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INNOVATION AND PRODUCTIVITY OF ITALIAN FIRMS: EVIDENCE AND POLICY

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SUMMARY

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Abstract

This work is a collection of three essays about innovation and productivity of Italian firms.

In the first chapter, we show that the historical North-South gap of the country has a relationship with firm-level productivity, which are more heterogeneous in the South than in the North. We find that new and more productive firms systematically self-select in the NUTS 3-digit locations where more productive firms are already present, even after controlling for agglomeration economies, and other classical determinants of firm location.

The second essay analyzes how knowledge spillovers can influence firm productivity. As compared to the previous literature in which spatial econometric models are used to investigate local geographical spillovers, we consider interfirm relationships. In particular, we focus our attention on the network of interlocking directorates. We find that a spatial model which includes interlocking directorates as well as distance performs better than traditional models of localized knowledge spillovers. We find that interlocking directorates play a crucial role for knowledge spillovers in science-based industries.

The third chapter studies the impact of Italian Law 221/2012 (i.e. "Startup Act"), which provides benefits for innovative, small, and young companies, in the aftermath of the Great Recession. We find that the Startup Act has met its main goals. In particular, we find that the positive effects on value-added and productivity continue even after the treatment period.

Disclaimer

Chapter 1 (co-authored with Armando Rungi) is almost a reproduction of the working paper "Sorting of Heterogenous Firms and the North-South Divide in Italy" available at SSRN: https://ssrn.com/abstract=3069542. Some variations have been implemented based on referees' comments. This work was presented by Armando Rungi at ETSG 2017, Florence, Italy.

Chapter 2 is an original piece of work about knowledge spillovers between Italian firms.

Chapter 3 (co-authored with Dirk Czarnitzki and Massimo Riccaboni) is a part of an ongoing collaborative research project. A previous version of this work has been presented by Dirk Czarnitzki at Treasury, Victoria State Government, Australia (August 2017) and at Annual Meeting of the Technology Transfer Society, Arlington, VA, USA (November 2017).

General introduction

This thesis is organized into three chapters. The silver line, which links my work, is the empirical analysis of innovation and productivity of Italian firms in the aftermath of the Great Recession. Italy represents an important case study due to the critical situation Italian firms faced in recent years. Italy has been defined as the "sleeping beauty of Europe" by the international press. Indeed, since the mid-nineties the Italian economy has been experiencing a persistent lack of growth and low productivity. Therefore, Italian firms have been struggling to be competitive in the European and global markets. Chronical lack of competitiveness and innovation have been amplified by the Great Recession. Since 2009, many manufacturing enterprises went out of business and there has been a sudden increase in employment, especially among the youngest. The policy debate about the determinants of the Italian crisis and potential way out is still open, as many factors are at play such as the Euro currency, rigid labor markets, lack of competition, inefficiencies in the public sector and high tax burden, low public and private R&D expenditures, political instability, etc.

The Italian crisis started well before the Great Recession since firm productivity has declined sharply in comparison with other European countries such as France and Germany. Moreover, the historical economic gap between the prosperous North and the undeveloped South has been widening in recent years. The after-crisis recovery in the North has been faster than in the South, where the general employment is largely below the pre-crisis level. For all these reasons, we decided to investigate the current situation of Italian firms from multiple points of view.

The first chapter, co-authored with Armando Rungi, investigates firm entry and exit dynamics across different Italian regions at the NUTS-3 level. We find that the Northern manufacturing firms are generally more productive than the Southern ones, as suggested by the common wisdom. Moreover, new companies tend to locate in productive areas. At the same time, inefficient firms, which decide to enter in high productive provinces, have higher probability of exit. Our results confirm theories on endogenous sorting of heterogeneous enterprises across multiple potential locations. Endogenous sorting contributes to the productivity gap between the North and the South of Italy.

The second chapter studies the spatial effects of productivity through a sample of Italian manufacturing companies in science-based industries. Agglomeration economies are known to be important in the Italian case, where similar firms are typically co-localized in industrial districts. Traditional industrial districts are restricted productive areas specialized in a set of related activities such as the textile district of Prato (near Florence). It has been argued that within industrial districts, tacit knowledge flows through formal and informal connections, and specialized knowledge is spread across firms. In the second chapter, we investigate the role that formal interfirm relationships play in the transmission of localized knowledge spillovers. In particular, we analyze the effect of interlocking directorates and managerial connections on firm productivity. By combining network and geographical effects, our analysis highlights the crucial role of interfirm networks, which is typically neglected in the recent spatial econometric literature on local spillovers. By focusing on knowledge intensive sectors, we find that managerial connections are key in the transmission of knowledge spillovers.

The third chapter (co-authored with Dirk Czarnitzki and Massimo Riccaboni) also investigates innovation by Italian firms. It analyzes the impact of an Italian startup law entered into force in December 2012. This law provides special benefits (as tax incentives, special labor law, etc.) for firms registered as 'innovative startups'. This special regulation has been implemented by the Italian government to increase R&D expenditures and investments by small and medium enterprises in Italy. Our goal is to assess the impact of the policy on the survival and growth of young and small innovative firms. Overall, we find that this startup policy has reached its primary goals. The treated firms under this act show higher survival rates, value-added, and labor productivity than untreated comparable firms. These effects persist and are also significant in the post-treatment period, but more time is needed to assess the long-run impact of the policy. However, this policy does not reduce the gap between the North and the South: in the Northern regions, the treated firms are growing faster than in the Southern ones.

I. Sorting of heterogeneous firms and the North-South divide in Italy

1 Introduction

Italy is an interesting case to study the demography of firms across geography, given the polarized distribution of economic activity in the country and the disparities in productivity over space and time. Understanding which type of firms emerge in one region, why, and how they are selected by local market forces is crucial as aggregate productivity eventually depends on the ability to allocate resources towards most productive firms (Hsieh & Klenow, 2009), and the demography of firms play a central role on aggregate dynamics (see Clementi & Palazzo, 2016).

In this chapter, we investigate the location choices of new firms through a conditional logit model and the exit of inefficient firms in the period 2004-2012 in a relationship with the local distributions of productivity by incumbent firms at the NUTS 3-digit level. Recent theory suggests that firms sort endogenously into space according to their productivity (Baldwin & Okubo, 2006; Behrens et al., 2014; Gaubert, 2017) because firms that are more efficient benefit relatively more from local externalities (see Combes et al., 2012). Therefore, firms that are more efficient eventually locate in larger cities, feeding into existing agglomeration economies, and possibly reinforcing the initial geographic disparities.

Indeed, we find that new firms are more likely to emerge in the Italian provinces that already host many firms. Moreover, productivity of new firms is positively correlated with the productivity of incumbents. We also find that a higher probability of exiting is associated with a higher productivity at the province level. In other words, a higher churning in more productive territories points to selection processes driven by local competitive forces. Results are robust to control for local agglomeration externalities driven by labor markets or knowledge spillovers (see Duranton & Puga, 2003).

Our results depict a strong geographic divide between the North and the South of the country in productivity distributions. As already documented in official statistics, we find that total factor productivity is higher in the North than in the South; however, we also find that lower productivity in the so-called '*Mezzogiorno*'[1] is also associated to higher productivity dispersions at the province-level.

Our findings suggest that endogenous sorting plays a crucial role in increasing the productivity divide between '*Mezzogiorno*' and the rest of the country. Overall, we find that in the '*Mezzogiorno*',

[1] '*Mezzogiorno*' traditionally includes the NUTS 2-digit administrative regions of the South: Abruzzo, Apulia, Basilicata, Campania, Calabria, Molise, Sicily, and Sardinia. See also ISTAT (2017).

in the period of our analysis: i) there is less than half the probability that a new firm starts its activity; ii) new firms are about 21% less productive in the first years from incorporation; iii) incumbent firms are on average about 30% less productive than in the rest of the country; iii) less productive firms are more likely to survive in the market.

The rest of the Chapter is organized as follows. In Section I.2, we briefly introduce the reader to the Italian context. In Section I.3, we present data and preliminary evidence on geographic disparities. Section I.4 describes our econometric results. Section I.5 is the conclusion.

2 The Italian context

To frame our analyses, we provide a bird's-eye view on the long-run trends of productivity in Italy, on its long-standing geographical divide, and the debate about its determinants. In the period 2001-2015, Italy's average real GDP growth was zero due primarily to its sluggish total factor productivity (European Commission, 2017). According to Calligaris et al. (2016), the Italian productivity slowdown has been accounted for by a misallocation of resources at the micro-level since its beginning in 1995, as indicated by an increasingly higher share of less efficient firms, which push down the average and up the dispersion in productivity distributions.[2] Increasing firm-level productivity dispersion seems to come from a within-sector component

[2] A problem of misallocation of resources is also detected by Linarello & Petrella (2016).

(Bugamelli et al., 2010) rather than from a specialization pattern in sectors with low human capital and technology intensity (Faini & Sapir, 2005): heterogeneity in productivity is increasing within sectors because firms that are more efficient sit next to less efficient firms. Along these lines, Calligaris et al. (2016) find that the overall increase in misallocation comes from a higher dispersion both within different firm-size classes and geographical areas. Moreover, Giacomelli & Menon (2017) find that a misallocation of resources is detected also among big firms in the North-West of the country, which is traditionally considered the "spearhead" of the Italian economy.

In the aftermath of the most extended economic downturn in Italian history, the manufacturing industries emerged with fewer firms and fewer employees, at the end of a selection process that allowed healthy and more viable firms to gain market shares at the expense of more fragile firms (ISTAT, 2017).

Despite the recent signs of recovery, major geographic differences persist between the North and the South of the country, dating back to the time when an internal economic integration started, after the reunification of the country in 1861. At the time, decreasing transportation costs and the elimination of trade barriers boosted an agglomeration of manufacturing activity in a few provinces, mostly located in the North-West of the country (Basile & Ciccarelli, 2017). Economic disparities already present before the reunification have been magnified (A'Hearn & Venables, 2013) as a consequence of a regional comparative advantage of the North of the country based on a relatively higher endowment of water as an important source for the production of energy (Cafagna, 1989; Bardini, 1997), in a country where coal was lacking.

Interestingly, a different strand of research in economic history also debates that regions in the South could have undergone a process of "passive" rather than "active" modernization (Felice & Vasta, 2015), because no dominant political or social actor had taken responsibility for a modernization of the country, since reunification, based on "inclusive" rather than "exclusive" institutions in the sense proposed by Acemoglu & Robinson (2012).

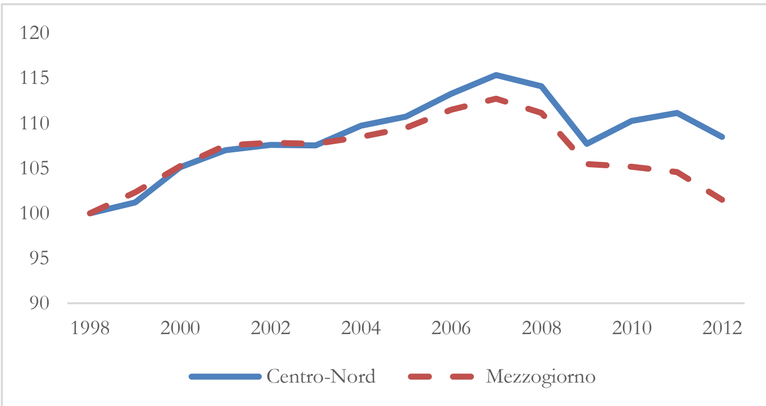
In the name of territorial cohesion, most of the Italian regions in the South started to benefit from a Cohesion Policy funded by the European Union. Having in mind the possible disparities arising from a core-periphery model of development (Quah, 1996; Farole et al., 2011), European funds have accrued to Southern regions to offset the imbalances coming from geographic remoteness and different growth opportunities (Puga, 1999; Overman & Puga, 2002; Puga, 2002) which are common to other peripheral regions within other European countries.

Having a look at recent trends in economic fundamentals[3], Figure I.1 shows how in the last decade the gap between '*Mezzogiorno*' and the rest of the country has been widening. Although starting from different levels, GDP in the South and in the North had been growing at the same pace from 1998 until 2003, when the South started to lag behind. Total GDP in the North between 1998 and 2014 increased by 8.5% versus 1% in the South. Employment has been traditionally lower in the South of the country, but Figure

[3] At the moment we are writing, 2012 is the latest available year for information at the NUTS 3-digit level from official statistics. Therefore, we aggregate NUTS 3-digit Italian provinces according to the traditional classification in '*Mezzogiorno*' and '*Centro-Nord*' reported also by ISTAT (2017).

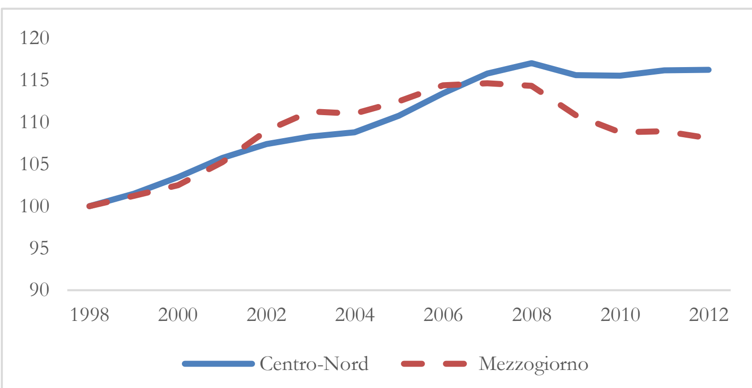
I.2 shows how a divergence in employment rates started in 2007. Indeed, in the post crisis period (2008-2012) the South lost more than 5% of jobs, conversely the North in 2012 recovered to almost lost position during the crisis.

Figure I.1 Gross Domestic Product



Author's elaboration on ISTAT (2017).

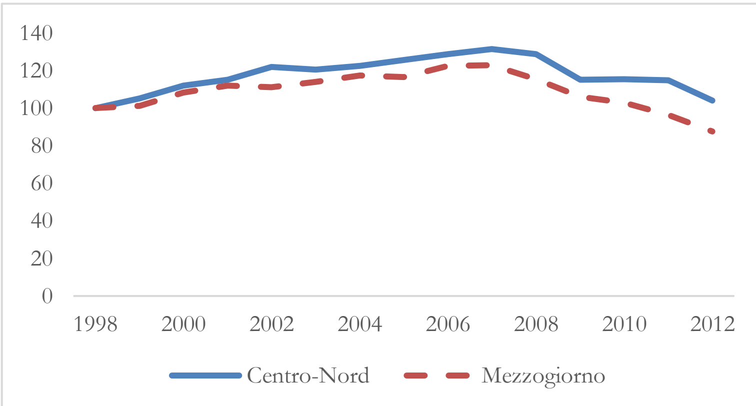
Figure I.2 Employment level



Author's elaboration on ISTAT (2017).

A wedge in capital formation between the North and the South is observed throughout the period. Figures I.1-3 represent the North-South widening gap, base year 1998=100.

Figure I.3 Capital Formation



Author's elaboration on ISTAT (2017).

3 Data and preliminary evidence

3.1 A sample of manufacturing firms

We source firm-level data from ORBIS, a commercial database compiled by the Bureau van Dijk that aggregates information from several national registries around the globe. Specifically, our sample is made of 187,674 Italian companies active in manufacturing industries with information on financial accounts, geolocation, dates of entry, and exit in the period 2004-2012.

In Table I.1, we report a snapshot of the sample geographic coverage by Italian regions at the NUTS 2-digit level and compare with census data collected by the national statistics office, ISTAT, at the end of our period of analysis, in 2012. As expected, Lombardia in the North-West of the country is the most populated of firms, both in our sample and in population statistics, as it is also the most industrialized region of the country, collecting almost one-fourth of the total number of firms.

Five regions in the '*Centro-Nord*' (Lombardia, Veneto, Emilia-Romagna, Piemonte, and Toscana) account for more than half of manufacturing companies in Italy; at the same time, the resident population of these five Italian regions is 45% of the total. Just this simple evidence denotes a high geographic concentration of manufacturing firms in a specific area of the country, in line with the historical agglomeration documented in Section 2.

In Figures I.4 and I.5, we plot the demographics of firms in the period 2004 – 2012 as derived from our sample and according to census data by ISTAT. We determine the year of entry of new firms based on the incorporation date reported in financial accounts, which is the year when the firm is registered as a legal entity. We assume firms exit based on the information on the 'status' and the relative 'status date', as retrieved from financial accounts. Hence, we assume that firms are out of the market when they are reported in a status of bankruptcy or liquidation and when a firm is finally declassified from national registries.

Table I.1 Number of manufacturing firms by region (NUTS-2) in 2012

	Sample		Population (ISTAT)		Regional coverage
Italian region	**# of firms**	**%**	**# of firms**	**%**	**%**
Lomardia	44,105	23.0	83,939	19.97	52.54
Veneto	24,086	12.3	47,411	11.28	50.80
Toscana	17,289	9.21	40,032	9.52	43.19
Emilia Rom.	16,774	8.92	39,599	9.42	42.4
Campania	14,334	7.64	28,072	6.68	51.06
Piemonte	13,021	6.94	33,289	7.92	39.11
Lazio	12,892	6.87	22,790	5.42	56.57
Puglia	8,024	4.28	22,740	5.41	35.29
Sicilia	6,386	3.40	22,434	5.34	28.47
Marche	6,383	3.40	17,261	4.11	36.98
Abruzzo	4,747	2.53	9,653	2.30	49.18
Friuli-V.G.	4,581	2.44	8,452	2.01	54.2
Sardegna	2,935	1.56	8,218	1.96	35.71
Umbria	2,695	1.44	7,023	1.67	38.37
Liguria	2,634	1.41	8,367	1.99	31.48
Calabria	2,557	1.36	8,963	2.13	28.53
Trentino A.A.	2,015	1.07	6,420	1.53	31.39
Basilicata	1,233	0.66	3,071	0.73	40.15
Molise	738	0.39	1861	0.44	39.66
Valle Aosta	245	0.13	725	0.17	33.79
'Centro-Nord'	146,720	77.13	315,308	75.01	46.53
'Mezzogiorno'	40,954	21.82	105,012	24.99	39.00
Total	**187,674**	**100**	**420,320**	**100**	**44.65**

Figure I.4 Entry of firms 2004-2012

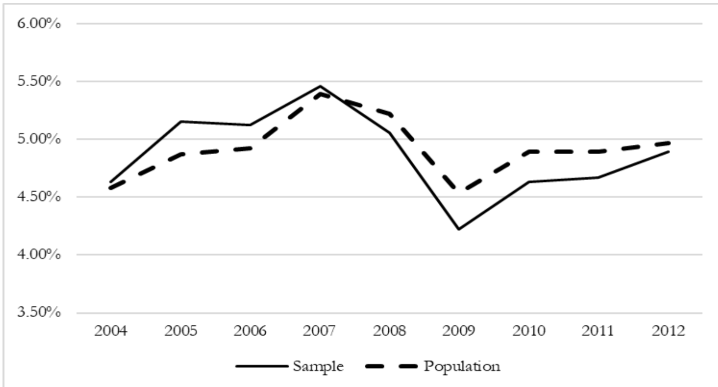
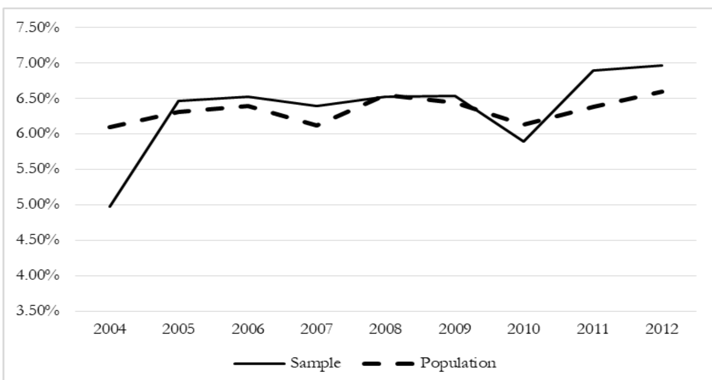


Figure I.5 Exit of firms 2004-2012



Sample demographic dynamics do not seem to differ significantly when compared to the census. As in the population, we register a constant net exit of firms, i.e., the exit rates are always higher than the entry rates, because of an ongoing selection process in line with what reported by ISTAT (2017), which is bringing an aggregate increase in productivity since 2014. Unfortunately, we cannot track latest periods in our analyses because province-level data are not available from ISTAT as of we are writing this text.

