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**By**

**Stefania Miricola**

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**The dissertation of Stefania Miricola is approved.**

PhD Program Coordinator: Ennio Bilancini, IMT School for Advanced Studies Lucca

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

Co-Advisor: Gianluca Santoni, CEPII - Centre d'Etudes Prospectives et d'Informations Internationales

The dissertation of Stefania Miricola has been reviewed by:

Anna Maria Ferragina, University of Salerno

Enrico Marvasi, Roma Tre University

IMT School for Advanced Studies Lucca
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# Vita

*Education*

| | |
|---|---|
| **2018-2024** | Ph.D. Candidate in Economics, Networks and Business Analytics<br>IMT - School for Advanced Studies Lucca, Lucca (Italy) |
| **2022** | Visiting Researcher<br>CEPII (Centre d'Études Prospectives et d'Informations Internationales), Paris (France) |
| **2015-2018** | M.Sc. in Economics and Economic Policy<br>Final mark: 110/110 cum laude<br>Alma Mater Studiorum - Università degli Studi di Bologna, Bologna (Italy) |
| **2010-2015** | B.Sc. in Business and Administration<br>Final mark: 108/110<br>Università degli Studi di Bari Aldo Moro, Bari (Italy) |

*Work Experience*

| | |
|---|---|
| **2022-2024** | Research Fellow<br>Department of Economics and Management (DISEI) - University of Florence, Florence (Italy) |
| **2020-2021** | Service Contract<br>European Commission, DG –Internal Market, Industry, Entrepreneurship and SME |

# Publications

## Working papers

1. S. Miricola, A. Rungi, G. Santoni ”Ownership chains in multinational enterprises” ArXiv Preprint, 2023.

# Presentations

1. RES 2024 Annual Conference - Royal Economic Society - 25-27 March 2024 - Queen's University, Belfast - England
2. ASSA 2024 Annual Meeting - American Economic Association - 5-7 January 2024 - San Antonio, Texas - USA
3. 25th Annual Conference – European Trade Study Group (ETSG) – 14-16 September 2023 - University of Surrey – England;
4. 13th Annual Conference - Economics of Global Interactions - 11-12 September 2023 - University of Bari - Italy
5. 64th Annual Conference - Italian Trade Study Group - 6-7 July 2023 - University of L'Aquila - Italy
6. 24th Annual Conference – European Trade Study Group (ETSG) – 8-10 September 2022 - University of Groningen – Netherlands;
7. 16th Annual Conference - Warsaw International Economic Meeting (WIEM) - 24-25 June 2021 - University of Warsaw – Poland;
8. 4th International Conference on Cluster Research – Rethinking Clusters – 22-23rd September 2021 – University of Florence – Italy;
9. 62nd Annual Conference - Italian Economic Association - 26-29 October 2021 - Marche Polytechnic University - Italy

# Abstract

Economic activities are unevenly distributed in space. The economic literature has extensively investigated the potential reasons behind the emergence of cities and local specialization, on one hand, and foreign trade and investment patterns, on the other. These essays aim to analyze some of the components explaining the spatial variation of economic activities, leveraging an extensive amount of firm-level data. First, I investigate the interplay between regional productivity disparities and local agglomeration advantages. Although I find evidence for agglomeration advantages stemming within Italian firms' clusters, I find them to be much smaller than the productivity premium for firms located in northern Italy. Second, I investigate the rationale for the ownership chains developed by multinational enterprises across different national borders. Based on the insight that the placement of subsidiaries along ownership chains is driven by the existence of communication costs to transmit management decisions, I develop a theoretical model for corporate control where parent companies can delegate monitoring activities to middlemen subsidiaries that are located in intermediate jurisdictions. I derive a two-step empirical strategy enabling the structural estimation of a gravity equation for foreign investments. Third, I investigate the ability of European Union regions to retain foreign investments, evaluating how crucial regional characteristics, such as an R&D-friendly economic environment and good local institutions, affect the life duration of companies targeted by foreign investments.

# Chapter 1

# Introduction

As a matter of fact, economic activities are unevenly distributed in space. The economic literature has indeed extensively investigated the potential reasons behind the emergence of cities and local specialization, on one hand, and foreign trade and investments patterns on the other. A fundamental point of location theory claims that the economic landscape we observe is the result of a trade-off between different types of increasing returns and mobility costs. Indeed, a crucial question arises from the observation of the geographical distribution of enterprises: why a production activity is located in a given space? This leads to the question of what type of optimization problem the firm is facing. Furthermore, in a global production system characterized by increasingly fragmented value chains and complex organizational choices within big business groups, it is also crucial to understand how location decisions are interdependent with each other. These essays aim to analyze some of the components explaining the spatial variation of economic activities, leveraging an extensive amount of firm-level data.

The first chapter takes a more purely geographical economics approach and examines the spatial distribution of manufacturing firms in Italy. As widely known, the latter is characterized by a concentration of economic activity in the North and a general tendency to organize into industrial clusters throughout the whole peninsula. I focus on the empirical evaluation of the productivity advantages within two different location patterns and address a specific question: is the productivity premium higher for firms located in a specific geographical area or for firms taking part in agglomeration economies? I propose a sophisticated way of identifying firms' agglomerations, applying an unsupervised density-based clustering algorithm to the geographic coordinates of about 400,000 manufacturing firms. This approach allows for overcoming the limitations of administrative definitions. Afterward, I borrow from Combes et al. (2012)'s contribution their quantile approach to disentangle the effect of agglomeration and selection and apply their estimator to total factor productivity distributions inside and outside Italian firms' clusters. I find that the average productivity advantage of the North over the South is far more considerable than the one originating from local agglomeration economies. Nevertheless, I find evidence for agglomeration externalities generated inside clusters, although a difference between the North and the South emerges again: top producers in the South are not as capable as those in the North and Center to take advantage of agglomeration mechanisms and boost their competitiveness even further.

The second chapter links the geographical aspect to industrial organization dynamics. In this case, I examine the geographical patterns of multinational corporate structures, concentrating on the interdependence between the locations of subsidiaries within the same business group. According to my interpretation, the location of subsidiaries is also driven by the need to optimize the communication of management decisions. This work is based on a novel database with worldwide coverage, allowing for the analysis of long corporate ownership chains spanning multiple countries. This allows observing, at the firm-level, both the geographical location and hierarchical position within the corporate network. I take advantage of the concept of the firm as a knowledge-based hierarchy (Garicano (2000)) and hypothesize that the geographical location of a foreign subsidiary depends on optimizing communication costs. As a main contribution of this chapter, I end up deriving a structural estimation of a gravity equation for foreign direct investments. This is achieved by developing a theoretical model for competition on corporate control that considers the possibility that parent companies in the origin countries can delegate their monitoring activities in final subsidiaries to middlemen subsidiaries that are located in intermediate jurisdictions. The model returns a two-step empirical strategy with two gravity equations: i) a triangular gravity for establishing a middleman by the parent, conditional on final investments' locations; ii) a classical gravity for the location of final investments. Structural gravity estimates confirm the predictions that ease of communication at the country level shapes the heterogeneous locations of subsidiaries along global ownership chains.

The third chapter examines the geographical distribution of foreign affiliates in the European Union, focusing more on aspects of regional policy and institutions. Building on the literature that has demonstrated the benefits of foreign investments on the host territory, I analyze which characteristics of the local economy promote a longer-lasting presence of multinational enterprises, which is presumed to better ensure the unfolding of positive effects on the economic environment. To capture the extent of retention of foreign investment, I perform a survival analysis on a sample of more than 100,000 foreign-owned manufacturing firms that primarily considers the effects of local propensity to innovation and institutional quality. The model of choice is a multi-level regression aimed at evaluating at the same time firm-level and location-specific features at two different geographic scales. I find that government quality and financial development inside national boundaries play a fundamental role not only in attracting foreign capital but also in promoting a long-term presence. Importantly, the multilevel framework allows us to pinpoint the geographic scale at which the effects of certain characteristics unfold. Some contextual factors may be crucial to survival, but may not emerge when examined at too granular or aggregated levels. Indeed, this holds for the quality of institutions, a pivotal element for extending market presence that is significant primarily at the country-level.

# Chapter 2

# Regional Disparities and Firms' Agglomerations

*This chapter is based on the work "Regional Disparities and Firms' Agglomerations" in collaboration with Armando Rungi and Dimitrios Exadaktylos (Exadaktylos, 2022).*

## 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 paper 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.

[1] Major economic differences between the North and the South of the country date back to its reunification in 1861, when an agglomeration of manufacturing activity in a few provinces in the North-West was favored by decreasing costs and trade barriers (Basile and Ciccarelli, 2018). Regional disparities existing before the reunification were magnified in the wave of the industrial revolution(A'Hearn and Anthony J. 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.

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, TFPs are on average 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 the details, we observe that the regional gap is 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. In contrast, when we look across the 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 449,262 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 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 $24\%$ higher productivity. It immediately emerges that Italian regional disparities are preserved within firms' agglomerations, as we find a $85\%$ 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 (Edward L. 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 in a more challenging business environment (Baldwin and Okubo, 2005; 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. In terms of truncation, one would expect that market competition is tougher in denser areas, where inefficient firms are more likely to be 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 macroregions allow us to investigate if agglomeration externalities and local market selection can explain the regional gap in productivity.

Interestingly, we do not find evidence of a significant difference in left-truncation. We only observe evidence of benefits from agglomeration economies, which are relevant across the whole country. We moreover find that more productive firms benefit more from agglomeration advantages in every macro-region, except for the south, where we do not find any significant evidence of dilation of the productivity distribution inside firm clusters.

Although it is beyond the scope of our paper 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.

## 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 the continental average, while others still fall behind (Crescenzi and Giua, 2020). To address regional divergence, the European Union designs cohesion policies through the 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 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 that regional discrepancies have increased in the country (OECD, 2018), and are associated with considerable heterogeneity in terms of education, innovation, institutional quality, and public investments. On top of that, high-skilled 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).

Against the previous background, we specifically focus on the geography of firm-level productivity because the latter allows us to sketch a microfoundation for the misallocation of productive resources. For the Italian case, we refer to Calligaris et al. (2018) and Bugamelli et al. (2018), who find that misallocation of resources plays a sizeable role in slowing down Italian productivity on a national scale. However, we note that previous studies so far have neglected the geographic dimension of the problem. An exception is Rungi and Biancalani (2019), who find that there are less inefficient firms established in Northern regions because these are places where they are less likely to survive to local competition.

In this contribution, 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. 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 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 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). In fact, there is a wider tradition of literature that aims to understand whether location in an agglomerated area affects firm-level economic performance (J. Henderson, 2003; Martin, Mayer, and Mayneris, 2011) and, as a result, economic growth of entire territories (Edward L 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 about by both positive local externalities and market selection mechanisms. On top of static benefits, in our analyses, we also control for 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) performs 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 chose 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 of 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 to georeferencing business activities, as well as the dates of a firm's entry and

[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).

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 the one hand, and firms that report postal addresses, on the other. 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 by 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 panel sample of 401,043 firms with geographic coordinates, of which only a subset of about 158,651 firms report full financial accounts. In the following paragraphs, we first describe how we obtain firms' coordinates. In paragraph 2.3.2, we discuss sample representativeness and coverage, validating 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 1.

**Table 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.

As from the fourth column of Table 1, we find that coordinates are not always correct. Geolocation failures are mainly due to 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. In order to ensure a minimum quality of the matching, we implement a procedure that spots mistakes at the municipality level, which is the smallest administrative boundary available to us. Indeed, in some cases, the error was minimal and negligible (e.g., a few meters difference within the same city), but in other cases there were significant errors, such as a company being incorrectly assigned to a different city than the one indicated in the address. To control for these larger errors, we source Italian administrative boundaries updated to 2019 from the national statistics office, ISTAT. In an iterative process, we project the administrative boundaries of each municipality on a map and overlay the coordinates of companies that, according to Orbis data, are located in that municipality. Any point falling outside the administrative boundaries is classified as a significant georeferencing error and is excluded from the sample. Eventually, we find that only about 4% of the firms have unavoidable mistakes and have to be removed from the original sample.

### 2.3.2 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 our disposal all financial accounts to estimate TFPs. 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, and 4, we report geographical, 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 shows that there is a bias by firm size, which is relatively mild in the set of firms with coordinates 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. However, we have about $74.5\%$ and $53.3\%$ of them, respectively, in columns 5 and 7. Overall, we cover up to 54% of the population in the georeferenced set and up to $29\%$ of the population in the TFP set.

When we look at the industry-level breakdown in Table 3, our sample shows relatively high correlations. Percentage shares computed on geo-referenced firms and firm with TFP, respectively, show a correlation of 0.96 and 0.83 with the census provided by Eurostat. Relatively small discrepancies in the TFP subsample are mainly an indirect consequence of the absence of financial information about micro-firms, which are ex-

[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. More simplifications have been implemented since 2016.

pected to be more present in some industries with a lower capital intensity. Remarkably, when looking at coverage shares by NUTS 2-digit in Table 4, any hint of sample selection disappears with correlations up to 0.99, possibly thanks to an even distribution of firms of different size across regions.

Finally, we prefer to keep as wide as possible the set of firms on which we identify firms' clusters through firm-level coordinates. In this way, we make sure that firms' densities are not biased by firm size. On the other hand, we will have to deal with possible sample selection bias in the subset of firms for which we estimate TFPs. Accordingly, specific robustness checks are presented in the Appendix.

**Table 2:** Sample coverage by size-class, reference year 2015

| Size Class | Eurostat SBS | | Coordinates sample | | TFP sample | |
|---|---|---|---|---|---|---|
| | N. of firms | % | N. of firms | % | N. of firms | % |
| 0-9 Employees | 321,837 | 82.67% | 156,251 | 74.47% | 60,477 | 53.34% |
| 10-19 Employees | 39,159 | 10.06% | 27,800 | 13.25% | 26,628 | 23.49% |
| 20-49 employees | 18,771 | 4.82% | 16,578 | 7.90% | 16,839 | 14.85% |
| 50-249 employees | 8,338 | 2.14% | 7,927 | 3.78% | 8,156 | 7.19% |
| More than 250 employees | 1,212 | 0.31% | 1,256 | 0.60% | 1,283 | 1.13% |
| Total | 389,317 | 100.00 | 209,812 | 100.00 | 113,383 | 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 financial accounts (columns 6 and 7). Firm size is measured by number of employees. Population figures come from Eurostat Structural Business Statistics in year 2015.

**Table 3:** Sample coverage by industry, reference year 2015

| Industry (NACE 2-digits) | Eurostat SBS | | Coordinates sample | | TFP sample | |
|---|---|---|---|---|---|---|
| | N. of firms | % | N. of firms | % | N. of firms | % |
| Food | 53,096 | 13.64% | 37,360 | 11.60% | 10,914 | 8.82% |
| Beverages | 3,219 | 0.83% | 3,064 | 0.95% | 1,496 | 1.21% |
| Tobacco | 6 | 0.00% | 44 | 0.01% | 22 | 0.02% |
| Textiles | 13,866 | 3.56% | 10,440 | 3.24% | 4,380 | 3.54% |
| Wearing Apparel | 28,865 | 7.41% | 29,894 | 9.28% | 6,415 | 5.19% |
| Leather | 15,235 | 3.91% | 14,043 | 4.36% | 4,784 | 3.87% |
| Wood | 28,163 | 7.23% | 17,774 | 5.52% | 4,198 | 3.39% |
| Paper | 3,723 | 0.96% | 3,349 | 1.04% | 1,994 | 1.61% |
| Printing | 15,109 | 3.88% | 11,028 | 3.42% | 4,217 | 3.41% |
| Refined petroleum | 281 | 0.07% | 336 | 0.10% | 240 | 0.19% |
| Chemicals | 4,308 | 1.11% | 5,041 | 1.57% | 3,241 | 2.62% |
| Pharmaceutical | 453 | 0.12% | 744 | 0.23% | 513 | 0.41% |
| Plastic | 9,971 | 2.56% | 8,930 | 2.77% | 5,584 | 4.51% |
| Non-metallic Mineral | 19,189 | 4.93% | 15,777 | 4.90% | 6,572 | 5.31% |
| Basic metals | 3,407 | 0.88% | 2,894 | 0.90% | 1,831 | 1.48% |
| Fabricated metals | 63,185 | 16.23% | 60,291 | 18.72% | 25,656 | 20.74% |
| Computer, electronic, optical | 4,912 | 1.26% | 7,313 | 2.27% | 4,072 | 3.29% |
| Electrical equipement | 8,363 | 2.15% | 8,703 | 2.70% | 4,772 | 3.86% |
| Machinery | 22,761 | 5.85% | 21,258 | 6.60% | 13,572 | 10.97% |
| Motor vehicles | 2,242 | 0.58% | 2,695 | 0.84% | 1,546 | 1.25% |
| Other transport | 2,409 | 0.62% | 4,277 | 1.33% | 1,730 | 1.40% |
| Furniture | 18,108 | 4.65% | 13,637 | 4.23% | 5,152 | 4.17% |
| Others | 29,488 | 7.57% | 22,029 | 6.84% | 4,377 | 3.54% |
| Repair and installation | 38,958 | 10.01% | 21,140 | 6.56% | 6,406 | 5.18% |
| Total | 389,317 | 100.00 | 322,061 | 100.00 | 123,684 | 100.00 |

Note: we report industry coverage of the sample set with geographic coordinates only (columns 4 and 5), and with both coordinates and financial accounts (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 4:** Sample coverage by geography, reference year 2015

| NUTS-2 Region | Eurostat SBS | | Coordinates sample | | TFP sample | |
|---|---|---|---|---|---|---|
| | N. of firms | % | N. of firms | % | N. of firms | % |
| Piemonte | 30,771 | 7.85% | 22,356 | 6.94% | 8,444 | 6.94% |
| Valle d'Aosta | 678 | 0.17% | 392 | 0.12% | 125 | 0.10% |
| Liguria | 7,646 | 1.95% | 5,889 | 1.83% | 1,654 | 1.36% |
| Lombardia | 78,838 | 20.10% | 62,083 | 19.28% | 30,244 | 24.87% |
| Abruzzo | 8,938 | 2.28% | 8,028 | 2.49% | 2,612 | 2.15% |
| Molise | 1,729 | 0.44% | 1,418 | 0.44% | 388 | 0.32% |
| Campania | 26,162 | 6.67% | 28,478 | 8.85% | 8,011 | 6.59% |
| Puglia | 21,074 | 5.37% | 17,084 | 5.31% | 5,466 | 4.50% |
| Basilicata | 2,863 | 0.73% | 2,581 | 0.80% | 654 | 0.54% |
| Calabria | 8,034 | 2.05% | 8,364 | 2.60% | 1,414 | 1.16% |
| Sicilia | 20,667 | 5.27% | 18,839 | 5.85% | 4,054 | 3.33% |
| Sardegna | 7,406 | 1.89% | 6,328 | 1.97% | 1,473 | 1.21% |
| Trentino Alto Adige | 6,293 | 1.60% | 4,220 | 1.31% | 1,575 | 1.30% |
| Veneto | 44,701 | 11.40% | 33,514 | 10.41% | 15,687 | 12.90% |
| Friuli-Venezia Giulia | 7,918 | 2.02% | 5,849 | 1.82% | 2,719 | 2.24% |
| Emilia Romagna | 36,586 | 9.33% | 28,848 | 8.96% | 12,844 | 10.56% |
| Toscana | 38,018 | 9.69% | 28,096 | 8.73% | 10,366 | 8.53% |
| Umbria | 6,624 | 1.69% | 4,816 | 1.50% | 1,823 | 1.50% |
| Marche | 16,222 | 4.14% | 12,529 | 3.89% | 5,158 | 4.24% |
| Lazio | 20,978 | 5.35% | 22,247 | 6.91% | 6,883 | 5.66% |
| Total | 392,146 | 100.00 | 321,959 | 100.00 | 121,594 | 100.00 |

Note: we report geographic coverage of the sample set with geographic coordinates only (columns 4 and 5), and with both coordinates and financial accounts (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 the advantages of agglomeration of firms, one encounters a common challenge in spatial analyses. Administrative boundaries are drawn based on political and historical determinants, less on economic patterns. The findings risk being biased because identical data points appear 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. The findings could be

and Puga (2020), according to whom the increasing availability of georeferenced data allows adapting the definition of clusters to the actual purpose of the analysis.

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 does not require fixing an *a priori* number of clusters, and it complies with irregular shapes on maps. Similarly to other density-based clustering algorithms, e.g., DBSCAN, 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 always be 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 identify 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 $\epsilon_i$-neighborhood of a firm-point as all the firm-points that locate at distance $\epsilon_i$ from a firm. We define a *core-point* as a firm-point $p_i$ when its $\epsilon_i$-neighborhood includes at least $M$ other firm-points. In other words, if the cardinality of a firm-points set in the $\epsilon_i$-neighborhood is $Card(N_\epsilon(i))$, a firm-point constitutes a *core-point* if $Card(N_\epsilon(p_i)) \geq M$. The latter is also referred to as the *core-point condition*. OPTICS works following two different concepts of distance both

affected by both the shape and the scale of the aggregation units. For details, see also Arbia (1989) represented in Figure 1a:

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.

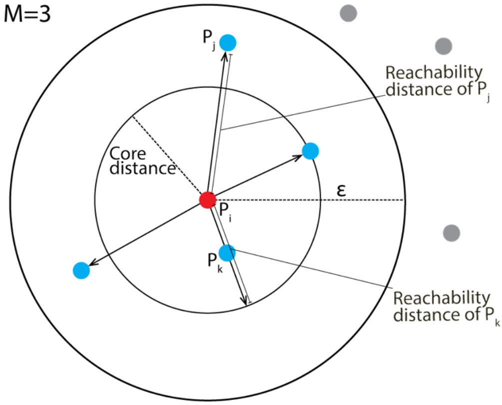
2. The *reachability distance* of a point $p_j$ with respect to a point $p_i$ is the maximum between $c(p_i)$ and $d(p_i, p_j)$, with the latter representing the distance between $p_i$ and $p_j$.

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 $\epsilon$-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 $\epsilon$-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 not yet processed point until all the objects in the database are orderly stored in the *OrderList* with their respective *reachability distances*.

