that the spatial scale we consider here is not able to efficiently capture selection mechanisms.

In Chapter 3 we tested the impact of foreign managers on productivity of manufacturing firms operating in the UK for the period 2009-2017. Our evidence suggests that domestic firms become more competitive after recruiting foreign managers as they increase productivity. These productivity gains are explained by foreign managers with previous industry-specific experience. In the case of foreign firms, we found no significant effects after recruiting foreigners. Therefore, we argue that productivity gains already occurred after acquisition by multinationals. However, foreign managers' know-how is still valuable for domestically-owned enterprises as they allow them to become more competitive and catch up their foreign rivals.

In Chapter 4 we empirically assessed the impact of patenting on market share and labor productivity on a sample of firms operating in the ICT sector globally. Our main findings indicate that companies increase market share after granting patents. However, we did not find significant productivity gains. We argue that IPR protection enhances firms' market power while it does not boost competitiveness. However, the IPR does not hamper the efficient allocation of production resources, as productive firms have enjoyed a larger market share over the years. In any case, policymakers should be skeptical about the implications of IPR protection on the emerging ICT sector.

Appendix A

Appendix to Chapter 2

A.1 Total Factor Productivity at the firm-level

The identification strategy proposed by Ackerberg, Caves, and Frazer (2015) currently represents one of the most robust solution to the traditional challenges littering the econometric estimation of production functions. It represents a refinement of the previous semi-parametric techniques (Olley and Pakes, 1996; Levinsohn and Petrin, 2003) designed to overcome the well-known simultaneity bias affecting most basic OLS estimates. The simultaneity bias arises because firms optimally choose input levels at the moment they take stock of their productivity. To introduce the problem, let us consider a log-transformed Cobb-Douglas production function as the following:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_\ell \ell_{it} + \beta_m m_{it} + v_{it}$$

where y is output, k is capital, ℓ is labour and m is material. We represent a composed error as $v_{it} = \epsilon_{it} + \omega_{it}$. As usual, ϵ_{it} is the idiosyncratic component, whereas ω_{it} is the unobservable productivity shock correlated with the choice of inputs.

So called control-function methodologies previously addressed this sort of endogeneity by introducing an input demand function to catch any productivity shock. The latter is consequently proxied by $\omega_{it} = f_t^{-1}(k_{it}, d_{it})$, where d_{it} can be intermediate inputs (Levinsohn and Petrin, 2003) or investment (Olley and Pakes, 1996). Once ω_{it} is plugged into the production function, a two-steps semi-parametric estimator can be implemented to derive both productivity and marginal contributions of production factors.

In this context, Ackerberg, Caves, and Frazer (2015) preserves the intuition of the identification strategy above but with a variation into the set of preliminary assumptions. The authors consider the existence of hiring and firing costs that hinder the immediate adjustment of labour, thus incorporating it in the intermediate input demand function, $m_{it} = f_t(k_{it}, \omega_{it}, \ell_{it})$. In other words, Ackerberg, Caves, and Frazer (2015) prove that if labour is a predetermined variable of the production system, then it becomes functionally dependent on the other inputs. This aspect *per* *se* makes the first stage of both Olley and Pakes (1996) and Ackerberg, Caves, and Frazer (2015) inconsistent and prone to collinearity issues. The production function is therefore correctly written as:

$$\begin{aligned} y_{it} &= \beta_0 + \beta_k k_{it} + \beta_l \ell_{it} + \beta_m m_{it} + f_t^{-1}(k_{it}, m_{it}, \ell_{it}) + \epsilon_{it} \\ &= \Phi_t(k_{it}, m_{it}, \ell_{it}) + \epsilon_{it} \end{aligned}$$

In a first stage, only the composite term $\Phi_t(k_{it}, m_{it}, \ell_{it})$ is identified, which can be specified as a polynomial expression, Φ_t, and estimated with simple OLS. In the second stage, productivity and inputs' elasticities are derived as follows.

By assumption, productivity evolves according to a first order Markov process $\omega_{it} = \mathbb{E}[\omega_{it}|\omega_{it-1}] + \xi_{it} = g(\omega_{it-1}) + \xi_{it}$. Given this hypothesis and the estimates for $\hat{\Phi}_t$ from the first step, the Cobb-Douglas can be rearranged as:

$$y_{it} = \beta_k k_{it} + \beta_l \ell_{it} + \beta_m m_{it} + \rho(\tilde{\Phi}_{t-1}(\bullet) - \beta_0 - \beta_k k_{it-1} - \beta_m m_{it} - \beta_\ell \ell_{it-1}) + \xi_{it} + \epsilon_{it}$$

At this point, a generalised method of moments (GMM) must be applied to derive $\beta_0, \beta_k, \beta_\ell$, β_m and ρ. Ackerberg, Caves, and Frazer (2015) impose a set of moment conditions drawn on the orthogonality between ξ_{it} and the state variable, as well as on the orthogonality between ξ_{it} and lags of inputs potentially correlated with productivity:

$$\mathbb{E}\left[(\xi_{it} + \epsilon_{it}) \otimes \begin{pmatrix} 1 \\ k_{it} \\ m_{it-1} \\ \ell_{it-1} \\ \tilde{\Phi}_{t-1}(k_{it-1}, m_{it-1}, \ell_{it-1}) \end{pmatrix}\right] = 0$$

The procedure is originally implemented on a production function whose output is value added and, hence, where no intermediate inputs show up on the right-hand side. In our analysis, we perform both a gross output and a value added variant.