3.2 Mapping Total Factor Productivity

A mapping of Total Factor Productivity (TFP) distributions at the NUTS 3-digit level of Italian 'province' is reported in Figures I.6 and I.7, respectively, for the average and the standard deviation of manufacturing firms. TFP is estimated mainly following a standard Levinsohn & Petrin (2003)[4] procedure for the possible simultaneity bias deriving from the choice of inputs and the unobserved firm-specific productivity processes.[5]

In Figure I.6, we observe a clear pattern of decreasing average productivities from the North to the South of Italy, which is consistent with aggregate official statistics. On average, the most productive manufacturing firms can be found in Lombardia,

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[4] As robustness check we consider also the method introduced by Ackerberg, Caves, Frazer (ACF) to compute the TFP. Main results do not change (see the Appendix).

[5] For each 2-digit NACE industry, we estimated a Cobb-Douglas firm-level revenue-based production function with three inputs: i) labor is proxied by number of employees; iii) capital is proxied by fixed assets; iii) intermediates is proxied by material costs. Monetary values of firm-level revenues are deflated with yearly industry-specific producer price indices, fixed assets are deflated with instrumental goods index. Intermediate goods are deflated according an input-output table. All these price indices are sourced from EUROSTAT, taking as base year 2010.

Emilia Romagna, the west of Veneto and Piemonte, and the north of Tuscany.

Interestingly, however, when we look at the standard deviations of Figure I.7, provinces that are more productive also show, on average, less dispersion. In general, in the South and the Center of Italy, including the region of the capital, Rome, firms that are more productive sit next to largely inefficient firms.

Figure I.6 Average TFP (in logs) by province (NUTS-3) in 2004.

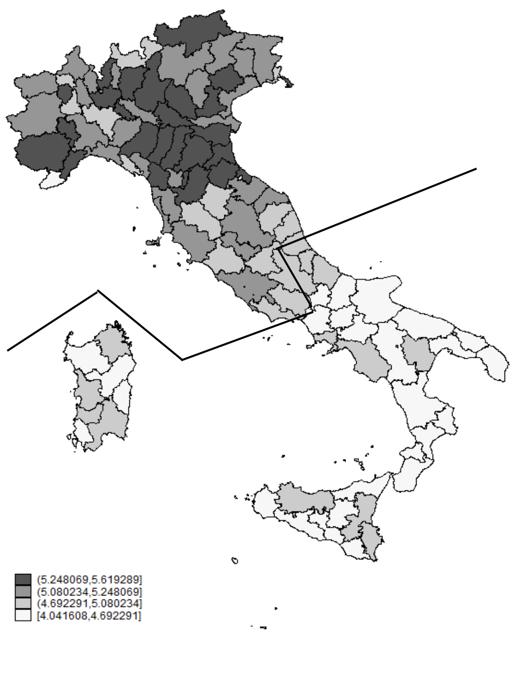
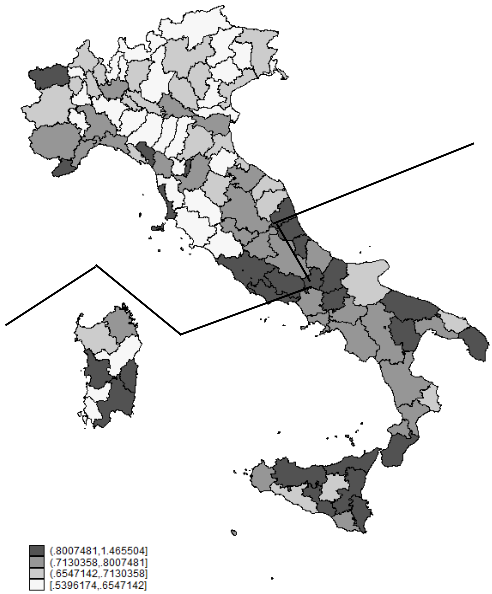


Figure I.7 Standard deviations of TFP (in logs) by province (NUTS-3) in 2004.



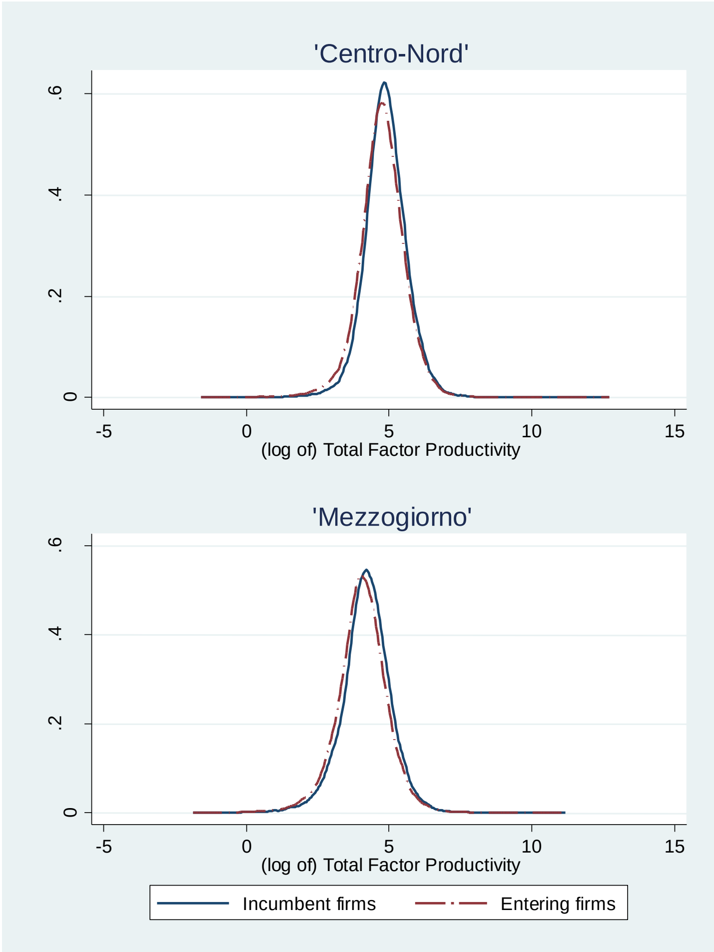
This evidence is *prima facie* consistent with the hypothesis of local diverse selection processes, which allow only more productive firms to survive when competition is fiercer because competitors are also more productive. In other words, it is possible that an entering firm that wants to start its activity in the north must be on average more productive than if it wants to operate in the rest of the country. At similar levels of productivity, it is possible that a firm is more likely to go bankrupt in the north than in the rest of the country. This evidence is consistent with the existence of a higher productivity threshold in some more productive areas, below which entry is more difficult and exit is easier.

In Figure I.8, we also report the distributions of firm-level lnTFP collecting provinces in the '*Centro-Nord*' and in the '*Mezzogiorno*', further differentiating by incumbent firms and new firms that entered into activity in our period of analyses. In fact, we observe that average productivity is higher in the '*Centro-Nord*', although the heterogeneity in dispersion by provinces is hidden in the aggregation by these two macro-regions. In both cases, the distribution in productivity of new entering firms is similar and almost overlapping with the corresponding distributions by incumbent firms. Entering firms are, on average, more productive in the North than in the South.

Table I.2 The distribution of TFP in 2012, North versus South of Italy

	lnTFP for '*Centro-Nord*'	lnTFP for '*Mezzogiorno*'
5th percentile	3.669	2.777
10th percentile	3.993	3.197
25th percentile	4.448	3.732
50th percentile	4.920	4.249
75th percentile	5.415	4.791
90th percentile	5.892	5.323
95th percentile	6.200	5.652
average	4.920	4.237
standard deviation	0.659	0.926

Figure I.8 Kernel densities of (log of) TFP: '*Centro-Nord*' vs '*Mezzogiorno*', entering vs incumbent firms



At this stage of the analysis, we cannot exclude that different local specialization patterns as well as province-level and firm-level characteristics are also potential drivers of the observed geographical divide. We will try to separate these effects in the following analyses.

4 Empirical results

We aim to test the relationship between the entry and exit of firms and the characteristics of the NUTS 3-digit Italian provinces with a focus on the productivity of incumbent firms. First, we will adopt a location model that considers the entry of a new firm as a choice made by the entrepreneur conditional on the *ex-ante* characteristics of all Italian provinces. Second, we will consider the probability of a firm to exit from a NUTS 3 region (i.e. Italian province) also controlling for location-specific factors. Third, we will test the premium on the productivity of entering firms after the decision of location is made, along our period of analysis.

4.1 Entering firms

We adopt a conditional logit model for considering the *ex-ante* characteristics of alternative locations (see McFadden, 1974; Maddala, 1982), i.e., the characteristics of all the 103 NUTS 3-digit provinces[6] where a firm could have entered. That is, we assume an underlying discrete choice proxied as a multinomial model, according to which firms maximize their profits based on the characteristics of the alternative locations. In this way, we have:

[6] The number of Italian provinces in 2004. The number has varied in the recent years.

Equation I.1

$$\mathbf{\Pi}_{ij} = \boldsymbol{\pi}_{ij} + \varepsilon_{ij}$$

where firm i can emerge in any alternative province j included in the set J made of all 103 Italian provinces, with a systematic component $\boldsymbol{\pi}_{ij} = \boldsymbol{Z}'_{ij}\boldsymbol{\beta}$, where $\boldsymbol{Z}_{ij}$, includes the characteristics of any location j as evaluated by entering firm i, and coefficients $\boldsymbol{\beta}$ catch their impact on the emergence of new firms.[7] We introduce fixed effects for new firms, which do not reveal any information on their potential productivity when they enter the market. We end up with firm-level fixed-effects conditional logit model, in the form:

Equation I.2

$$p_{ij} = \frac{\exp(\boldsymbol{Z}'_{ij}\boldsymbol{\beta})}{\sum_{i=1}^{J}\exp(\boldsymbol{Z}'_{ij}\boldsymbol{\beta})}$$

where p_{ij} are the odds that a firm emerges in a province conditional on the distribution of characteristics among all provinces.

[7] See also Stam (2007) for a similar use of a multinomial model to test the firms' locational behavior as the outcome of entrepreneurial initiatives constrained by local resources and capabilities.

Our main coefficient of interest is the one on province-level productivity measured as the average of incumbent firms[8], i.e. the firms that were already active before the new firm started its activity. Among other province-level controls, we include population, GDP per capita and endowment of the physical infrastructure for transportation, proxied by kilometres of road. The variables Mountain, Island and Region Capital are binary and indicate respectively whether the province is mainly mountainous, it is located on an island, or it also hosts the administrative headquarters of the NUTS 2-digit region. An indicator of agglomeration is included, which is equal to one when the new firm is active in the industry that produces more value-added in the province. Market potential is proxied by the total sales of incumbent firms in the same industry of the new entrants. Competition is proxied by the number of incumbent firms in the same industry. Details on the construction of variables are included in a Data Appendix. In Table I.3, we report different specifications.

Results show that new firms are more likely to emerge in larger provinces. A higher average productivity of incumbent firms is associated with more firms entering that province. These results are in line with an endogenous sorting of firms at the local level, as predicted for example by Baldwin & Okubo (2006) and Gaubert (2017).

[8] We consider the average firm productivity in 2004 as the average lnTFP observed by new entrants.

Table I.3 Conditional logit for entering firms

	(1)	(2)	(3)	(4)	(5)
(log of) Province-level productivity	1.106***		0.885***	0.599***	0.519***
	(0.210)		(0.249)	(0.188)	(0.156)
(log of) Population		0.941***	0.947***	1.083***	0.945***
		(0.027)	(0.026)	(0.026)	(0.037)
(log of) GDP per capita		0.661***	-0.166	-0.067	-0.138
		(0.211)	(0.129)	(0.115)	(0.100)
(log of) Road				-0.092	-0.008
				(0.112)	(0.112)
(log of) Area				-0.006	-0.023
				(0.055)	(0.065)
Mountain				-0.374***	-0.280***
				(0.109)	(0.069)
Island				-0.445***	-0.463***
				(0.119)	(0.112)
Region Capital				-0.333***	-0.323***
				(0.064)	(0.054)
Agglomeration					0.663***
					(0.253)
Market Potential					0.025***
					(0.005)
Competition					0.101*
					(0.061)
Observations	5,397,097	5,397,097	5,397,097	5,397,097	5,397,097
Pseudo-R squared	0.0125	0.0795	0.0816	0.0846	0.0918
Log likelihood	-239823	-223538	-223036	-222299	-220573

Clustered standard errors (NACE 2-digit) in parentheses; p-value < 0.01***,0.05**,0.10*

Interestingly, when we do not control for province-level productivity, a higher GDP per capita in the area correlated with a higher probability to start a new business, but a change in the sign is observed after that. In fact, we argue that there is an implicit correlation[9] that we can also find in our data between the prosperity of a province and the productivity of its firms. However, it is still possible that some areas have higher incomes that come from non-productive activities, as in the case of rent-seeking monopolies and public administration services. We argue that the latter could explain the negative sign after the introduction of a specific measure of local productivity. As expected, mountainous territories and islands attract fewer firms, due to the difficulty firms can encounter in logistics and transportation, although a specific control for the amount of road infrastructure does not show a robust statistical significance. Interestingly, region capitals attract less manufacturing firms, probably due to a higher cost for industrial real estate. Certainly, new firms emerge more likely when there is a higher market for that industry. In Appendix Table IV.3, we separate only the firms that we can consider as subsidiaries of multinational enterprises.[10] We find that the average province-level productivity is even more relevant for the attraction of subsidiaries of multinational enterprises.

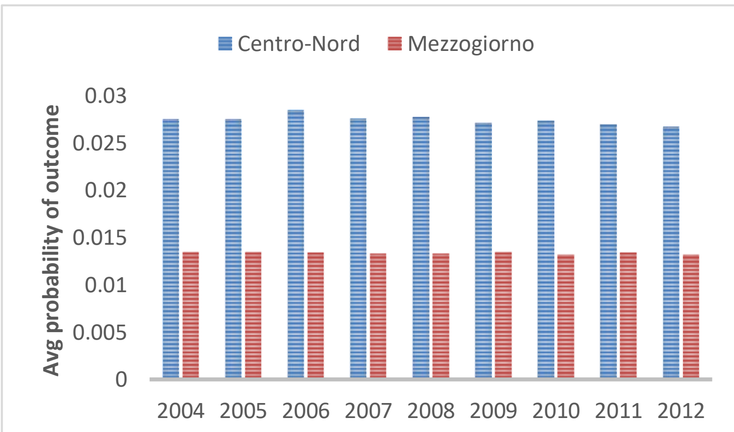
In Figure I.9, we report the post-estimation average probabilities that a new firm establishes in a province of the '*Centro-Nord*' and

[9] In our dataset correlation is about 0.4

[10] Following international standards (UNCTAD, 2011; OECD, 2015), we consider a company to be foreign when its parent company is located in a different country. For more details see Del Prete & Rungi (2017) and Rungi et al. (2017).

in a province of the '*Mezzogiorno*'. That is, after controlling for other possible determinants included in Table I.3, we predict what is the probability that a new firm establishes in a province. After obtaining a probability value for each NUTS-3 region, we average over the two macro-regions. We observe that there is around a half the probability that a new firm emerges in a province of the '*Mezzogiorno*' (1.3%, vis à vis 2.6%), with no significant change over the period of analyses.

Figure I.9 Post-estimation average probability of a new firm in a province of '*Centro-Nord*' vs '*Mezzogiorno*'



4.2 Exiting firms

We test the determinants of exiting of a firm after a probit model as follows:

Equation I.3

$$\Pr\left(exit_{ijt} = 1 \middle| \boldsymbol{X}_{ijt}\right) = \Phi(\boldsymbol{X}'_{ijt}\boldsymbol{\beta})$$

where the dependent variable $exit_{ijt}$ is binary and equal to one when it indicates whether the firm i active in a province j is not able to stay in the market at time t. The same controls of the previous subsection and Table I.4 are included, this time also adding the last productivity the company registered when active, and its domestic or foreign status. Industry-level and time-specific fixed effects are included to consider idiosyncratic shocks. Errors are clustered by NUTS-3 region. Nested results are reported in Table I.4.

As expected, less efficient firms are more likely to go out of the market. More importantly, the average productivity of the province is associated with a higher probability to exit. Considering also the results of Section I.4.1, we can conclude that more productive areas do present a higher churning of firms and, consequently, a fiercer selection process at the local level that is largely unaccounted for until now.

Other geographic indicators, the endowment of road infrastructure, agglomeration, and competition do not seem to play a significant role. Also, the industry plays a role in the probability of exit. The pharmaceutical industry had the lowest rate of exit; indeed, pharma is one of the most non-cyclical businesses. Conversely, furniture manufacturers showed the greatest rate of exit. Furniture companies are linked with the real estate market, which downturned after 2008.

Table I.4 Probit model for the exit of firms

Dependent variable: Exiting firm (Yes/No)	(1)	(2)	(3)	(4)	(5)	(6)
Firm-level productivity	-0.374***	-0.377***	-0.373***	-0.376***	-0.374***	-0.376***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Province-level productivity	0.331***	0.331***	0.287***	0.286***	0.288***	0.288***
	(0.050)	(0.051)	(0.077)	(0.077)	(0.077)	(0.077)
Foreign ownership			-0.220***	-0.220***	-0.219***	-0.220***
			(0.066)	(0.066)	(0.067)	(0.067)
(log of) Population			-0.021	-0.021	-0.015	-0.015
			(0.022)	(0.023)	(0.020)	(0.020)
(log of) GDP per capita			0.013	0.013	0.015	0.015
			(0.091)	(0.092)	(0.090)	(0.090)
(log of) Road			-0.057	-0.056	-0.062	-0.060
			(0.048)	(0.048)	(0.049)	(0.049)
(log of) Area			0.023	0.022	0.025	0.024
			(0.044)	(0.044)	(0.045)	(0.045)
Mountain			-0.169	-0.174*	-0.168	-0.173*
			(0.104)	(0.102)	(0.105)	(0.103)
Island			-0.086	-0.088	-0.085	-0.087
			(0.055)	(0.054)	(0.054)	(0.054)
Region capital			0.050	0.049	0.049	0.049
			(0.034)	(0.034)	(0.034)	(0.035)
Agglomeration					0.026	0.028
					(0.035)	(0.035)
Market potential					-0.001	-0.001
					(0.002)	(0.001)
Competition					-0.005	-0.004
					(0.011)	(0.011)
Constant	-3.366***	-2.846***	-2.760***	-2.250***	-2.849***	-2.337***
	(0.289)	(0.405)	(0.731)	(0.826)	(0.690)	(0.773)
Observations	510,797	499,660	510,79	499,660	510,797	499,660
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year dummies	No	Yes	No	Yes	No	Yes
Log likelihood	-12721	-12630	-12706	-12615	-12705	-12615
Pseudo R-squared	0.120	0.123	0.121	0.124	0.121	0.124

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

On the other hand, we cannot clearly identify a "chain reaction" among different industries for the exit analysis, since, according to the input-output table, most of manufacturing industries have customer-supplier relationships within the same industry.

Finally, we find that firms that are affiliated to multinational enterprises are, *ceteris paribus*, more resilient on the market, possibly because they can benefit from a larger pool of resources and they are less dependent on the local characteristics of the territories.