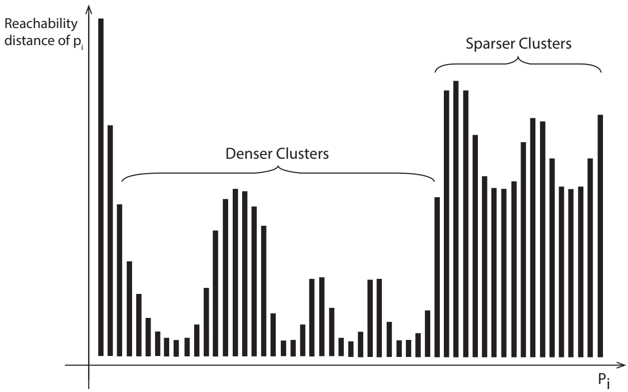
The set of *reachability distances* describe the clustering structure of point-data, which can be graphically represented in a so-called *reachability plot*. In Figure 1b, we provide a visual intuition of a *reachability plot* obtained at the end of a procedure. Reachability distances are reported on the y-axis and firm-points on the x-axis. Flatter regions in the graph (in gergon, '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 1:** Graphical representation of OPTICS main features

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




**(b)** *Reachability plot*




Note: (a) Given a certain value of $\epsilon$ 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 $\epsilon$-neighborhood. Note that the *core distance* can never exceed $\epsilon$. A *reachability distance* from $p_i$ is defined for each point in the $\epsilon$-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 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, $\xi$, which defines the steepness of the points a cluster should start and end with. In practical terms, $\xi$ should be set as the maximum ratio between the *reachability distances* of two points:

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

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

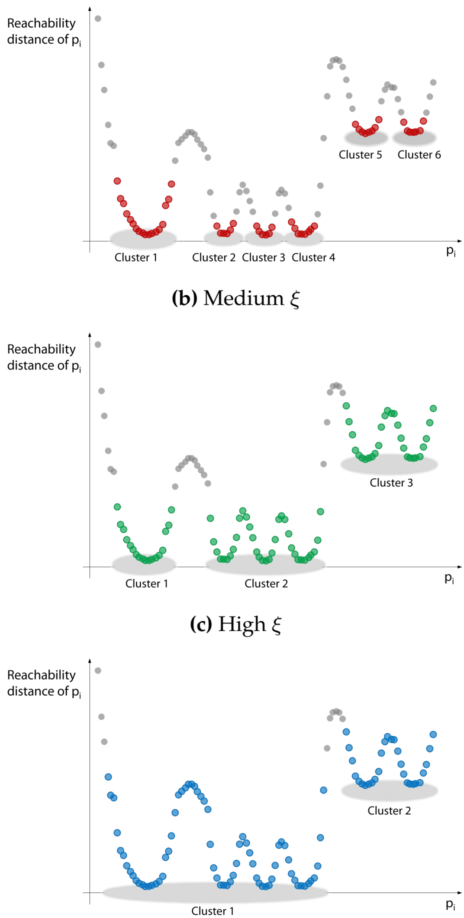
with $\xi \in [0, 1]$. The first equation holds for the end of clusters and the second for the start. Based on $\xi$, the algorithm recognizes the areas of the *reachability plot* that accomplish the following set of conditions. A potential cluster ending (starting) area should begin and terminate with two adjacent points that meet the steepness condition in Eq. 2.1 (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 might help to understand the meaning of $\xi$. For relatively small values of $\xi$, even slight differences in the *reachability distances* are sufficient to mark the boundaries of a cluster. As in Fig. 2a, this results in a greater number of clusters of reduced size in terms of points. As the value of $\xi$ 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 Fig. 2b and 2c).

**Figure 2:** Effect of $\xi$ setting

**(a)** Low $\xi$

**(b)** Medium $\xi$

**(c)** High $\xi$




Note: We simulate a *reachability plot* to show how $\xi$ setting affects cluster detection. We assume three levels for the $\xi$ parameter. Very small values of $\xi$ (2a) imply that virtually every 'valley' in the plot is considered a cluster. As $\xi$ switches to a medium level (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 $\xi(2c)$.

Several solutions of $\xi$ can make sense depending on the context and 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 $\epsilon$ 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 $\xi$. 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 have already been 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). Sources frequently have differing opinions regarding the number of clusters identified within an area, and most sources do not report precise information on the actual geographic boundary of firms' clusters, as they loosely relate to the wider region within which they could be found.

Our aim is to encompass different types of agglomerations, which may also include industrial districts as a subcategory.[6]Yet, previous ex-

[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 those 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 specialize in a main industry. Yet, agglom-

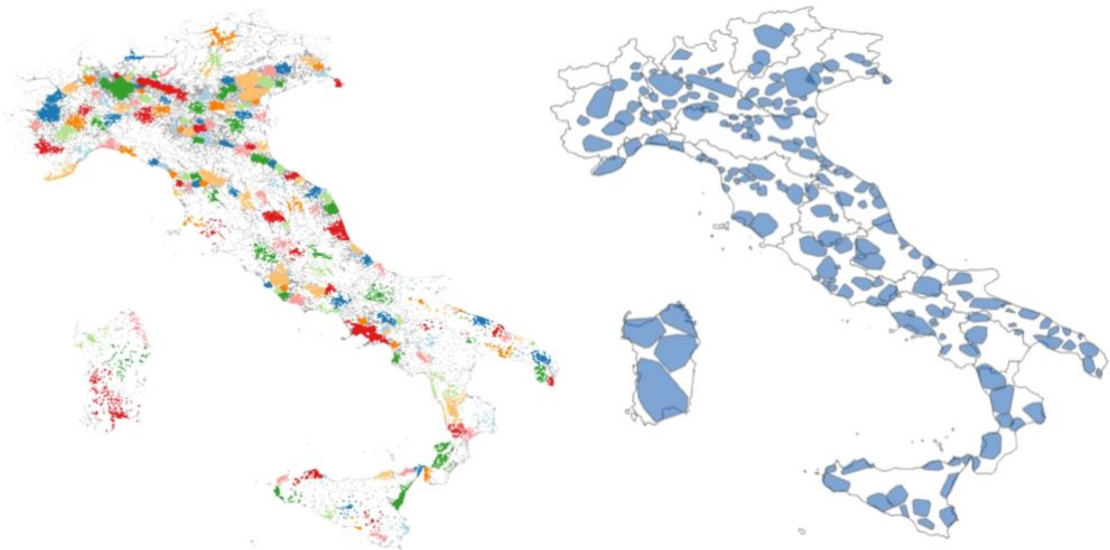
perience in mapping industrial districts is extremely valuable to us. We take it as a departing point to fine-tune our algorithm and identify the optimal value of $\xi$, and the number of minimum firm points, $M$, which we expect in a firms' agglomeration. In Appendix A.2 we provide an example of our fine-tuning procedure. Specifically, in Figure A1, we overlap sets of firm clusters identified at increasing values of the sensitivity parameter with the industrial districts identified by the regional law in Lombardy (Regional Law no 1, 2000). For a first approximation, we pick as baseline parameters $\xi = .45$ and $M = 350$.

Based on previously identified baseline parameters, we are able to draw $184$ clusters of firms in Figure 3. *Prima facie*, we observe that they are homogeneously distributed throughout the Italian territory[7]. The denser areas inside the clusters collect about $77\%$ of the total sample firms. Looking at the clusters up close, we note that they capture different types of agglomerations, including both urban areas and industrial districts.

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 definition, as exclusively based on firms' density, allows us encompassing both.

[7]Note that OPTICS tends to identify fewer clusters with larger areas in low-density regions (e.g., in the South) and a greater number of smaller clusters in high-density regions (e.g., in the North). This is due to the algorithm adjusting the minimum density required for cluster identification locally. This flexibility is particularly well-suited to the context of Italy, where the distribution of businesses is uneven. At the same time, it would be appropriate to establish a lower bound on the maximum area a cluster can encompass, as well as a minimum density threshold for a cluster in order to avoid the risk of identifying irrelevant agglomerations, as exemplified by the case of Sardinia where polygons are much larger than the others.

**Figure 3:** Italian manufacturing clusters, 2007-2017



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

**Figure 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

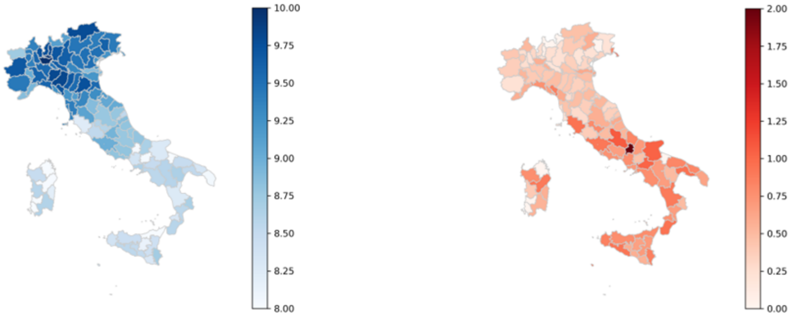
In this section, we provide novel stylized facts on the North-South productivity gap and on the benefits from firms' agglomerations. For our purpose, we rely on estimates of Total Factor Productivity (TFP) at the firm-level following the methodology of Ackerberg, Caves, and Frazer, 2015. See Appendix A.1 for an overview of the methodology and a discussion on the main advantages. The preliminary evidence reported here will pave the way for an informed discussion of the empirical findings in the following sections.

### 2.5.1 North-South productivity gap

The first stylized fact is illustrated in Figure 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 drop as we move along the map to the South. Yet, an opposite pattern is detected in the case of standard deviations, since we observe firm-level TFPs to be more dispersed in the South of the country. This is an interesting insight into the heterogeneity of TFP distributions at the firm level by geography[8]. Geographic patterns are similar for every year we consider from our albeit short timeline at our disposal. We believe that the latter evidence specifically points to an appraisal of differences in TFP distributions as a result of different local mechanisms of agglomeration and market selection that are worth further investigation. As from previous literature (Combes et al., 2012), we know that TFP firm-level distributions contain nontrivial information on how firms actually benefit (or not) from agglomeration economies.

[8]For a previous reference on a similar finding, see Rungi and Biancalani, 2019

**Figure 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. In Figure 6, we record a general downfall in the weighted average TFPs in the country after the financial crisis in 2007-2008[9], which is particularly harsh in the South. The difference in recovery speeds since 2011 has contributed to widening the gap because while the North-East now chases the North-West, the Centre diverges towards Southern flatter growth rates.

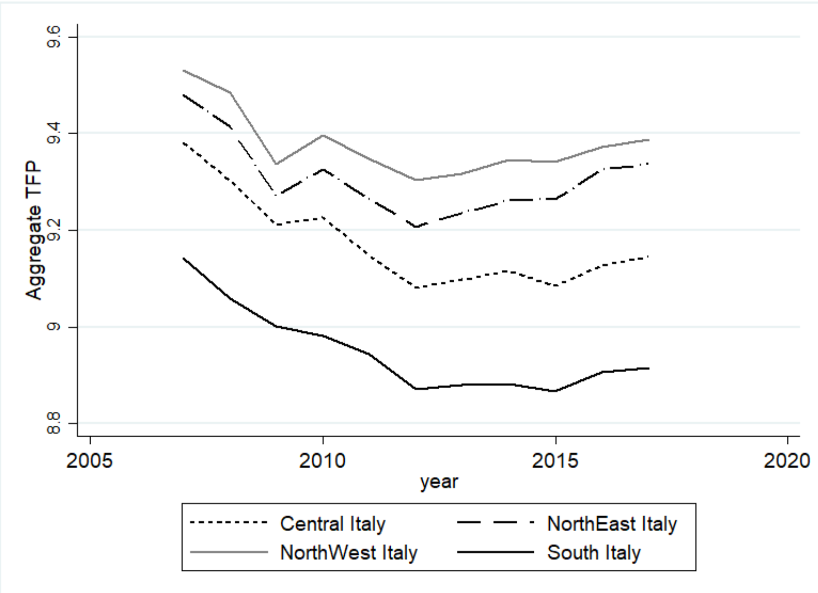
The recovery observed from 2012 on is mainly due to cyclical factors and is indicative of a general resurgence in TFP in many economies post-crisis (Mistretta and Zollino, 2021). Additionally, the crisis likely contributed to an enhancement in the allocation of productive factors by facilitating the exit of small and unproductive firms from the market[10]. However, the issue of misallocation is far from resolved. Calligaris et al.

[9]What we observe aligns closely with the findings of other studies on Italian productivity. Bugamelli et al. (2018) confirm that the decline in productivity since 2008 was followed by a recovery during 2013-2016, characterized by a moderate growth in TFP. Mistretta and Zollino (2021) note an improvement in TFP performance relative to the onset of the crisis, particularly within the manufacturing sector, although this improvement remains limited when compared to the European average.

[10]This is supported by ISTAT data presented in the annual report for 2016 of the Bank of Italy (Bank of Italy, 2017), which indicate a reallocation of resources toward better firms since 2011 due to strong market selection during the recession. The mortality rate increased among less efficient firms and new entrants were on average more productive.

(2016) observe that resource misallocation, while playing a crucial role in determining the aggregate level of inefficiency in the Italian manufacturing sector, has increased over time and has increasingly affected firms in the North-West, historically viewed as the engine of the Italian economy. This may explain why the dynamism of the North-East stands out (see Figure 6), as it is accentuated by the slowdown in the North-West.

**Figure 6:** Weighted average firm-level TFPs by macro-region, trend 2007-2017

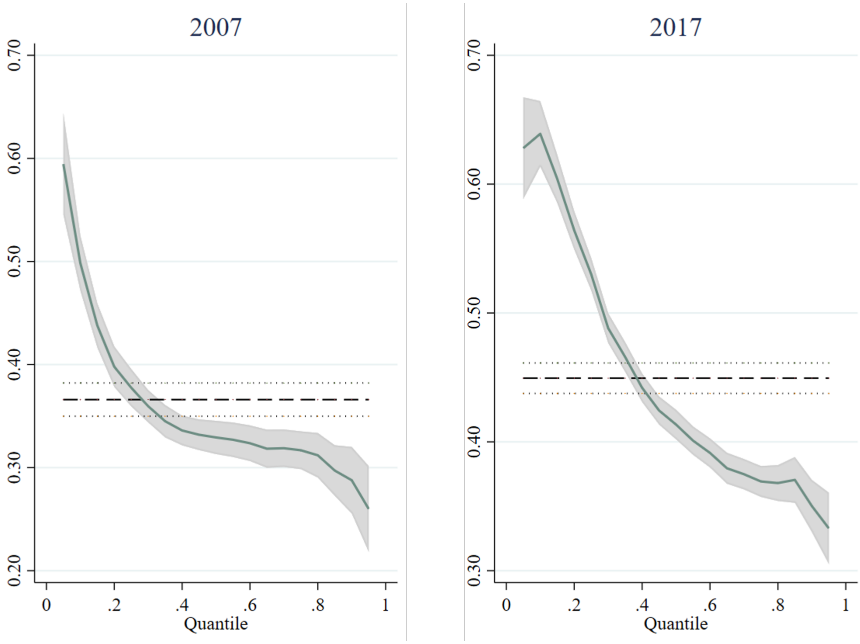



Note: Regions are defined following NUTS 1-digit classification. South and Islands are reported as a unique aggregate. TFP trends are weighted by firm-level market shares.

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 otherwise. For reference, we plot the results against a simple least-squares estimate in Figure 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 6.

**Figure 7:** Variation of the North productivity premium across the TFP distribution




Note: Both graphs in the figure display the coefficients associated with the dummy variable indicating firm location in Northern Italy. Coefficients are estimated using a quantile regression, where the dependent variable is the logarithm of TFP. The vertical axis presents the values of the dummy variable's coefficient, while the horizontal axis represents the quantiles of the log-transformed TFP distribution. The dummy coefficient reflects the productivity premium for firms in Northern Italy, and the figure illustrates how this premium varies across the quantiles of TFP distribution. Firm controls are not included. We report 95% confidence intervals. As a reference point, we plot OLS estimate on the horizontal line.

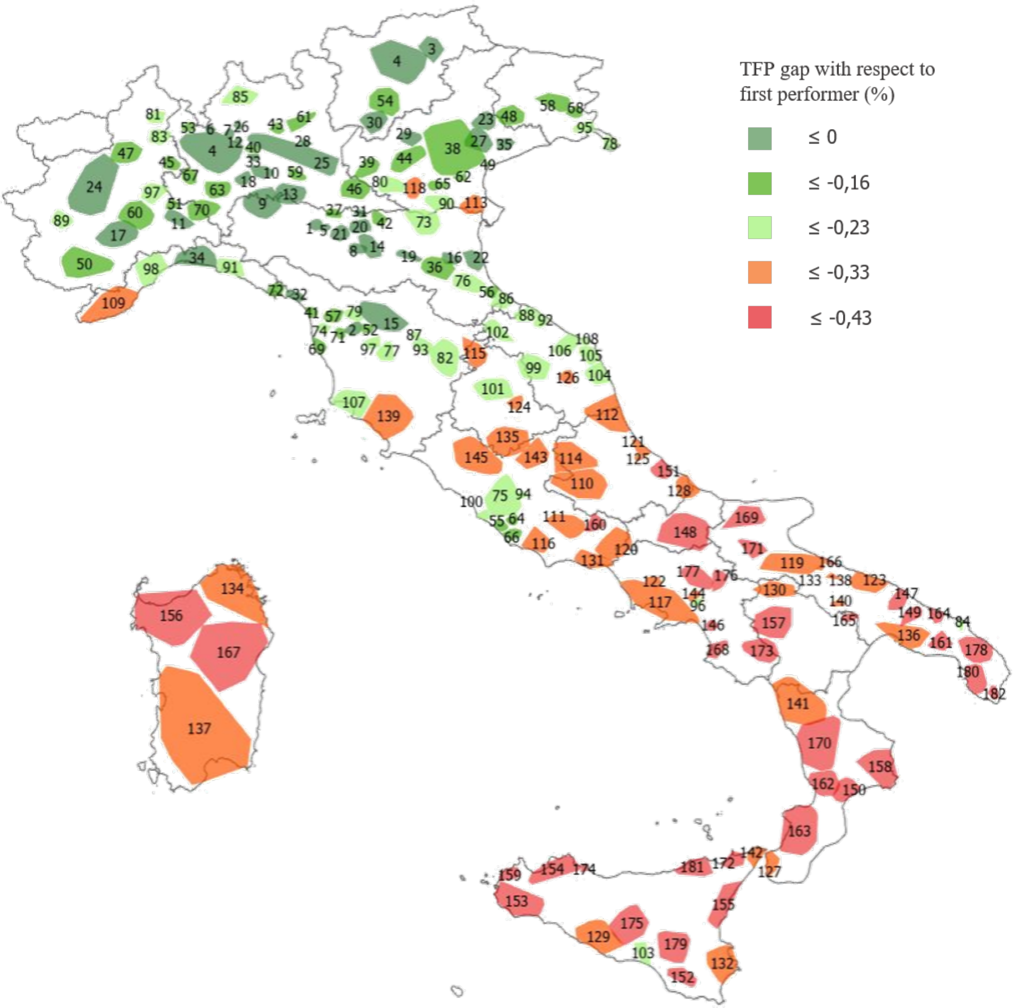
### 2.5.2 Ranking clusters by productivity

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

$$logTFP_{ijt} = \alpha + \beta\, clusterID_i + \delta\, X_{it} + \gamma_t \times \eta_j + \epsilon_{ijt} \tag{2.3}$$

where $X_i$ is a set of firm-level controls including age, employment and capital intensity, $\gamma_t$ and $\eta_j$ are, respectively, time and industry fixed effects and consider $\beta$ coefficients in an orderly fashion. The internal ranking thus obtained can be observed in Fig.8. The most productive agglomeration of firms 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 Tab.5, where coefficients for top and bottom performers are reported. There is a high productivity dispersion across clusters located in different areas, up to a maximum of $85\%$ difference between the best performer and the very last one, respectively located in the North and South. The top ten performers are in Lombardia, Emilia Romagna, Alto Adige and Toscana, 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 8:** Ranking clusters by productivity gains




Note: OPTICS clusters are ordered according to their average 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 5:** 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 | 183 | -0.574 *** |
| 4 | -0.065 *** | 181 | -0.553 *** |
| 4 | -0.065 *** | 180 | -0.552 *** |
| 5 | -0.067 ** | 179 | -0.544 *** |
| 6 | -0.07 *** | 178 | -0.534 *** |
| 7 | -0.076 *** | 177 | -0.531 *** |
| 8 | -0.084 *** | 176 | -0.523 *** |
| 9 | -0.085 *** | 175 | -0.514 *** |
| 10 | -0.096 *** | 174 | -0.508 *** |

Note: Each coefficient measures the difference in productivity (in percentage terms) 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[11].

### 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[12]. We adopt the same model as in Equation (2.3) and replace the categorical of interest with a dummy variable that indicates whether or not a company

[11] In Appendix A.3 we replicate the same exercise using NUTS3 areas in place of OPTICS clusters.

[12] Theoretical literature predicts agglomeration forces to trigger productivity improvements. However, 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 paper, agglomeration is measured in terms of the sole firm density criterion. Thus, we ignore sector-specificity, as well as city size.

belongs to a cluster. We also consider a regional categorical and specify the North as reference. According to the outcome reported in Table 6, 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 24% than one located in the South, whereas a company located in a cluster is on average more productive by 4.5% than one located in a sparse area.

**Table 6:** The relationship between firm agglomeration and firm-level productivity

| TFP (log) | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Inside clusters x Centre | | | -0.0998*** | | -0.103*** |
| | | | (0.0308) | | (0.0184) |
| Inside clusters x South | | | -0.270*** | | -0.255*** |
| | | | (0.0246) | | (0.0218) |
| Outside clusters x Centre | | | -0.178*** | | -0.145*** |
| | | | (0.0169) | | (0.0112) |
| Outside clusters x North | | | -0.0330** | | 0.00167 |
| | | | (0.0155) | | (0.0112) |
| Outside clusters x South | | | -0.335*** | | -0.306*** |
| | | | (0.0169) | | (0.0172) |
| Inside clusters | | 0.0442*** | | 0.0155* | |
| | | (0.0116) | | (0.00894) | |
| Centre | -0.108*** | -0.112*** | | -0.128*** | |
| | (0.0160) | (0.0262) | | (0.0135) | |
| South | -0.275*** | -0.279*** | | -0.282*** | |
| | (0.00856) | (0.0209) | | (0.0174) | |
| Constant | 8.823*** | 8.787*** | 8.828*** | 8.711*** | 8.716*** |
| | (0.0951) | (0.0905) | (0.0954) | (0.0788) | (0.0807) |
| Observations | 894,906 | 874,855 | 874,855 | 409,610 | 409,610 |
| $R^2$ | 0.265 | 0.265 | 0.265 | 0.269 | 0.269 |
| Firm controls | YES | YES | YES | YES | YES |
| Industry × Year FE | YES | YES | YES | YES | YES |

Note: Firm-level controls include age, employment and capital intensity (in logs). Two-way clustering of standard errors at cluster and 2-digit industry level. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.
Note: Columns (4) and (5) report the results of the regressions carried out excluding metropolitan clusters.