In order to account for structural characteristics of each industry, we estimate 2-digit NACE Rev.2 production functions. Labour, capital and intermediate inputs are measured by number of employees, fixed assets and material costs, respectively. Output is proxied by added value. Real values are obtained by deflating nominal accounts according to Eurostat producer price indices (PPI) in base year 2015.

Please note that balance sheet original values are previously treated for outliers detection. Our outlier detection method follows a *boxplot procedure with fences*. The *lower outter fence* is defined as the difference between the 10^{th} percentile *minus* $9\times$ the distance between the 10th and the 90th percentile. The *upper outter fence* is defined as the difference between the 90^{th} percentile *plus* $9\times$ the distance between the 10th and the 90th percentile. Once we spot growth rates falling under the *lower outter fence* above the *upper outter fence* (extreme outliers), we drop those companies that have at least one time observation with only one extreme outlier among labour, capital and materials.

Appendix B

Appendix to Chapter 3

B.1 Tables

Table B.1: Board, committee or department in which managers' belong

Title	No. of managers-*per*-role
Senior management	65,207
Board of Directors	56,044
Operations & Production & Manufacturing	11,180
Sales & Retail	8,788
Finance & Accounting	6,279
Administration department	4,684
Human Resources (HR)	3,974
Information Technology (IT) & Information Systems (IS)	3,344
Purchasing & Procurement	3,233
Research & Development / Engineering	3,063
Marketing & Advertising	2,770
Health & Safety	677
Branch office	271
Legal/Compliance department	119
Product/Project/Market Management	119
Executive Committee	105
Audit Committee	57
Nomination Committee	56
Remuneration/Compensation Committee	52
Corporate Governance Committee	34
Supervisory Board	16
Risk Committee	11
Safety Committee	7
Executive Board	5
Environment Committee	4
Public & Government Affairs	3
Quality Assurance	3
Ethics Committee	3
Others	17,752

Note: The table reports roles of managers as present from our sample. Any manager can cover more than one role in the same company, or she can participate to the management of more than one company at the same time. We exclude from original sources only shareholders and advisors without any role in the daily management of the firm. Please note how names of roles are not standard across firms, as they may follow the specific responsibilities attributed to individuals autonomously within firms.

Table B.2: Top 10 origin countries of foreign-owned firms

Nationality	No. of companies
United States	1,201
Germany	357
Japan	264
France	241
Sweden	172
Switzerland	148
Ireland	131
Netherlands	128
Italy	93
Luxembourg	87
Others	935

Note: We define a foreign-owned firm following international standards (OECD, 2005; UNCTAD, 2009; UNCTAD, 2016), according to which a subsidiary is controlled after a (direct or indirect) concentration of voting rights ($> 50\%$).

Appendix C

Appendix to Chapter 4

C.1 Tables

Table C.1: Countries included in the analysis

Austria	France	Lithuania	Slovenia
Belgium	Germany	Luxembourg	South Korea
Brazil	Greece	Malta	Spain
Bulgaria	Hungary	Netherlands	Sweden
Canada	India	Norway	Switzerland
China	Ireland	Poland	Taiwan
Croatia	Israel	Portugal	Turkey
Czech Republic	Italy	Romania	United Kingdom
Denmark	Japan	Russia	United States
Finland	Latvia	Slovakia	

Table C.2: The ICT perimeter based on NACE rev. 2 industries

NACE Rev. 2	Description	
26.1	Manufacture of electronic components and boards	
26.2	Manufacture of computers and peripheral equipment	**ICT manufacturing**
26.3	Manufacture of communication equipment	
26.4	Manufacture of consumer electronics	
58.2	Software publishing	
61	Telecommunications	
62	Computer programming, consultancy and related activities	**ICT services**
63.1	Data processing, hosting and related activities; web portals	
95.1	Repair of computers and communication equipment	

Note: The definition of the ICT perimeter based on Benages et al. (2018),

Table C.3: Firm-level outcomes and patenting activity. Correlations. Parents' patents.

Variable	θ_s^O	s. e.	N. obs.
(log) Market share	.036***	(.007)	931,613
(log) Labor productivity	.037***	(.007)	931,613
(log) Firm size	.076***	(.008)	931,613
(log) Capital intensity	.043***	(.007)	931,613

Note: Each coefficient is the result of a least-square regression of the firm-level outcome (by row) *vis á vis* the number of patents granted each year to the company standardized with the inverse of an inverse hyperbolic sine transformation ($ln(x + \sqrt{x^2 + 1})$) to approximate the natural logarithm while retaining zeros, as suggested by (Bellemare and Wichman, 2020). Firm-level controls, firm-level fixed effects, and country-year fixed effects are included. Firm-level clustered standard errors are reported.