4.3 Geographic premia on productivity

In this Section, we eventually assess what the difference in productivity is for entering firms and incumbent firms by main geographic area of the country and in line with what was reported in Figure I.6 and Figure I.8, but this time controlling for possibly different industrial compositions, firm-level characteristics, and year-specific shocks during the period of analyses.

We test a simple least squares model in the form:

Equation I.4

$$\ln TFP_{ijkt} = \beta_0 + \beta_1 X_i + \beta_2 Z_j + \lambda_k + \delta_t + \varepsilon_{ijkt}$$

where the dependent variable is the logarithm of the firm-level productivity, X_i indicates firm-level controls (size, capital intensity, age) and Z_j is either a set of geographic dummies for the five Italian NUTS-1 regions (North-West, North-East, Center, South, Insular) or a separation between the '*Mezzogiorno*' and the '*Centro-Nord*'. Industry λ_k and time δ_t industry fixed effects control for idiosyncratic shocks. Standard errors are clustered by NUTS-3 region.

The results in the first column of Table I.5 show that manufacturing firms in '*Mezzogiorno*' are on-average 30% less productive than in '*Centro-Nord*', even after controlling for industrial composition and firm-level heterogeneity in size and capital intensity. When we decompose Column 2 by NUTS-1 region, taking the North-West as the reference base group, we observe there is no statistically significant difference between the latter and the firms located in the North-East and in the Center of the country. Actually, the differences among these macro-regions disappear from our estimates after we control for industrial composition and firm size. On the other hand, a strong negative premium is detected for the firms located in the South and on the Islands, which are respectively 31.9% and 33.2% less productive than firms in the North-West of the country.

Finally, in columns 3 and 4 of Table I.5 we separate from our sample only the new entering firms and register the first productivities they report throughout the period of analyses.[11] We find that new firms already report significantly lower productivity in '*Mezzogiorno*' (-21.4%) in the first years of their activity, possibly because of weaker local selection processes, in line with previous findings on churning. That is, we argue that

[11] Please note how entering firms can show in our sample a variable number of observations for productivity, depending on the year they enter. Moreover, some of them can also not reporting data in the first years after foundation.

less efficient firms are in fact more likely to enter and survive in the provinces of the South, where also competitors are on average less productive.

Table I.5 Least squares for lnTFP by '*Centro-Nord*' and '*Mezzogiorno*'

Dependent variable:	**(1)**	**(2)**	**(3)**	**(4)**
(log of) TFP	**All firms**	**All firms**	**New entrants**	**New entrants**
Mezzogiorno	-0.304***	-0.304***	-0.214***	-0.214***
	(0.021)	(0.021)	(0.020)	(0.020)
Constant	1.481***	1.587***	0.536***	0.596***
	(0.052)	(0.054)	(0.050)	(0.084)
Observations	510,739	510,739	22,207	22,207
Firm-level controls	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Industry x Year dummies	No	Yes	No	Yes
R-squared	0.688	0.690	0.649	0.653

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table I.6 Least square for lnTFP by Italian macro-regions[12]

Dependent variable: (log of) TFP	(1) All firms	(2) All firms	(3) New entrants	(4) New entrants
North-East	-0.020	-0.020	-0.011	-0.011
	(0.026)	(0.026)	(0.015)	(0.015)
Center	-0.042	-0.042	-0.017	-0.016
	(0.037)	(0.038)	(0.023)	(0.023)
South	-0.319***	-0.319***	-0.228***	-0.226***
	(0.030)	(0.030)	(0.023)	(0.022)
Islands	-0.332***	-0.332***	-0.210***	-0.208***
	(0.028)	(0.028)	(0.034)	(0.033)
Constant	1.504***	1.609***	0.547***	0.607***
	(0.061)	(0.062)	(0.051)	(0.087)
Observations	510,739	510,739	22,207	22,207
Firm-level controls	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Industry x Year	No	Yes	No	Yes
R-squared	0.688	0.690	0.649	0.653

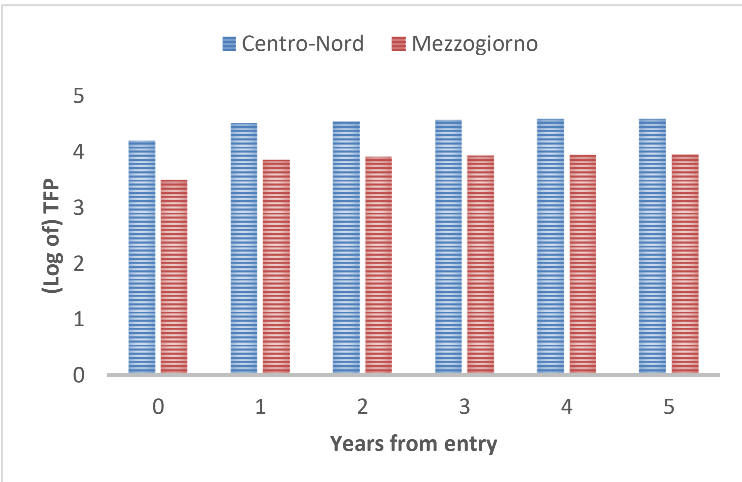
Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

However, the negative premium for entering firms is significantly less than the one for all firms, probably because other intervening factors that determine a wedge between the North and the South of the country have yet to display an impact on younger firms.

[12] '*Centro-Nord*' is composed by North-West, North-East and Center. '*Mezzogiorno*' is composed by Islands and South.

We can imagine that institutional factors can show up later during the life cycle of the firm, rather than at the beginning of their activity. For example, regarding the importance of the efficiency of institutions, Giacomelli & Menon (2017) find that reducing the length of civil procedure increases firm size in the area. In Figure I.8, we report the post-estimates premia on productivity by year after incorporation. We find no specific trend over time, although we can observe a maximum of only five years after a firm becomes operative.

Figure I.10 lnTFP after entry, post-estimation geographic premia.



5 Conclusions

In this chapter, we tested the entry and exit of Italian manufacturing firms in a relationship with characteristics of Italian provinces, in the NUTS-3 region, with a focus on the productivity distributions of incumbent firms. In line with recent theories, we detect a sorting of heterogeneous firms by geography. A higher churning of firms is associated with more productivity in the NUTS-3 region (i.e., Italian provinces). After entry, firms show a higher productivity premium where already more productive firms are. Our findings point to the presence of diverse local selection processes that contribute to shaping geographic disparities. Moreover, we do not think that our results can be affected by excessive heterogeneity due to LevPet estimation, because the ratio between the 95th-percentile and the 5th-percentile is around 2 -- not as large as the Chilean case of 20.90 as found in Gandhi et al. (2016). Our results are also confirmed by robustness checks with a lnTFP computed by ACF methodology (see appendix 1.1: Tables IV.5 – IV.8). In the specific Italian case, we argue that our findings point to a potential persistence of the historical geographic divide in the country, between a more developed North and a less developed South. Policies that do not consider such microeconomic dynamics from firm-level heterogeneity could fail in tackling regional disparities in Italy or elsewhere.

II. Productivity Spillovers and Interlocking Directorates in High-Tech Sectors

1 Introduction

Many determinants of business productivity have been identified in recent decades, for example, technological change and innovation (Van Biesebroeck, 2003; Sakellaris & Wilson, 2004), managerial skills (Ichniowski et al., 1997; Lazear, 2000; Hamilton et al., 2003), quality of human capital (Moretti, 2004; Ilmakunnas et al., 2004; Galindo-Ruenda & Haskel, 2005), learning-by-doing (Thornton & Thompson, 2001), product innovation (Acemoglu & Linn, 2004; Klette & Kortum, 2004; Bartel et al., 2007; Lentz & Mortensen, 2008), competition (Nicoletti & Scarpetta, 2005; Schmitz, 2005; Foster et al., 2006), flexible input markets (Maksimovic & Philips, 2001; Bartelsman et al., 2009; Petrin & Sivadasan 2013), and spillovers (Griffith et al., 2006b; Crespi et al., 2008; Keller & Yeaple, 2009; Syverson, 2011).

Among these factors, knowledge plays a key role, in particular, knowledge spillovers, defined as the sharing of know-how, ideas, and information, especially in high-tech sectors. Typically, individuals share information when they live or work in the same area, referring, in this case, to knowledge spillovers through geographical proximity (i.e., geographical spillovers). Knowledge spillovers can be further classified. Based on the work by Stoyanov & Zubanov (2012), knowledge spillovers can be divided into “codified” and “uncodified” knowledge spillovers. Patent citations represent a classic example of "codified" knowledge spillover (Griliches, 1992; Jaffe et al., 1993; Hall et al., 2001; Maurseth & Verspagen, 2002). "Uncodified" knowledge spillovers are typically investigated through concepts such as workers' mobility (Rao & Drazin, 2002; Song et al., 2003; Moretti, 2004; Gorg & Strobl, 2005; Balsvik, 2011; Poole, 2013).

Research on knowledge spillovers and agglomeration economies dates back to Alfred Marshall's “Principles of Economics”, first published in 1890. This topic has been popularized in the last few decades thanks to, among others, Jacobs (1969), Becattini (1979), Porter (1990), Glaeser et al. (1992), van der Panne (2004), Bellandi & Di Tommaso (2005), and Raffaelli et al. (2006). More recently, there has been a methodological upgrade in the literature by using spatial econometrics. Notable examples of this new trend are Cardamone (2014), Antonelli et al. (2010), Badinger & Egger (2016), Bottazzi et al. (2003), and Sangalli & Lamieri (2015). Scholars usually found that geographical spillovers do exist.

A significant way in which a director can influence a firm's productivity is through the crucial role of managerial practices, as demonstrated by a study based on large-scale survey data (Bloom et al., 2007). Due to the lack of data on directors' networks, there are only a handful of studies on the relationship between interlocking directorates and firm performance in Italy such as Croci & Grassi, 2014; (other recent works on Italian interlocking directorates composition are: Bellenzier & Grassi, 2014; Drago et al., 2011; Fattobene et al., 2017). Other contributions on different countries include: Yeo et al. (2003) for France, Rommens et al. (2007) for Belgium, Prinz (2006) for Germany, and Buchwald (2014) for European companies. Most of the work so far has considered only companies listed on the stock exchange due to a lack of data.

In this paper, we aim to shed light on the role of interlocking directorates as conduits of knowledge spillovers. In our analysis, we focus on knowledge intensive firms in Italy. As indicated by Van Biesebroeck (2003) and Sakellaris & Wilson (2004), technology changes and innovation are crucial for firm productivity and success. We assert that interlocking directorates can generate positive spillovers through innovation, especially in science-based industries. We use patent intensity[13] as an indicator of innovation in science-based sectors. Indeed, the most innovative sectors based on patent intensity are: pharmaceuticals, chemistry and electronics (they are the only ones with a patent intensity greater than 500, see Table II.1). These industries correspond to science-based sectors in the Pavitt's taxonomy (Pavitt, 1984). This is not surprising since innovation and intellectual property rights in pharmaceuticals, chemistry and electronics are fundamental for firms' survival, growth and competitiveness.

[13] As measured by the number of EPO patents per 100,000 employees.

Table II.1 EUIPO survey on patent intensity by NACE rev. 2

NACE rev. 2 (2 digits) description	Patent Intensity*
C10 Manufacture of food product	20.25
C11 Manufacture of beverages	7.97
C12 Manufacture of tobacco products	71.86
C13 Manufacture of textiles	43.34
C14 Manufacture of wearing apparel	7.93
C15 Manufacture of leather and related products	23.30
C16 Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	13.76
C17 Manufacture of paper and paper products	69.83
C18 Printing and reproduction of recorded media	19.01
C19 Manufacture of coke and refined petroleum products	32.19
<u>C20 Manufacture of chemicals and chemical products</u>	<u>506.77</u>
<u>C21 Manufacture of basic pharmaceutical products and pharmaceutical preparations</u>	<u>599.32</u>
C22 Manufacture of rubber and plastic products	213.20
C23 Manufacture of other non-metallic mineral products	56.35
C24 Manufacture of basic metals	80.15
C25 Manufacture of fabricated metal products, except machinery and equipment	105.69
<u>C26 Manufacture of computer, electronic and optical products</u>	<u>890.65</u>
C27 Manufacture of electrical equipment	361.97
C28 Manufacture of machinery and equipment not else where classified	477.72
C29 Manufacture of motor vehicles, trailers and semi-trailers	317.53
C30 Manufacture of other transport equipment	395.01
C31 Manufacture of furniture	25.75
C32 Other manufacturing	232.28
C33 Repair and installation of machinery and equipment	45.04

* Patent intensity computed as EPO applications over 100,000 employees. Underlined values over 500. Sourced European Union Intellectual Property Office

Conversely, as shown by the EUIPO survey reported in Table II.1, in the most traditional industries such as food, beverages, wearing apparel, and furniture, patent intensity is much lower.

The interlocking directorates play an important role in high-tech industries to share know-how and tacit knowledge. We find that the interlocking directorates' connections among science-based firms are 4.8 times denser than the average of all manufacturing sectors. Moreover, the majority (53%) of managerial connections by science-based firms are with other firms in the same sector.

For all these reasons, we choose to focus our analysis on the high-tech sectors or, more precisely, on the science-based industries according to Pavitt's taxonomy.

In this work, we combine two different streams of research on firm productivity. The first stream of literature is about spillovers and agglomeration effects through shared innovation knowledge in a particular geographical area (see, for instance, Cardamone, 2014). The second stream of research has focused on the role of interlocking directorates (i.e., whether members of the board of directors are simultaneously on the board of another firm; see, for example, Croci & Grassi, 2014). To the best of our knowledge, agglomeration effects and interlocking directorates have not been jointly investigated, mainly due to the lack of data for directors and the locations of firm activities. First, we apply a simple spatial model to examine the presence of knowledge spillovers through interlocking directorates. Then, we focus on models that control for firms' geographical proximity to determine if the effect of interlocking directorates on knowledge spillovers still holds.

This chapter is structured as follows. Section II.2 introduces our dataset. In Section II.3, we describe the spatial econometrics methodology. Section II.4 presents and describes the results of our research. Finally, Section II.5 concludes by discussing our findings.

2 Data

Our data are taken from AIDA, which is a commercial database managed by Bureau van Dijk Company. This database comprises data from Italian firms. We obtained observations for the year 2014 since data on interlocking directorates is a new feature in AIDA, introduced for 2014. We selected firms in the science-based industries (i.e., sectors 20, 21 and 26 in the NACE rev.2 classification). We collected data on total revenue, cost of materials, value of tangible assets, value of intangible assets, number of employees, value of patents, know-how, trademarks and other intellectual property rights, final owner nationality, geographical coordinates (latitude and longitude), and list of administration board members.

According to AIDA, there were approximately 7,000 science-based manufacturing firms in Italy in 2014. One-half of these firms reported data on revenues, tangible assets, cost of materials, and number of employees. Since intellectual property rights are also missing[14], we are left with 1,500 firms with complete

[14] Some studies use data on export and innovation from Unicredit Surveys. These surveys collect data about 150/200 Science Based manufacturing enterprises. We hope in the future to have more firms, which report data on innovation activities.

information. Additionally, some companies do not report information on the Board of Administration. Therefore, only 801 firms can be considered in our analysis. Our final sample includes firms that are quite heterogeneous in size whereas previous studies, such as Croci & Grassi (2014), have analyzed a smaller sample of companies listed on the Milan stock exchange (approximately 200 companies).

Table II.2 shows that small firms with less than 50 employees make up almost half of all the firms in our sample, whereas large firms with more than 250 employees are about 10% of our sample. The composition of our sample is in line with the Italian firm size distribution, where most companies belong to the SME (small-medium enterprise) category. Thus, our sample is more representative of the population of firms in Italy than the listed companies (on the stock market, large firms are overrepresented). About 24% of firms in the sample are subsidiaries of foreign multinational companies. As is well-known, multinational companies are overrepresented among science-based firms in Italy (MNCs are about 5% of all manufacturing companies in Italy).

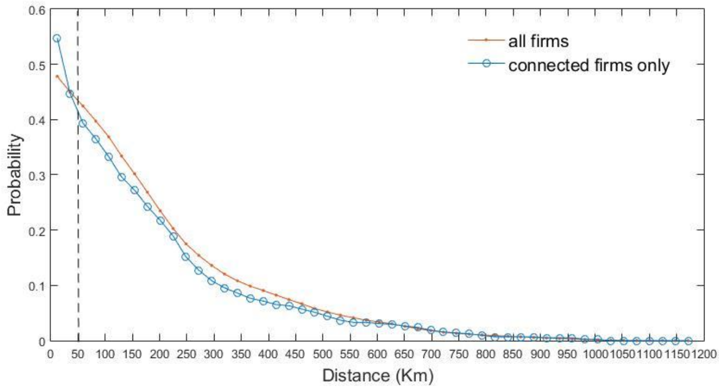
Table II.2 Descriptive statistics

Variables	Abbr.	min	median	mean	max	sd
Natural logarithm of Total Factor Productivity	lnTFP	8.859	11.279	11.271	12.890	0.547
Value in thousands of Euros of innovation per worker	Innovation	0	0.310	0.720	5.928	1.024
Firms with less than 50 employees	Small	0	0	0.422	1	0.494
Firms with employees between 50 and 250	Medium	0	0	0.472	1	0.500
Firms with more than 250 employees	Large	0	0	0.106	1	0.308
Firms who have an Italian control owner	Domestic	0	1	0.757	1	0.429
Firms who have a not Italian control owner	International	0	0	0.243	1	0.429

Table II.3 Key feature of high-tech firms with managerial connections

	Number of connected firms	% of connected firms	Number of non-connected firms	% of non-connected firm	% of AIDA data	% of the sample
Small	40	11.83%	298	88.17%	86.96%	42.19%
Medium	61	16.14%	317	83.86%	10.20%	47.19%
Large	32	37.65%	53	62.35%	2.83%	10.61%
International	36	18.46%	159	81.54%	4.98%	24.24%
Domestic	97	16.01%	509	83.99%	95.12%	75.66%
All	**133**	**16.60%**	**668**	**83.40%**	**100 %**	**100 %**

Figure II.1 Probability distribution



Focusing on the interlocking directorates, we built a network made of 801 firms (i.e., nodes) and 109 connections through mutual directories (i.e., edges), where the maximum number of connections for a company is four. Table II.3 shows that large companies are more connected (37.65% of the total) than SMEs. On the other hand, we cannot observe a very different ratio in connectivity between domestic and international firms. Moreover, as shown in Figure II.1, the probability to have an interlocking directorates' connection is higher for firms at a short distance, in a range below 20 kilometers. The average geographical distance between two connected firms is 131 km, which is well below the average distance between all firms in AIDA (228 km). These findings suggest that interlocking directorates may be influenced by the geographical distribution of firms, i.e, nearby firms are more likely to be connected.

3 Methodology

In our analysis firm productivity represents our dependent variable. Following a large body of literature on spillovers for manufacturing industries, we use Total Factor Productivity (TFP) as a measure of firm productivity. To compute TFP we use the same methodology as in Cardamone (2014)[15] to consider a log-linear Cobb-Douglas production function, which implies constant returns to scale:

Equation II.1

$$Y_i = {K_i}^{\alpha} \cdot {L_i}^{1-\alpha}$$

where Y_i is the value-added of firm i in 2014, K_i is the amount of tangible assets of firm i in 2014, and L_i is the number of employees of firm i in 2014[16].

After a logarithmic transformation, we get

Equation II.2

$$\ln\left(\frac{Y_i}{L_i}\right) = \alpha_0 + \alpha_1 \cdot \ln\left(\frac{K_i}{L_i}\right) + \varepsilon_i$$

In this way, we can estimate the parameter α_1 by a standard least squares regression. Later, we can calculate the natural logarithm of TFP for firm i as follows

[15] In robustness checks, we consider also LevPet and ACF.

[16] As written above, only data for 2014 are available for our analysis; thus, we cannot use techniques that need a panel dataset.