In the third column, we consider the interaction between macro region and cluster membership. With respect to those based inside a Northern cluster, companies in the Center are on average less productive by $9.4\%$ ($e^{-0.0998} - 1$) when they fall into an industrial agglomeration, otherwise, the TFP differential increases to $16\%$ ($e^{-0.178} - 1$). Southern enterprises are less productive by $24\%$ ($e^{-0.27} - 1$) when inside a cluster, and by $29\%$ ($e^{-0.335} - 1$) when outside. Overall, inside areas where the manufacturing activity is dense, the regional productivity gap is slightly dampened. As seen in Fig.8, many OPTICS clusters overlap with large cities. Due to these cases, the higher average productivity found within firm agglomerations may not be driven by the sole effect of firm density, as city size has an enhancing effect on TFP. As an additional exercise, we flag as "Metropolitan" those clusters intersecting with Eurostat *Metropolitan Regions*[13] and drop them from the analysis. In the last two columns of Tab.6, we report the estimates obtained when the 85 agglomerations classified as "Metropolitan" are excluded. Interestingly, the picture drastically changes when we rule out the influence of highly populated metropolises. The effect of firm-clustering on productivity falls to $1.6\%$ ($e^{0.0155} - 1$) and loses significance. Another interesting change is that in the North it no longer makes a difference in terms of TFP to be inside or outside a cluster. Possibly, the city-size effect (for instance, greater demand, as well as better access to service inputs) might boost the magnitude of the coefficient. Observing a higher productivity premium in urban areas is in fact supported by the literature investigating the effect of proximity of KIBS (knowledge-intensive business service) on manufacturing firms and the local factors that modulate this effect. We know that manufacturing firms increasingly rely on service providers, thereby redefining their value chains (Gebauer et al., 2017) and that there is a positive effect of proximity of KIBS on the local manufacturing system (Lafuente, Vaillant, and Vendrell-Herrero, 2017), also in terms of higher productivity (Lombardi, Santini, and Vecciolini, 2022). Moreover, the growing interdependencies between KIBS and manufacturing firms have

[13] *Metropolitan Regions* are combinations of NUTS3 populated by at least 250000 inhabitants.

led to increased colocation, promoting a trajectory of local growth based on territorial servitization. However, the contribution of these services varies depending on the local context and the knowledge base accumulated locally (Lombardi, Santini, and Vecciolini, 2022). In this regard, urban systems are typically regarded as the most conducive environment for the location of KIBS (Vaillant, Lafuente, and Serarols, 2012; Pinto, Fernandez-Esquinas, and Uyarra, 2015). This is attributable to their role as hubs of both local and global networking opportunities (Scott and Storper, 2015), as well as the enhanced interaction possibilities with a variety of innovative industries, research and educational infrastructures, and a highly skilled workforce (Pinto, Fernandez-Esquinas, and Uyarra, 2015). Although recent evidence indicates that non-urban systems can also undertake servitization paths (Horváth and Rabetino, 2019), there is still a notable decoupling, with KIBS primarily concentrated in urban areas and manufacturing firms located in non-urban industrial areas (De Propris and Storai, 2019).

## 2.6 Empirical strategy and results

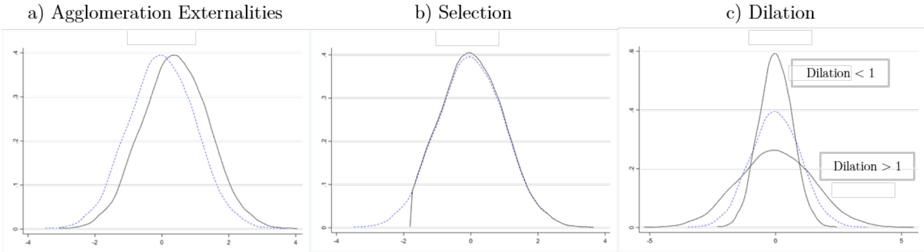
Our preliminary exercise indicates some productivity premia for companies located within clusters. In our main analysis, we examine whether this productivity advantage is related to agglomeration and selection mechanisms. Furthermore, we investigate whether the relative importance of these two drivers differ according to the geographical area.

We apply the empirical framework by Combes et al. (2012) to our firm clusters (Section 2.6.1)[14]. 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. Estimates are obtained as follows.We compare the productivity distribution of companies located in dense areas to the one of those located in non-dense areas in order to estimate three parameters respec-

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

tively quantifying 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 that productivity advantages are not equal in each distribution tail. When dilation is combined with the right-shift, the productivity advantages in denser areas are larger for the most productive companies. Left-truncation captures the effect of market selection and occurs when inefficient companies are not able to stay on the market due to more heated competition, causing the lowest productivity values to disappear from the distribution of firms in the denser areas. Figure 9 provides a representation of what each parameter represents. In the three panels, the dashed line represents a hypothetical distribution of log TFP for companies that are outside clusters, while the solid line sketches the distribution of firms inside clusters. The first panel illustrates the right-shift of the distribution due to agglomeration externalities, the second panel depicts the left-truncation due to market selection, the third panel shows the effect of higher ($> 1$) or lower ($< 1$) dilation in the distribution of firms inside clusters.

**Figure 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 ($\phi$) 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 $\phi$ 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 $S = \frac{S_i - S_j}{1 - S_j}$. The 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 $S$. 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 $m_\theta$ and $\hat{\tilde{m}}_\theta$ 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 $R^2 = 1 - \frac{M(\hat{A}, \hat{D}, \hat{S})}{M(0,1,0)}$.[15]

[15] 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).

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 7 reports the estimates for $\hat{A}$, $\hat{D}$ and $\hat{S}$ for the whole sample and by macro-region[16]. 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 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 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, the coefficient for dilation is not significant. As Combes et al. (2012) suggest,

[16]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.

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 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 7:** 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 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. With the help of the clustering technique that ignores administrative boundaries, we provide evidence that agglomeration occurs at a close distance, in line with recent findings by Rosenthal and Strange (2020). The productivity distribution is dilated inside clusters in the North and Center. 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 the Center to take advantage of agglomeration mechanisms and boost their 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 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

# Ownership Chains in Multinational Enterprises

*This chapter is based on the working paper "Ownership Chains in Multinational Enterprises" in collaboration with Armando Rungi and Gianluca Santoni (Miricola, Rungi, and Santoni, 2023).*

## 3.1 Introduction

A common feature in the organization of multinational enterprises is the development of ownership chains crossing multiple country borders. According to UNCTAD (2016), more than 40% foreign affiliates are indirectly controlled by parent companies through vertical chains, accounting for almost 50% of multinationals' revenues. Yet, despite their economic relevance, the emergence of hierarchical corporate structures across national borders has been neglected by the economic literature.

In this work, we hypothesise that the rationale behind global ownership chains relates to the organization of efficient communication of management decisions between affiliates and parent companies scattered across different countries. Communication barriers burden parent companies, which eventually start to delegate the monitoring of production activities when the boundaries of multinational enterprises extend on a wide geographic scale.

More specifically, we derive two structural gravity equations based on a model of competition for corporate control along global ownership chains where monitoring activities can be delegated with a cost. For our purpose, we elaborate on the original intuition of Head and Ries (2008) about the emergence of a market for corporate control when parent companies and affiliates are located in different countries. We extend to include cases of three-tier corporate structures, where an additional intermediate layer of ownership exists between a parent and its final affiliates. From our perspective, three-tier corporate structures are simplified ownership chains where (at least) a middleman subsidiary located in a country communicates management decisions from the parent company, which is located in an origin country, to a final subsidiary in a destination country.

Eventually, we derive two estimable gravity equations to evaluate the role of communication frictions in the emergence of sophisticated ownership chains:

1. a triangular gravity, which explains the extensive margin of establishing a middleman company that is controlled by the parent and monitors activities performed by final affiliates, conditional on final investments' locations;

2. a bilateral gravity for the extensive margin of locating multinational firms' final investments.

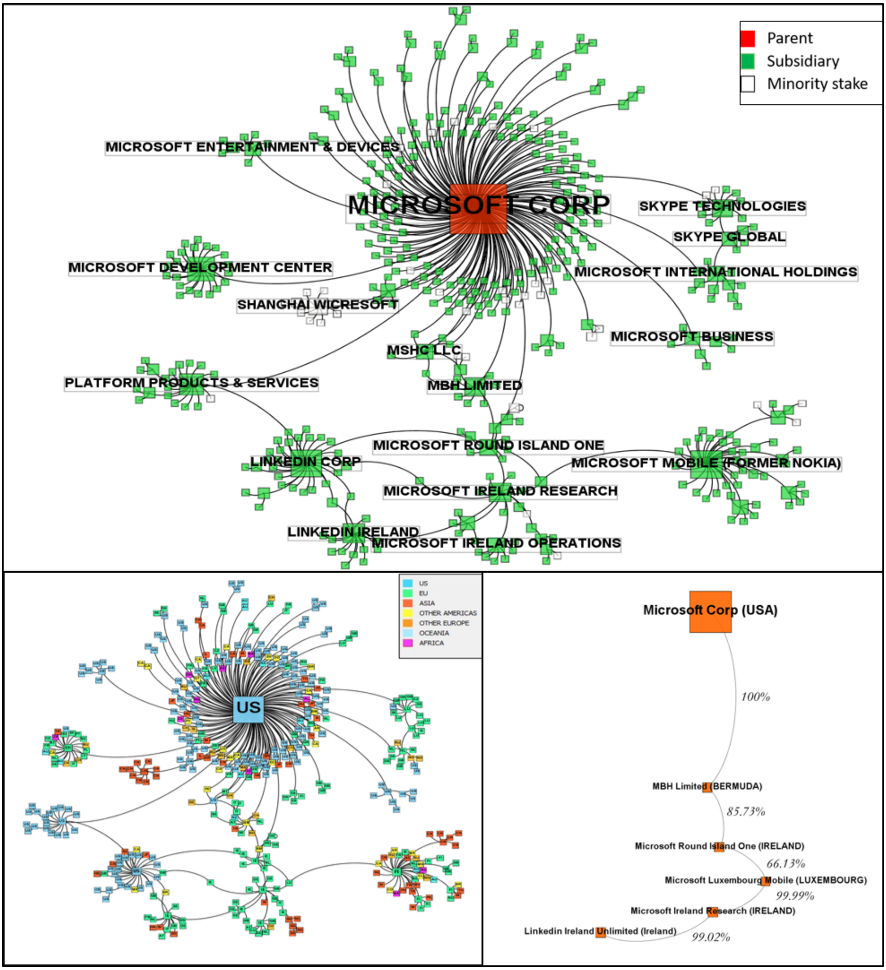
Model predictions are confirmed after a pseudo-Poisson maximum likelihood estimator. According to our model, a middleman's location is determined by the cost of monitoring final subsidiaries plus the cost of delegating the monitoring function by a parent company. Yet, the delegation cost is always lower than the monitoring cost; otherwise, establishing an ownership chain would not be convenient. The delegating cost decreases with the ease of communication between a parent and its middleman subsidiary, while the monitoring costs decrease with the ease of communication between the middleman and the final subsidiaries.

Eventually, our model also predicts that the location of the final subsidiaries is driven by the expected multilateral cost of controlling a company in a given country.

Our theory is positively tested on information about ownership chains by 226,993 parent companies as developed in 190 countries in the year 2019. Adopting a network approach, our sample reconstructs global ownership chains from a matrix considering original firm-level shareholder lists, as in Rungi, Morrison, and Pammolli (2017). Anytime a corporate shareholder is present in a list of shareholders, an ownership network may exist upstream, and a network majority rule allows us to detect chains of corporate relationships starting from the bottom up until reaching an ultimate parent company. Eventually, an overview of our sample shows that complex ownership chains emerge in about 50% multinational enterprises. An ownership chain can include up to 21 companies and cross up to 8 different countries.

To provide a general idea of how global ownership chains look like, we visualize the case of Microsoft Corp in Figure 10. Microsoft Corp is a well-known leading tech company providing computer software and consumer electronics since 1975. According to our data, it coordinates 404 subsidiaries operating in 79 countries in 2019. Each node represents the parent or a subsidiary of Microsoft Corp, and each edge represents an equity stake directed from one company to another. In the first panel, the parent company is coloured in red, and the subsidiaries are coloured in green. At the same time, a few relevant minority stakes are also reported as white nodes linked to either the parent company or any of its subsidiaries.

**Figure 10:** The network structure of Microsoft Corp




Note: The first panel shows the corporate network structure of Microsoft Corp in 2019, as from our data. Each node is a company, and each edge is an equity stake. In the second panel, we show the geographical span of the multinational enterprise with ISO 2-digit codes written on nodes. The third panel extracts a peculiar case of a long ownership chain starting from Microsoft's parent and crossing several national borders.

The structure of Microsoft Corp shows a big collection of subsidiaries on the first hierarchical layer around the parent company. More downstream, we find a constellation of sub-holdings that monitor the activities of indirectly controlled subsidiaries. Some of them are the result of previous acquisitions (e.g., Skype Technologies, Linkedin Corp, and Microsoft Mobile - former Nokia), whereas others are the result of an all-internal organization (e.g., Microsoft Platform Products and Services, Microsoft Development Center, Microsoft Entertainment Devices, Microsoft Business Divisions, Microsoft Island One, and Microsoft Ireland Research).

In general, we observe that Microsoft Corp has a multi-centre spider-like organization where some central subsidiaries establish cross-holdings and ownership loops among them. The second panel of Figure 10 indicates where each subsidiary is located. Each node is labeled with the hosting country's ISO 2-digit code, whereas colors indicate the main continents. Interestingly, we find that most ownership loops and cross-holdings are established among subsidiaries that operate in the US, Ireland, Luxembourg, and Bermuda. Ownership chains cross several national borders before reaching a final subsidiary. This is the case of Linkedin Ireland Unlimited reported at the bottom of 10, whose pattern of control includes four middlemen, respectively located in Ireland (Microsoft Ireland Research, 99.02% stake), Luxembourg (Microsoft Luxembourg Mobile, 99.99%), back in Ireland (Microsoft Round Island One, 66.13%), crossing the Atlantic Ocean in the Bermuda Islands (MBH Limited, 85.13%) and finally reaching the US headquarters (Microsoft Corp, 100%). In some cases, minority albeit dominant stakes may represent FDI operations. This is the case of Wicresoft in Shanghai, a white node originating a spider in the top panel of Figure 10. Reportedly, Wicresoft was jointly established in 2002 by Microsoft Corp and a venture capital fund owned by the Shanghai municipality. Traditionally, China discourages majority stakes by foreign investors and promotes forms of corporate governance that favor local technological spillovers. Over time, Wicresoft has developed its global network of operations in the US and Europe while keeping its original connection with Microsoft Corp.

## 3.2 Literature

This paper adds to the existing literature on the determinants of business groups organization, a topic that lies at the center of multiple economic fields. In the last decades, organizational economics has put effort in advancing our understanding of the activities conducted within a firm's boundaries. Notable contributions look at the role of information transmission and communication costs. Among them, Garicano (2000) introduces the concept of companies as knowledge-based hierarchies, where hierarchical differentiation raises to optimize the creation and transfer of knowledge required for the production process. Many authors later employed the same theoretical framework. Altomonte, G. I. Ottaviano, et al. (2021) propose and test a model where efficiency in problem solving contributes to determining the optimal hierarchical shape of a business group, with parent companies supervising subsidiaries and managing communication among them. Altomonte and Rungi (2013) look at the relation between hierarchical complexity and vertical integration and find consistencies with predictions from knowledge-based models. Another aspect emphasized in the economic theory of firm organization, starting from the seminal model of Aghion and Tirole (1997), is the trade-off between information processing and corporate control decentralization. Along these lines, Bloom, Sadun, and Van Reenen (2012)'s work illustrates how trust, as a fundamental factor in the decision to delegate control, affects the organization of businesses. The study of the pyramidal structures of business groups has also gathered interesting contributions in the field of international management. Belenzon, Hashai, and Pataconi (2019) examine how the monitoring attention of the headquarter is distributed across the layers of corporate group hierarchies, and establishes a positive relationship between corporate distance and the subsidiary's autonomy.

Our work is also related to the literature on the determinants of investments in multinational companies. Starting from the early application of Eaton and Tamura (1994), a plethora of contributions have analyzed patterns of foreign direct investments within the framework of gravity models, where either the extensive or intensive margin of investments is affected by the size of source and destination countries, and on a set of bilateral frictions between country pairs. Gravity-type equations have been employed to estimate the impact of destination country taxation (Mutti and Grubert, 2004), institution quality (Bénassy-Quéré, Coupet, and Mayer, 2007), time zone proximity (Stein and Daude, 2007) and bilateral investment treaties (Egger and Pfaffermayr, 2004), just to mention a few. Differently from these works, we do not look at direct investments, but rather look at the ownership chains a direct investment could be part of. Few works have instead provided theoretical foundation to gravity equations for investments, and among them, the vast majority assume either vertical or horizontal integration between multinational companies and their subsidiaries (Kleinert and Toubal, 2010; J. H. Bergstrand and Egger, 2007; J. Bergstrand and Egger, 2010; Anderson, Larch, and Yotov, 2019). Head and Ries (2008) take a different perspective and propose a model where direct investments consist in corporate acquisitions, and, as anticipated, our paper is closely related to their work. Their theoretical framework is particularly suitable for our case as, besides using a discrete choice approach (similar to the one seen in Eaton and Kortum (2002) work), remains quite flexible on the motivations for which investments occur. More remotely, our work is related to the literature on multinational production that models interdependencies in firm-level decisions (Tintelnot, 2017; Arkolakis et al., 2018; Wang, 2021; Head and Mayer, 2019). Within this class of models, multinational companies organizing their global operations make multiple nested decisions on locations and quantities. Importantly, the choice on where to locate production sites is analyzed in relation to other connected activities, such as export or intermediate goods sourcing, that involve a third country, giving rise to triangular geographic patterns. Similarly, we model the location of multinational investments as dependent on the need to shift monitor activities to a third country, with the parent company simultaneously deciding where to invest and where to place the monitoring unit.

## 3.3 Data on ownership chains and motivating evidence

We source data from the Orbis ownership database compiled by the Bureau van Dijk, which collects shareholding information on companies worldwide. To retrieve the topology of corporate networks developed by a multinational enterprise, we adopt the methodology of Rungi, Morrison, and Pammolli (2017), where ownership chains are reconstructed following equity links established among legally autonomous firms, all leading upwards to an ultimate parent company thanks to the backward solution of majority rule ($> 50\%$) that allows management decisions to be enforced. The methodology allows us to consider cases of direct control, indirect control by transitivity of direct control, and cases where the parent company can consolidate indirect control through otherwise fragmented ownership chains that together combine to reach an absolute majority ($> 50\%$) in a subsidiary. Notably, an ownership chain allows a parent company to exert indirect control over final subsidiaries. For our purpose, we define a middleman subsidiary as one we can encounter along an ownership chain before reaching a final subsidiary in a destination country. As we are interested only in ownership chains that cross countries' borders, we will focus only on corporate networks defined by multinational enterprises defined by a parent company with at least a subsidiary in a country different from the parent's origin. Additional details about the methodology and the original dare are reported in the Appendix B.1.

We end up with a sample of 226,993 parent companies controlling 1,785,493 subsidiaries that are located in 190 countries and territories around the world. In Table 8, we show the geographical distribution of multinational enterprises in our sample based on the location of both parents and subsidiaries. Among subsidiaries, we separate in the last columns of the table the geographic distribution of middlemen. The largest shares of parent companies (42%) and subsidiaries (33%) are detected in the European Union. If we look inside country aggregates, we observe a relative concentration of parent companies in Cyprus and the Caribbeans, which are known for having business-friendly tax systems. As for subsidiaries, they mostly locate in the USA, UK, China, and Germany. Yet, their distribution slightly changes when we focus on *middlemen*, in the third column of Tab.8, where we observe comparatively fewer *middlemen* in the Asian countries, and we note a greater concentration of firms in both the United Kingdom and the Netherlands.

**Table 8:** Geographic distribution of companies participating to multinational groups

| | | Parent | % | Subsidiaries | % | *of which* | Middlemen | % |
|---|---|---|---|---|---|---|---|---|
| **EU27** | | **94,780** | **41.77%** | **590,017** | **33.05%** | | **105,376** | **39.22%** |
| | *of which* | | | | | | | |
| | Cyprus | 11,390 | 5.02% | 13,645 | 0.76% | | 3,403 | 1.27% |
| | Netherlands (the) | 11,060 | 4.87% | 64,656 | 3.62% | | 17,215 | 6.41% |
| | Germany | 10,608 | 4.67% | 107,659 | 6.03% | | 16,856 | 6.27% |
| | Italy | 7,729 | 3.41% | 41,617 | 2.33% | | 7,192 | 2.68% |
| | France | 6,980 | 3.08% | 51,774 | 2.90% | | 9,163 | 3.41% |
| | Luxembourg | 5,952 | 2.62% | 32,448 | 1.82% | | 9,457 | 3.52% |
| **Asia** | | **33,395** | **14.72%** | **344,736** | **19.31%** | | **38,693** | **14.40%** |
| | *of which* | | | | | | | |
| | China | 5,915 | 2.61% | 127,154 | 7.12% | | 14,583 | 5.43% |
| | Singapore | 1,498 | 0.66% | 35,547 | 1.99% | | 6,416 | 2.39% |
| **Rest of Europe** | | **30,495** | **13.44%** | **204,749** | **11.47%** | | **40,188** | **14.96%** |
| | *of which* | | | | | | | |
| | UK | 14,856 | 6.55% | 133,366 | 7.47% | | 30,363 | 11.30% |
| | Switzerland | 8,790 | 3.87% | 13,047 | 0.73% | | 2,873 | 1.07% |
| **USA** | | **24,507** | **10.80%** | **389,691** | **21.83%** | | **51,520** | **19.18%** |
| **Latin America** | | **21,771** | **9.59%** | **80,703** | **4.52%** | | **8,002** | **2.98%** |
| | *of which* | | | | | | | |
| | Caribbean | 17,769 | 7.83% | 29,220 | 1.64% | | 4,536 | 1.69% |
| **Africa** | | **6,100** | **2.69%** | **43,656** | **2.45%** | | **4,022** | **1.50%** |
| **Oceania** | | **6,034** | **2.66%** | **57,071** | **3.20%** | | **11,589** | **4.31%** |
| | *of which* | | | | | | | |
| | Australia | 4,336 | 1.91% | 41,371 | 2.32% | | 9,418 | 3.51% |
| **Canada** | | **4,587** | **2.02%** | **33,725** | **1.89%** | | **4,272** | **1.59%** |
| **Russia** | | **3,178** | **1.40%** | **37,313** | **2.09%** | | **4,170** | **1.55%** |
| **Rest of the World** | | **2,084** | **0.92%** | **3,832** | **0.21%** | | **817** | **0.30%** |
| **Total** | | **226,931** | **100.00%** | **1,785,493** | **100.00%** | | **268,649** | **100.00%** |

Note: The table details the geographic coverage of parent companies and subsidiaries of multinational enterprises as classified by hosting economies. The third column specifies how many subsidiaries are *middlemen* in a given location. We show values for the relatively more populated countries inside an aggregate.