Table C.4: Firm-level outcomes and patenting activity. Correlations. Subsidiaries' patents.

Variable	Coeff.	s. e.	N. obs.
(log) Market share	.012*	(.007)	931,613
(log) Labor productivity	.013*	(.007)	931,613
(log) Firm size	.027***	(.009)	931,613
(log) Capital intensity	.058***	(.008)	931,613

Note: Each coefficient is the result of a least-square regression of the firm-level outcome (by row) *vis á vis* the number of patents granted each year to the company standardized with the inverse of an inverse hyperbolic sine transformation ($ln(x + \sqrt{x^2 + 1})$) to approximate the natural logarithm while retaining zeros, as suggested by (Bellemare and Wichman, 2020). Firm-level controls, firm-level fixed effects, and country-year fixed effects are included. Firm-level clustered standard errors are reported.

Table C.5: Treatment group: baseline and robustness checks

Year of treatment	(1) First observed patents granted either to headquarters or subsidiaries	(2) First observed patents granted to headquarters only	(3) First observed patents granted to subsidiaries only	(4) First observed patents to subsidiaries in headquarters' sector	(5) First observed patents to subsidiaries of a different sector
2010	125	69	39	21	8
2011	104	63	28	7	16
2012	64	39	20	11	7
2013	52	30	17	5	9
2014	54	36	15	8	7
2015	51	28	20	10	5
2016	48	29	19	9	8
2017	48	33	15	6	8
Total	546	327	173	77	68

Table C.6: Aggregate ATT for patents in parent firms only.

Variable	θ_s^O	s. e.	No. of treated firms	No. of untreated firms
(log) Market share	.099***	(.035)	327	24,506
(log) Labor productivity	.030	(.026)	327	24,506
(log) Firm size	.104***	(.035)	327	24,506
(log) Capital intensity	.034	(.044)	327	24,506

Note: The table illustrates aggregate treatment effects under the assumption of parallel trends conditional on firm level control variables, 2-digit sector and regional dummies, allowing for clustering at the firm level. *, ** and *** denotes significance at 10%, 5% and 1% respectively.

Table C.7: Aggregate ATT for patents in subsidiaries only.

Variable	θ_s^O	s. e.	No. of treated firms	No. of untreated firms
(log) Market share	.102**	(.043)	173	24,506
(log) Labor productivity	.050	(.035)	173	24,506
(log) Firm size	.114***	(.044)	173	24,506
(log) Capital intensity	.172***	(.066)	173	24,506

Note: The table illustrates aggregate treatment effects under the assumption of parallel trends conditional on firm level control variables, 2-digit sector and regional dummies, allowing for clustering at the firm level. *, ** and *** denotes significance at 10%, 5% and 1% respectively.

Table C.8: Aggregate ATT for patents only in subsidiaries of the same 2-digit sector.

Variable	θ_s^O	s. e.	No. of treated firms	No. of untreated firms
(log) Market share	.111*	(.061)	77	24,506
(log) Labor productivity	.049	(.051)	77	24,506
(log) Firm size	.122**	(.060)	77	24,506
(log) Capital intensity	.176*	(.093)	77	24,506

Note: The table illustrates aggregate treatment effects under the assumption of parallel trends conditional on firm level control variables, 2-digit sector and regional dummies, allowing for clustering at the firm level. *, ** and *** denotes significance at 10%, 5% and 1% respectively.

Table C.9: Aggregate ATT for patents only in subsidiaries of a different 2-digit sector.

Variable	θ_s^O	s. e.	No. of treated firms	No. of untreated firms
(log) Market share	.064	(.066)	68	24,506
(log) Labor productivity	.026	(.052)	68	24,506
(log) Firm size	.080	(.064)	68	24,506
(log) Capital intensity	.224**	(.104)	68	24,506

Note: The table illustrates aggregate treatment effects under the assumption of parallel trends conditional on firm level control variables, 2-digit sector and regional dummies, allowing for clustering at the firm level. *, ** and *** denotes significance at 10%, 5% and 1% respectively.

Table C.10: Patenting and firm-level outcomes - ATT obtained with an outcome regression approach.

Variable	$\theta_{s,or}^O$	s. e.	No. of treated firms	No. of untreated firms
(log) Market share	.124***	(.027)	546	24,506
(log) Labor productivity	.023	(.020)	546	24,506
(log) Firm size	.129***	(.026)	546	24,506
(log) Capital intensity	0.065*	(0.034)	546	24,506

Note: The table illustrates aggregate treatment effects using outcome regression estimands by Callaway and Pedro HC Sant'Anna, 2020 and under the assumption of parallel trends conditional on firm level control variables, 2-digit sector and regional dummies, allowing for clustering at the firm level. *, ** and *** denotes significance at 10%, 5% and 1%, respectively.

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