Equation II.3

$$\ln\left(\widehat{TFP_i}\right) = \ln Y_i - (1 - \widehat{\alpha_1}) \cdot \ln L_i - \widehat{\alpha_1} \cdot \ln K_i$$

Thus, for each firm, we obtain a specific value of ln TFP. The next step consists in studying which variables could affect TFP at the firm level.

To estimate possible spillover effects on firm TFP, we employ spatial econometrics with parametric linear models (Anselin, 1988). In the literature, different spatial econometric models are available (LeSage & Pace, 2009 and Elhorst, 2014). Each model could be considered for a specific issue, such as for example Spatial Error Model for missing variables or Spatial AutoRegressive model for spatial spillovers. Partially following the structure employed in Sangalli & Lamieri (2014) for the Italian case, we believe that the most useful models in our analysis are the Spatial Autoregressive model (usually abbreviated as SAR) and the combined SAC model. In both models, spillover effects are considered: the firm productivity (our dependent value) depends on the productivity of the other firms.

As explained in Elhorst (2014), a SAR model[17] can be written as

Equation II.4

$$\boldsymbol{y} = \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

[17] We use R software. The parameters of the different spatial models are estimated through maximum likelihood.

where $\boldsymbol{y}$ (n x 1) is the dependent variable (in our case ln TFP), and $\boldsymbol{X}$ (n x k) is the matrix of independent variables. Obviously, $\boldsymbol{\beta}$ (k x 1) are the associated coefficients, and $\boldsymbol{\varepsilon}$ (n x 1) the error term. Finally, $\boldsymbol{W}$ (n x n) is the spatial weight matrix, and ϱ is the spatial coefficient. The main novelty of the SAR model consists in a dependent variable expressed as a function of the dependent variables of other individuals.

Transposing this model to our case means that TFP of a firm in a science-based industry is also influenced by other firms' TFP values and not only its own level of innovation.

Since our research question is about the existence of spillovers (i.e. indirect effects), we are intersted how to calculate them in SAR model. For the SAR model, it is relevant to clarify that direct and indirect impacts (i.e., spillovers) need to be calculated. Indeed, we cannot consider just β_k and ϱ as indicators. Following the reasoning in LeSage & Pace (2009), the SAR model can be written as

Equation II.5

$$(I_n - \rho W)y = X\beta + \varepsilon$$

Equation II.6

$$y = \sum_{r=1}^{k} S_r(W)x_r + (I_n - \rho W_{ij})^{-1}\varepsilon$$

where: $S_r(W) = (I_n - \rho W_{ij})^{-1} I_n \beta_r$

Thus, its derivative is given by

Equation II.7

$$\frac{\partial y_i}{\partial x_{jk}} = (I_n - \rho W_{ij})^{-1}\beta_k$$

This can be rewritten, with a lighter notation, as

Equation II.8

$$(I - \rho W)^{-1}\beta_k$$

One can conclude that the diagonal elements of the equation above give the direct impacts and the off-diagonal elements represent the indirect impacts. We must highlight that the coefficients β_k, ϱ and their p-values cannot provide information on the existence of positive or negative impacts. However, one necessarily needs to compute separately impacts and their p-values. Thus, we conclude that spillovers exist if and only if indirect impacts are statistically significant.

Finally, to complete the analysis, we also introduce a second model called SAC, which is a generalization of SAR. Loosely speaking, a SAC model as a different error term (Kelejian & Prucha, 2010). In more detail, the model is expressed as follows

Equation II.9

$$\boldsymbol{y} = \rho \boldsymbol{W_1 y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon}$$
$$\boldsymbol{\varepsilon} = \lambda \boldsymbol{W_2 \varepsilon} + \boldsymbol{u}$$

where **y** (n x 1) is the dependent variable (in our case ln TFP), and **X** (n x k) is the matrix of independent variables. Obviously, **β** (k x 1) are the associated coefficients, and **ε** (n x 1) the error term. Finally, $\mathbf{W_1}$ (n x n) is the first spatial weight matrix linked with the other dependent variables of other individuals, and ϱ is the spatial coefficient. Moreover, in an SAC model we have also $\mathbf{W_2}$ (n x n), which is the second weight matrix linked with error term, whereas **u** (n x 1) is the innovation part. For more information see Kelejian & Prucha (2010) and LeSage & Pace (2009).

In the SAC model, the two contiguity matrices may be generated by two different rules or phenomena (for example, one based on the geographical distance, and the other one based on social connections). Hence, one gets that $\mathbf{W_1} \neq \mathbf{W_2}$. Conversely, one can also assume that the two weight contiguity matrices are created by the same rule, in which case $\mathbf{W_1} = \mathbf{W_2}$.

To select the most suitable exogenous matrix **W** and model (inside a set of "reasonable" such matrices), we use the Akaike Information Criterion[18] (AIC). AIC, as suggested by its name, is a criterion that can indicate which model fits better among a given set of models. From a practical point of view, the AIC chooses the model with the lowest associated value. The main reason for using the AIC consists in its capacity to compare different models, which are not necessarily nested.

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[18] The AIC value has the following formula: $2k - 2\ln(L)$, where k is the number of parameters and L the value of the likelihood function. Other popular criteria are represented by the level of likelihood and Bayesian Information Criterion (BIC). BIC takes into account also the number of observations.

4 Results

4.1 Preliminary evidence

First, in this section we present results from a simple Least Square regression. Here, following a similar framework to Cardamone (2014), we specify the productivity levels as follow

Equation II.10

$$\ln TFP_i = \beta_0 + \beta_1 \cdot innovation_i + \beta_2 \cdot international_i + \varepsilon_i$$

On the productivity side, we confirm the main findings in the literature: innovative firms show higher level of productivity. Not surprisingly, international manufacturers are on average more productive than Italian firms, because a process of self-selection exists where only efficient and productive firms can enter foreign markets.

Table II.4 Preliminary results from LS model

variable	lnTFP
Innovation	7.154*** (1.843)
International	0.236*** (0.044)
Constant	11.163*** (0.025)
R^2	0.051
Adjusted R^2	0.049
Observations	801

Standard errors in parentheses; p-value < 0.01***, 0.05**, 0.10*

As already conjectured, we find from the results of the LS regression that innovation has a positive effect on lnTFP, since the coefficient associated with innovation is positive and strongly significant at the 1% level, as in Cardamone (2014). Therefore, firms' productivity clearly positively depends on innovation. This result is still debated in the literature. For instance, Griffith et al. (2006a) study innovation effects on labor productivity, but results in their analysis vary across the four analyzed European countries (i.e., France, Germany, Spain and the UK).

In this preliminary regression, since we consider a simple LS, we do not have any clue about the existence of knowledge spillovers. In the next sections we focus on this important research question.

4.2 The role of interlocking directorates

So far, we have not considered in our regression model possible spillovers among firms. As we have already written above, a large body of the literature focuses on spillovers generated by neighboring firms. In this work we would like to show the existence of spillovers generated by interlocking directorates. For this reason, we must introduce a weight contiguity matrix W to adopt a SAR model and investigate possible indirect impacts of innovation and international ownership. In our interlocking directorates' contiguity matrix, entries have value one when the two firms have at least one mutual director and a value close to zero otherwise[19]:

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[19] The motivation for inserting a very low value (but not zero) for firms, which do not have at least a director in common, resides in not dropping any

Equation II.11

$$m_{ij} = \begin{cases} 1 \; if i \; and \; j \; share \; at \; least \; one \; director \\ 0 \; if \; i \neq j \\ \dfrac{1}{(n-1)^2} \; otherwise \end{cases}$$

We consider now a SAR model, which has the same independent variables of LS regression above and the W matrix defined according to the interlocking directorates' network.

Table II.5 Regressions results for geographical SAR

	lnTFP
Innovation	6.316***
	(1.804)
International	0.228***
	(0.043)
Intercept	7.865***
	(0.672)
Rho	0.292***
	(0.060)
Loglikelihood	-620.512
AIC	1251.025
Observations	801

Standard errors in parentheses; p-value < 0.01***, 0.05**,0.10*

observation in our sample. Otherwise, we would have incurred the risk of having a biased sample.

As before, the coefficients associated with Innovation and International are positive and significant. We also find that rho (i.e. spatial autoregressive coefficient) is positive and significant.

After running regressions and computing impact analysis of the chosen model, we do find that interlocking directorates' spillovers do exist.

Table II.6 SAR model with the chosen geographical matrix

	Direct	Indirect	Total
Innovation	6.396***	2.592**	8.989***
	(1.826)	(1.069)	(2.683)
International	0.2314***	0.094***	0.325***
	(0.044)	(0.032)	(0.066)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

In Table II.6, we observe positive direct effects for innovation and International ownership. Both coefficients associated with these two variables are positive and significant at the 0.01 p-value level. Thus, we find positive direct effects. Focusing on our core research question, i.e. the existence of indirect effects (spillovers), we find a positive coefficient associated with innovation. Given that this time the associated p-value is 0.012, we conclude that spillovers based on interlocking directorates are also positive. Therefore, we find empirical evidence in favor of spillovers that positively affect firm productivity. Here, in the SAR model spillovers account for around 29% of the total effects. We also reach similar conclusions for the effect of spillovers by multinational companies: international firms produce positive externalities on lnTFP as in Lu et al. (2017).

4.3 Geographical spillovers

We pass now to compare the effect of interlocking directorates to geographical spillovers.

Different models have been used in the literature to estimate geographical spillovers. For example, some scholars estimate geographical distance through ZIP codes, information on municipalities, or they consider two firms as neighbors if they are in the same or an adjacent region. Due to the availability of geographical coordinates (i.e., longitude and latitude) for all firms in our sample, we decide to estimate distance for each firm pair through a standard Haversine formula[20].

Since different contiguity matrices can be defined for the geographical distance, in our analysis we considered the most frequently used in the literature.

[20] The Haversine formula is employed in case one needs to compute the distance between two points on the surface of a sphere or globe. The Haversine formula is defined as follow (Aldieri & Cicera, 2009)

$d_{ij} = 2 \cdot r_{earth} \cdot \sqrt{\sin^2\left(\frac{lat_j - lat_i}{2}\right) + \cos(lat_j) \cdot \cos(lat_i) \cdot \sin^2\left(\frac{lon_j - lon_i}{2}\right)}$, where $r_{earth} = 6371.0\ Km$

We start by considering a "simple geographical" contiguity matrix version without any cut-off[21]. In this case, entries are given by the following expression[22]:

Equation II.12

$$m_{ij} = \begin{cases} \min\left(1, \frac{1}{d_{ij}}\right) \; if \; i \neq j \\ 0 \; if \; i = j \end{cases}$$

In this case, we assume that possible spillover effects among enterprises decrease linearly with their geographical distance. Moreover, we consider also more sophisticated geographical contiguity matrices, which are based on the squared distance[23], namely

Equation II.13

$$m_{ij} = \begin{cases} \min\left(1, \frac{1}{d_{ij}^2}\right) \; if \; i \neq j \\ 0 \; if \; i = j \end{cases}$$

Here, possible spillover effects diminish more than proportionally with distance.

[21] We abbreviate this matrix *lin* as linear distance: Moreover, m_{ij} is not yet a standardized matrix, the associated standardized matrix is indicated as W_{ij}

[22] We set a minimum distance of 1 Km to avoid any problem with a distance close to zero. Other solutions may be implemented, for example see Cardamone (2014).

[23] We abbreviate this matrix as *squ* as squared distance.

Finally, we try to introduce some cut-offs – namely, 20 Km, 50 Km, and 80 Km[24] - in the linear and square geographical distance[25]. In in the case of cut-offs, firms that are farther than the given cut-offs will have an almost zero effect. Analytically, the linear case reads as[26]

Equation II.14

$$m_{ij} = \begin{cases} \min\left(1, \frac{1}{d_{ij}}\right) \; if \; i \neq j \,, i \; and \; j \; are \; at \; a \; given \; distance \; or \; closer \\ 0 \; if \; i = j \\ \frac{1}{1250} \; otherwise \end{cases}$$

Similarly, the square case reads as

Equation II.15

$$m_{ij} = \begin{cases} \min\left(1, \frac{1}{d_{ij}^2}\right) \; if \; i \neq j \,, i \; and \; j \; are \; at \; a \; given \; distance \; or \; closer \\ 0 \; if \; i = j \\ \frac{1}{1250^2} \; otherwise \end{cases}$$

---

[24] These three thresholds are chosen between the 10th percentile (i.e. 20.74 Km) and the 26th percentile (i.e. 80.09 Km) of the geographical distance distribution.

[25] We abbreviate the linear distance matrices, respectively as: lin20, lin50, and lin80. The squared distance matrix as squ20, squ50, squ80.

[26] We insert a notional distance of 1250 Km to avoid a smaller biased subsample.

Among the proposed geographical matrix, we choose the best one[27] following Akaike Information Criterion (AIC).

Table II.7 AIC values for SAR models using different geo distance matrices

	20 Km	50 Km	80 Km	No cut-off
Linear distance	1268.663	1267.169	<u>1265.339</u>	1266.908
Squared distance	1270.694	1270.397	1269.111	1268.988

The lowest value is underlined

According to Table II.7, the geographical model that fits better our data is the one, which considers as contiguity matrix a linear distance with a cut-off of 80 Km. Anyway, this geographical model has a higher AIC value than the previous interlocking directorates' model (its AIC value was 1251.025). Thus, we must underline that spillovers through interlocking directorates performs better any knowledge location spillover model.

4.4 Interlocking directorates and geographical spillovers

As was already hinted in the data section, we observe that connected firms have, on average, a shorter geographical distance than unconnected ones. For this reason, we assert that a negative

[27] As already hinted above, there is not any "rule" *a priori* to decide which is the best contiguity matrix to be used.

relationship between geographical distance and interlocking directorates exists, as found by Kono et al. (1998), where closer firms have higher chances to be connected through interlocking directorates.

To further investigate this relationship, we employ a logit model to check whether the probability of having an interlocking directorates connection negatively depends on distance. Our logit regression has 320,400 unique pairs of observations, since our model is made of 801 firms[28]. For the dependent variable, we use a dummy variable, which is one if the selected pair shares at least one director, zero otherwise. For each pair, we compute as independent variable the geographical distance in kilometers, employing the standard Haversine formula.

Table II.8 The relationship between managers at distance

	Directorship
Haversine distance	-0.010 ***
	(.0010)
Constant	-6.973 ***
	(0.134)
Pseudo-R^2	0.017
Observations	320,400

Standard errors in parentheses; p-value < 0.01***, 0.05**, 0.10*

As shown in Table II.8, distant firms show a lower probability of mutual directors. In other words, we find a "local directors' market" where firm tend to share directors when they are in the same sector and close by. Indeed, directors should have enough

[28] The number of possible pairs in a given group of individuals is $\frac{n^2-n}{2}$.

time to attend meetings in the different boards of administration and that can be done efficiently when firms are in the same region.

This means that some parts of the interlocking directorates spillovers' aspect might be affected by geographical correlation.

To control for that, we employ a SAC model, where the interlocking directorates matrix is linked with the spillover part $\varrho W_1 Y$, and the geographical matrix is in the error part $\lambda W_2 \varepsilon$. This SAC model should represent an improvement of the SAR model where only the interlocking directorates effect is considered. For this reason, we prefer the SAC models to the interlocking directorates' SAR model.

Table II.9 AIC values for SAC models using geographical matrix as W_1 and interlocking directorates' matrix as W_2

	20 Km	50 Km	80 Km	No cut-off
Linear distance	1250.580	1249.393	<u>1248.148</u>	1249.585
Squared distance	1251.530	1251.402	1250.528	1250.578

The lowest value is underlined

As in the previous case, Table II.9 shows that the model with the lowest AIC is the one which considers a linear distance with a 80 Km cut-off.

Since the chosen SAC model shows a smaller AIC value than the interlocking direcotrates SAR model, this model should be preferred.

Table II.10 Regressions results SAC with for interlocking directorates network (W_1) and geographical distance (W_2)

	lnTFP
Innovation	6.220***
	(1.805)
International	0.222***
	(0.043)
Intercept	8.003***
	(0.681)
Rho	0.277***
	(0.061)
Lambda	0.298**
	(0.138)
Loglikelihood	-618.074
AIC	
Observations	801

Standard errors in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table II.11 SAC model with the chosen matrices

	Direct	Indirect	Total
Innovation	6.232***	2.295**	8.528***
	(1.794)	(0.904)	(2.523)
International	0.229***	0.084***	0.313***
	(0.045)	(0.028)	(0.065)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

Regression results, shown in Tables II.10 and II.11, confirm our findings for Innovation and the FDI. P-values associated with indirect impacts are similar to the interlocking directorates' case, and the indirect effects are around 27% of total impacts (they were 29% in the SAR case). Moreover, since the coefficient associated with lambda is positive and statistically significant at 5% level (associated p-value 3%), there might be important missing variables related to geographical dimension. We can conclude that the interlocking directorates' spillovers are confirmed even when we control for distance. From a policy perspective, the innovation policy should target not only specific areas (such as firms, which patent and perform R&D expenses in undeveloped regions or science parks), but should also consider the interfirm networks. Indeed, targeted policies on central firms in the directors' network may have a positive effect on the productivity of connected firms.

4.5 Robustness checks

We perform a series of robustness checks to corroborate our findings. Specifically, we change the dependent variable to consider the natural logarithm of TFP estimated through: a LevPet technique (Levinsohn & Petrin, 2003) to control simultaneity bias, and an ACF technique (see Ackerberg et al., 2015) to control for hiring/firing employee costs. We repeat the same regressions as before, that is to say the Least Squares model, the SAR model with interlocking directorates, and the SAC model with interlocking directorates and the geographical effect.

Table II.12 Regressions results for LS

	LevPet lnTFP	ACF lnTFP
Innovation	20.245***	15.224***
	(2.223)	(2.167)
International	0.331***	0.003
	(0.053)	(0.051)
Intercept	5.630***	4.431***
	(0.031)	(0.030)
R^2	0.130	0.058
Adjusted-R^2	0.127	0.051
Observations	801	801

Standard errors in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table II.13 Regressions results for geographical SAR

	LevPet lnTFP	ACF lnTFP
Innovation	18.679***	14.457***
	(2.168)	(2.149)
International	0.323***	0.004
	(0.051)	(0.051)
Intercept	3.792***	3.596***
	(0.332)	(0.294)
Rho	0.313***	0.184***
	(0.057)	(0.064)
Loglikelihood	-767.254	-757.109
AIC	1544.5	1524.2
Observations	801	801

Standard errors in parentheses, p-value < 0.01***, 0.05**, 0.10*

Table II.14 SAR model LevPet lnTFP

	Direct	Indirect	Total
Innovation	18.954***	8.405***	27.350***
	(2.193)	(2.353)	(3.776)
International	0.328***	0.145***	0.473***
	(0.052)	(0.045)	(0.085)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

Table II.15 SAR model ACF lnTFP

	Direct	Indirect	Total
Innovation	14.530***	3.295**	17.826***
	(2.158)	(1.499)	(2.986)
International	0.004	0.001	0.005
	(0.051)	(0.013)	(0.063)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

Table II.16 Regressions results SAC with for interlocking directorates network in W_1 and geographical distance in W_2

	LevPet lnTFP	ACF lnTFP
Innovation	17.796***	14.147***
	(2.163)	(2.145)
International	0.308***	-0.004
	(0.052)	(0.051)
Intercept	3.932***	3.747***
	(0.341)	(0.300)
Rho	0.288***	0.149***
	(0.059)	(0.066)
Lambda	0.398***	0.388***
	(0.128)	(0.129)
Loglikelihood	-762.345	-752.842
AIC	1536.689	1517.685
Observations	801	801

Standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

Table II.17 SAC model LevPet lnTFP

	Direct	Indirect	Total
Innovation	17.950***	6.990***	24.940***
	(2.192)	(2.238)	(3.737)
International	0.309***	0.121***	0.430***
	(0.044)	(0.044)	(0.091)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

Table II.18 SAC model ACF lnTFP

	Direct	Indirect	Total
Innovation	13.886***	2.343**	16.223***
	(1.960)	(1.210)	(2.752)
International	-0.008	-0.001	-0.010
	(0.059)	(0.010)	(0.061)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

In all models, our findings on the indirect effects of innovation do not substantially change. Indeed, they are always positive and statistically significant at 5% level. In more details, in the LevPet lnTFP estimation case, the indirect effects account for about 30% of the total effect whereas for ACF lnTFP, the indirect effect does not reach 20% of the total.