We now look at the full extension of ownership chains, from their origin, the parent company, to the last subsidiary in which they terminate. In table 9, we report the number of subsidiaries comprised by an ownership path, from beginning to end, and the number of foreign countries visited. In our MNEs sample, we find 1,517,138 paths connecting parent companies to final subsidiaries, which, in the simplest case, consist of a single direct control link. MNEs may either have a *simple* structure, where no *middlemen* are employed, and control occurs only directly from the parent to its subsidiaries, or a *complex* structure featuring at least one case of indirect control through *middlemen*. Notably, 82% of ownership chains derive from *complex* MNEs. In particular, for a 55% of ownership chains, one or more companies are interposed between parent and final subsidiary, up to a maximum of 20 *middlemen*. The grey area highlights how many of them cross national borders (33 % of the total) even more than once, up to a maximum of 7 countries visited by a single ownership chain. Complex and global ownership chains definitely represent a relevant feature in MNEs' organization. For this reason, we wonder if ignoring the hierarchical aspect of MNE organization when analyzing the geography of foreign investments risks providing incomplete results. More concretely, this amounts to neglecting the interdependence between companies that compose ownership chains described in the grey area of table 9. This interdependence has an economic significance that could affect the geographical distribution of subsidiaries and deserve to be considered.

**Table 9:** Extension of MNEs ownership chains

| | | N. of country borders crossed | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **N. of subsidiaries** | | Domestic | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Total |
| Simple MENs | 1 | 51,680 (3.406%) | 222,186 (14.645%) | | | | | | | 273,866 (18.051%) |
| Complex MNEs | 1 | 223,995 (14.764%) | 191,138 (12.599%) | | | | | | | 415,133 (27.363%) |
| | 2 | 181,428 (11.959%) | 174,195 (11.482%) | 41,266 (2.720%) | | | | | | 396,889 (26.160%) |
| | 3 | 94,778 (6.247%) | 80,172 (5.284%) | 30,602 (2.017%) | 5,522 (0.364%) | | | | | 211,074 (13.913%) |
| | 4 | 42,333 (2.790%) | 37,480 (2.470%) | 19,856 (1.309%) | 6,037 (0.398%) | 1,081 (0.071%) | | | | 106,787 (7.039%) |
| | 5 | 17,663 (1.164%) | 18,363 (1.210%) | 11,407 (0.752%) | 5,189 (0.342%) | 961 (0.063%) | 205 (0.014%) | | | 53,788 (3.545%) |
| | 6 | 7,177 (0.473%) | 8,010 (0.528%) | 6,558 (0.432%) | 3,865 (0.255%) | 1,014 (0.067%) | 203 (0.013%) | 7 (0.000%) | | 26,834 (1.769%) |
| | >=7 | 5,595 (0.369%) | 8,375 (0.552%) | 8,622 (0.568%) | 6,273 (0.413%) | 2,869 (0.189%) | 810 (0.053%) | 196 (0.013%) | 27 (0.002%) | 32,767 (2.160%) |
| Total | | 624,649 (41.173%) | 739,919 (48.771%) | 118,311 (7.798%) | 26,886 (1.772%) | 5,925 (0.391%) | 1,218 (0.080%) | 203 (0.013%) | 27 (0.002%) | 1,517,138 (100.000%) |

Notes: This table is based on the observation of ownership chains in their full extension, from parent company to final subsidiary. For a total of 1,517,138 distinct ownership chains, we indicate by row how many subsidiaries they are composed of, and by column how many foreign countries they cross. In the first row, we report direct control links extracted from *simple* MNEs, i.e. MNEs that never show cases of indirect control in their corporate structure. In the grey area, we highlight values related to ownership chains crossing national borders and involving one or more *middlemen*.

### 3.3.1 Motivating evidence

We start by investigating the geographic distribution of subsidiaries of *complex* MNEs. In particular, we want to verify whether ownership chains fit into a gravity-type framework, assuming cross-country corporate relationships can be subject to bilateral country frictions.

The empirical literature that applies gravity equations, especially to trade data, generally uses the geographical distance between countries to control for transportation costs, as well as variables capturing cultural ties. However, in the case of FDI, some contributions have stressed the importance of other cost components related to the need to transfer information between companies in real-time (Stein and Daude, 2007). This is because the economic relationship between a company and its affiliates involves activities, such as management, monitoring, and coordination, that require frequent real-time interactions. It becomes thus relevant to capture those barriers that inhibit the ability to engage in real-time exchanges. While the traditional concept of physical distance fails to capture barriers to communication, the time-zone difference between a company pair is proposed as the best solution.

With this in mind, we start by specifying a *corporate control gravity*, where instances related to coordinating production are expected to play a role in the location of subsidiaries. In this perspective, control relationships might benefit from the ease of communication. To account for the latter, we follow Bahar (2020) and introduce in the gravity the daily number of overlapping working hours between companies[1]. When two companies are located in different time zones, the more their working schedules match, the more likely it is that when communicating a decision, the counterparty will instantly receive it. We add other standard bilateral controls that might affect the cost of multinational production organization[2], also to prevent their effect, especially that of geographic distance, to be absorbed by the number of overlapping working hours. After aggregating control links into a count variable summing over country pairs, our chosen specification is:

$$N_{ij} = exp(\beta^{wh} wh_{ij} + \boldsymbol{\beta'}\mathbf{x}_{ij} + \gamma_i + \gamma_j)\epsilon_{ij} \tag{3.1}$$

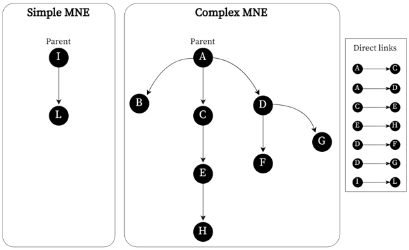
where i and j stand for origin and destination country and $N_{ij}$ counts the number of companies in country j controlled by companies located in country i. $wh_{ij}$ measures overlapping working hours between i and j, while $\mathbf{x}_{ij}$ is a vector of gravity controls we source from the CEPII Gravity dataset (namely, the logarithm of distance measured in km, and indicator variables for the presence of, respectively, contiguous borders, common language, common legal origins, colonial ties and regional trade agreements between countries). $\gamma_i$ and $\gamma_j$ capture origin and destination country fixed effects.

[1] Bahar (2020) assume a working day to last ten hours and count the hours during which the parent company and its subsidiary offices are simultaneously open.

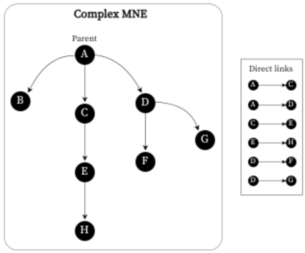
[2] Beyond intra-group coordination activities, there might be horizontal and vertical integration choices (see theoretical foundations for FDI gravity, such as Kleinert and Toubal (2010) and J. H. Bergstrand and Egger (2007)), which depend on the cost of transporting goods and affect the location of investments.

**Figure 11:** Ignoring versus considering ownership chains

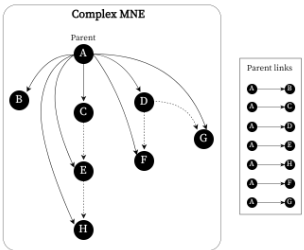
**(a)** Direct ownership links in MNEs



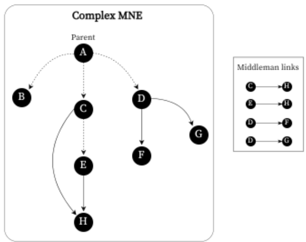

**(b)** Direct ownership links in *complex* MNEs




**(c)** Parent ownership links




**(d)** Middleman ownership links




Notes: This figure shows how different measurements of the number of control relationships by country-pair are obtained starting from corporate control networks. Each panel reports an example of a corporate control network on the left and the list of correspondent bilateral control links on the right. Panel a) and b) refer, respectively, to the dependent variables in columns (1) and (2) of table 10. In both cases, the organizational structure is left aside to simply aggregate direct ownership links between companies. Yet, in column (1), we include simple MNEs in the analysis. Panels c) and d) refer, respectively, to the dependent variables in columns (3) and (4) of table 10 and display what happens when the corporate structure is accounted for. In column (3), we count all direct and indirect links between a parent company and its subsidiaries; in column (4), all direct and indirect control relationships between middlemen and final.

Recalling the previous paragraph, in table 9, we shed light on how relevant the interdependence between subsidiaries along complex ownership chains is. Our purpose is to incorporate this aspect into the analysis. To do this, we test different definitions of the extensive margin of MNEs investments, which we exemplify in figure 11, and compare results obtained from the different dependent variables obtained. In Figure 11, each panel corresponds to a distinct dependent variable depending on whether or not we ignore the hierarchical structure of *complex* MNEs. Indeed, ignoring the hierarchical structure of ownership chains generates a set of control links that might differ from the one obtained when the control network is accounted for. If the corporate structure were unknown, each subsidiary would be deemed to be controlled by the immediately preceding node, in which case the dependent variable would be a count of direct and independent control links. These are the cases displayed in panels (a) and (b) of figure 11. When the corporate structure is observable, control power can be attributed to parent companies proceeding up each subsidiary's ownership chain. In this case, we sum up all direct and indirect control links connecting a parent company to each of its subsidiaries at any level of the hierarchy, as shown in panel (c) of fig. 11. Moreover, our data structure allows to isolate the control relationship between intermediate and final subsidiaries. Panel (d) illustrates the latter case, where the dependent variable counts the direct and indirect links that connect a middleman to the final subsidiary in an ownership chain.

**Table 10:** Gravity for multinational firms with and without ownership chains

| **Dep. Var.** | $N_{ij}$= # of companies country i controls in country j | | | |
|---|---|---|---|---|
| | All MNEs | Complex MNEs | | |
| Sample | Direct links | Direct links | Parent-subsidiary links | Middleman-final links |
| | (1) | (2) | (3) | (4) |
| N. of overlapping working hours | 0.058** | 0.046* | 0.006 | 0.068** |
| | (0.023) | (0.025) | (0.023) | (0.027) |
| RTA | 0.292* | 0.275* | 0.136 | 0.291* |
| | (0.154) | (0.165) | (0.195) | (0.168) |
| Log distance (km) | -0.252*** | -0.263*** | -0.336*** | -0.227*** |
| | (0.088) | (0.084) | (0.072) | (0.088) |
| Home | 3.355*** | 3.693*** | 2.516*** | 3.472*** |
| | (0.251) | (0.265) | (0.315) | (0.250) |
| Language | 0.780*** | 0.828*** | 0.747*** | 0.641*** |
| | (0.102) | (0.098) | (0.089) | (0.108) |
| Colony dependence | 0.304** | 0.300** | 0.312** | 0.385*** |
| | (0.130) | (0.133) | (0.129) | (0.124) |
| Legal origins | 0.377*** | 0.324*** | 0.238*** | 0.268*** |
| | (0.084) | (0.079) | (0.087) | (0.101) |
| Observations | 39,786 | 36,771 | 32,952 | 35,012 |
| Fixed Effects | i,j | i,j | i,j | i,j |

Note 1: Standard errors clustered by origin country in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).
Note 2: $N_{ij}$ counts the number of companies in country j controlled by companies in country i; what changes by column, is the set of control links the dependent variable is summing up by country-pair. Results reported in column (1) refer to all direct links composing the corporate structure of both simple and complex MNEs (see panel a) of Fig.11). Subsequent columns focus on complex MNEs only. Column (2) shows results for the sample of direct control links of complex MNEs (see panel b) of Fig.11). In the last two columns, the hierarchical structure of complex MNEs is controlled for and the dependent variable is counting respectively, all the direct and indirect control links held by parent companies at all levels (3) (see panel c) of Fig.11); all the direct and indirect control links held by middlemen (4) (see panel d) of Fig.11).

At this point, equation 3.1 is estimated using each of the four alternative $N_{ij}$s. Column (1) of table 3.1 reports coefficients estimated running eq.3.1 on direct investments. As expected, the number of overlapping working hours between countries is significant, implying that the ease of communication encourages direct control relationships. We find the same for *complex* MNEs in column (2), though the effect is less significant. In the following column, we apply gravity to parent-subsidiary control relations and notice that the ease of communication no longer matters. Thus, the location of subsidiaries does not seem to be driven by the need to communicate in real time with the parent. Interestingly, the coefficient returns to significantly positive in column (3). It follows that the possibility to interact in real-time with a middleman up in the ownership chain affects the location of a final subsidiary. Altogether these results suggest that if we zoom out from the single direct control link to get a full view of the corporate control network, we find that the ease of communication matters only in a limited area, that is, in the relationships between middlemen and final subsidiaries. As a side note, all versions of bilateral gravity we tested and reported in tab.10 obey the standard gravity model. Coefficients for distance are negative, while contiguity and cultural and historical similarities have a positive sign.

Building on recent influential contributions (Head and Mayer, 2019; Wang, 2021), we check whether a triangular gravity framework can explain the contemporary presence of three sets of frictions along ownership chains: (i) the relation between a parent and its middlemen; (ii) the relation between the middleman and the final subsidiary; (iii) the relation between the parent and its final subsidiary. The main intuition is that this is the best framework to check how communication costs operate differently along ownership chains. As seen in Table 9, almost a 50% of indirect ownership chains employ only one middleman and naturally show a trilateral framework. Longer ownership paths need instead to be simplified to three-tier corporate structures. Our dependent variable is the number of final subsidiaries in county j indirectly controlled by a parent company in county i through a middleman located in county k ($N^I_{ikj}$, where the superscript specifies we do not consider paths consisting in a direct control link between the parent and the final subsidiary.). The following equation is empirically tested:

$$\begin{aligned}N^I_{ikj} = exp(&\beta^{wh} wh_{ij} + \rho^{wh} wh_{ik} + \upsilon^{wh} wh_{kj} + \boldsymbol{\beta'}\mathbf{x}_{ij} + \boldsymbol{\rho'}\mathbf{x}_{ik} + \boldsymbol{\upsilon'}\mathbf{x}_{kj} + \\ &+ \gamma_i + \gamma_k + \gamma_j)\epsilon_{ikj}\end{aligned} \tag{3.2}$$

where $wh$ is the number of overlapping working hours between country pairs, and subscripts specify whether location refers to the parent (i), to the middleman (k) and to the final subsidiary (j). $\gamma_i$, $\gamma_k$ and $\gamma_j$ are country-level fixed effects. For each side of the triangle, we include the vector of standard bilateral explanatory variables $\mathbf{x}$.

**Table 11:** Triangular gravity for indirect corporate control

| Dep. Var. | $N_{ikj}$ |
|---|---|
| N. of overlapping working hours$_{ik}$ | 0.059*** (0.017) |
| N. of overlapping working hours$_{kj}$ | 0.088*** (0.019) |
| N. of overlapping working hours$_{ij}$ | -0.065*** (0.023) |
| Log distance$_{ik}$ | -0.027 (0.039) |
| Log distance$_{kj}$ | -0.146*** (0.044) |
| Log distance$_{ij}$ | -0.309*** (0.049) |
| Home$_{ik}$ | 3.120*** (0.139) |
| Home$_{kj}$ | 3.568*** (0.119) |
| Home$_{ij}$ | -0.358* (0.184) |
| Observations | 1,281,743 |
| Fixed effects | i, k, j |
| Standard gravity controls | ik, kj, ij |

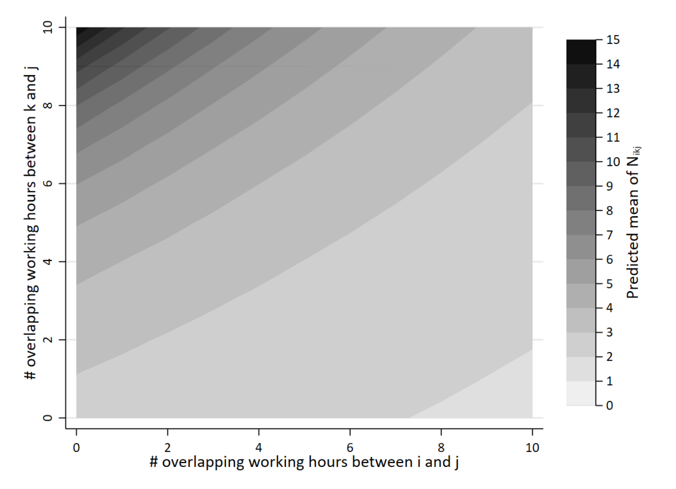
Note: Standard errors clustered by i $\times$ j in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 11 shows results for our variable of interest, the ease of communication. Indirect investments increase with ease of communication between the parent and the middleman (5. 9%), and the same is observed in the relationship between the middleman and the final, with a slightly larger magnitude of the effect (8.8%). In contrast, the ease of communication between a parent and its final subsidiaries seems to discourage indirect investments. This might suggest that an indirect path is more convenient when the parent is less able to communicate in real-time with the final. Also, it is noteworthy that opposite signs are observed for the effect of overlapping working hours. To further investigate this, we look at the interaction between the effects of the ease of communication on the different sides of the triangle. We stick to the specification in Eq.3.2 and simply add an interaction term between $wh_{ij}$ and $wh_{kj}$

$$N^I_{ikj} = exp(\zeta^{wh} wh_{ij} wh_{kj} + \beta^{wh} wh_{ij} + \rho^{wh} wh_{ik} + \upsilon^{wh} wh_{kj} + \boldsymbol{\beta'}\mathbf{x}_{ij} + \\ + \boldsymbol{\rho'}\mathbf{x}_{ik} + \boldsymbol{\upsilon'}\mathbf{x}_{kj} + \gamma_i + \gamma_k + \gamma_j)\epsilon_{ikj}$$

To better understand the interplay between the two effects, we represent predictions from our model in Figure 12. The latter reports on the axes the number of overlapping working hours separating a final subsidiary from the parent (x-axis) and the middleman (y-axis). The legend details the predicted value for indirect investments $N_{ikj}$ in all possible combinations of $wh_{ij}$ and $wh_{kj}$ levels. The curvature of the lines in the graph captures the interaction term and shows how the coefficient of $wh_{ij}$ varies across the different levels of $wh_{kj}$ and vice versa. As already read in Table 11, a difficult communication between the parent and the final, and, on the other side, an improved communication between the middleman and the final subsidiary correlates with a higher number of indirect control paths. Another element we deduce from the graph is that, since the curves are increasing and convex, the positive effect of $wh_{kj}$ intensifies as the number of working hours a parent shares with its final subsidiary decreases.

**Figure 12:** Interaction of the ease of communication




Note: This graph shows how the predicted mean of $N_{ikj}$ varies according to different values of both $wh_{ij}$ and $wh_{kj}$. The curvature of the lines in the graph captures the interaction term and shows how the coefficient of $wh_{ij}$ varies across the different levels of $wh_{kj}$ and vice versa. For high values of $wh_{ij}$, an increase in $wh_{kj}$ has a positive but nuanced effect on the predicted mean of $N_{ikj}$. For low values of $wh_{ij}$, the positive effect of $wh_{kj}$ on the predicted mean of $N_{ikj}$ is much stronger.

## 3.4 Theoretical model

Motivated by previous preliminary evidence, we present a variation on the model by Head and Ries (2008) to introduce ownership chains in multinational enterprises. In this framework, investments are determined by competition to control foreign assets, where the headquarters might choose to monitor activities carried out by remote subsidiaries incurring a cost. Our extension introduces an intermediate level of investment between the competing company and the final target to allow for the presence of middlemen subsidiaries. We assume that, differently from the original model, monitoring tasks can be delegated to intermediate subjects. Therefore, we configure a delegation of monitoring framework, where the decision process faced by a parent company can be divided into two steps. The parent participates in an auction for a final target and, conditional on the final target location, chooses where to locate the monitoring unit to minimize monitoring costs.

**Table 12:** The Head and Ries, 2008 inspection game

| | | | **Subsidiary** | |
|---|---|---|---|---|
| | | | $Work$ | $Shirk$ |
| | | | $x$ | $(1-x)$ |
| **Parent** | $Trust$ | q | $a+b-w, w-e$ | $a-w, w$ |
| | $Monitor$ | (1-q) | $a+b-w-c, w-e$ | $a-c, 0$ |

In the original Head and Ries, 2008's set-up, costs and benefits of controlling a subsidiary are defined through an inspection game between a parent company and a subsidiary. Strategies and payoffs for the two players are reported in normal form in Table 12. Control gains are given by the value produced by the controlled subsidiary (b), which is conditional on the effort exerted by the subsidiary's manager (e). Managers may choose to shirk, in which case $b = 0$. However, the parent can sustain a cost (c) to verify the manager's activity and avoid paying the salary (w) every time a manager does not work. The authors assume $b \geq w \geq e \geq c \geq 0$, which implies no Nash equilibrium in pure strategies. Hence, the parent company will not always choose one strategy over the other, and, in a mixed strategy equilibrium, will maximize its expected payoff to obtain the value function:

$$v = a + b - 2\sqrt{bc} \tag{3.3}$$

where a is the value added that the parent company produces regardless of the game's development. Eq.3.3 represents a parent's evaluation of the final subsidiary. All parent companies on the market, respectively, play the inspection game with each of the subsidiaries on the market and evaluate each of them according to Eq.3.3. For each subsidiary, a competition is set among all parent companies to obtain control stakes. The parent company offering the highest evaluation wins the competition.

Up to this point, we accept Head and Ries (2008)'s model assumptions. A substantial change from the original model comes with the definition of c. Originally, monitoring costs were an increasing function of the bilateral distance between the parent's and subsidiary's country. In our extension, parent companies are not able to directly supervise subsidiaries as they lack time or technology[3]. Thus, a parent cannot verify a subsidiary's effort without delegating to a third managerial unit, the middleman. Note that, with respect to the literature modelling delegation of monitoring within hierarchical corporate structures (Holmstrom and Tirole, 1989), we are implicitly making a series of assumptions. Firstly, we assume no information asimmetry between parent company and middlemen, as the parent perfectly observes middleman's effort. Secondly, we rule out any possibility of side contracting, which excludes collusion between the middleman and the subsidiary. To conclude, we assume middleman's effort to be exogenous. In the upcoming section, we show how these assumptions modify the decision process of the parent company and, accordingly, monitoring costs in Eq.3.3.

A parent company willing to monitor a subsidiary will now need to shift control to a third corporate entity, i.e. a *middleman*. Both shifting control and supervising entail a cost. Hence, a parent located in country i, willing to monitor a subsidiary in country j, has to minimize the following cost function:

$$c_{ikj} = \delta_{ik} + \delta_{kj} - \epsilon_{ikj}$$

where $\delta_{kj}$ is the cost for a middleman in country k to monitor a subsidiary in country j. $\delta_{ik}$ is the cost for a parent in country i to delegate monitoring functions to a middleman in country k. Importantly, we assume $\delta_{kj} \geq \delta_{ik} \geq 0$. Note that the degree of delegation can vary from firm to firm, with the extreme case of full delegation where the $\delta_{ik}$ is

[3]As in the first axiom from Tirole (1986): "The principal, who is the owner of the vertical structure or the buyer of the goods produced by the agent, or, more generally, the person who is affected by the agent's activity, lacks either the time or the knowledge required to supervise the agent".

zero. We assume $\epsilon_{ikj}$s to be independently and identically distributed according to a Type I extreme value distribution. The probability that a parent located in country i picks country k as a monitoring location, conditional on investing in country i, is equal to the probability that $c_{ikj}$ is the smallest possible. This yields

$$\begin{aligned}\pi_{ik|j} = \mathbb{P}(\mathcal{M}_{ikj} = 1) &= \mathbb{P}(c_{ikj} \leq c_{i\ell j}, \forall \ell \neq k) \\ &= \mathbb{P}(\delta_{ik} + \delta_{kj} - \epsilon_{ikj} \leq \delta_{i\ell} + \delta_{\ell j} - \epsilon_{i\ell j}, \forall \ell \neq k) \\ &= \mathbb{P}(\epsilon_{i\ell j} \leq \delta_{i\ell} + \delta_{\ell j} - \delta_{ik} - \delta_{kj} + \epsilon_{ikj}, \forall \ell \neq k)\end{aligned}$$

$$\Rightarrow \mathbb{P}(\mathcal{M}_{ikj} = 1) = \int_{-\infty}^{+\infty} F[\delta_{i\ell} + \delta_{\ell j} - \delta_{ik} - \delta_{kj} + \epsilon_{ikj}, \forall \ell \neq k] f(\epsilon_{ikj})\, d\epsilon_{ikj} \tag{3.4}$$

where $\mathcal{M}_{ikj} = 1$ if a parent company in country i willing to invest in country j locates her monitoring unit in country k. F[•] is the joint cumulative distribution function, which is conditional on the value of $\epsilon_{ikj}$. Integrating F(.) using the marginal probability $f(\epsilon_{ikj})$ we obtain the unconditional probability (the probability of choosing k as monitoring location for any given realization of $f(\epsilon_{ikj})$).

Since $f(\epsilon_{ikj})$ are iid, the conditional probability is the product of $K - 1$ univariate cumulative density functions:

$$\begin{aligned}\mathbb{P}(\mathcal{M}_{ikj} = 1) &= \int_{-\infty}^{+\infty} \prod_{\ell \neq k} F_\ell[\delta_{i\ell} + \delta_{\ell j} - \delta_{ik} - \delta_{kj} + \epsilon_{ikj}] f(\epsilon_{ikj})\, d\epsilon_{ikj} \\ &= \int_{-\infty}^{+\infty} e^{-\epsilon_{ikj}} exp(-e^{-\epsilon_{ikj}}) \prod_{\ell \neq k} exp(-exp(-(\delta_{i\ell} + \delta_{\ell j} - \delta_{ik} - \delta_{kj} + \epsilon_{ikj})\end{aligned} \tag{3.5}$$

Using the change of variable $z_k = e^{-\epsilon_{ikj}}$ and $y_\ell = e^{-(\delta_{i\ell} + \delta_{\ell j})}$ integrating by substitution:

$$
\begin{aligned}
\mathbb{P}(\mathcal{M}_{ikj}=1) &= \int_0^{+\infty} e^{-z_k} \prod_{\ell \neq k} e^{-\frac{y_\ell}{y_k} z_k}\, dz_k \\
&= \int_0^{+\infty} e^{-z_k} e^{-z_k \sum\limits_{\ell \neq k} \frac{y_\ell}{y_k}}\, dz_k \\
&= \int_0^{+\infty} e^{-z_k \sum\limits_{\ell} \frac{y_\ell}{y_k}}\, dz_k \\
&= -\frac{y_k}{\sum\limits_{\ell} y_\ell} \left[ e^{-z_k \sum\limits_{\ell=1}^{N} \frac{y_\ell}{y_k}} \right]_0^{+\infty} \\
&= \frac{y_k}{\sum\limits_{\ell} y_\ell} \\
&= \frac{e^{-(\delta_{ik}+\delta_{kj})}}{\sum\limits_{\ell} e^{-(\delta_{i\ell}+\delta_{\ell j})}}
\end{aligned}
$$

Therefore, the probability that a parent located in country i chooses country k as a location to monitor a subsidiary located in j is given by:

$$
\pi_{ik|j} = \mathbb{P}(\mathcal{M}_{ikj}=1) = \frac{e^{-(\delta_{ik}+\delta_{kj})}}{\sum\limits_{\ell} e^{-(\delta_{i\ell}+\delta_{\ell j})}} \tag{3.6}
$$

where the denominator represents the expected cost of monitoring a subsidiary in country j for a parent located in country i:

$$
C_{ij} = \ln \sum_{\ell} e^{-(\delta_{i\ell}+\delta_{\ell j})}
$$

The inspection game described before is modified as follows. We replace the bilateral monitoring cost with the multilateral monitoring cost index $C_{ij}$. Value function in Eq.3.3 becomes

$$
v = a + b - 2\sqrt{bC_{ij}} \tag{3.7}
$$

### 3.4.1 Competition for corporate control

After defining the multilateral cost index $C_{ij}$, we go back to Head and Ries (2008) derivation. Parent companies compete to obtain control over final subsidiaries. The competition takes the form of an auction (one auction for each final subsidiary). Each parent company participates in each auction, making a valuation of the final subsidiary given by Eq.3.7, and the highest valuation wins the auction. The marginal probability for a parent in country i to win an auction and obtain control over a subsidiary in country j is equal to the probability that the highest valuation for a given subsidiary in j is done by a parent company located in i (i.e., the maximum valuation in i is the highest among all the other countries' maxima).

$$\begin{aligned}\pi_{ij} = \mathbb{P}(\mathcal{N}_{ij} = 1) &= \mathbb{P}(v_{ij}^{max} \geq v_{nj}^{max}, \forall n \neq i) \\ &= \mathbb{P}(a_n^{max} \leq a_i^{max} - 2\sqrt{bC_{ij}} + 2\sqrt{bC_{nj}}, \forall n \neq i)\end{aligned}$$

where $\mathcal{N}_{ij} = 1$ if a parent located in i controls a final subsidiary located in j. We denote by $m_i$ the number of parent companies in country i. $a_i$ is distributed as a Gumbel with parameters $\mu$ and $\sigma$ and the maximum of $m$ Gumbel draws is distributed as a Gumbel with same $\sigma$ and $\mu$ right-shifted by a quantity $\sigma \ln(m)$. After reproducing the same passages shown in Eq.3.4 and Eq. 3.5, and integrating by substitution, we obtain the probability that a parent located in country i wins the auction for a subsidiary located in j:

$$\pi_{ij} = \frac{m_i \exp\Bigg( -(2\sqrt{bC_{ij}})/\sigma + \mu_i/\sigma \Bigg)}{\sum_n m_n \exp\Bigg( -(2\sqrt{bC_{nj}})/\sigma + \mu_n/\sigma \Bigg)} \tag{3.8}$$

## 3.5 The structural model

In this section, we illustrate the empirical strategy we adopt to identify the structural parameters of the delegation of monitoring model. We first need to deliver an estimable version of Eq.3.6, which defines the parent's behavior when picking the location of monitoring units. We assume $\pi_{ik|j}$ to be the same for all parent companies and sum location choices into a variable $M^I_{ikj}$ counting the number of parent companies in country i that delegates to middlemen in country k the monitoring of final subsidiaries in country j. The superscript I specifies we refer to indirect control paths only. The expected value of $M^I_{ikj}$ is then given by:

$$\begin{aligned}\mathbb{E}[M^I_{ikj}] &= \pi_{ik|j} M^I_{ij} \\ &= exp(-\delta_{ik} - \delta_{kj} - C_{ij} + \ln M^I_{ij})\end{aligned} \tag{3.9}$$

where $M^I_{ij}$ counts the total number of indirect control paths connecting a parent in country i to a final subsidiary in country j. In our framework, we conceive both the delegation and monitoring cost as governed by frictions to real-time communication. Yet, to estimate Eq.3.9, we interpret $\delta_{ik}$ and $\delta_{kj}$ as the inverse of a cost, and establish their empirical content to be given by the number of overlapping working hours. Thus, we denote by $wh_{ik}$ and $wh_{kj}$ the number of shared working hours between parent and middleman, and between middleman and final, respectively, and assume them to enter with a positive sign in the following structural gravity specification.

$$\mathbb{E}\left[\frac{M^I_{ikj}}{M^I_{ij}}\right] = exp(\beta^{wh} wh_{ik} + \rho^{wh} wh_{kj} - FE_{ij}) \tag{3.10}$$

Equation 3.10 expresses a triangular gravity for the share of indirect control paths that pass through country k. Thus, the bilateral fixed effect $FE_{ij}$ allows to recover the *multilateral cost of monitoring* $C_{ij}$, which we will use later in a second step of the estimation process. We also add two vectors of standard bilateral controls, $\mathbf{x}_{ik}$ and $\mathbf{x}_{kj}$. $\mathbf{x}$ includes geographic distance, and a set of indicator variables for geographic contiguity, common language, common legal origins, colony dependence and regional trade agreements. We now turn to the final investment decision described in Eq.3.8. As already done before, we let the probability of choosing destination j be constant among parent companies in a given country i. Investment choices are then aggregated into the variable $M^A_{ij}$, where the superscript A indicates we are summing up all the final subsidiaries in j held by parent companies located in i through both direct and indirect control paths. The expression for the expected value of $M_{ij}^{A}$ is

$$\mathbb{E}[M_{ij}^{A}] = exp(-\theta\sqrt{\widehat{C_{ij}}} + FE_i + FE_j) \tag{3.11}$$

where $S_j = \sum_n \frac{m_n}{\sum_n m_n} \exp(-(2\sqrt{bC_{nj}})/\sigma + \mu_n/\sigma)$ and $M_j^A$ stands for the total number of subsidiaries operating in j. The term $S_j$ sums up the average productivity level of competitors from other countries, weighed by the cost they face when monitoring activities in j. Thus, we consider $S_j$ as a measure of the degree of *competition for corporate control* in market j. To estimate Eq.3.8, we let the share of the world's parent companies headquartered in j and their average productivity to be enclosed into a parent's country fixed effect, implying $FE_i = \ln\left(\frac{m_i}{\sum_n m_n}\right) + \frac{\mu_i}{\sigma}$. Fixed effects on j are instead introduced to capture the size and competitiveness of the destination market, $FE_j = \ln M_j - \ln S_j$. With $\theta = \frac{2\sqrt{b}}{\sigma}$, the structural gravity for final investments is given by:

$$\mathbb{E}[M_{ij}^{A}] = exp(-\theta\sqrt{\widehat{C_{ij}}} + FE_i + FE_j) \tag{3.12}$$

## 3.6 Results

We proceed by estimating structural equations 3.10 and 3.12 using our sample of *complex* MNEs. The empirical version of Eq.3.10 is obtained computing the actual share of indirect ownership chains visiting country k and adding two vectors of standard bilateral controls, $\mathbf{x}_{ik}$ and $\mathbf{x}_{kj}$. $\mathbf{x}$ includes geographic distance, and a set of indicator variables for geographic contiguity, common language, common legal origins, colony dependence and regional trade agreements. Thus, we get

$$\frac{M_{ikj}^{I}}{M_{ij}^{I}} = exp(\beta^{wh} wh_{ik} + \rho^{wh} wh_{kj} - \gamma_{ij} + \boldsymbol{\beta'}\mathbf{x}_{ik} + \boldsymbol{\rho'}\mathbf{x}_{kj})\eta_{ikj} \tag{3.13}$$

where $\gamma_{ij}$ stands for bilateral fixed effects between the parent and the final subsidiary locations. Coefficients of bilateral fixed effects yield the vector of *multilateral monitoring costs*, thus, once estimates for $C_{ij}$ are retrieved from Eq.3.13, we sum up the observed number of both direct and indirect investments into $M_{ij}^A$ and obtain the empirical equivalent of Eq. 3.12

$$M_{ij}^A = exp(-\theta\sqrt{\widehat{C_{ij}}} + \gamma_i + \gamma_j)e_{ij} \tag{3.14}$$

where $\gamma_i$ and $\gamma_i$ respectively stand for origin and destination fixed effects. Following Silva and Tenreyro (2006), we use the Poisson Pseudo Maximum Likelihood estimator and report in Table 13 coefficients for each of the two gravity equations. First column shows results for the trilateral gravity equation specified in Eq.3.10, which defines the geographical distribution of middlemen.

We find the ease of monitoring to be relevant for middlemen's location. Increasing by 1 the number of working hours that overlap between the middlemen and the final locations raises the expected share of indirect control paths that pass through k by 10% ($e^{0.098}-1$)[4]. In addition, the number of overlapping hours between parents and middlemen is significantly positive, which implies that a lower cost of delegation encourages the deployment of monitoring units in a given country. Hence, our variables of interest enter the gravity with the expected sign. As assumed in our model, the results confirm the cost of delegation to be less binding than the cost of monitoring. The effect of a decrease in the latter (0.1) is twice the effect of a decrease in the former (0.05). All the other bilateral variables are out-of-model standard controls that do not interfere with the control activity of the parent. These are the traditional predictors commonly found in empirical gravity applications to FDI. We introduce them to capture frictions hindering all the other economic interactions possibly generated by an investment decision. To mention a relevant example, beyond intra-group coordination activities, there might be

[4]Coefficients in a Poisson regression are interpreted as semi-elasticity.

horizontal and vertical integration motives driving the location choice, which, in this case, strongly depends on transportation costs (refer to the theoretical underpinnings of FDI gravity, such as those developed by Kleinert and Toubal (2010) and J. H. Bergstrand and Egger (2007)). Physical distance and proxies for cultural proximity between countries obey the gravity model. Distance has a negative impact which is way stronger in the relationship between middlemen and final subsidiaries, where we find a -17.3 elasticity of the indirect control paths share, against -4.8 observed between parent companies and middlemen. The opposite is observed for the dummy indicating the existence of a regional trade agreement: coefficients are always positive and around 1. The historical and cultural ties a given location has with both the parent and the final subsidiary country foster intermediate investments. The second column of Tab.13 reports estimates of the bilateral gravity for the final investments. Estimates of the vector of multilateral cost indexes $C_{ij}$s are derived from bilateral fixed effects in Eq.3.10. As already mentioned, $\hat{C}_{ij}$ represent the expected cost of monitoring subsidiaries in country j for a parent in country i, and, as largely expected, it affects negatively MNEs investments.

**Table 13:** Results

| **Location:** | **Middlemen** | **Final subsidiaries** |
|---|---|---|
| Dep. var. | $M^I_{ikj}/M^I_{ij}$ | $M^A_{ij}$ |
| **N. of overlapping working hours**$_{ik}$ | **0.051****** | |
| | (0.005) | |
| **N. of overlapping working hours**$_{kj}$ | **0.098****** | |
| | (0.006) | |
| Log distance$_{ik}$ (km) | -0.049*** | |
| | (0.011) | |
| Log distance$_{kj}$ (km) | -0.190*** | |
| | (0.013) | |
| RTA$_{ik}$ | 1.169*** | |
| | (0.026) | |
| RTA$_{kj}$ | 0.907*** | |
| | (0.025) | |
| Language$_{ik}$ | 0.733*** | |
| | (0.030) | |
| Language$_{kj}$ | 0.391*** | |
| | (0.032) | |
| Colony dependence$_{ik}$ | 1.382*** | |
| | (0.048) | |
| Colony dependence$_{kj}$ | 1.585*** | |
| | (0.047) | |
| Legal origins$_{ik}$ | 0.280*** | |
| | (0.027) | |
| Legal origins$_{kj}$ | 0.214*** | |
| | (0.025) | |
| Home$_{ik}$ | 5.317*** | |
| | (0.049) | |
| Home$_{kj}$ | 3.735*** | |
| | (0.054) | |
| $\hat{C}_{ij}$ | | -1.004*** |
| | | (0.090) |
| Observations | 1,288,546 | 7,309 |
| Fixed effects | $i \times j$ | i,j |

Standard errors clustered by origin-destination dyads in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

## 3.7 Robustness checks

We subject our gravity estimates to a set of robustness checks to address two main concerns. First, as we claim that communication motives determine the location of subsidiaries, we need to ensure that coefficients of interest stay significant when controlling for other possible explanations. Fiscal optimization reasons most certainly play a role as well as factor costs minimization. In Table 14 we report some alternative specifications of the baseline gravity in Eq.3.13. As we can see in column (1), gravity results remain almost unaltered when we add differentials in corporate taxation[5] (CT) between origin and destination country (coefficients for the ease of communication both scale up by the same amount). Note that the share of indirect investments passing through country k increases when the tax environment of k is more favorable with respect to both the parent and final investment location. In column (2), we augment the gravity with differentials in the cost of labour[6] (LC) and, again, we do not find any relevant change with respect to estimates in column (1) of Tab. 13. Finally, in column (3), we include an additional proxy for the ease of communication between countries, i.e. the common language index (CLI) by Gurevich et al. (2021). This is an aggregate index of linguistic similarity between populations that accounts for several dimensions related to language, such as translation and interpretation, and, despite having a strong positive impact on investments, does not affect the coefficients of overlapping working hours.

Second, we need to check whether results are confirmed in subsamples of multinational ownership chains defined according to the primary operating industry. Table 15 reports new estimates from the triangular gravity in Eq.3.13 run over ownership chains of parent companies ac-

[5] Differentials are expressed as the ratio between destination and origin profit tax, where the latter is sourced by the World Bank's *Doing Business* database for the year 2019 and measures the total amount of taxes paid by the business as a percentage of commercial profits.

[6] Differentials are expressed as the ratio between destination and origin compensation of employees, where the latter is sourced by the World Bank's *Doing Business* database for the year 2019.

tive in manufacturing, in column (1), and in service (finance and real estate excluded), in column (2). Column (3) reproduces estimates on cases where parent, middleman and final subsidiary all work in the finance sector[7]. In manufacturing, we observe a widening in the gap between the ease of communication coefficients with respect to the baseline results, whereas we observe the opposite for financial companies, where a rise in the effect of sharing office hours between parent and middleman completely closes the gap. In service, coefficients remain stable. It follows that our assumption that delegation cost is lower than the monitoring one is confirmed in the service sample and even strengthened in the manufacturing. At the same time, in financial conglomerates, the ease of communication is equally important amid all companies involved in the ownership chain, and, interestingly, distance in kilometers becomes irrelevant.

[7]A company's sector is identified according to NAICS 2017 classification at the 2-digit aggregation level. We define of finance sector merging "*Finance and Insurance*" (code 52) and "*Real Estate and Rental and Leasing*" (code 53). The service sector encompasses all the other entries related to service.

**Table 14:** Robustness: adding control variables

| **Dep Var.** | $M^I_{ikj}/M^I_{ij}$ | | |
|---|---|---|---|
| **Control for** | Tax differentials | Wage differentials | Common language |
| **N. of overlapping working hours**$_{ik}$ | 0.078*** | 0.063*** | 0.048*** |
| | (0.007) | (0.008) | (0.006) |
| **N. of overlapping working hours**$_{kj}$ | 0.126*** | 0.115*** | 0.097*** |
| | (0.007) | (0.008) | (0.006) |
| $\frac{CT_k}{CT_i}$ | -0.006*** | | |
| | (0.002) | | |
| $\frac{CT_j}{CT_k}$ | 0.008*** | | |
| | (0.000) | | |
| $\frac{LC_k}{LC_i}$ | | -0.844*** | |
| | | (0.033) | |
| $\frac{LC_j}{LC_k}$ | | -0.028 | |
| | | (0.023) | |
| CLI$_{ik}$ | | | 1.792*** |
| | | | (0.057) |
| CLI$_{kj}$ | | | 1.206*** |
| | | | (0.055) |
| Log distance$_{ik}$ | -0.161*** | -0.221*** | -0.014 |
| | (0.013) | (0.015) | (0.011) |
| Log distance$_{kj}$ | -0.228*** | -0.265*** | -0.156*** |
| | (0.016) | (0.018) | (0.013) |
| RTA$_{ik}$ | 1.136*** | 0.920*** | 1.093*** |
| | (0.031) | (0.040) | (0.027) |
| RTA$_{kj}$ | 0.881*** | 0.728*** | 0.835*** |
| | (0.030) | (0.037) | (0.026) |
| $Home_{ik}$ | 5.061*** | 4.203*** | 4.228*** |
| | (0.055) | (0.064) | (0.054) |
| $Home_{kj}$ | 3.716*** | 3.409*** | 3.056*** |
| | (0.064) | (0.068) | (0.056) |
| Language$_{ik}$ | 0.717*** | 0.818*** | |
| | (0.035) | (0.039) | |
| Language$_{kj}$ | 0.347*** | 0.547*** | |
| | (0.037) | (0.042) | |
| Colony dependence$_{ik}$ | 1.530*** | 1.383*** | 1.321*** |
| | (0.051) | (0.053) | (0.048) |
| Colony dependence$_{kj}$ | 1.684*** | 1.347*** | 1.478*** |
| | (0.050) | (0.054) | (0.047) |
| Legal origins$_{ik}$ | 0.199*** | 0.311*** | 0.132*** |
| | (0.030) | (0.034) | (0.028) |
| Legal origins$_{kj}$ | 0.171*** | 0.288*** | 0.122*** |
| | (0.028) | (0.032) | (0.026) |
| Observations | 912,444 | 501,500 | 1,288,546 |
| Fixed effects | $i \times j$ | $i \times j$ | $i \times j$ |

Note1: Standard errors clustered by origin-destination dyads in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Note2: i, k and j stand for parent, middleman and final subsidiary location country, respectively. $CT_k/CT_i$ is the ratio between corporate tax rate in country k and corporate tax rate in country i; the same holds for $CT_j/CT_k$. $LC_k/LC_i$ is the ratio between cost of labour in country k and cost of labour in country i. The same holds for $LC_j/LC_k$.

**Table 15:** Gravity results compared between sectors

| **Dep. var.** | | $M^I_{ikj}/M^I_{ij}$ | |
|---|---|---|---|
| **Sample** | Manufacturing | Service | Finance |
| **N. of overlapping working hours**$_{ik}$ | 0.021*** | 0.041*** | 0.142*** |
| | (0.0075) | (0.007) | (0.022) |
| **N. of overlapping working hours**$_{kj}$ | 0.105*** | 0.096*** | 0.134*** |
| | (0.008) | (0.008) | (0.023) |
| Log distance$_{ik}$ | -0.237*** | -0.117*** | -0.028 |
| | (0.019) | (0.014) | (0.032) |
| Log distance$_{kj}$ | -0.197*** | -0.201*** | -0.030 |
| | (0.020) | (0.016) | (0.034) |
| RTA$_{ik}$ | 0.818*** | 1.064*** | 0.637*** |
| | (0.040) | (0.036) | (0.090) |
| RTA$_{kj}$ | 0.849*** | 0.867*** | 0.668*** |
| | (0.038) | (0.034) | (0.092) |
| $Home_{ik}$ | 4.099*** | 5.360*** | 4.892*** |
| | (0.077) | (0.062) | (0.151) |
| $Home_{kj}$ | 3.281*** | 3.605*** | 4.984*** |
| | (0.080) | (0.071) | (0.160) |
| Language$_{ik}$ | 0.605*** | 1.023*** | 0.613*** |
| | (0.046) | (0.041) | (0.096) |
| Language$_{kj}$ | 0.316*** | 0.449*** | 0.670*** |
| | (0.047) | (0.044) | (0.111) |
| Colony dependence$_{ik}$ | 0.863*** | 1.226*** | 0.940*** |
| | (0.078) | (0.064) | (0.151) |
| Colony dependence$_{kj}$ | 1.236*** | 1.658*** | 1.168*** |
| | (0.074) | (0.060) | (0.156) |
| Legal origins$_{ik}$ | 0.244*** | 0.206*** | 0.473*** |
| | (0.038) | (0.036) | (0.094) |
| Legal origins$_{kj}$ | 0.303*** | 0.184*** | 0.234** |
| | (0.037) | (0.033) | (0.097) |
| Observations | 464,032 | 712,212 | 127,599 |
| Fixed effects | $i \times j$ | $i \times j$ | $i \times j$ |

Note 1: Standard errors clustered by origin-destination dyads in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).
Note 2: Column (1) and (2) report gravity results for the subsample of indirect ownership chains held by parent companies operating in the manufacturing and service (finance excluded) sectors, respectively. Coefficients in column (3) refer to parent-middleman-final combinations where all subjects belong to the finance sector. Sectors are defined according to the NAICS 2017 classification at the 2-digit level.