There is a discrepancy between the baseline model and the ones used in robustness checks about the role of multinational companies: regressions with LevPet confirm the positive role of international companies for direct and indirect effects, but in regressions with ACF lnTFP, results are always statistically insignificant. All in all, the crucial role of innovation is confirmed in all of our robustness checks.

5 Final discussion

The main contribution of this chapter consists in studying the role of interfirm networks, such as interlocking directorates, for knowledge spillovers in a spatial econometrics framework. We show that interlocking directorates are important channels of knowledge spillovers among firms. This result holds even when we control for spatial spillovers and alternative methodologies to compute TFP. We contribute to the literature on spatial knowledge spillovers by highlighting the key role of managerial interfirm networks.

We find that interlocking directorates' spillovers through levels of firm innovation are strong and significant. Even though managerial connections do depend on geographical proximity since closer firms tend to share directories, when we employ spatial econometric models that also consider geographical aspect in the error part, to avoid that, the interlocking directorates might be affected by a latent effect of geographical proximity, we confirm our results. In general, SAC models with the geographical proximity in the error part should be preferred since they show lower values than SAR based on interlocking directorates' network (i.e., less information is lost as indicated by the AIC). As further robustness checks, we also consider different ways to compute the Total Factor Productivity. The new regressions confirm the main finding about innovation spillovers based on interlocking directorates' network. As for multinational companies, our findings are ambiguous since both direct and indirect effects are not robust compared to alternative way to compute TFP.

All in all, our result contributes to the literature on knowledge spillovers, which is mostly focused on spatial effects and propinquity. In our analysis, we show that interfirm networks and managerial connections play a fundamental role in knowledge intensive industries. By targeting central firms in the directorship network, innovation policies can take advantage of productivity spillovers to peripheral firms. In other words, central firms are the ideal targets for innovation policies to boost firm productivity in science-based sectors.

Our work has some limitations. First, there is a problem of endogeneity, since more productive firms tend to have many links with other firms and to be central in managerial networks. Even though this is an important limitation of our study, it applies in the same way to the analysis of firm location choice (i.e. more productive firms tend to co-locate their activities in the same region, as discussed in Chapter 1). As future steps, we would like to build contiguity matrices with different interfirm networks such as ownership networks and strategic alliances. Here, we consider contiguity matrices through interlocking directorates. However, there exist other important connections among firms[29] , which we did not consider due to lack of data. A rigorous approach should be developed to select the best combination of interfirm networks and models. Another important limitation of our work is the use of a static sample with only one year of observations whereas current work on spatial spillovers, such as by Wanzenboeck et al. (2015), employs panel data. This relevant restriction in our sample is due to the lack of panel data for the network of interlocking directorates. Since those data will become available in the next few years, we plan to extend our analysis to investigating variations across time and also further investigate the causal relationship between network formation and productivity.

[29] For example, connections given by input/output firms, production claims, workers' mobility, inventors' mobility, R&D collaborations, mutual qualified owners, and temporary joint ventures might be also relevant for the innovation process.

III. The Italian Startup Act: Empirical Evidence and Policy Effects

1 Introduction

Small and young companies are often seen as the engine of innovation and growth. However, these companies are also known to be the most financially constrained (Himmelberg & Peterson, 1994; Schneider & Veugelers, 2009). This argument is especially pertinent for newly founded, innovative firms (Carpenter & Petersen, 2002). Capital market imperfections in financing R&D investments are usually put forward as a theoretical justification for public support to private R&D (Hall, 2002). R&D investments are riskier than other investments with negative consequences both for ereay financing, as investors discount uncertainty, and for debt financing, since collateralization becomes problematic due to sunk costs and intangibles (Hall et al., 2016). Moreover, the problems of contract incompleteness and information asymmetry between firm and investors are exacerbated in the case of R&D financing (Hall & Lerner, 2010). As a result, innovative firms rely more on their own internal finance, when available. Market failures in innovation can be particularly severe in countries that lack well-functioning capital markets for innovative startups (Myers & Majluf, 1984).

Italy, especially in the aftermath of the 2008-2009 financial crisis followed by the economic recession and the sovereign debt crisis, can be considered as one of those countries where the functioning of the financial markets became highly debatable, at the very least. The recognition that the crisis might have hit innovative, small and young firms more severely than other companies called for policy actions especially for these disadvantaged but potentially highly important companies for the economic growth (cf. OECD, 2009; OECD, 2014; and Bergner et al., 2017).

As a response to the crisis, Italy passed the law 221 in 2012, which can be seen as an active high-tech startup policy. This policy scheme is a composite measure made of a set of complementary interventions aimed at unleashing the growth potential of innovative young and small companies. Among other features, it combines investment tax benefits, public loan guarantees and a more flexible labor legislation as benefits for the program participants.

The purpose of this paper is to provide a first look at the effects of this newly designed, and in the context of science and technology policy, innovative program to incent startup activity and to enhance the growth potential of innovative companies. We apply state-of-the-art econometric techniques to estimate treatment effects of the policy on relevant target variables at the firm-level. We mainly rely on difference-in-difference regressions with adequate control group designs but also address possible self-selection mechanisms and attrition.

The remainder of this Chapter is as follows: the Section III.2 introduces the data, the Section III.3 presents the empirical strategy, the Section III.4 show results, and the Section III.5 concludes.

1.1 Theoretical Background

As already experimented across the world, industrial policies to be effective must target a specific population of firms. Targeted firms can be selected according to multiple criteria such as age, size, region, industry, R&D propensity, etc.

Small and Medium Enterprises (SMEs) have been one of the favorite targets of growth policies. Not all small and young firms have demonstrated the same incredible growth potential, but innovative startups are the ones, which can significantly contribute to growth and employment. Among them, the group of young enterprises, namely startups, have been identified as primary beneficiaries because of financial constraints problems and high growth potential. Timing and targeted regions of policy intervention are also critical, with a more massive impact during economic recessions and in depressed areas. The Italian law 221/2012, also referred as Startup Act, represents a significant example of the evolution of industrial and innovative policy. Similar initiatives to support high-tech startup have been recently introduced in other countries such as: India (Companies Act 2013), Latvia (2016), Austria (startup program 2017), Belgium (2017), the Netherlands (upcoming in 2018).

The leading role of young and small firms in job creation is widely supported (Davis et al., 1996 and Criscuolo et al., 2014). Empirical evidence generally confirms firm size and age to be negatively correlated with rates of job creation and firm growth (Birch, 1981; Harhoff et al., 1998; Buldyrev et al., 2007; Headd & Kirchhoff, 2009; Haltiwanger et al., 2013). It has been found that firm births account for a significant share of net job creation and since firms do not grow much after an initial high growth period (Armington & Odle, 1982; Kirchhoff & Phillips, 1988; Audretsch & Mahmood, 1994; Broersma & Gautier, 1997; Voulgaris et al., 2005; Lotti, 2007). More importantly, it is noteworthy that not *all* small firms grow faster than larger firms but only the group of *small and young* firms (the so-called "gazelles").

The innovativeness of the small business sector is another argument brought up in the literature and policy debate to support SMEs incentives. However, as it is well known there is no linear, monotonic relationship between firm size and innovativeness (see among others Acs & Audretsch, 1988; Symeonidis, 1996; Freel, 2005; Hausman, 2005; Lee & Sung, 2005; Laforet & Tann, 2006; Baregheh et al., 2016). More compelling is the argument that problems in the acquisition of financing are particularly pronounced in the SME sector for many reasons: retrieving information on SMEs is more expensive, their securities are less frequently traded, and their financial statements do not have to be audited. The lack of assets to pledge as collateral is another problem of startups, particularly innovative newly founded firms centered around R&D activities. Information asymmetries between insiders and external potential investors and stakeholders are magnified by the overlap of ownership and management in most of the young and small firms. The theory thus suggests asymmetric information to induce an adverse selection, in particular about debt financing. Empirical evidence indeed confirms that the problems above cause an insufficient provision of capital to young, innovative and small firms (Audretsch &Lehmann, 2004; Freel, 2007; Stucki, 2013; Duarte et al. 2016; Bergner et al., 2017).

This is the main rationale of law 221/2012 targeting the group of innovative, high-growth and young small and micro firms in Italy, since they are the ones experiencing the highest demand for capital and featuring specific characteristics complicating the acquisition of funds, especially during recessions (Gompers & Lerner, 2001; Audretsch & Lehmann, 2004; North et al., 2013).

This policy is meant to contribute to filling the gap between Italy and other OECD countries regarding high-tech startups and high skilled labor force. Italy is well-known to be the country with the most considerable fraction of micro (< 10 employees) and small firms (< 50 employees) among OECD countries. Also, small Italian firms account for the most relevant share of employment in OECD countries, well above 60% of total employment (Criscuolo et al., 2014). By taking a closer look at the age composition of small business, we notice that in Italy less than one-half of small companies are less than five years old. Among OECD countries, only Finland has a lower share of young firms (Criscuolo et al., 2014).[30]

In the aftermath of the global financial crisis, there has been a steep decline in the number and share of startup companies. This fact is extremely negative for a country like Italy, primarily by considering that young companies (up to five years after incorporation) contribute disproportionally to job creation. The Great Recession hit young firms relatively harder, but since when they have recovered faster from the crisis.

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[30] Also Japan's share of young companies is lower than in Italy, but Japanese data are only available at the establishment level, thus no direct comparison is allowed.

1.2 The Italian for innovative startups: rational and potential impact

In this chapter, we study the impact of the Italian law 221/2012 to support innovative startups. The primary goal of the policy intervention is "[...] to create favorable conditions for the establishment and the development of innovative enterprises to contribute significantly to economic growth and employment, especially youth employment." (Italian Ministry of Economic Development, 2014). The law 221/2012 includes several support measures as stated in the "Restart, Italia!" report by the Minister of Economic Development.

The target enterprises of the policy are small newly incorporated companies headquartered in Italy with shared capital, which have been operational for less than 5 years and with a yearly turnover lower than 5 million euros. According to the Law, innovative startups must develop and commercialize innovative products or services of high technological value[31], and they should fulfill at least one of the following criteria as reported in:

(1) at least 15% of the company's expenses can be attributed to research and development (R&D) activities;

[31] The definition of innovation related to this law is quite wide, reading the list of registered innovative startups in 2017, we get among the others: companies that are involved in the production of soft drinks and wine; commercialization of jewels; preparation of typical Italian food; factories of mattresses.

(2) at least 1/3 of the e are PhD students, the holder of a PhD or researchers; alternatively, 2/3 of the total workforce must hold a Master's degree;
(3) the enterprise is the holder, depositary or licensee of a registered patent or software (industrial property).[32]

Information extrapolated from MiSE (2016)

As only a small group of young and upcoming enterprises accounts for the bulk of net job creation, law 221/2012 tries to target incentives more specifically to those firms.[33]

Summing up, financial constraints, as a consequence of asymmetric information, high growth potential and job creation are the main arguments for a policy like the law 221/2012 designed to sustain young innovative and small firms. Though those arguments are not sufficient to prove the effectiveness of public policies for innovative startups, those initiatives can play a role in countries like Italy when structural problems have been exacerbated by a prolonged financial and economic crisis. This context is, in principle, an ideal setting to test the impact of such a policy, also considering that the beneficiaries of the incentives have been accurately identified by the Law and monitored throughout the implementation of the policy. Indeed, firms that meet all the criteria set by law 221/2012 can register free of charge at a special register of 'innovative startups' and are entitled to the

[32] Other requirements are not to have distributed profits and not to be the result of a merger, split-up or selling-off of a company or branch.

[33] Similar legislations offering special reliefs for newly founded SMEs and their shareholders have been set in place in France and Portugal (Bergner et al., 2017).

benefits of the new legislative framework. This aspect of the policy is particularly important to evaluate the impact of the new legislation, since it rules out any risk of contamination of the treated group of firms (only registered firms get access to the benefits of the policy, with no exception). The main benefits for innovative startups can be divided into three categories: (a) tax incentives for equity investments; (b) an easy procedure to get credit guarantees on bank loans; and (c) tailored made labor rules to subscribe fixed-term contract which lasts up to the end of the fourth year of a startup's life. Investors in innovative startups get a 30% tax credit as individuals and fiscal deduction as legal entities (as of 2016). As for credit guarantees, it covers up to 80% of the bank loans and up to a maximum of 2.5 m EUR, and it is provided through a Government Fund called "*Fondo Centrale di Garanzia*."[34] When firms are no more eligible for the benefits of the policy, they exit the "innovative startup" register, and special treatments immediately stop. A report is published every year by the Italian Ministry of Industry, providing an in-depth analysis of the evolution of the policy, its impact and cost (MiSE, 2015).

Since the main interventions are on equity investments, access to bank loans and employment, we will focus first on whether this new policy has spurred equity collection, bank loans and creation of new jobs by startup firms, conditional upon survival. Thus, we

[34] The list of benefits to innovative startups includes other aspects like easy access to equity crowdfunding, a waiver to the ratio of fixed-term/open-ended labor contracts (i.e. innovative startups can have only fixed-term employees). Other benefits are a special service for internationalization, no registration fees and annual fees due to Chambers of Commerce, and a special regulation for bankruptcy.

will investigate the impact of the policy on productivity, value-added and job creation.

2 Data and preliminary evidence

To evaluate the impacts of the program, we merge the participant data as published by the Ministry of Economic Development for the years 2013 to 2015 with firm-level (accounting) data from the AIDA database of Bureau van Dijk for the years 2007 to 2015.

As the policy program is focused on startup companies we restrict our sample to small enterprises, i.e. medium-sized and large companies are omitted from the analysis upfront. Small companies are defined by the European Commission as having fewer than 50 employees and at most € 10 million sales.

In addition, we omit firms from highly regulated industries or industries with a high share of publicly owned firms, such as agriculture (NACE rev. 2 A industries), quarrying and mining (NACE rev. 2 B industries), utilities and waste management industries (NACE rev. 2 D and E industries), as well as financial, bank, real estate, insurance industries. Note that less than 2.5% of program participants are active in these sectors. Therefore, we drop only a negligible share of participating companies by applying this industry restriction.

Furthermore, we apply some outlier cleaning to the data in order to avoid that our empirical results are determined by potentially erroneous entries in the AIDA database. Accordingly, we delete all small firms, which show an amount of equity greater than 20 m EUR, or bank debts more than 10 m EUR[35].

Our final sample consists of 403,339 Italian small enterprises including 1,580 program participants. As we observe firms for multiple years, the resulting unbalanced panel contains 2,152,839 firm-year observations.

Table III.1 Description of the main variables, all firms

VARIABLES	mean	min	max	Correlation			
				Cap. st.	Bank	Workers	VA
Capital stock	68.62	0	20,000	1			
Bank debts	192.51	0	10,000	0.1787	1		
Workers	2.48	0	49	0.0931	0.1875	1	
Value-added*	252.02	0	7,388	0.0262	0.1720	0.6554	1

Since the Startup Act has explicitly effects on capital stock, bank loans and number of employees we first focus our analysis on the direct impact of the policy. Moreover, the policy should also enhance value-added and labor productivity (measured as value-added per worker). In our sample, the mean capital stock is about 69 k EUR, the average bank debts are more than 190 k EUR, and the mean number of workers per firm is less than three. It is important to highlight that entrepreneurs, who work actively in their firms, but are not registered at National Social Security Authority (called "INPS"), they are not counted as workers. Indeed, the fact that, on average, small firms have fewer than

35 As a total, about 6% of selected firms.

three employees, means that in the majority exclusively owners with their families work in their enterprises. In a second phase we study whether the increasing availability of capital and qualified labor force translates into higher survival rates, firm productivity and contribution to GDP.

In our sample of SMEs the three most treated representative industries (computer programming, consultancy and related activities; scientific R&D; information service activities) represent more than 50% of total innovative startups (see Table III.2). Conversely, these three industries represent only the 5% of the untreated companies. Looking at the geographic composition of our sample (Table III.3), we notice that just two provinces (Roma and Milano), have around one-fourth of the total analyzed enterprises and innovative startups. This is not surprising since they are the most important provinces in Italy: Rome is the official political capital and Milan represents the most developed financial and business district, where many MNEs locate their Italian headquarters. We notice that treated companies tend to be located in the northern part of the country. This is partially due to a different composition by sector, with high-tech companies which tend to be located in the most innovative areas of the country (see also results in Chapter 1).

Table III.2 Most treated representative industries by number of firms

NACE 2	Untreated		Treated	
	Freq.	**Percent**	**Freq.**	**Percent**
62-Computer programming, consultancy and related activities	9,814	2.43	487	30.82
72-Scientific research and development	1,454	0.36	283	17.91
63-Information service activities	9,733	2.41	98	6.20
71-Architectural and engineering activities; technical testing and analysis	8,699	2.16	84	5.32
26-Manufacture of computer, electronic and optical products	2,353	0.58	80	5.06
28-Manufacture of machinery and equipment n.e.c.	5,731	1.42	71	4.49
74-Other professional, scientific and technical activities	7,913	1.96	63	3.99
70-Activities of head offices; management consultancy activities	17,797	4.41	55	3.48
27-Manufacture of electrical equipment	2,533	0.63	45	2.85
46-Wholesale trade, except of motor vehicles and motorcycles	46,369	11.49	30	1.90

Table III.3 Most treated representative NUTS-3 regions

NUTS-3 Italian region	Untreated		Treated	
	Freq.	Percent	Freq.	Percent
Milano (Center-North)	38,508	9.54	221	13.99
Roma (Center-North)	53,956	13.37	145	9.18
Torino (Center-North)	11,718	2.90	93	5.89
Bologna (Center-North)	7,621	1.89	56	3.54
Napoli (South)	20,629	5.11	56	3.54
Trento (Center-North)	3,192	0.79	53	3.35
Modena (Center-North)	5,742	1.42	43	2.72
Firenze (Center-North)	7,217	1.79	39	2.47
Padova (Center-North)	6,343	1.57	36	2.28
Brescia (Center-North)	9,037	2.24	26	1.65

3 Empirical strategy

For the identification of policy effects, we mainly rely on difference-in-difference regressions (see e.g. Angrist & Pischke, 2009, 2015). We compare capital stock, debt, employment, total value-added and labor productivity of participating companies before and after the policy was launched in December 2012. Possible differences are related to a control group of non-participating firms. We will present a number of robustness tests that basically rest on the idea to make the control group comparable to the treatment group in several dimensions. Initially, we start to use all small firms that did not register for the program as control group. Subsequently, we narrow the control group gradually to see how the estimated treatment effects vary. Finally, we also consider Propensity Score Matching (PSM) and Mahalanobis Matching to mitigate the selection bias problem in the analysis (Arnold & Javorcik, 2009).