To conclude, Table 16 presents the estimates of the triangular gravity equation on subsamples of ownership chains in which the middleman is located in countries classified as tax havens by Hines Jr and Rice (1994) and Hines Jr (2010). In column (2), where the first issued academic list of tax havens, encompassing around 40 jurisdictions, is used, the ease of communication does not remain significant between the parent company and the middleman. This indicates that when the middleman is based in a tax haven, it is the only entity incurring communication costs. In contrast, the coefficients related to overlapping working hours are both significantly positive in column (1), which uses the updated list by Hines Jr (2010) that extends the number of countries to 52.

**Table 16:** When a middleman is in a Tax Haven

| | (1) | (2) |
|---|---|---|
| Tax Havens List: | Hines Jr, 2010 | Hines Jr and Rice, 1994 |
| **N. of overlapping working hours**$_{ik}$ | 0.0262*** | -0.0150 |
| | (0.0101) | (0.0125) |
| **N. of overlapping working hours**$_{kj}$ | 0.0808*** | 0.0631*** |
| | (0.0106) | (0.0131) |
| Log distance$_{ik}$ | -0.167*** | -0.192*** |
| | (0.0257) | (0.0323) |
| Log distance$_{kj}$ | -0.311*** | -0.340*** |
| | (0.0289) | (0.0376) |
| RTA$_{ik}$ | 1.207*** | 1.108*** |
| | (0.0464) | (0.0534) |
| RTA$_{kj}$ | 1.023*** | 0.862*** |
| | (0.0507) | (0.0580) |
| $Home_{ik}$ | 2.743*** | 2.713*** |
| | (0.135) | (0.163) |
| $Home_{kj}$ | 2.037*** | 1.837*** |
| | (0.152) | (0.196) |
| Language$_{ik}$ | -0.279*** | -0.00376 |
| | (0.0491) | (0.0611) |
| Language$_{kj}$ | -0.230*** | -0.0657 |
| | (0.0555) | (0.0673) |
| Colony dependence$_{ik}$ | 0.491*** | 0.619*** |
| | (0.122) | (0.231) |
| Colony dependence$_{kj}$ | -0.0447 | 0.0898 |
| | (0.157) | (0.306) |
| Legal origins$_{ik}$ | 0.222*** | 0.279*** |
| | (0.0414) | (0.0495) |
| Legal origins$_{kj}$ | 0.221*** | 0.198*** |
| | (0.0384) | (0.0476) |
| Observations | 175,155 | 120,676 |
| Fixed effects | $i \times j$ | $i \times j$ |

Note 1: Standard errors clustered by origin-destination dyads in parentheses (*** p$<$0.01, ** p$<$0.05, * p$<$0.1).
Note 2: The table reports gravity results from Eq.3.13 for the subsample of indirect ownership chains where at least one middleman is located in a tax haven. In column (1) the tax haven list is defined according to Hines Jr, 2010. In column (2) the tax haven list is defined according to Hines Jr and Rice, 1994.

## 3.8 Conclusions

We analyse the importance of coordination of production in shaping the geography of corporate control networks, identifying the ability of communicating in real time as a driver for the location of subsidiaries along ownership chains. Thanks to a more sophisticated approach to MNE's investments data, we manage to account for the position of subsidiaries along ownership chains and collect new insights on location determinants. We find that the ease of communication is an important driver that shapes trajectories of ownership in a multinational enterprise, although its impact is heterogeneous along ownership chains. At a preliminary level, we observe that the location of an MNE's investments is not affected by the ease of communication with the parent company, but rather by the need to exchange information in real-time with intermediate subsidiaries inside the corporate boundaries. On top of that, the promoting effect of an easier communication between intermediate and final subsidiaries is actually intensified the more difficult it is for a parent to communicate with a final subsidiary. Moreover, we observe that intermediate investments show an unexplained divergence in the country-level determinants of location with respect to other subsidiaries. Motivated by these findings, we adapt the Head and Ries (2008) model of corporate control competition to allow for indirect control paths and provide theoretical underpinnings to a system of gravity equations explaining the geographic distributions of both intermediate and final subsidiaries. We propose a delegation of monitoring framework, where parent companies willing to supervise their subsidiaries must shift control to third companies sustaining a cost. We deploy data on worldwide MNEs' corporate control networks to estimate structural parameters. We confirm our model predictions that a decrease in delegation and monitoring costs discourages middleman location. Increasing the ease of communication between middlemen and final subsidiaries reduces the expected share of indirect control paths passing through a given country by 10%. This value is twice the effect we find between parents and middlemen. This supports our model assumption claiming the cost of delegation to be less binding than the cost of monitoring for a parent company. We derive and estimate a multilateral cost of control, i.e. a bilateral index capturing the expected cost for a parent company to monitor a remote target in a given location. As predicted by our model, we find the expected cost of monitoring to negatively affect MNEs investments.

# Chapter 4

# The survival of foreign affiliates: a multi-level analysis

*This chapter is based on the paper "The survival of foreign affiliates: a multi-level analysis" in collaboration with Giorgio Ricchiuti and Margherita Velucchi (Miricola, Ricchiuti, and Velucchi, 2024).*

## 4.1 Introduction

A substantial body of research has been dedicated to understanding the underlying motives driving multinational corporations' engagement in foreign direct investment (FDI) activities. Four primary drivers have emerged as key determinants of FDI location, namely the pursuit of scarce resources in the home economy, the expansion into new markets, the enhancement of production efficiency, and the acquisition of novel technological capabilities. (Dunning, 1996). In addition to these considerations, the capacity of the host economy to foster a business-friendly environment is of significant consequence for the strategic decision-making processes of multinational corporations. (Lim, 2008; Hebous, Kher, and Tran, 2020). It is in the interest of the host economy to provide adequate institutions with the objective of attracting and promoting FDI. Most countries, irrespective of their level of economic development, engage in competition to attract FDI and subsequently allocate resources in a manner that is conducive to this objective. Multinational enterprises (MNEs) have traditionally been the subject of policy attention on the grounds that they contribute to economic growth and employment by creating new jobs, making new investments, and developing new technologies. (Markusen, 1984; Markusen and Anthony J Venables, 1999; Javorcik, 2004; Keller and Yeaple, 2009; Poole, 2013). Moreover, the economic literature has showed that inward foreign investment has the potential to enhance the productivity of domestic firms (Javorcik, 2004; Keller and Yeaple, 2009).

Nevertheless, the importance of attracting FDI extends beyond the immediate economic effects, as the most substantial and enduring benefits originate from the establishment of long-term relationships. In other words, the realisation of positive spillovers is a process that, in a reasonable estimation, will unfold over the long term. (Echandi, Nimac, and Chun, 2019; Potter, 2002). Consequently, the length of time a foreign investor remain in a market becomes of great importance as conditioning the full realization of FDI beneficial effects. Indeed, the FDI definitions provided by both the OECD[1] and the IMF[2] emphasize its long-term nature. Specifically, these definitions describe FDI as involving a *long-term* relationship and reflecting a *lasting interest*, highlighting the importance of sustained engagement over time. It has been highlighted that encouraging a long-term stay in a market and reinvest is equally important as attracting foreign investors (Echandi, Nimac, and Chun, 2019). In 2019, the World Bank issues a report focusing on how MNEs decision to stay or expand their FDI projects in developing countries has been affected by government conduct, and highlights that the most common reason for FDI withdrawals was the lack of transparency and predictability in deal-

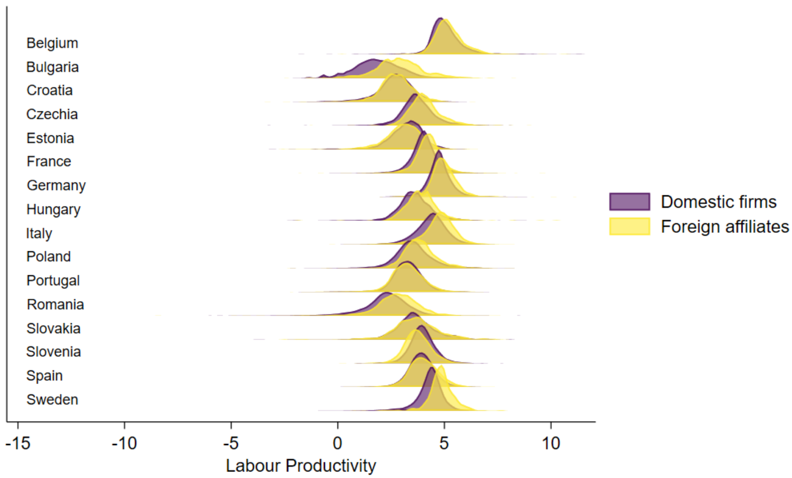
[1] OECD, Detailed Benchmark Definition of Foreign Direct Investment, third edition (OECD, 1996)

[2] International Monetary Fund, Balance of Payments Manual, fifth edition (IMF, 1993)

ing with public agencies, along with abrupt adverse regulatory changes.

Although previous studies have established the expectation that foreign direct investments (FDI) have a positive impact on the host economy, there is concern that dependence on foreign multinationals may pose risks, as these firms tend to be less integrated into the local economy and may be more susceptible to withdrawing their operations rapidly Bernard and Sjoholm, 2003. On the other hand, amidst the debate about the impact of their presence on the host economy, it has been widely demonstrated that firms that participate in international activities, whether through exports or foreign direct investment (FDI), exhibit several key differences from purely domestic firms, including in terms of productivity, wages, and workers' skill (Mayer and G. Ottaviano, 2007). Indeed, in most European Union countries, as illustrated in Figure 13, multinational companies show higher productivity levels compared to domestic firms. This productivity advantage is often attributed to selection mechanisms described in the economic literature, which argue that only the most efficient and competitive firms are able to operate profitably in foreign markets. Furthermore, this selection process suggests that international engagement not only filters out less productive firms but also incentives those who participate to enhance their operational efficiencies to remain competitive globally.

**Figure 13:** Distribution of firm-level productivity by country




Note: For each country of the European Union, the distribution of firm-level labor productivity of foreign affiliates and domestic firms, respectively. Labor productivity is obtained as the ratio between value added and number of employees. Values reported in the graph refer to the 2005-2021 time period.

We focus on the survival probability of foreign affiliates based within the European Union, analyzing those factors that potentially facilitate a long-term stay. Specifically, we assess both firm-level and contextual features, both at the regional and country level, on the survival of foreign affiliates. As we aim to evaluate how the geographic context a foreign affiliate is plunged into affects her survival probabilities, we identify our model of choice in a multilevel survival framework. Hierarchical models are useful to account and explicitly model the correlation between study units within the same cluster, such as foreign affiliates in countries and regions. Given the strong territorial component driving business demography (OECD, 2017), the use of a multilevel modeling approach is particularly suitable for firm survival analysis. Our analysis begins by focusing on local market characteristics at the regional level and then broadens to include national factors. In both cases, our aim is to include the most examined factors in the literature that explain inward FDI at the local level, and then assess their impact on the duration of foreign firms in a local market. We analyse almost two decades of important transformations for the global economy, from 2005 to 2021, and we employ Orbis longitudinal data for around 100,000 thousand firms. In the first place, we find that the quality of institutions has a significantly positive impact on the survival of foreign-owned firms in Europe. From our findings, it emerges that the relevance of government quality is manifested both directly and also through the mediation effect that coordinates other determinants of FDI, such as annual value-added growth in the region. However, within an empirical framework accounting for both between-country and within-country variability, it emerges that the factor leading to a longer duration of foreign investments in the market is the quality of institutions evaluated at the national level, rather than at the regional level. However, investments in R&D and workforce quality at the regional level negatively impact the survival of foreign subsidiaries, indicating that these factors do not support long-term presence. This finding can be interpreted in several ways. In our view, it may be attributed to the fact that an environment that supports research and produces workers in scientific fields makes all firms in the market, including domestic ones, more competitive, thereby reducing the survival probability of foreign-owned companies. In contrast, we find that financial development at the national level has an outstanding impact on the survival of foreign affiliates, reducing substantially the risk of exit.

In light of previous considerations, our paper makes two contributions to the empirical literature on the impact of location characteristics on foreign multinational activity. On the one hand, the survival of overseas subsidiaries can be an important performance indicator for local economic policies. On the other hand, gaining new insights on this topic might help to foster a friendly environment for sustained foreign direct investments and pursue local economic prosperity. The remainder of the paper is organized as follows. In Section 4.2, we present an overview of the pertaining literature. In Section 4.3, we introduce data and motivating evidence. Section 4.4 illustrates the econometric model, and section 4.6 concludes.

## 4.2 Literature review

Location advantages are a fundamental pillar that influences an enterprise's propensity to engage in international production (Dunning, 1980). Four main motives have been identified for locating production abroad: seeking unavailable resources in their home economy, accessing new markets, improving production efficiency, and acquiring new technological capabilities (Dunning, 1996). To comprehend the impact of contextual factors on the foreign operations of multinational enterprises, it is crucial to examine the motivations driving a company to engage in foreign direct investment (FDI). In theoretical models for FDI, two motives are generally considered: a firm might choose horizontal FDI to save on transport costs by locating production in the destination market, providing an alternative to exports. Alternatively, vertical FDI occurs when a firm leverages comparative advantages across countries by locating different stages of production abroad, leading to intra-firm trade between the parent company and its affiliates (Brainard, 1993; Helpman, Melitz, and Yeaple, 2004; J. H. Bergstrand and Egger, 2007; Kleinert and Toubal, 2010).

Several studies in different fields have identified the potential factors influencing the attractiveness of a destination for FDI. The most empirically investigated factors determining a country's attractiveness are its level of technology, the quality of the workforce, the financial development (Desbordes and Wei, 2017) and the quality of institutions (Wei, 2000; Bénassy-Quéré, Coupet, and Mayer, 2007; Daude and Stein, 2007; Dellis, Sondermann, and Vansteenkiste, 2017). Wei, 2000 and Mutti and Grubert, 2004 also look at the effect of taxation. Locations with poor-quality institutions are generally considered less attractive for FDI, as companies may face additional costs due to negative aspects of the institutional framework, such as corruption (Wei, 2000), and increased investment risks from uncertainties related to inefficient governance or weak enforcement of property rights. According to Costinot, 2009, strong institutions and a more educated workforce are complementary sources of comparative advantage in complex industries, as high-quality institutions increase the likelihood of contract enforcement. Zhao, 2006 observes that multinational R&D efforts are increasingly focused on countries with weak intellectual property rights and suggests that firms may use internal organizational structures to compensate for the shortcomings of weak external institutions.

Within our research, we are also interested in understanding the factors that influence the duration of foreign investors' presence in a region. This concept, known as FDI retention, refers to the ability of a host region to maintain foreign capital once it has been invested. In the economic literature, as far as we know, there is still much work to be done on the examination of FDI retention. Existing contributions in this field can be categorized into two main areas: those that investigate factors that affect the survival of foreign investors and those that analyze decisions related to divestment and expansion. Tang and Beer, 2022 specifically address locational advantages to retain FDI. In particular, they investigate whether the regional innovation environment has an impact on FDI retention in China, where the latter is measured through a survival analysis conducted on foreign ventures by MNEs. They find both the regional supply of technicians and the flexibility of intellectual property to positively affect the permanence of MNEs in the local market, although the second aspect is much more relevant than the first for MNEs with high expenditure in R&D. In the international business field, Dhanaraj and Beamish, 2009 examine how the institutional environment, measured as political openness, impacts the survival of foreign subsidiaries and find that it reduces their mortality rate. Their focus on institutions stems from the investment risks associated with regulatory policies in a country. Desai, Foley, and Hines Jr, 2006 and Bilir, Chor, and Manova, 2019 find that the expansion of the activities of U.S. foreign affiliates is fostered in countries where external finance is readily available and relatively cheaper. Desai, Foley, and Forbes, 2008 finds that, unlike local firms, affiliates of multinationals expand their activities after depreciation.

More in general, our work is related to the literature on firm survival analysis. Many contributions analyse how firm-level characteristics, such as size, productivity, innovation and technological level, affect firms' survival (Agarwal and Audretsch, 2001). The positive effect of size and productivity has gathered a large consensus in literature, whereas there is definitely divergence on the role of innovation activity, both empirically and theoretically, with predictions differing according to the model (Ugur and Vivarelli, 2021). Indeed, the effect of innovation depends on several other factors, such as the technological intensity of the sector and the type of innovation. Other works empirically investigate the relationship between firm survival rates and ownership structures. Giovannetti, Ricchiuti, and Velucchi, 2011 find that Italian firms involved in export activities and foreign investments exhibit a higher risk to exit the market as they face a heightened competition in international markets. Ferragina, Pittiglio, and Reganati, 2012 observe that Italian firms owned by foreign MNEs are more likely to exit than domestic ones and interpret this finding in terms of *different degree of persistence* between foreign and domestic: the global networks established by multinational enterprises (MNEs) lead to promptly adjust to adverse shocks in a host economy by relocating their production. It is worth to mention a more recent literature focusing exclusively on determinants of foreign affiliates survival and introducing bilateral covariates to account for the distance between affiliate and parent locations (Arte and Larimo, 2023). In the same line, Giovannetti, Ricchiuti, and Velucchi, 2017 examine how firm characteristics influence affiliate survival, focusing on size and technological relationships. Findings show that larger affiliates of large investors have a competitive advantage and are more likely to survive. Network ties and technological gaps between affiliates and investors also impact survival probability. Bernard and Sjoholm, 2003's study finds that, in the Indonesian manufacturing sector, foreign-owned plants are less likely to close down compared to domestically-owned plants. However, this higher survival rate is attributed to the larger size and higher productivity of foreign plants, rather than the foreign ownership itself. When controlling for size and productivity, foreign ownership is actually linked to an increased probability of closure. The authors attribute this evidence to the fact that multinational enterprises have higher flexibility in adjusting labor on the extensive margin, i.e. through plant shutdowns. In line with this findings, Bandick, 2010 observes for the swedish manufacturing sector that foreign MNE plants are more likely to close down than non-MNE plants, also when controlling for other plant-level factors affecting survival. Furthermore, foreign market presence negatively impacts the survival rate of plants owned by domestic firms that do not engage in any international activities.

## 4.3 Data

We collect a comprehensive set of firm-level, region-level (NUTS2) and country-level variables. We source firm-level information from Orbis, the commercial database compiled by the Bureau van Dijk that collects balance sheets and income statements from national public registries of worldwide countries. We focus on EU27 manufacturing firms and cover a time period of sixteen years, from 2005 to 2021.
We define foreign-owned companies according to the nationality of the Global Ultimate Owner (GUO) as reported by Orbis[3]. All EU based companies linked to a GUO incorporated in a foreign country, whether intra or extra-EU, are included in the sample, amounting to a total of almost 80,000 enterprises active at least one year over the observed time period[4].

[3]Note that we are not able to tell wheather firms in the sample represent greenfield or brownfield investments, and, most importantly, we do not observe the acquisition year.

[4]Unfortunately, we do not have entry-exit data for any foreign affiliate in Ireland, which is consequently excluded from the analysis.

We source the time series for sales, cost of materials, number of employees and tangible fixed assets[5], for which we report some general statistics in Table 17. We obtain labour productivity as the ratio between valued added and number of employees, and capital intensity as the ratio between tangible fixed assets and number of employees[6].

**Table 17:** Financial variables statistics for foreign-owned companies, 2005-2021

| **Variable**: | **Mean** | **SD** | **p1** | **p99** |
|---|---|---|---|---|
| Sales | 32,050.22 | 426,871.20 | 0.00 | 456,990.10 |
| Tangible Fixed Assets | 6,592.20 | 71,827.56 | 0.00 | 105,272.00 |
| Material Costs | 21,406.75 | 401,641.10 | 0.22 | 287,837.00 |
| Value Added | 11,315.87 | 101,057.60 | 1.54 | 167,609.40 |
| Number of Employees | 101 | 575 | 0 | 1342 |

The table presents, in column order, the mean, standard deviation, as well as the 1st and 99th percentiles of the distribution of financial variables used in our analysis. All values are reported in thousands of Euros.

Orbis usefully provides information on incorporation date, firm's status and status date, which allows to identify market entry and exit and define companies' life-span in years. Our sample comprises all foreign-owned enterprises that were active for at least one year during the 2005–2021 period. This includes both newly established firms, which entered the market in 2005 or at any time during the observation period, as well as incumbent firms that entered the market prior to 2005, both of which are considered in the survival analysis. Unfortunately, our duration data suffer from severe right censoring since only 1160 firms out of the total exit the market during the observed period. To address this concern, we reproduce and confirm in the Appendix C.0.1 some well-established stylized facts to ascertain the consistency of our sample.

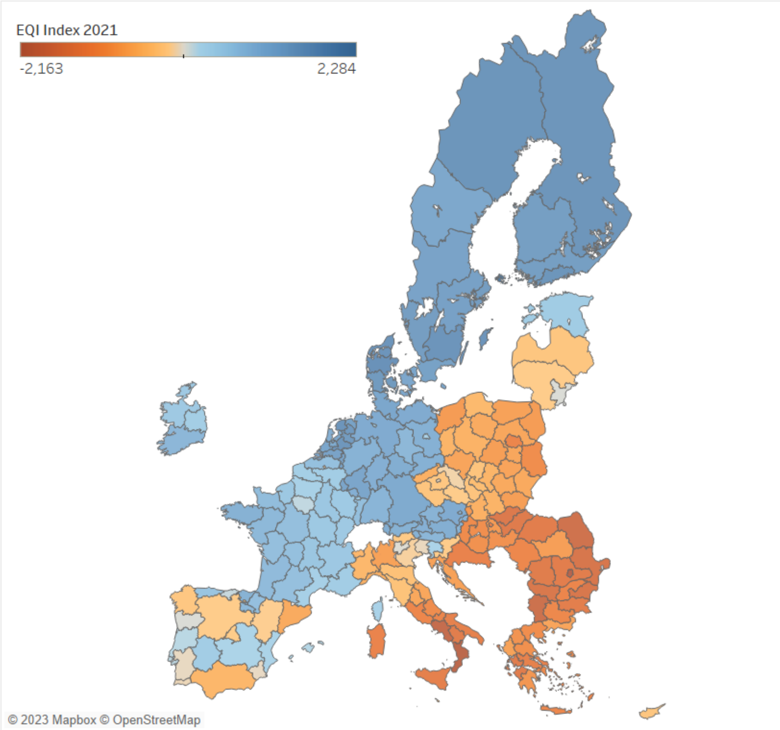
[5]Due to missing data among firm-level variables, some countries (Malta, Cyprus, Lithuania, Greece, and Denmark) are entirely excluded from the sample.

[6]In order to compute labour productivity and capital intensity, both value added and tangible fixed assets have been deflated using the Eurostat producer price indexes

At the NUTS2 level, we use the European Quality of Government Index (EQI) Charron et al., 2022. This index focuses on both perceptions and experiences with public sector corruption, along with the extent to which citizens believe various public sector services are impartially allocated and of good quality in the EU [7].Fig. 14 shows the most recent estimates of the EQI index. EU average is normalized to zero, whereas negative and positive values are, respectively, below and above the EU average. Red (blue) NUTS2 region report a negative (positive) value for the 2021 EQI index.

[7] The EQI index was first published in 2010, and it is issued every three years. To ensure consistency between the three-year index and the panel analysis, which features annual variability (as do all other variables in our study), EQI values are held constant for the three years preceding the measurement. For instance, the values for 2021 are also applied to the years 2019 and 2020.

**Figure 14:** The European Quality of Institution Index for 2021




Note: The figure shows the most recent estimates of the EQI index. EU average is normalized to zero, whereas negative and positive values are, respectively, below and above the EU average. Red (blue) NUTS2 region report a negative (positive) value for the 2021 EQI index.

In order to account for the availability of qualified labour and a favorable environment for technological development, we source from Eurostat NUTS2-level values for human resources employed in science and technology as a percentage of total labour force (HRSTO) and gross domestic expenditure on R&D in all economic sectors expressed as percentage of gross domestic product (GERD)[8]. R&D investments serve as a crucial de-

[8]In Appendix C.0.2 we provide some more statistics displaying the geographical distri-

terminant of a region's propensity to create a favorable environment for scientific research. Regions with higher R&D allocations are expected to exhibit a more robust infrastructure for scientific inquiry, ultimately influencing the trajectory of technological development within those areas. We also use the annual growth rate of gross value added, which tells us whether a certain region has experienced economic growth compared to the previous year.

At the country level, we use the institutional variables developed by Kaufmann, Kraay, and Zoido, 1999[9]. They construct six indicators, each capturing a different dimension of governance, based on information collected from cross-country surveys and covering from 1996 to 2022 worldwide countries. The first two indicators, *Voice and Accountability* and *Political Stability and Lack of Violence*, describe the quality of the process of selecting and replacing authorities (for instance, the degree at which individuals can control government actions). *Government efficiency* and *Regulatory Quality* reflect the government's capacity to design and implement policies. *Rule of Law* measures perceptions about contract enforceability, as well as predictability of the judiciary, while *Control of Corruption* captures the extent to which public power is exercised for private gain. *Control of corruption* and *Rule of Law* are both highly correlated with the other indicators. This correlation might induce serious problems of multicollinearity, which we avoid by excluding these last two measures from the analysis. This choice is also driven by our particular interest in isolating the effects of political risk and legal certainty, which are the most investigated aspects when studying what leads multinational corporations to divest from a specific region. The World Bank also provides, within the World Development Indicators database, the time series of employee compensation for countries worldwide, which we usefully adopt as a measure of factor cost. We use the Financial Development Index provided by the International Monetary Fund (IMF), which ranks countries

bution of NUTS2-level variables.

[9]The database is available at `http://info.worldbank.org/governance/wgi/home`

based on the efficiency, depth, and access of both financial markets and institutions. This variable is intended to capture the ease of access to external financing for firms.

## 4.4 Econometric model

In the study of firm survival, the variable of interest is the duration a company stays active in the market, measured in time units from market entry to market exit. The objective is to estimate the probability that a company surviving until period t, exits the market in period t+1, based on a sample of firm life spans. In our case, durations are expressed as the number of years between the incorporation date and the exit event, whether it is due to insolvency, corporate transactions, or any other reason. The exit event does not occur during the observation period for most companies, as the latter survive beyond the observable time window. This causes the duration variable to be right-censored at the last year of the analysis. Moreover, in our dataset, firms may enter at any point in time, either during or before the observation period.

The Cox proportional hazards model accounts for the data censoring issue described above and it is generally formulated as follows:

$$h_i(t) = h_0(t)exp(X_i\beta)$$

where $h_i(t)$ is the probability that firm i exit at time t given that it has survived in $t-1$, with $i = 1, ..., N$ and $t = 1, ..., T$. $h_0(t)$ represents the baseline hazard function, e.g. the hazard rate when all of the covariates are set to zero, $X$ is a set of firm-level explanatory variables and $\beta$ represents the set of parameters to be estimated. As we are working with panel data and our model features time-varying regressors, we allow the baseline hazard to vary by year.

Moreover, our data are hierarchically structured with firms nested within increasingly aggregated geographic units. We are interested in a survival analysis that, while assessing the impact of contextual features, accounts for the hierarchical structure of data, whereby companies can be grouped by regions at the lower level and by countries at the higher level. We accordingly apply a multilevel survival model, also referred to as random intercept model. The multilevel approach allows one to consider within the model that the data are hierarchically structured by assuming that the error in the regression is structured according to the known hierarchy. In a standard regression framework, this equals passing from this

$$y_{ij} = \alpha + \gamma x_{ij} + e_{ij} \tag{4.1}$$

where i observations, with $i = 1, ..., N$ are nested into $j = 1, ..., M$ groups, to this

$$y_{ij} = \alpha + \gamma x_{ij} + v_{ij} + u_j \tag{4.2}$$

where the error has been partitioned into two components corresponding to the levels of the hierarchy. $u_j$ are also defined *cluster effects* and incorporate the unobserved cluster characteristics affecting the outcome of the regression and inducing correlation between the observed outcomes within the same cluster. The residual variance is consequently partitioned into within-cluster ($\sigma_{ij}$) and between-cluster ($\sigma_j$). This allows generating the correct standard errors and properly weighting the variation between and within to generate the estimated coefficients based on both $\sigma_{ij}$ and $\sigma_j$. Thi method extends to settings with more than two levels in the data hierarchy.

Returning to our specific context, we employ a multilevel proportional-hazard model to allow for the estimation of both firm-specific and regional-level effects. Assuming a two-tiered nesting structure, the survival model is defined as:

$$h_{ij}(t) = h_0(t) exp(X_{ij}\beta + Z_j\delta) \tag{4.3}$$

where i and j refer to firms and NUTS2 areas, respectively and $h_0(t)$

denotes the baseline hazard function. $X_{ij}$ denotes the set of observable covariates at the firm-level, whereas $Z_j$ represent a set of covariates at the NUTS2 level.

## 4.5 Results

We specify a multi-level model to evaluate the effect of *contextual* factors that potentially foster an environment conducive to attracting foreign businesses. As a start, we examine whether certain regional (NUTS2-level) characteristics help sustain the long-term presence of foreign-owned firms in the territory. In this regard, based on the existing literature on factors that enhance FDI activity (both in terms of quantity and performance), we look at the effect of high-quality institutions, a highly educated workforce, R&D investments, and the short-term economic growth. In order to account for the availability of qualified labour and a favorable environment for technological development, we source from Eurostat NUTS2-level values for human resources employed in science and technology as a percentage of total labour force (HRSTO) and gross domestic expenditure on R&D in all economic sectors expressed as percentage of gross domestic product (GDP) (GERD).

In Table 18, we report the hazard ratios obtained from the mixed-effects Cox model, where we also control for an arrow of firm-level covariates. We have firm size measured by a time-invariant categorical directly provided by Orbis[10]. Labour productivity is calculated by dividing value added by the number of employees, while capital intensity is obtained as the ration between tangible fixed assets and number of employees. We then include the technological category of the sector in which the company operates leveraging the Eurostat classification, which divides NACE Rev.2 3-digit level sectors into High, Medium-high, Medium-low, and Low tech[11]. For comparison purposes, we show in Column (1) re-

[10]This consists of four categories (namely *Very large companies, Large companies, Medium-sized companies, Small companies*) to which firms are assigned based on a list of criteria based on operating revenues, total assets, and number of employees.

[11]Further details on the High-tech classification of manufacturing industries can be

sults from a simple Cox regression. A large variation is seen across regions starting from Column (2), amounting to 14.79 when considering the whole sample of firms, which could have biased results if left unaddressed.

As seen in each column of Table 18, firm-level controls diminish the risk of exit for foreign affiliates[12]. Bigger and more productive firms are more likely to survive on the market, as well as capital-intensive firms. The greater advantage in terms of survival is found between high-tech firms and low-tech: firms operating in low tech industries have an exit probability more than two times bigger than firms in high-tech sectors. These results are in line with findings from the empirical literature on firm survival. Indeed, a negative relationship is systematically found between size and exit risk, most probably because larger companies are more likely to operate near the minimum efficient scale and benefit from easier access to capital markets and skilled labour (Jovanovic, 1982; Ericson and Pakes, 1995; Audretsch and Mahmood, 1995). Moreover, literature suggests lower exit rates for more productive firms (Javorcik, 2004; Hopenhayn, 1992) and firms with higher capital-labour ratios. The latter instance could be attributed to the fact that firms with elevated capital-to-labor ratios may experience a lower ratio between variable and fixed costs (Doms, Dunne, and Roberts, 1995).

found at https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries

[12] All the tables in this section present hazard ratios, which are the exponentiated $\hat{\beta}$ values estimated by the survival model. These ratios show how the hazard (i.e., the probability of firm exit occurring, given that it has not happened until that point in time) is multiplied when the covariate changes by one unit. A hazard ratio greater than 1 suggests that the covariate increases the risk, while a ratio less than 1 implies that the covariate decreases the risk of exit.

**Table 18:** Two-level Cox model - Hazard ratios

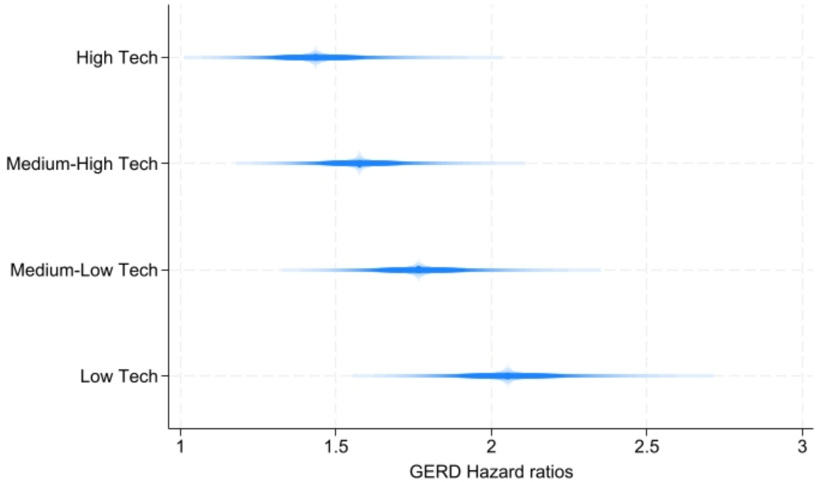
| Model: | **Cox** | **Multi-level Cox** | | |
|---|---|---|---|---|
| Sample: | All | All | High EQI | Low EQI |
| | (1) | (2) | (3) | (4) |
| **Firm-level Covariates:** | | | | |
| Size Category | 0.783*** | 0.662*** | 0.854** | 0.411*** |
| | (0.0340) | (0.0339) | (0.0537) | (0.0374) |
| $\mathrm{LP}_{t-1}$ | 0.678*** | 0.733*** | 0.738*** | 0.740*** |
| | (0.0137) | (0.0169) | (0.0209) | (0.0296) |
| Capital Intensity$_{t-1}$ | 0.811*** | 0.855*** | 0.825*** | 0.942** |
| | (0.0120) | (0.0131) | (0.0144) | (0.0282) |
| Low Tech | 2.229*** | 2.352*** | 2.385*** | 2.052** |
| | (0.452) | (0.483) | (0.625) | (0.683) |
| Medium-low Tech | 1.251 | 1.590** | 1.572* | 1.488 |
| | (0.261) | (0.331) | (0.417) | (0.502) |
| Medium-high Tech | 1.093 | 1.210 | 1.178 | 1.244 |
| | (0.232) | (0.258) | (0.318) | (0.432) |
| **NUTS2-level Covariates:** | | | | |
| GVA Growth | 0.941*** | 0.966*** | 0.957*** | 0.978* |
| | (0.00583) | (0.00699) | (0.00886) | (0.0114) |
| GERD | 1.249*** | 1.810*** | 1.745*** | 2.164*** |
| | (0.0589) | (0.196) | (0.223) | (0.542) |
| HRSTO | 1.031*** | 1.109*** | 1.113*** | 1.087*** |
| | (0.00487) | (0.00853) | (0.00967) | (0.0215) |
| EQI | 0.881** | 0.564*** | | |
| | (0.0442) | (0.0910) | | |
| **Variance of the frailty term** | | | | |
| NUTS2-level | | 14.79*** | 42.70*** | 4.702*** |
| | | (6.823) | (36.80) | (2.053) |
| Observations | 737,520 | 737,520 | 421,903 | 315,617 |
| Number of groups | No | 207 | 124 | 83 |

Note: Standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Firm-level variables are in log-levels. $\mathrm{LP}_{t-1}$ stands for the first lag of firm-level labour productivity. *Size category* is measured by a time-invariant categorical dividing firms into *Very large companies, Large companies, Medium-sized companies* or *Small companies*. The technological category of the sector in which the company operates is included with *High tech* firms being the omitted category. *GVA Growth* stands for the annual percentual variation of gross value added in the region. *EQI* stands for European Quality of Government Index. *GERD* stands for gross domestic expenditure on R&D in all economic sectors expressed as percentage of gross domestic product.

We now focus on the effect of regional characteristics. In column (2) we estimate the effect of NUTS2-level characteristics based on our full sample of foreign affiliates. The hazard ratio for the yearly growth rate of gross value added is lower than one, indicating that foreign-owned companies have a higher probability of surviving in a market that experienced economic growth with respect to the previous year. The same is observed for the quality of government index, which plays a prominent role. Indeed, a one-unit rise in the EQI index leads to a decrease in the exit risk by $44\%$[13]. Foreign affiliates stay longer in regions with a higher quality of institutions. We find, however, that both expenditures on R&D and the share of human resources absorbed by highly technological sectors increase the risk of exit from the market for foreign affiliates. A possible explanation for this is that in regions where larger resources are allocated to research activities and high-tech sectors are larger, there is a heightened level of competition. In other words, domestic companies are more competitive. Another factor that could help explain why investments in research do not represent a positive element for long-term presence might stem from an intrinsic problem with European investments in R&D. Indeed, not all R&D investments have the same potential to lead to strategic innovations, which are crucial for attracting and retaining foreign capital. A recent report from the European Policy Analysis Group (Fuest et al., 2024) strongly questions the quality of European efforts to promote innovation, drawing a comparison with the American model. First, R&D spending appears to be concentrated in the wrong sectors, namely mid-tech industries, rather than high-tech sectors, where investment has the potential to achieve a strategic advantage. It is also highlighted that while public sector R&D spending is currently at the same level as a key competitor like the USA, private sector spending is around the half of the American benchmark. Public spending from European programs is also considered problematic, as only a marginal share is allocated to breakthrough innovation. Instead, priority is given to projects with immediate commercial applications, often at the expense of their potential to drive disruptive innovation. Consequently, the focus remains largely on incremental improvements to existing technologies, rather than on industries with greater potential for radical innovation.

[13]In other words, a one-unit rise in the EQI index multiplies the hazard, i.e. the conditional probability of market exit, by $0.564$.

**Figure 15:** The effect of R&D investments according to technological classification of sectors




Note: The figure shows the hazard ratios of the GERD variable estimated using the specification reported in column 2 of Table 18. In the same model, an interaction between the GERD variable and a categorical variable indicating the technological classification of the sector to which the firm belongs is introduced.

Using the same specification as in column 2 of Table 18, we assess whether the effect of the GERD variable varies according to the technological classification of the sector to which the firm belongs. To do this, we introduce an interaction between the GERD variable and a categorical variable indicating whether the firm operates in a high tech, medium-high tech, medium-low tech or low tech sector. The hazard ratios of GERD by technological sector are shown in Figure 15.

Regional governance is an important factor that deserves further investigations. In particular, we are interested in how the behaviour of other variables is conditioned by deficient institutions. We thus proceed splitting the sample into two set of NUTS2 areas defined according to the

EQI index. This also allows gathering some additional insights into the duality observed in Figure 14 between regions with good and bad institutions. Column (3) and (4) report the same specification run on the subsample of firms located in NUTS2 areas lying above and below the average value, respectively. By comparing the two columns, we note that firm size has a greater relevance in preventing the risk of exit in regions with a low quality of institutions. Another interesting element is that the positive effect of the growth rate of regional value added is less significant. Note that *GVA Growth* is the only other regional variable, besides *EQI*, that has a positive effect on survival, albeit slightly below unity and, therefore, mild. Thus, the only regional variable that helps increasing foreign affiliates longevity loses significance in poor governance NUTS2 areas. This might imply the positive effect to unfold fully when coupled with an efficient institutional framework, thereby reinforcing the argument that quality of institutions plays a leading role on survival.

So far, we ignored the variability in firms' behavior across countries. While we find variance between NUTS2 areas to most certainly play a role in the survival model in Tab. 18, it is important to recognize that, in specific aspects, regions within the same country demonstrate a certain level of homogeneity. We address this by adding a higher hierarchical level in the multilevel analysis to assess the distinct roles of regional and national geographic components. This allows to evaluate the heterogeneity in survival estimates across national economies and across regions within countries. In column (1) of Table 19, we run the baseline model considering firms to be nested into NUTS2 and NUTS2 to be nested into countries. In this case EQI is not significant. This might imply that the effect of institutional quality on survival needs to be evaluated at a more aggregated geographical scale. We thus proceed by introducing the country-level Governance Indicators (GI) created by Kaufmann, Kraay, and Zoido, 1999. The latter provide a set of measures capturing different factors concurring to national institutions quality. In particular, we employ GIs to disentangle the effects on survival of political stability, regulatory quality, government efficiency and accountability.

**Table 19:** Three-level Cox model

| **Model:** | (1) | (2) |
|---|---|---|
| **NUTS2-level Covariates:** | | |
| GVA growth | 0.959*** | 0.961*** |
| | (0.00697) | (0.00736) |
| GERD | 1.228*** | 1.138* |
| | (0.0920) | (0.0770) |
| HRSTO | 1.108*** | 1.093*** |
| | (0.00766) | (0.0100) |
| EQI | 0.809 | |
| | (0.156) | |
| **Country-level Indicators:** | | |
| *Stability* | | 0.972*** |
| | | (0.00566) |
| *Regulatory Quality* | | 0.960*** |
| | | (0.0128) |
| *Government efficiency* | | 1.078*** |
| | | (0.0123) |
| *Accountability* | | 0.963*** |
| | | (0.0124) |
| Financial Development | | 0.010*** |
| | | (0.00917) |
| Compensation of employees (logs) | | 1.054*** |
| | | (0.0179) |
| **Variance of the frailty term:** | | |
| Country-level | 5.776*** | 12.35*** |
| | (3.762) | (11.57) |
| NUTS2-level | 1.407*** | 1.257*** |
| | (0.134) | (0.0927) |
| Observations | 737,520 | 737,608 |
| Number of groups | 21 | 21 |
| Firm-level controls | YES | YES |

Note: Standard errors are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). All the World-Bank Governance Indicators (GIs) (namely *Stability*, *Regulatory Quality*, *Government efficiency* and *Accountability*) are expressed as percentile ranks. Larger values of GIs indicate better institutions. Financial development is measured using the Financial Development Index, which ranks countries globally and is normalized between 0 and 1. Compensation of employees is provided by the World Bank in local currency units (in our case in Euros).

We also include two important national-level controls: the compensation of employees, to evaluate the impact of labor costs on survival, and the IMF's financial development index. Previous research has demonstrated that greater financial development in the host country positively impacts both the intensive and extensive margins of inbound FDI. This occurs because companies may source part of the external financing for their FDI activities locally, making them more likely to choose investment locations with favorable financing conditions (Desai, Foley, and Hines Jr, 2004; Harrison, Love, and McMillan, 2004). We might expect that the positive impact of easy access to local external financing would also extend to the duration of the foreign-owned company's presence in the host market. The results of the three-level model, which includes national-level variables, are presented in the second column of Table 19. All four national governance indicators are statistically significant: three of them reduce the risk of market exit, while government efficiency has the opposite effect, increasing the risk of exit. In countries with higher employee compensation, the survival probability of foreign-owned firms is lower. National level of financial development turns out to have an outstanding positive impact on survival, playing a crucial role in reducing the risk of exit. The hazard ratio is observed to be 0.010, indicating that a one-unit increase in the financial development index leads to an approximate 99% reduction in the risk of market exit ($1 - 0.010$).

## 4.6 Conclusions

In this work, we aimed to gather insights into the characteristics of local economies that promote a longer stay on the market for foreign-owned businesses. We employ a multilevel survival model that simultaneously assesses the impact of regional and national contextual features. This allows us to pinpoint the geographical scale at which the effects of certain characteristics unfold. Some contextual factors may be crucial to survival but might not emerge when examined at either too granular or at too aggregated a level. Indeed, this holds for the quality of institutions, a pivotal element for extending market presence that is significant primarily at the country-level. Conversely, we find that the effects of local GVA growth and of the propensity to innovation activities can be adequately evaluated at the regional level. Our analysis reveals opposite signs for these two variables. Specifically, in a local economy where innovation is encouraged, foreign-owned enterprises have a lower survival rate. This is likely due to more innovative environments also being much more competitive.

We find that government quality inside national boundaries plays a role, not only in attracting foreign capital, but also in promoting a long-term presence. Foreign-owned enterprises have a longer lifespan in locations where institutions function well and are stable. Venturing an interpretation, when multinational corporations evaluate long-term foreign investments, they hinge their decisions on how reliable is a central government. Therefore, when a region performs exceptionally well compared to others within the same country, it does not influence long-term strategic decisions. It is beyond doubt that the most important factor is the financial development of the destination country, which drastically increases the survival probability of foreign-capital enterprises.

# Appendix A

# Supplementary materials for Chapter 2

*This Appendix is based on the work "Regional Disparities and Firms' Agglomerations" in collaboration with Armando Rungi and Dimitrios Exadaktylos (Exadaktylos, 2022).*

## 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, $\ell$ is labour and $m$ is material. We represent a composed error as $v_{it} = \epsilon_{it} + \omega_{it}$. As usual, $\epsilon_{it}$ is the idiosyncratic component, whereas $\omega_{it}$ 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 $\omega_{it}$ 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, $\Phi_t$, 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:

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

At this point, a generalised method of moments (GMM) must be applied to derive $\beta_0, \beta_k, \beta_\ell$, $\beta_m$ and $\rho$. Ackerberg, Caves, and Frazer, 2015 impose a set of moment conditions drawn on the orthogonality between $\xi_{it}$ and the state variable, as well as on the orthogonality between $\xi_{it}$ 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.