In the most simple textbook case, a difference-in-difference estimation may consist only of two time periods (*T*=2), one before (t_0) and one after (t_1) a policy change. The difference-in-difference estimator would amount then to calculate the difference in an outcome variable, y, for the treated companies as well as for the control group, calculate the means of these two differences and subtract the averge difference of the controls from the average difference of the treated companies. This would be equivalent to running the regression

Equation III.1

$$\Delta y_{it} = \gamma_1 \cdot treatment_{it} + \varepsilon_{it} \qquad \text{with i = 1,..., N,}$$

and treatment is a dummy variable that is equal to one for the program participants, and zero for the control group. If desired, one could add exogenous control variables, X, such that

Equation III.2

$$\Delta y_{it} = \gamma_1 \cdot treatment_{it} + \beta \Delta X_{it} + \varepsilon_{it}$$

This is also equivalent to running a fixed effects "within" regression:

Equation III.3

$$y_{it} = \gamma_1 \cdot treatment_{it} + \beta X_t + \alpha_i + \varepsilon_{it}$$

The advantage of the latter specification is that a difference-in-difference estimation can also be easily implemented for $T>2$. In that case the variable treatment is a dummy variable that is always zero for all firms before the policy change, and it switches to one for the program participants as soon as they participate in the program.

The difference-in-difference (DiD) estimator is usually applied to situation where a policy affects a subpopulation of companies, e.g. all small and young firms in an economy. In that case, the firms cannot self-select into treatment. It is exogenously determined which firms are in the treatment group and which firms are in the control group. In our set-up, the firms can self-select into the treatment, however. This bears some potential for a bias in the estimation as the firms may have different participation probabilities. For instance, there might be some firms that expect less benefits from the program than others and therefore do not select into the program. These firms may not have a growth interest in the first place and are therefore not a good control group. In order to address the self-selection problem, we also conduct so-called conditional difference-in-difference estimations where we try to adjust the control group such that it has a similar participation likelihood as the treated firms. In that case, one would assume that the firms are either treated or not only because of purely random shocks. In practice, it means that we gradually narrow the control group to become as similar as possible to the treatment group.

As discussed in the literature, the standard errors in DiD applications might be biased because of autocorrelation and the so-called Moulton bias. We address this concern by clustering the standard errors at a higher level (province level) than the observational unit, as recommended in the literature (see the discussion in Bertrand et al., 2004, or Angrist & Pischke, 2009).

Our first DID specification implemented as fixed effects panel regression is:

Equation III.4

$$y_{it} = \gamma_1 \cdot treatment_{it} + \gamma_2 \cdot start_{it} + \beta X_t + \alpha_i + \varepsilon_{it}$$

with i= $1 \ldots N$ (firms) and t=2007…2015 (years).

In this regression our dependent variables (y_{it}) are: capital stock in thousands of Euros, bank loans in thousands of Euros, the number of employees, value-added in thousands of Euros and value-added per worker in thousands of Euros (as proxy for labor productivity), and we also consider the natural logarithms of these variables. Given our goal to evaluate the policy, our principal independent variable is represented by the treatment status ($treatment_{it}$). We add also a startup dummy $start_{it}$ as an additional control of eligibility. This dummy variable is one in case firm i is at most 5 years old and has 5 million in revenues, otherwise 0. Moreover, we insert a full set of time dummies (X_{it}) to control for macro-economics shocks that might affect all firms.

We first consider all small firms, then we adjust the control group by selecting a sample of untreated firms that show similar size and age as the treated group. We limit the control group to companies which do not exceed 2.5 m EUR in revenue at least one year during our sample period and are at most 5 years in 2013. For example, a company founded in 2009 with 1 million in revenue will be incluced in the sample. The choice of 2.5 m EUR is due to the observation that the largest innovative startup has revenues around 2 m EUR. Thereby, including companies with 3 or 4 m EUR in revenues may create a not appropriate control group. Moreover, we do no longer include companies founded in 2007, because they were six years old in 2013.

In a futher regression, we also limit the inlcuded sectors to those that have most treated companies.

The model specification is similar to the one used in the previous case, but this time we also insert a post-treatment dummy (called $posttreatment_{it}$) to avoid that formerly treated firms enter the control group of never-treated ones and to observe if the effects continue after the treatment period. The post-treatment dummy takes the value 1 once the firm drops out of the program because it became too large, too old, or it loses some mandatory requiriments for an innovative startup.

The new specification for the main analysis is

Equation III.5

$$y_{it} = \gamma_1 \cdot treatment_{it} + \gamma_2 \cdot posttreatment_{it} + \beta X_{it} + \alpha_i + \varepsilon_{it}$$

with *i*= 1… *N* (firms) and *t*= 2008…2015 (years).

We also search for heterogeneous treatment effects by treatment year, and by the Italian geographical area (North vs. South):

Equation III.6

$$y_{it} = \sum_{year=2013}^{2015} \left[\gamma_{1year} \cdot (treatment_{it} * dummy\_year_{it}) \right] + \gamma_2 \cdot posttreatment_{it} + \beta X_t + \alpha_i + \varepsilon_{it}$$

with *i*= 1… *N* (firms) and *t*= 2008…2015 (years), and

Equation III.7

$$y_{it} = \gamma_{1n} \cdot (treatment_{it} * north_{it}) + \gamma_{1s} \cdot (treatment_{it} * south_{it}) + \gamma_2 \cdot posttreatment_{it} + \beta X_t + \alpha_i + \varepsilon_{it}$$

with *i*= 1… *N* (firms) and *t*= 2008…2015 (years).

Another concern might be attrition. It could happen that program participants are more or less likely to survive than non-treated firms. On the one hand, treated firms may be able to make more risky investment because of improved access to equity and loans. Failures of such more risky investment projects may increase the probability of bankruptcy and thus exit (relative to the control group). On the other hand, the improved access to capital may also allow the companies to implement their business plans appropriately which might not have been possible without the program participation. As a result, firms with well implemented business plans might also survive longer. In order to account for attrition, we follow Wooldridge (2010: chapter 19) and estimated a series of probit regression on an indicator variable for survival. We estimate a cross-section probit model for each year *t* separately (always with the sample that was alive in *t-1*). From these probit models, we obtain the linear predictions and we calculate the inverse Mills' ratio which is then included in the DiD regression as selection term accounting for attrition.

Equation III.8

$$y_{it} = \gamma_1 \cdot treatment_{it} + \gamma_2 \cdot posttreatment_{it} + \delta \cdot mills_{it} + \beta X_t + \alpha_i + \varepsilon_{it}$$

with *i*= 1… *N* (firms) and *t*= 2008…2015 (years).

Finally, as a further robustness checks, we also consider Propensity Score Matching and Mahalanobis Matching.

4 Results

4.1 Preliminary results

In this Section, we show our findings on the effects of the Startup Act. Since this law provides direct incentives for collecting capital stock, receiving bank loans and hiring people, we study the effects of these three variables (direct effects) and also consider their logarithm values as robustness check. Then, we will estimate the impact of the policy on firms' value-added and productivity.

Table III.4 shows that the coefficients associated with the start dummy are negative and significant. This means, as easily to predict, that young firms usually have fewer resources such as equity and bank debts. Also, for this reason, a growth policy, such as the Startup Act, may be desirable.

Table III.4 Treatment effects

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**Cap stk**	**Bank**	**Workers**	**lncapstk**	**lnbank**	**lnworkers**
Start	-3.760***	-6.720***	-0.248***	-0.019***	-0.060***	-0.044***
	(0.678)	(1.227)	(0.009)	(0.001)	(0.005)	(0.002)
Treatment	26.038***	45.167***	1.091***	0.218***	0.803***	0.262***
	(8.791)	(4.212)	(0.071)	(0.021)	(0.055)	(0.018)
Constant	69.789***	185.406***	2.789***	2.952***	2.277***	0.637***
	(0.765)	(1.394)	(0.010)	(0.001)	(0.005)	(0.002)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,152,839	2,152,839	2,152,839	2,152,839	2,152,839	2,152,839
Firms	403,339	403,339	403,339	403,339	403,339	403,339
R-squared	0.000	0.001	0.022	0.001	0.001	0.040

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

We also find positive treatment effects of the policy. In all regressions, the coefficient associated with the treatment variable is positive and significant at 1% level. Specifically, the treated firms have about 26 000 Euros more in equity, 45 000 Euros more in bank loans and they hire 1.1 workers more after they have entered the program than the companies in the control group. Similar findings are shown in all cases, where we consider the logarithm values.

4.2 Refining the control group

In the preliminary analysis, we considered the entire sample of Italian Small Enterprises (fewer than 50 employees and 10 million in revenues). Since we find that revenues for registered innovative startups do never exceed the amount of 2.5 m EUR (the limit of 5 m EUR has not been very binding), we select as the control group firms that are comparable in size and age to the treated companies, but that have never joined the program during our sample period. This means that our control group is made of firms that were at most five years old in 2013 and show at most 2.5 m EUR in revenues. These rules may define more appropriate control group of firms, because they are quite similar to the treated ones.

As reported in Table III.5, also in this case, the treatment effects are strongly significant and positive. However, the magnitude of the effects is somewhat smaller than in the previous case.

In this analysis, we added also the post-treatment variable. In this way, we avoid that the post-treated firms are considered as never treated ones and we can observe if effects continue after the treatment. In the specific case, the post-treatment effect is positive and significant. For this reason, we can also conclude that the effects do not terminate with the treatment period, but they persist at least two years after the firms dropped out of the program as they became ineligible. The positive post-treatment effect represents a strong argument to advocate this policy. Indeed, one of the primary concerns in temporary subsidy policies consists in obtaining only temporary effects, which vanish after the conclusion of the policy.

Table III.5 Treatment and post-treatment effects

VARIABLES	(1) **Cap stk**	(2) **Bank**	(3) **Workers**	(4) **ln(Capstk)**	(5) **ln(Bank)**	(6) **ln(Workers)**
Treatment	27.536***	20.859***	0.738***	0.202***	0.541***	0.185***
	(10.495)	(3.453)	(0.076)	(0.021)	(0.052)	(0.020)
Post-treatment	20.431**	25.232*	0.655***	0.189***	0.479**	0.184***
	(8.698)	(13.046)	(0.196)	(0.034)	(0.212)	(0.058)
Constant	21.156***	6.696	0.568***	2.534***	0.397***	0.150***
	(3.569)	(5.079)	(0.060)	(0.004)	(0.039)	(0.014)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	433,169	433,169	433,169	433,169	433,169	433,169
Firms	117,262	117,262	117,262	117,262	117,262	117,262
R-squared	0.001	0.007	0.050	0.008	0.054	0.091

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

4.3 An analysis of the policy impact on firm growth and productivity

So far, we focused on variables such as capital stock and bank loans, which cannot be considered as the final goal for a policy. Indeed, one of the real goals of a Government policy should be to increase total production and the level of employment. For what concerns employment level, we have already demonstrated in the previous subsection that the Startup Act helped creating some additional jobs. Moreover, these "additional" positions remain also in the post-treatment phase. In this section we turn our attention to the indirect effects of the policy on total production, GDP growth and productivity. It might happen that firms have collected more capital stock due to tax benefits, but no real productive investment has been made. Namely, the additional amount of collected equity does not imply additional investments and a consequent increase in total production. In other words, we may observe a moral hazard behavior, as described in the literature on firm subsidies (Gustafsson et al., 2016; de Blasio et al., 2017), where entrepreneurs act in bad faith to embezzle public resources, or private investments can be displaced by the subsidies.

For all these reasons, we estimate the treatment and post-treatment effects on value-added, value-added per worker (productivity) and total employment for innovative startups. We consider also a more restricted sample of firms in the most 'innovative' sectors. So far, we have analyzed various industries, some of which are not the typical target of innovative policies. Indeed, one may assert that the positive effects of the policy we found depend on the selected target of innovative startups in high-tech sectors and consultancy. Indeed, one may argue that hi-tech companies, regardless of the official 'innovative startup' status, create *ceteris paribus* higher levels of value-added. Similarly, one may think that young high-tech firms hire more people because of their potential growth, even if they do not benefit of a special labor legislation.

For this reason, we would like to analyze whether the conclusions still hold for a sample of treated and untreated firms belonging only to these industries. We also limit the control group again to firms of similar age and size in high-tech sectors. In this way, we can estimate if the new policy is really effective in increasing survival, growth and competitiveness of innovative startups.

As shown in Table III.6, we observe a significant positive impact of the policy on total value-added. This effect persists also in the post-treatment phase, with an effect estimates of around 60 k EUR per firm. Restriction to high-tech sectors, does not significantly modify our main result about the effectiveness of the policy. Similar results are obtained also when turn to labor productivity and employment (Table III.7).

In another set of regressions, we estimate annual treatment effects instead of a time-constant average. We create three dummy variables: *treatment2013*, *treatment2014*, *treatment2015* to see how the policy works over the years. As we can observe from the Table III.9, the treatment effects increase year by year. This growing trend may be due to the typical time lag needed to observe the actual impact of a new policy. For example, in our case, firms need some months to collect capital stocks or receive loans from banks, and the final effect on the total production may be delayed. As before, also in this case we observe a significant and positive effect in the post-treatment phase, that means that also controlling by treatment year, the policy produces desirable effects. Similar results are found for the labor productivity and employment levels (see Table III.10 and Table III.11).

Table III.6 Value-added analysis for eligible startup sample and selected industries

VARIABLES	(1) VA	(2) VA	(3) ln(VA)	(4) ln(VA)
Treatment	45.109***	43.600***	0.941***	0.998***
	(4.295)	(4.607)	(0.046)	(0.057)
Post-treatment	63.326***	65.852***	0.743***	0.870***
	(22.525)	(20.077)	(0.158)	(0.158)
Constant	36.242***	40.590***	2.002***	2.262***
	(2.670)	(4.289)	(0.034)	(0.051)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	433,169	76,940	433,169	76,940
Firms	117,262	20,000	117,262	20,000
R-squared	0.057	0.063	0.105	0.094

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table III.7 Value-added per worker analysis for eligible startup sample and selected industries

VARIABLES	(1) VA/wrk	(2) VA/wrk	(3) ln(VA/wrk)	(4) ln(VA/wrk)
Treatment	20.345***	19.981***	0.756***	0.824***
	(2.323)	(2.654)	(0.050)	(0.057)
Post-treatment	27.981***	30.226**	0.559***	0.698***
	(10.428)	(12.001)	(0.122)	(0.131)
Constant	24.126***	36.704***	1.852***	2.203***
	(1.795)	(2.850)	(0.024)	(0.044)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	433,169	76,940	433,169	76,940
Firms	117,262	20,000	117,262	20,000
R-squared	0.014	0.013	0.063	0.056

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table III.8 Employment analysis for eligible startup sample and selected industries

VARIABLES	(1) Workers	(2) Workers	(3) ln(Workers)	(4) ln(Workers)
Treatment	0.738***	0.698***	0.185***	0.175***
	(0.076)	(0.097)	(0.020)	(0.027)
Post-treatment	0.655***	0.665***	0.184***	0.172**
	(0.196)	(0.247)	(0.058)	(0.068)
Constant	0.568***	0.185***	0.150***	0.059***
	(0.060)	(0.058)	(0.014)	(0.012)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	433,169	76,940	433,169	76,940
Firms	117,262	20,000	117,262	20,000
R-squared	0.050	0.063	0.091	0.085

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table III.9 Value-added analysis for eligible startup sample and selected industries by treatment year

VARIABLES	(1) VA	(2) VA	(3) ln(VA)	(4) ln(VA)
Treatment 2013	27.631***	25.145***	0.548***	0.580***
	(6.952)	(6.584)	(0.070)	(0.084)
Treatment 2014	40.671***	41.445***	0.843***	0.910***
	(5.158)	(5.156)	(0.052)	(0.063)
Treatment 2015	60.388***	58.908***	1.282***	1.384***
	(4.884)	(5.486)	(0.054)	(0.064)
Post-treatment	58.462***	62.432***	0.634***	0.785***
	(22.120)	(21.007)	(0.134)	(0.150)
Constant	36.247***	40.597***	2.002***	2.262***
	(2.670)	(4.288)	(0.034)	(0.051)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	433,169	76,940	433,169	76,940
Firms	117,262	20,000	117,262	20,000
R-squared	0.057	0.063	0.105	0.095

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table III.10 Value-added per worker analysis for eligible startup sample and selected industries by treatment year

VARIABLES	(1) VA/wrk	(2) VA/wrk	(3) ln(VA/wrk)	(4) ln(VA/wrk)
Treatment 2013	12.806***	11.609***	0.465***	0.503***
	(3.503)	(4.347)	(0.063)	(0.077)
Treatment 2014	19.142***	19.465***	0.691***	0.761***
	(2.649)	(2.878)	(0.054)	(0.064)
Treatment 2015	26.271***	26.474***	1.002***	1.114***
	(3.497)	(3.749)	(0.062)	(0.064)
Post-treatment	26.087**	28.765**	0.481***	0.634***
	(10.809)	(12.385)	(0.125)	(0.137)
Constant	24.127***	36.706***	1.852***	2.203***
	(1.795)	(2.849)	(0.024)	(0.044)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	433,169	76,940	433,169	76,940
Firms	117,262	20,000	117,262	20,000
R-squared	0.014	0.013	0.063	0.057

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table III.11 Value-added per worker analysis for eligible startup sample and selected industries by treatment year

VARIABLES	(1) Workers	(2) Workers	(3) ln(Workers)	(4) ln(Workers)
Treatment 2013	0.328***	0.288***	0.083***	0.077***
	(0.078)	(0.089)	(0.023)	(0.026)
Treatment 2014	0.658***	0.642***	0.152***	0.149***
	(0.089)	(0.110)	(0.023)	(0.030)
Treatment 2015	1.074***	1.048***	0.280***	0.270***
	(0.091)	(0.118)	(0.024)	(0.032)
Post-treatment	0.547***	0.587**	0.153***	0.151**
	(0.184)	(0.236)	(0.057)	(0.067)
Constant	0.568***	0.185***	0.150***	0.059***
	(0.060)	(0.058)	(0.014)	(0.012)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	433,169	76,940	433,169	76,940
Firms	117,262	20,000	117,262	20,000
R-squared	0.050	0.064	0.092	0.086

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

As we have seen in the first Chapter the gap between the Northern area and the Southern part of Italy has been widening after the Great Recession. Specifically, the Northern part has a developed economy (partially included in the European Blue Banana) with efficient firms and institutions. Conversely, the Southern part often meets more difficulties into innovation and economic progress, because it has an undeveloped infrastructure system and a fragile industrial base. To analyze the impact of the Startup Act in the two areas, we repeat the treatment analysis with a dummy variable for firms located in the Southern part of the country (called '*Mezzogiorno*', in Italian). We got from Table III.12 that the treatment effects vary according to geography. In the Northern part, the treatment effect on value-added is higher in absolute values than in the South, where the effect is of about 37 000 Euros versus over 47 000 Euros as an average in the North. Conversely, regarding the study of relative values (through natural logarithm), we find that the effect on value-added is larger in the Southern part of the country. Thus, this fact may mean that the relative effect is higher in the South, but Southern potential startups have a lower initial value-added. This gap in the impact of the policy is reduced when we restrict the sample to innovative sectors. Therefore, the gap of the treatment between the North and South is partially due to different sector composition. Additionally, the effect on productivity is higher in the North, and this time the impact does not change if we restrict our analysis to innovative sectors. As for the employment analysis, we do not observe very different effects between North and South: in both geographical areas, the effect is around +0.7 employees per treated startup. But when we focus on the innovative sectors the employment effect is more pronounced in the South. All in all, we can conclude that the growth of value-added for Northern treated firms is mostly due to a positive effect on labor productivity, whereas the main impact in the South is on job creation.

Table III.12 Geographical effects on value-added

	(1)	(2)	(3)	(4)
VARIABLES	**VA**	**VA**	**ln(VA)**	**ln(VA)**
Treatment north	47.217***	43.855***	0.913***	0.956***
	(4.564)	(4.660)	(0.050)	(0.058)
Treatment south	37.453***	42.653***	1.042***	1.155***
	(9.098)	(11.215)	(0.124)	(0.150)
Post-treatment	63.888***	65.914***	0.736***	0.860***
	(21.307)	(20.272)	(0.134)	(0.147)
Constant	36.242***	40.590***	2.002***	2.262***
	(2.668)	(4.288)	(0.034)	(0.051)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	433,169	76,940	433,169	76,940
Firms	117,262	20,000	117,262	20,000
R-squared	0.057	0.063	0.103	0.094

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table III.13 Geographical effects on value-added per worker

VARIABLES	(1) VA/wrk	(2) VA/wrk	(3) ln(VA/wrk)	(4) ln(VA/wrk)
Treatment north	21.935***	21.135***	0.728***	0.788***
	(2.662)	(3.181)	(0.055)	(0.059)
Treatment south	14.567***	15.698***	0.857***	0.956***
	(2.467)	(2.493)	(0.135)	(0.169)
Post-treatment	28.405***	30.507**	0.552***	0.689***
	(10.379)	(11.961)	(0.122)	(0.131)
Constant	24.125***	36.703***	1.852***	2.203***
	(1.793)	(2.846)	(0.023)	(0.044)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	433,169	76,940	433,169	76,940
Firms	117,262	20,000	117,262	20,000
R-squared	0.014	0.013	0.063	0.0056

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table III.14 Geographical effects on value-added per worker

VARIABLES	(1) Workers	(2) Workers	(3) ln(Workers)	(4) ln(Workers)
Treatment north	0.740***	0.675***	0.185***	0.168***
	(0.078)	(0.099)	(0.019)	(0.025)
Treatment south	0.731***	0.787***	0.185***	0.199***
	(0.195)	(0.245)	(0.058)	(0.074)
Post-treatment	0.655***	0.659***	0.184***	0.171**
	(0.196)	(0.246)	(0.057)	(0.067)
Constant	0.568***	0.185***	0.150***	0.059***
	(0.060)	(0.058)	(0.014)	(0.012)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	433,169	76,940	433,169	76,940
Firms	117,262	20,000	117,262	20,000
R-squared	0.050	0.063	0.091	0.085

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

As a further investigation and robustness check, we consider the effect of firm survival and potential selection bias in our analysis by including Mills' ratio in our regressions. Indeed, different average survival rates between treated and untreated firms could introduce a bias in the analysis. Thus, in the following regression, we include Mills' ratio. Once again, our general findings about the effectiveness of the policy still do hold. Namely, the Startup Act has a positive impact on the three main variables of interest in the post-treatment phase.

Table III.15 Treatment effects on value-added and Mills' ratio

	(1)	(2)	(3)	(4)
VARIABLES	**VA**	**VA**	**ln(VA)**	**ln(VA)**
Treatment	21.481***	13.367***	0.696***	0.741***
	(4.149)	(4.965)	(0.048)	(0.055)
Post-treatment	69.883***	64.603***	0.804***	0.857***
	(21.168)	(19.820)	(0.141)	(0.151)
Mills' ratio	-930.992***	-1,010.799***	-9.387***	-8.353***
	(48.015)	(72.128)	(0.310)	(0.439)
Constant	41.988***	44.547***	2.057***	2.284***
	(2.458)	(5.205)	(0.040)	(0.067)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	416,950	74,085	416,950	74,085
Firms	112,963	19,264	112,963	19,264
R-squared	0.067	0.076	0.115	0.104

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table III.16 Treatment effects on value-added per worker and Mills' ratio

	(1)	(2)	(3)	(4)
VARIABLES	**VA/wrk**	**VA/wrk**	**ln(VA/wrk)**	**ln(VA/wrk)**
Treatment	17.131***	14.606***	0.590***	0.650***
	(2.317)	(2.745)	(0.053)	(0.057)
Post-treatment	28.287***	29.343**	0.597***	0.685***
	(10.452)	(12.025)	(0.131)	(0.137)
Mills ratio	-104.667***	-149.483***	-6.187***	-5.456***
	(15.628)	(24.602)	(0.264)	(0.386)
Constant	24.768***	36.946***	1.886***	2.214***
	(1.769)	(3.047)	(0.026)	(0.055)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	416,950	74,085	416,950	74,085
Firms	112,963	19,264	112,963	19,264
R-squared	0.067	0.076	0.115	0.104

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table III.17 Treatment effects on value-added per worker and Mills' ratio

	(1)	(2)	(3)	(4)
VARIABLES	**Workers**	**Workers**	**ln(Workers)**	**ln(Workers)**
Treatment	0.417***	0.386***	0.106***	0.091***
	(0.082)	(0.112)	(0.021)	(0.028)
Post-treatment	0.758***	0.667***	0.207***	0.172***
	(0.175)	(0.235)	(0.055)	(0.065)
Mills ratio	-13.515***	-11.144***	-3.200***	-2.897***
	(0.466)	(0.863)	(0.089)	(0.167)
Constant	0.650***	0.230***	0.170***	0.070***
	(0.069)	(0.077)	(0.016)	(0.017)
Year dummies	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	416,950	74,085	416,950	74,085
Firms	112,963	19,264	112,963	19,264
R-squared	0.056	0.070	0.101	0.095

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

As shown in Table III.15, the treatment and post-treatment effects on value-added are always positive and statistically significant. The persistency of the effects in the post-treatment phase should be confirmed in future research, since we have only a few years of data available after treatment and about one hundred post-treament observations in our sample.

The impact of the Startup Act's costs for the Italian taxpayer should also be considered. Indeed, the cost of the policy is mostly to the partial tax exemption. Also public guarantees are provided for bankrupted firms under the loan guarantee program, and firm registration fees are lowered. For these reasons, we compute a back-of-the-envelope estimate of the cost of the policy, which include lower tax collection, losses for the guarantee fund, and exemptions for administrative fees (in the sample period 2013-2015). After some simple computations, we get that the costs of the policy were 6.5 m EUR in 2013, 11 m EUR in 2014, and 12 m EUR in 2015. The cost compares to the benefits of the policy. We found that each "former startup" in the post-treatment phase has 30 k/60 k EUR in value-added more than untreated firms, and assuming that each year 2,000 firms will move to the post-treatment phase, the overall effect on value-added will be of about 60 m/120 m EUR a year. Therefore, we can conclude that the Startup Act is going to the right direction, since generated benefits seems to exceed the policy costs. However, more time is needed to better estimate the post-treatment effect on different aspects, e.g. the duration of post-treatment effects, additional taxation that State can collect from the production increase, the real number of firms in the post-treatment phase, etc.

By considering the value-added per worker, we see that the policy has a positive impact on labor productivity too. Once again as main result we have that the positive effect does not dissapear after treatment period, but it persists over time. The post-treatment on treated firms is about 25 k-30 k EUR per employee. Theoretically, this effect can translate into higher salaries for workers, who have higher labor productivity. Ultimaltely, the post-treatment effect on employment is around 0.7 new positions per former treated firm. Assuming that 2,000 firms pass each year into the post-treatment phase, we get a positve contribution of 1,500 more jobs per year. The employment effect is positive, but negigible if we consider that Italian workforce is composed by around 20 m/25 m employees.

4.4 Propensity Score Matching

As another robustness check, we employ a Propensity Score Matching technique, which considers for the sample selection the intangible assets, and R&D expenses. We choose to consider intangible assets and R&D expenses, because they may be linked with innovative startup eligibility criteria. Intangible assets may be seen as a proxy of the presence of patents or software. The R&D expenses are linked with the criteria that required at least 15% of R&D expenses over the total. Using a Propensity Score Matching, we would like to reduce the selection bias that may affect our conclusions. In particular, we are interested to see if post-treatment effects hold.

Table III.18 Treatment and post-treatment effects using a Propensity Score Matching

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	**VA**	**VA/wrk**	**Workers**	**ln(VA)**	**ln(VA/wrk)**	**ln(Workers)**
Treatment	29.336***	16.683***	0.599***	0.839***	0.698***	0.142***
	(4.962)	(2.518)	(0.093)	(0.054)	(0.056)	(0.024)
Post-treatment	44.140*	24.066*	0.529***	0.660***	0.522***	0.138**
	(26.365)	(12.461)	(0.188)	(0.154)	(0.146)	(0.053)
Constant	16.104	23.632***	0.080	1.713***	1.651***	0.062*
	(12.502)	(5.401)	(0.185)	(0.136)	(0.126)	(0.036)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,223	15,223	15,223	15,223	15,223	15,223
Firms	4,358	4,358	4,358	4,358	4,358	4,358
R-squared	0.103	0.019	0.080	0.184	0.118	0.119

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

From Table III.18, we can state that for all analyzed variables post-treatment effects are positive and significant. In particular, the post-treatment is high significant when we consider the natural logarithm of the variables such as value-added and value-added per worker. Once again, we can conclude that policy is working well also when the treatment program is over. However, more years of post-treatment may be necessary to have the correct conclusions on the real effectiveness of the duration of post-treatment phase.

4.5 Mahalanobis matching

As a further robustness control, we apply the Mahalanobis matching[36] to refine our control group of untreated firms. In particular, we consider only small firms founded in the first half of 2012. We choose the first half of 2012, because in the first half 2012 nobody could forsee the launch of the Startup Act (which was set with a governmental decree in October 2012 and entered into force in December 2012), thereby these firms could not have be founded on purpose to benefit of Startup Act. Additionally, by limiting the control group to the firms founded in first half of 2012, we exclude firms active before the Startup Act have which have already distributed profits (according to the policy an innovative startup must have never distributed profits). In this way the control group of untreated firms is very similar to the treated firms for their *ex-ante* characteristics. In this case, he independent variable is "ever_mise" assumes value 1 when the firm is, or used to be, under treatment. We use a Mahalanobis matching, which considers as continuous variables the natural logarithm of revenues and ROA (return on assets). The choice of logarithm of revenues is to avoid that the probability to be treated is in function of the size. The ROA is fundamental because the ability of the management, measured through ROA, can affect the chances to join the startup program. Moreover, as dummy variables for the exact matching we opt for two dummies linked with intangible and R&D expenditure, which assume value 1 if the firms report at least 1,000 Euros in intangible assets (or 1,000 Euros in R&D). These two dummy variables are proxies for the

[36] We use the teffects nnmatch STATA 14 command.

requirements of Intellectual Property Rights set by the policy.[37] As usual, to be sure that control group is appropriate we verify also the quality of balancing; that in our case is very good.

Table III.19 Treatment effect using Mahalanobis matching

	Sample raw diff.	ATE	ATE b.a.	ATET	ATET b.a.
VA	-50.799***	5.465	7.910	14.389***	14.216***
	(10.931)	(6.309)	(6.302)	(4.068)	(4.071)
VA/wrk	-14.049**	1.956	2.839	7.276**	7.186*
	(5.923)	(4.668)	(4.667)	(3.692)	(3.689)
Workers	-1.121***	-0.652***	-0.625***	-0.336*	-0.339*
	(0.241)	(0.136)	(0.136)	(0.188)	(0.188)
ln(VA)	-0.356***	0.176***	0.219***	0.172***	0.168***
	(0.126)	(0.044)	(0.044)	(0.049)	(0.048)
ln(VA/wrk)	-0.081	0.266***	0.301***	0.251***	0.248***
	(0.107)	(0.050)	(0.050)	(0.065)	(0.065)
ln(Workers)	-0.275***	-0.091**	-0.082*	-0.079*	-0.080*
	(0.051)	(0.044)	(0.044)	(0.046)	(0.046)
Obs.	Treated	259	Control	20,106	

Standard errors in parentheses; p-value < 0.01***, 0.05**, 0.10*

In this analysis we consider the estimated average treatment effect (ATE) and the estimate of the average treatment effect on the treated (ATET). Results in Table III.19 confirms that the policy has a significant impact on value-added and the labor productivity, even when the natural logarithms are considered.

[37] Unfortunately, we do not have data (or proxies) for the minimum ratios of Ph.D degree holders in the workforce (i.e. another potential critarion for innovative startup).

Even though the impact on value-added creation is much smaller than in our previous estimate (see Table III.15), our computation confirms that the Startup Act policy positively contributes to increase value-added and productivity. Conversely, this time when we consider the ATET, we find that the effect on employment is no more positive. In conclusion, we find some positive contribution of the policy to GDP growth and productivity whereas the effect on job creation must be further investigate in future work when better data will be available.

5 Conclusions and final remarks

In our analysis, the effect of Italian Startup Act (Law 221/2012) is positive on multiple dimensions by easing firm access to fresh risk capital and bank debt. Specifically, tax benefits for new equity investors alleviate the problem of shortage in equity and risk capital, since treatment effect associated to innovative startups is positive and statistically significant. Another issue tackled by the Startup Act is access to bank loans by small enterprises. Small firms meet some problems to get bank loans, because they do not have essential collaterals. In this way, the development of new firms is hurdled by liquidity problems. Following our results, we get that innovative startup have more bank loans than never-treated ones[38]. Namely, innovative startups can obtain more capital in both forms: risk capital and

[38] About bank debt analysis, in the future, we would like to collect data on which innovative startups really received the guaranty, since in this case the state guaranty is not automatic as special benefits for capital stock or employment.

debts. Thus, they have more resources for developing their activities. In our analysis we investigate whether the Startup Act is beneficial to the Italian economy. Overall, we find after the treatment period the "former startups" show a higher level of total value-added and value-added per employee (i.e. labor productivity) than similar untreated firms. These conclusions are robust to alternative specifications and robustness checks. Conversely, we found that the startup labor regulation, which consists of more flexible hiring and firing procedures than standard Italian labor law, does not have clear-cut effects on job creation. All in all, some simple back-of-envelope computations show that the policy positively contributed to firm survival, value-added creation and productivity.

This result is particularly important since positive effects extend to the post-treatment phase. For all these reasons, this policy shows that a targeted public intervention can spur economic growth. Indeed, the Startup Act is similar to government policies, which incentive innovation through higher R&D expenses. Nowadays, in many countries private R&D is subsidized since higher levels of innovation (such as R&D, patents, software, skilled workers) means higher level of wellbeing. These kinds of public interventions are also justified by the fact that positive effects are not limited only to the subsided firms, but the effects reach a multitude of stakeholders (government, employees, other firms etc.). Moreover, during downturns, policies which focus on firm innovation and new entrepreneurship can be seen as a good measure to stimulate recovery. As compared to unproductive interventions (such as longer unemployment benefits) the Startup Act unleashes the growth potential of new firms, thus favoring innovation and value-added creation. It is also important to underline that a policy is financially sustainable and adopts appropriate actions to reduce moral hazard and adverse selection.

So far we have good evidence that the Startup Act benefits for GDP exceed implicit and explicit costs. Anyway, more time is needed to collect data on long-term effects, since the post-treatment effect we found may be just a lagged effect of treatment.

In conclusion, the law 221/2012 seems to reach its main goal in the treatment period and to maintain its positive effect on value-added and productivity even after the treatment period. Our results contribute to a better understanding of the impact of similar startup policies which have been recently implemented in many countries around the world such as Belgium, India, and Latvia. As a future investigation, the effects of different startup policies should be compared across countries. Also, the long-term impact should be further investigated.

IV. Appendices

1 Appendix first chapter

Appendix 1.1 Descriptive statistics and robustness checks

Table IV.1 Sample coverage by industry*

	Sample - Orbis		**Population - ISTAT**	
Industry NACE rev. 2	Number of firms	%	Number of firms	%
10 - food products	15,871	8.46	55,100	13.20
11 – beverages	2,202	1.17	2,891	0.69
13 – textiles	8,324	4.44	15,291	3.66
14 - wearing apparel	14,100	7.51	32,376	7.76
15 - leather and related products	7,478	3.98	15,692	3.76
16 - wood products except furniture	6,521	3.47	31,720	7.60
17 - paper and paper products	3,037	1.62	4,054	0.97
18 - printing and reproduction of recorded media	7,118	3.79	16,289	3.90
19 - coke and refined petroleum products	301	0.16	320	0.08
20 - chemicals and chemical products	4,415	2.35	4,436	1.06
21 - pharmaceutical products	451	0.24	464	0.11
22 - rubber and plastic products	8,183	4.36	10,588	2.54

To be continued….

…Continued…

23 - other non-metallic mineral products	10,872	5.79	21,420	5.13
24 - basic metals	3,047	1.62	3,811	0.91
25 - fabricated metal products	38,526	20.53	69,528	16.66
26 - computer, electronic and optical products	5,443	2.90	5,520	1.32
27 - electrical equipment	8,336	4.44	8,971	2.15
28 - machinery and equipment n.e.c.	21,953	11.70	23,685	5.68
29 - motor vehicles, trailers and semi-trailers	2,295	1.22	2,326	0.56
30 - other transport equipment	2,607	1.39	2,638	0.63
31 – furniture	9,293	4.95	19,332	4.63
32 - other manufacturing	7,301	3.89	30,883	7.40
Total	**187,674**	**100**	**417,306**	**100**

*all manufacturing industries, excluding Tobacco (NACE 12) and Repairing of machinery and equipment (NACE 33).

Table IV.2 Firms and population by region

Italian region	Number of firms according ISTAT	Resident population in thousands	Number of firms per 1,000 inhabitants
Lombardia	83,939	10,019	8.378
Veneto	47,411	4,906	9.663
Toscana	40,032	3,742	10.698
Emilia	39,599	4,448	8.903
Campania	28,072	5,839	4.808
Piemonte	33,289	4,932	6.750
Lazio	22,790	5,898	3.864
Puglia	22,740	4,063	5.600
Sicilia	22,434	5,056	4.437
Marche	17,261	1,538	11.223
Abruzzo	9,653	1,322	7.302
Friuli-V.G.	8,452	1,219	6.934
Sardegna	8,218	1,653	4.972
Umbria	7,023	889	7.900
Liguria	8,367	1,565	5.346
Calabria	8,963	1,965	4.561
Trentino	6,420	1,062	6.045
Basilicata	3,071	570	5.388
Molise	1,861	310	6.003
Valle	725	126	5.754
Total	**420,320**	**61,122**	**6.866**

Here we report additional regressions.

Table IV.3 Conditional logit for new firms - the case of multinational enterprises

	(1)	(2)	(3)	(4)	(5)
Province-level productivity	3.733***		2.254***	1.063***	0.892**
	(0.295)		(0.629)	(0.379)	(0.373)
(log of) Population		0.993***	1.096***	1.296***	1.120***
		(0.058)	(0.051)	(0.055)	(0.074)
(log of) GDP per capita		3.640***	1.383***	2.053***	1.986***
		(0.295)	(0.526)	(0.378)	(0.366)
(log of) Road				-0.532**	-0.405*
				(0.250)	(0.226)
(log of) Area				0.116	0.083
				(0.169)	(0.149)
Mountain				-0.017	0.062
				(0.260)	(0.260)
Island				-0.822**	-0.904**
				(0.374)	(0.378)
Region capital				-0.366***	-0.405***
				(0.128)	(0.125)
Agglomeration					0.738*
					(0.441)
Market potential					0.035***
					(0.004)
Competition					0.102*
					(0.053)
Observations	116,596	116,596	116,596	116,596	116,596
Pseudo R-squared	0.0874	0.202	0.208	0.214	0.223
Log likelihood	-4788	-4187	-4153	-4126	-4076

Clustered standard errors (NACE 2-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

As further robustness check, we apply the ACF methodology to compute TFP. As shown below our main findings still hold. We start to show some statistics on ACF lnTFP by '*Centro-Nord*' and '*Mezzogiorno*'.