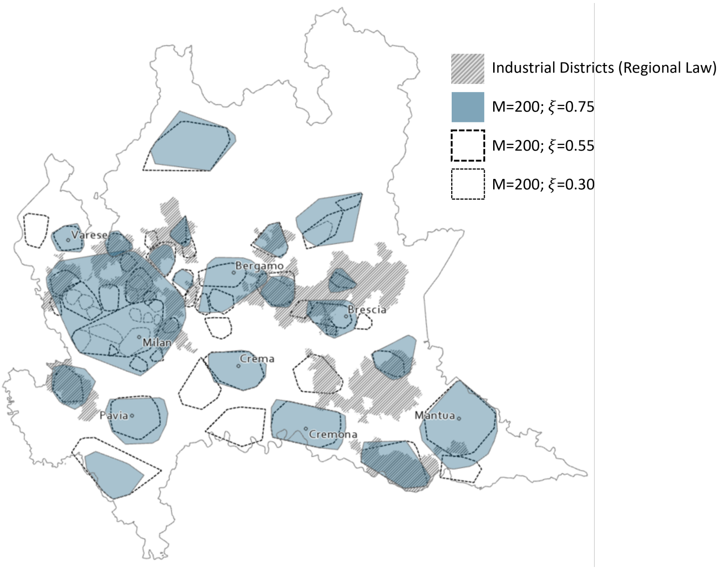
In order to account for structural characteristics of each industry, we estimate 2-digit NACE Rev.2 production functions. Labour, capital and intermediate inputs are measured by number of employees, fixed assets and material costs, respectively. Output is proxied by added value. Real values are obtained 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. Once we spot variable growth rates falling under the $10^{th}$ or above the $90^{th}$ percentile, we drop those companies that have at least one time observation with only one outlier among revenues, labour, capital and materials.

## A.2 Fine-tuning for entry parameters

In this Appendix we provide an example of how we proceed in the identification of entry parameters for the clustering algorithm. We choose the minimum number of firms and the sensitivity value that generate, in an administrative area of choice, the set of clusters that is closer to existent mappings of agglomerations according to various sources. Then, we apply the chosen pair of entry values to the entire Italian territory.

**Figure A1:** Fine-tuning applied to firms in Lombardy




Note: The striped areas represent the industrial districts identified by the regional law of 2000. The polygons represent clusters generated by OPTICS. The blue clusters are those generated by OPTICS with $M = 200$ and $\xi = 0.75$.

Figure A1 displays the fine-tuning procedure run on firms located in Lombardy. As an existent benchmark to refer to, we use the industrial districts map identified by regional law based on self-disclosure information by companies (Decision of the Lombardy Regional Council No 7/3839 of 16 March 2001, complying with Regional Law No 1/2000). We then project three different sets of clusters generated by OPTICS at three different combinations of entry parameters. The process described by the example in Figure A1 is quite simple: we proceed with progressive adjustments of the input parameters, evaluating each time how the generated cluster map overlaps with the already existing map of industrial districts. In this specific case, we observe how, given a minimum number of firms, as the sensitivity parameter varies, the cluster map evolves, encompassing significant urban centers and known industrial districts.

## A.3 Productivity ranking by NUTS3 area

In equation 2.3, we replace the categorical variable for the cluster IDs with a categorical variable indicating NUTS3 areas. We obtain a TFP ranking for Italian provinces, which we partially report in Table A1, controlling for sector, year, and firm-level characteristics (see Eq. 2.3). The top performer is again Parma, so all other provinces are ranked relative to it. We notice that, differently from Table 5, there are no significant productivity differences among top performers (to mention some of them Prato, Milan, Bolzano, Monza and Brianza) and the differences are much smaller. This is probably due to the ”watering-down” effect caused by administrative boundaries. However, the gap between the best and worst performers is deeper when comparing NUTS3 areas rather than clusters.

**Table A1:** Internal productivity ranking of NUTS3 areas: top and bottom performers

| **Top 10 Performers** | | **Bottom 10 Performers** | |
|---|---|---|---|
| Ranking | $\hat{\beta}$ | Ranking | $\hat{\beta}$ |
| 2 | -0.001 | 182 | -0.049*** |
| 3 | -0.006 | 183 | -0.049*** |
| 4 | -0.007 | 181 | -0.049*** |
| 4 | -0.008 | 180 | -0.051*** |
| 5 | -0.010** | 179 | -0.052*** |
| 6 | -0.011* | 178 | -0.054*** |
| 7 | -0.012* | 177 | -0.054*** |
| 8 | -0.012 | 176 | -0.057*** |
| 9 | -0.013** | 175 | -0.063*** |
| 10 | -0.013*** | 174 | -0.063*** |

Note: Each coefficient measures the difference in productivity (in percentage terms) between each NUTS3 area and the NUTS3 area with the highest productivity level, i.e. Parma. NUTS3 areas sitting at the bottom of the list are ITG15 - Caltanissetta, ITF21 - Isernia, ITG2A - Ogliastra, ITG13 - Messina, ITG16 - Enna, ITF45 - Lecce and ITF32 - Benevento. *, ** and *** stand for $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

# Appendix B

# Supplementary materials for Chapter 3

*This appendix is based on the working paper "Ownership Chains in Multinational Enterprises" in collaboration with Armando Rungi and Gianluca Santoni (Miricola, Rungi, and Santoni, 2023).*

## B.1 Ownership chains and corporate control networks

In this Appendix, we provide a better understanding of how raw ownership data are used to extract corporate control networks with Rungi, Morrison, and Pammolli (2017)' identification process, along with some statistics on the set of corporate control networks for year 2019.

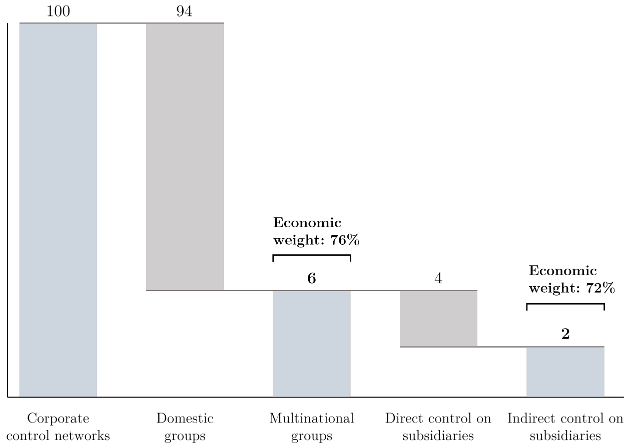
A corporate control network is a hierarchy of legally autonomous firms headed by a parent company that exerts control over the others by means of shareholding links. In order to identify them, Rungi, Morrison, and Pammolli (2017) propose a network oriented methodology based on the observation of the full matrix of ownership links (excluding non-corporate ultimate owners). Ownership structures can get extremely intricate. They can be characterized by complex patterns such as cross-holdings and ownership cycles, and companies can be indirectly connected through multiple sequences of ownership links. Rungi, Morrison, and Pammolli (2017) manage to address this complexity and detect corporate control relationships developed through these ownership webs. A control relationship is set when a shareholder obtains the majority of voting rights in a company, i.e. more than 50% of capital shares[1] and entails the ability to influence and contribute to the decision-making of another company. However, when a controller company is in turn controlled by a third entity, its decisions have to rely on decisions taken upstream, and this is when knowing the entire ownership structure becomes critically important. Besides the most elementary case where a parent directly hold the absolute majority (more than 50% of voting rights) in a subsidiary, Rungi, Morrison, and Pammolli (2017) assume two ways for a parent to extend control on other companies: (i) *by transitivity* of control along vertical chains of subsidiaries, where each subsidiary has direct control on the subsequent one; (ii) *by consolidation* of shares, when a parent gains the majority of voting rights in an assembly by summing up capital shares owned by her subsidiaries[2]. Thanks to an algorithm that repeatedly filters the original matrix of ownership links according to control rules defined above, this methodology allows to identify the ultimate controller, i.e. the parent company[3], and its hierarchy of subsidiaries. For a detailed description of the methodology see Rungi, Morrison, and Pammolli (2017)'s work.

[1]This is the definition of control accepted by international accounting standards, see for example the OECD Guidelines for multinational enterprises (OECD, 2005), the UNCTAD Training Manual on Statistics for FDI and the Operations of TNCs (UNCTAD, 2009) and the Eurostat Reccomendations Manual on the Production of Foreign Affiliates Statistics (Eurostat, 2007).

[2]Rungi, Morrison, and Pammolli (2017) also capture cases of dominant stakes, when a parent is able to control a subsidiary without holding an absolute majority. This occurs every time the ownership is extremely fragmented, to the point that other minority shareholders have no possibility to form a coalition and affect management decisions.

[3]A parent company is defined as a company that controls one or more subsidiaries and is not controlled by any corporate shareholder.

**Figure B1:** Relevance of multinational groups and indirect control




Note 1: The total sample of corporate control networks is broken down into domestic groups (when a parent company and all her subsidiaries are located in the same country) and multinational groups (when the parent company holds at least one foreign subsidiary in her corporate network). A further distinction is made between multinationals that control firms only through direct ownership links, and multinationals that indirectly control at least one subsidiary.
Note 2: Economic weight is estimated as the sum of operating revenues generated by the firms within the corporate control boundaries, parent company included. Data on operating turnover for 2019 are sourced from Orbis.
Note 3: Starting from a sample of 4,095,482 corporate control networks, the 94% are domestic groups. Albeit multinational groups represent the 6%, they account for the 76% of total revenues produced by our sample of companies in 2019. Multinational enterprises developing indirect control links are 2% of the sample, yet their network of firms contribute to 72% of total revenues.

We identify 4,095,482 corporate control networks, each headed by a parent company. Figure B1 illustrates the sample composition. Multinationals, which we identify as business groups crossing country borders at least once, amount to a total of 226,993 observations. Although multinational groups represent a residual share of the sample, their economic weight is relevant. As a matter of fact, firms belonging to multinational groups produce the 76% of the total operating revenues observed in our sample. The sample narrows further as we consider multinational groups featuring indirect control relationships. Only 2% of identified networks include cases where the parent controls at least one subsidiary through a chain made of one or more *middlemen* and spanning more than one country. Yet, turnover generated within such complex structures accounts for 72% of the total.

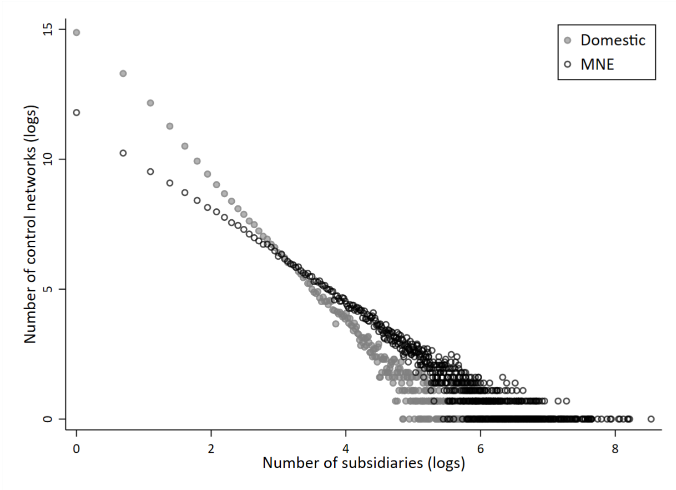
**Table B1:** Corporate control networks characteristics

| | All (N=4,095,482) | | | | Multinational (N=226,993) | | | | Domestic (N=3,868,489) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Min. | Max. | Mean | SD | Min. | Max. | Mean | SD | Min. | Max. |
| # of controlled subsidiaries | 1.93 | 12.40 | 1 | 5,075 | 7.93 | 50.09 | 1 | 5,075 | 1.58 | 3.65 | 1 | 1,989 |
| # of middlemen | 0.12 | 1.89 | 0 | 688 | 1.18 | 7.72 | 0 | 688 | 0.06 | 0.45 | 0 | 95 |
| # of final subsidiaries | 1.81 | 10.70 | 1 | 4,305 | 6.68 | 42.92 | 1 | 4,305 | 1.52 | 3.41 | 1 | 1,988 |
| # of countries crossed | 1.10 | 1.01 | 1 | 147 | 2.81 | 3.92 | 2 | 147 | 1 | 1 | 1 | 1 |

Note: We report some statistics on the main features related to the structure of corporate control networks, such as dimension, shape and geographic spread. We distinguish between multinational and domestic groups.

In Tab.B1, we provide some statistics on the main features related to the structure of corporate control networks, such as dimension, shape and geographic spread. At first glance, multinational groups tend to be bigger in terms of number of controlled firms, with an average of 7 subsidiaries against less than 2 reported for domestic groups. Yet, the former value does not adequately reflect the high incidence of simple organisational structures among multinationals, due to overdispersion in the right tail of their size distribution. This is made evident when looking at Fig.B2, where we compare the distribution by size of domestic and multinational corporate networks. Both plots show high concentration on the lowest values of the number of subsidiaries, while cases of large corporate groups are few. 58.5% (74.7%) of multinational (domestic) networks *de facto* are composed by two companies, a subsidiary and a parent that directly owns it.

**Figure B2:** Corporate control networks size distribution - Number of subsidiaries




Note: Size of control networks is measured as the logarithm of the number of subsidiaries on the x-axis. On the y-axis, we report the number of control networks by size in logarithmic scale.

# Appendix C

# Supplementary materials for Chapter 4

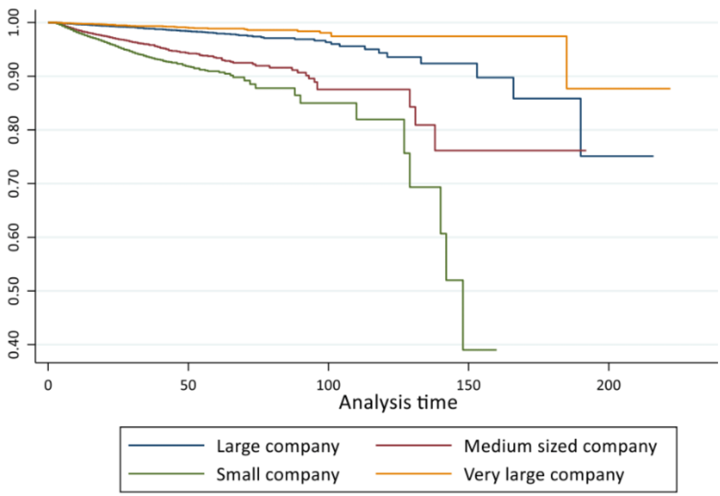
*This appendix is based on the paper "The survival of foreign affiliates: a multi-level analysis" in collaboration with Giorgio Ricchiuti and Margherita Velucchi (Miricola, Ricchiuti, and Velucchi, 2024).*

### C.0.1 Survival data Validation

As outlined in the data Section, the Orbis sample has a limitation: the proportion of firms exiting the market is significantly lower compared to those that remain active. This is further emphasized by our sample selection process. Unlike most survival studies, which typically track a cohort of firms entering the market in a specific year, we also include firms that entered in prior years (incumbents) and those entering in subsequent years. This approach increases the number of active firms in the sample. To show that our survival estimates remain consistent despite this limitation, we provide some descriptive evidence to test our sample's ability to reproduce well-established stylized facts from the firm survival literature.

Figures C1 and C2 display the Kaplan-Meier survival curves for foreign-owned companies, grouped by size class and technological category, respectively. The Kaplan-Meier method is a non-parametric approach used to estimate and visualize survival functions, which take the form of a declining step function, reflecting the decreasing probability of a firm's survival as its time in the market increases.

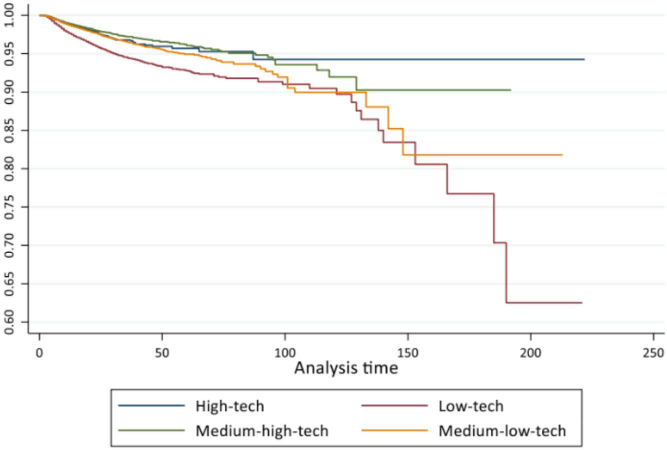
**Figure C1:** Non-parametric survival estimates by size category




Note: Figure shows the Kaplan-Meier survival curves for foreign-owned firms active between 2005 and 2021, categorized by size class. The horizontal axis represents time measured in years, while the vertical axis shows the probability of surviving up to a specific point in time, conditional on having survived in the previous periods.

In both graphs, the curves are positioned one above the other. Those lying in the higher (lower) areas of the graph indicate higher (lower) conditional survival probabilities for each given value of years spent in the market. In our sample, larger firms and firms operating in high-tech sectors show a higher probability of survival compared to others. The ranking of categories derived from our survival function estimates is fully consistent with the findings in the existing literature on the topic.

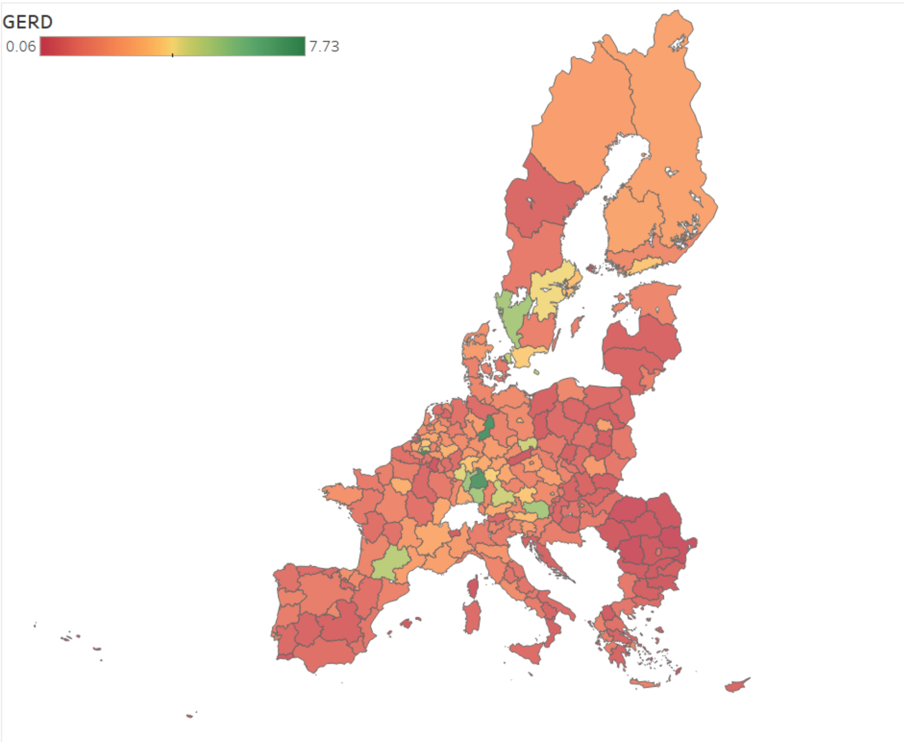
**Figure C2:** Non-parametric survival estimates by technology




Note: Figure shows the Kaplan-Meier survival curves for foreign-owned firms active between 2005 and 2021, categorized by the technological category they belong to. The horizontal axis represents time measured in years, while the vertical axis shows the probability of surviving up to a specific point in time, conditional on having survived in the previous periods.

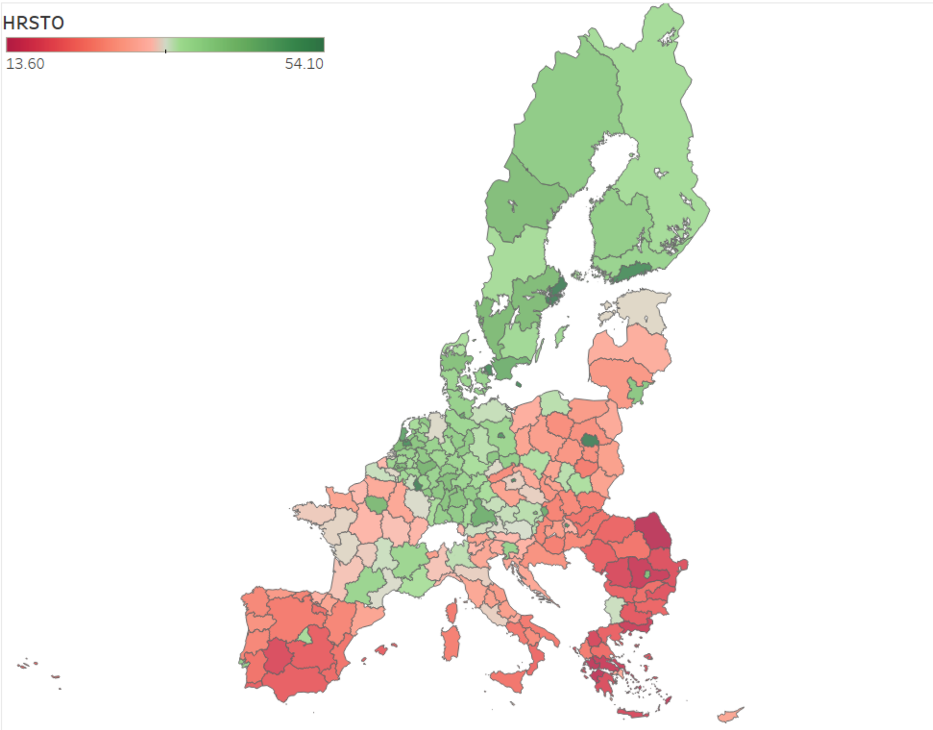
### C.0.2 Additional maps

**Figure C3:** Gross domestic expenditure on R&D, 2019




Note: The map displays the gross domestic expenditure on R&D (GERD) across NUTS2 regions for the year 2019. GERD is expressed as a percentage of domestic GDP, with the lowest value of 0.06% observed in Ciudad de Ceuta, Spain, and the highest at 7.73% in the Arrondissement of Nivelles, Belgium.

**Figure C4:** Human resources employed in science and technology, 2019




Note: The map shows the percentage of the labor force employed in science and technology across NUTS2 regions in 2019. The lowest value, 13.60%, is recorded in Nord-Est, Macroregiunea Doi, Romania, while the highest, 54.10%, is observed in Stockholm.

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