Table IV.4 ACF lnTFP statistics by '*Centro-Nord*' and '*Mezzogiorno*'

	lnTFP for '*Centro-Nord*'	lnTFP for '*Mezzogiorno*'
5th percentile	2.688	1.924
10th percentile	3.066	2.398
25th percentile	3.553	2.997
50th percentile	3.995	3.531
75th percentile	4.519	4.107
90th percentile	5.167	4.785
95th percentile	5.671	5.275
average	4.055	3.553
standard deviation	0.942	1.053

Table IV.5 Conditional logit for entering firms (ACF lnTFP)

	(1)	(2)	(3)	(4)	(5)
(log of) Province-level productivity	1.439***		1.055***	0.897***	0.907***
	(0.169)		(0.255)	(0.229)	(0.180)
(log of) Population		0.941***	0.913***	1.058***	0.915***
		(0.027)	(0.028)	(0.029)	(0.038)
(log of) GDP per capita		0.661***	-0.089	-0.119	-0.251
		(0.211)	(0.208)	(0.225)	(0.174)
(log of) Road				-0.083	0.010
				(0.113)	(0.115)
(log of) Area				0.026	0.010
				(0.054)	(0.072)
Mountain				-0.169	-0.087
				(0.107)	(0.076)
Island				-0.366***	-0.377***
				(0.102)	(0.098)
Region capital				-0.349***	-0.329***
				(0.072)	(0.059)
Agglomeration					0.677***
					(0.220)
Market potential					0.026***
					(0.005)
Competition					0.098
					(0.061)
Observations	5,397,097	5,397,097	5,397,097	5,397,097	5,397,097
Pseudo-R squared	0.0219	0.0795	0.0844	0.0867	0.0941
Log likelihood	-237542	-223538	-222361	-221801	-220009

Clustered standard errors (NACE 2-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table IV.6 Probit model for the exit of firms (ACF lnTFP)

Dependent variable: Exiting firm (Yes/No)	(1)	(2)	(3)	(4)	(5)	(6)
Firm-level productivity	-0.308***	-0.310***	-0.308***	-0.310***	-0.308***	-0.311***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Province-level productivity	0.238***	0.238***	0.170**	0.170**	0.170**	0.169**
	(0.058)	(0.059)	(0.078)	(0.078)	(0.078)	(0.079)
Foreign ownership			-0.429***	-0.430***	-0.428***	-0.429***
			(0.064)	(0.063)	(0.064)	(0.064)
(log of) Population			-0.016	-0.016	-0.011	-0.011
			(0.020)	(0.021)	(0.020)	(0.020)
(log of) GDP per capita			0.034	0.034	0.038	0.038
			(0.071)	(0.073)	(0.071)	(0.073)
(log of) Road			-0.070	-0.069	-0.074	-0.072
			(0.049)	(0.049)	(0.050)	(0.050)
(log of) Area			0.031	0.030	0.033	0.032
			(0.043)	(0.043)	(0.044)	(0.044)
Mountain			-0.137	-0.142	-0.136	-0.141
			(0.099)	(0.098)	(0.100)	(0.099)
Island			-0.043	-0.045	-0.042	-0.044
			(0.053)	(0.053)	(0.053)	(0.053)
Region capital			0.049	0.048	0.049	0.049
			(0.031)	(0.032)	(0.032)	(0.032)
Agglomeration					0.027	0.028
					(0.035)	(0.036)
Market potential					-0.001	-0.001
					(0.001)	(0.001)
Competition					-0.003	-0.002
					(0.009)	(0.009)
Constant	-3.481***	-3.104***	-3.072***	-2.694***	-3.171***	-2.788***
	(0.265)	(0.360)	(0.635)	(0.734)	(0.617)	(0.703)
Observations	510,797	499,660	510,79	499,660	510,797	499,660
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year dummies	No	Yes	No	Yes	No	Yes
Log likelihood	-13129	-13036	-13097	-13004	-13096	-13003
Pseudo R-squared	0.0915	0.0948	0.0937	0.0971	0.0938	0.0971

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table IV.7 Least squares for ACF lnTFP by '*Centro-Nord*' and '*Mezzogiorno*'

Dependent variable: (log of) TFP	**(1)** All firms	**(2)** All firms	**(3)** New entrants	**(4)** New entrants
'Mezzogiorno'	-0.351***	-0.351***	-0.301***	-0.298***
	(0.024)	(0.024)	(0.026)	(0.025)
Constant	2.442***	2.404***	0.864***	0.898***
	(0.079)	(0.083)	(0.080)	(0.171)
Observations	510,739	510,739	22,207	22,207
Firm-level controls	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Industry x Year dummies	No	Yes	No	Yes
R-squared	0.296	0.301	0.327	0.337

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table IV.8 Least square for ACF lnTFP by Italian macro-regions[39]

Dependent variable: (log of) TFP	**(1)** All firms	**(2)** All firms	**(3)** New entrants	**(4)** New entrants
North-East	-0.033	-0.034	-0.027	-0.025
	(0.033)	(0.033)	(0.024)	(0.023)
Center	-0.071	-0.072	-0.091**	-0.088**
	(0.050)	(0.050)	(0.035)	(0.034)
South	-0.383***	-0.382***	-0.342***	-0.337***
	(0.035)	(0.035)	(0.028)	(0.027)
Islands	-0.375***	-0.377***	-0.333***	-0.331***
	(0.035)	(0.035)	(0.050)	(0.050)
Constant	2.480***	2.442***	0.918***	0.953***
	(0.089)	(0.092)	(0.083)	(0.174)
Observations	510,739	510,739	22,207	22,207
Firm-level controls	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Industry x Year dummies	No	Yes	No	Yes
R-squared	0.296	0.302	0.328	0.338

Clustered standard errors (NUTS 3-digit) in parentheses; p-value < 0.01***, 0.05**, 0.10*

39 '*Centro-Nord*' is composed by North-West, North-East and Center. '*Mezzogiorno*' is composed by Insular and South.

Appendix 1.2. Methodology[40]

To estimate a firm level production function, and the relative TFP (Total Factor Productivity) we exploit firm-level financial accounts. We take value-added (Y_{it}) as a proxy for output, fixed assets (K_{it}) as the proxy for capital, and the number of workers (L_{it}) as the proxy for labor.

We consider a production function *à la* Cobb Douglas (the lower-case letters indicate the natural logarithm of the variables):

Equation IV.1

$$\boldsymbol{y_{it} = \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \varepsilon_{it}}$$

As a consequence, productivity of firm *i* at time *t*, ω_{it}, combines with the error part ε_{it}, due to a simultaneity bias because of the unobserved (to the econometrician) correlation between productivity shocks and changes in the combination of factors of production, see Van Beveren (2012).

We use the estimator proposed by Levinsohn & Petrin (2003), which solves the simultaneity bias adopting a two-stage procedure between inputs and unobservable productivity shocks. Indeed, considering the correlation between factors of production and productivity shocks is essential, otherwise results may be inconsistent. The estimator by Levinsohn & Petrin can be seen as an evolution of Olley & Pakes' estimator proposed in 1996. In Olley & Pakes (1996), the authors use the amount of investments as a proxy for the correlation between final inputs and unobserved productivity shocks. In that approach, some problems arise when firms do not report investments or investments are zero. Levinsohn & Petrin's estimator solve this aspect taking into account intermediate inputs such as: materials, energy, electricity, fuels,

[40] We follow Petrin et al. (2004)

etc.

Moreover, the estimator by Levinsohn & Petrin makes three main assumptions, see Petrin et al. (2004):

(i) the intermediate input, in our case proxied with materials (M_t), depends on capital-transmitted productivity and capital, i.e.:

Equation IV.2

$$m_{it} = m_{it}(k_{it}, \omega_{it})$$

(ii) the demand function is monotonically increasing in the productivity correlated error part, in this way one can write the correlated error part in function of intermediate goods and capital:

Equation IV.3

$$\omega_{it} = \omega_{it}(k_{it}, m_{it})$$

(iii) the productivity behavior can be described by a first-order Markov process, namely:

Equation IV.4

$$\omega_{it} = E[\omega_{it} | \omega_{t-1}] + \vartheta_{it}$$

where $\vartheta_{it}$is an innovation to productivity uncorrelated with the capital.

At this point, the production function can be rewritten as:

Equation IV.5

$$y_{it} = \varphi_{it}(k_{it}, m_{it}) + \beta_l l_{it} + \varepsilon_{it}$$

where $\varphi_{it}(k_{it}, m_{it}) = \beta_{ik} k_{it} + \omega_{it}(k_{it}, m_{it})$

One proceeds with the substitution of φ_{it} with a third-order polynomial approximation. Two main stages follow in order to estimate the coefficients. Precisely, in the first stage, one estimates β_L and in the second stage one identifies the coefficient β_k (Petrin et al., 2004).

Appendix 1.3. Data

Total Factor Productivity is estimated at the firm-level using a Levisohn & Petrin (2003) procedure for a Cobb-Douglas production function at industry level. Firm-level data on number of employees, fixed assets, cost of materials and revenues proxy labor, capital, intermediate inputs and output, respectively. Monetary values of revenue and material are deflated with yearly industry-specific producer price indices sourced from ISTAT, taking as base year 2010.

Population is the number of inhabitants of an Italian 'provincia', which corresponds at a NUTS (Classification of Territorial Units for Statistics) 3-digit level.

GDP per capita is the NUTS 3-digit level gross development product divided by population.

Road indicates the kilometers of road in a NUTS 3-digit area.

Area indicates the square kilometers surface of a NUTS 3-digit area.

Mountain is a binary variable equal to 1 when a NUTS 3-digit province is mainly mountainous, i.e. Aosta, Trento and Bolzano.

Island is a binary variable equal to 1 if a NUTS 3-digit province is mainly insular: Olbia-Tempo, Sassari, Nuoro, Oristano, Ogliastra, Medio Campidano, Carbona-Iglesias, Cagliari, Trapani, Palermo, Messina, Catania, Enna, Agrigento, Caltanissetta, Siracusa, Ragusa.

Region capital is a binary variable equal to 1 when the NUTS 3-digit hosts also the capital of the region, namely: Roma, Milano, Napoli, Torino, Palermo, Genova, Bologna, Firenze, Bari, Venezia, Trieste, Perugia, Cagliari, Trento, Ancona, Catanzaro, L'Aquila, Potenza, Campobasso, Aosta.

Agglomeration is a firm-level binary variable equal to 1 when the firm is active in the NACE 2-digit industry that is prevalent in the NUTS 3-digit province.

Market potential is proxied by the total amount of revenues sold by all the firms in the NUTS 3-digit province, active in the NACE 2-digit industry to which the firm belongs.

Competition is the number of firms in the NUTS 3-digit province, active in the NACE 2-digit industry to which a firm belongs.

2 Appendix second chapter

Appendix 2.1. Moran tests

In this appendix, we report Moran tests for all the contiguity matrices in the second chapter:

Table IV.9 Moran test for every spatial matrix LevPet lnTFP

	20 Km	50 Km	80 Km	No cut-off
Linear distance	5.212***	6.574***	7.628***	9.212***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared distance	3.716	4.173	4.668***	4.783***
	(0.000)	(0.000)	(0.000)	(0.000)
Interlocking directorates				7.588***
				(0.000)

Moran tests' value p-values in parentheses *0.1 **0.05 ***0.01

Table IV.10 Moran test for every spatial matrix ACF lnTFP

	20 Km	50 Km	80 Km	No cut-off
Linear distance	4.489***	4.441***	5.005***	6.087***
	(0.000)	(0.000)	(0.000)	(0.000)
Squared distance	3.306***	3.398***	3.663***	4.489***
	(0.000)	(0.000)	(0.000)	(0.000)
Interlocking directorates				4.125***
				(0.000)

Moran tests' value p-values in parentheses *0.1 **0.05 ***0.01

Table IV.11 AIC values matrix LevPet lnTFP SAR and SAC

		20 Km	50 Km	80 Km	No cut-off
Linear distance	SAR	1564.095	1560.838	1556.498	1555.996
	SAC	1541.429	1539.720	1536.689	1536.973
Squared distance	SAR	1568.449	1567.898	1564.732	1564.339
	SAC	1543.844	1544.083	1542.225	1542.144

Table IV.12 AIC values matrix ACF lnTFP SAR and SAC

		20 Km	50 Km	80 Km	No cut-off
Linear distance	SAR	1519.434	1521.360	1519.689	1519.369
	SAC	1517.080	1518.072	1517.685	1517.968
Squared distance	SAR	1523.299	1523.763	1522.384	1522.095
	SAC	1520.448	1520.830	1519.794	1519.624

Table IV.13 LM tests SEM/SAR with interlocking directorates' matrices

	LS lnTFP	LevPet lnTFP	ACF lnTFP
LM SEM	23.787***	35.824***	6.818***
	(0.000)	(0.000)	(0.000)
LM SAR	26.337***	44.620***	10.568***
	(0.000)	(0.000)	(0.000)
RLM SEM	1.160	2.484	8.346***
	(0.281)	(0.115)	(0.000)
RLM SAR	3.709*	11.280***	12.096***
	(0.054)	(0.000)	(0.000)

p-value < 0.01***, 0.05**, 0.10*

Appendix 2.2. Data

We shortly describe the variables used in the analysis:

$lnTFP_i$ is the natural logarithm of TFP, which is computed as described in Section II.3. This variable is considered a measure of firm productivity.

$Innovation_i$ is the of total value (in current thousands of Euros) of patents, software, know-how, other Intellectual Property Rights, trademarks and brands divided by number of workers of the firm *i*[41]. This index is expected to be a proxy of total innovation level, not only of

[41] To avoid any problem for firms with zero values in innovation, we add a notional value of 1 k EUR for any firm.

technological innovation as in the case of patents[42]. Moreover, considering simple indicators (such as the number of patents) may be unfair, since their values cover a large range, as stated in Gambardella et al. (2008).

International$_i$ is a dummy variable, which assumes value 1 if the ownership of firm *i* is not Italian. We expect that multinational firms usually have a higher lnTFP than domestic ones, because they may own a better organization. Indeed, only more productive firms usually tend to open new branches abroad.

Table IV.14 Average values of innovation and productivity by firm type

Firms characteristics	Number of firms	Innovation	lnTFP
Small	338	0.645	11.219
Medium	378	0.735	11.283
Large	85	0.946	11.428
International	195	0.675	11.447
Domestic ownership	606	0.734	11.215
All	**801**	**0.720**	**11.271**

Table IV.14 shows that larger firms tend to have higher values for innovation than SMEs. This evidence means that innovation propensity usually increases by firm size.

[42] Since the innovation concept could be quite wide (it may mean a strictly technological innovation or an innovation in design, marketing, etc.), we need to explain what we are considering as innovation within firm business and how we quantify it. Our choice falls on total value of know-how, trademark and industrial property; in this way, we can catch various forms of innovation (which do not only have a technological dimension).

Appendix 2.3. Further results considering specific sector

Table IV.15 Least-squares regressions

	LS lnTFP	LevPet lnTFP	ACF lnTFP
Innovation	4.953***	16.836***	13.369***
	(1.821)	(2.190)	(2.108)
International	0.208***	0.283***	-0.013
	(0.043)	(0.052)	(0.050)
Pharma	0.070	0.218***	-0.107*
	(0.054)	(0.065)	(0.063)
Electronics	-0.286***	-0.312***	-0.440***
	(0.041)	(0.049)	(0.047)
Intercept	11.270***	5.737***	4.612***
	(0.003)	(0.036)	(0.035)
R^2	0.119	0.199	0.153
Adjusted-R^2	0.115	0.195	0.149
Observations	801	801	801

Standard errors in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table IV.16 SAR with interlocking directorates

	LS lnTFP	LevPet lnTFP	ACF lnTFP
Innovation	4.331**	15.614***	12.750***
	(1.789)	(2.138)	(2.094)
International	0.203***	0.278***	-0.0126
	(0.042)	(0.050)	(0.049)
Pharma	0.067	0.208***	-0.096
	(0.053)	(0.064)	(0.062)
Electronics	-0.270	-0.292***	-0.430***
	(0.040)	(0.048)	(0.047)
Intercept	8.374***	4.076***	3.953***
	(0.678)	(0.332)	(0.295)
Rho	0.256***	0.282	0.144**
	(0.060)	(0.056)	(0.064)
Loglikelihood	-593.177	-736.349	-716.269
AIC	1200.4	1486.7	1446.5
Observations	801	801	801

Standard errors in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table IV.17 Impacts of SAR model LS lnTFP

	Direct	Indirect	Total
Innovation	4.372**	1.485*	5.856**
	(1.805)	(0.775)	(2.466)
International	0.205***	0.070***	0.275***
	(0.043)	(0.026)	(0.060)
Pharma	0.680	0.023	0.091
	(0.054)	(0.022)	(0.074)
Electronics	-0.273***	-0.093***	-0.366***
	(0.040)	(0.034)	(0.063)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

Table IV.18 Impacts of SAR model LevPet lnTFP

	Direct	Indirect	Total
Innovation	15.790***	6.064***	21.860***
	(2.162)	(1.853)	(3.423)
International	0.281***	0.108***	0.389***
	(0.051)	(0.036)	(0.077)
Pharma	0.210***	0.080**	0.291***
	(0.065)	(0.032)	(0.090)
Electronics	-0.295***	-0.113***	-0.409***
	(0.048)	(0.035)	(0.073)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

Table IV.19 Impacts of SAR model ACF lnTFP

	Direct	Indirect	Total
Innovation	12.791***	2.184*	14.976***
	(2.100)	(1.184)	(2.679)
International	-0.013	-0.002	-0.015
	(0.049)	(0.009)	(0.058)
Pharma	-0.096	-0.017	-0.113
	(0.062)	(0.014)	(0.074)
Electronics	-0.431***	-0.074**	-0.505***
	(0.047)	(0.038)	(0.064)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

Table IV.20 Regressions results SAC with for interlocking directorates network in W_1 and geographical distance in W_2

	LS lnTFP	LevPet lnTFP	ACF lnTFP
Innovation	4.309**	15.138***	12.577***
	(1.789)	(2.136)	(0.021)
International	0.201***	0.271***	-0.015***
	(0.042)	(0.050)	(0.021)
Pharma	0.069	0.204***	-0.092
	(0.054)	(0.064)	(0.063)
Electronics	-0.264***	-0.280***	-0.421
	(0.040)	(0.048)	(0.047)
Intercept	8.427***	4.165***	4.002***
	(0.683)	(0.339)	(0.298)
Rho	0.251***	0.265***	0.132**
	(0.06)	(0.058)	(0.065)
Lambda	0.145	0.282**	0.163
	(0.150)	(0.139)	(0.149)
Loglikelihood	-592.708	-734.275	-715.720
AIC	1201.4	1484.6	1447.4
Observations	801	801	801

Standard errors in parentheses based on 1000 replications; p-values < *0.1 **0.05 ***0.01

Table IV.21 Impacts of SAC model LS lnTFP

	Direct	Indirect	Total
Innovation	4.457**	1.525**	5.982**
	(1.840)	(0.076)	(2.505)
International	0.200***	0.069***	0.269***
	(0.039)	(0.024)	(0.058)
Pharma	0.071	0.024	0.095
	(0.052)	(0.020)	(0.071)
Electronics	-0.267***	-0.091***	-0.358***
	(0.039)	(0.028)	(0.058)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

Table IV.22 Impacts of SAC model LevPet lnTFP

	Direct	Indirect	Total
Innovation	15.370***	5.590***	20.960***
	(2.453)	(1.824)	(3.650)
International	0.273***	0.098***	0.370***
	(0.047)	(0.028)	(0.063)
Pharma	0.197***	0.071**	0.268***
	(0.06)	(0.031)	(0.084)
Electronics	-0.290***	-0.104***	-0.394***
	(0.046)	(0.03)	(0.062)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

Table IV.23 Impacts of SAC model ACF lnTFP

	Direct	Indirect	Total
Innovation	12.740***	1.814**	14.554***
	(0.018)	(0.941)	(2.178)
International	-0.015	-0.002	-0.017
	(0.056)	(0.008)	(0.063)
Pharma	-0.094	-0.013	-0.108
	(0.061)	(0.011)	(0.070)
Electronics	-0.418***	-0.061*	-0.479***
	(0.042)	(0.033)	(0.061)

Simulated standard errors in parentheses based on 1000 replications; p-value < 0.01***, 0.05**, 0.10*

3 Appendix third chapter

Appendix 3.1. Survival Analysis

Table IV.24 Startup survival

VARIABLES	s_var
Tr_mise	-0.053
	(0.067)
Intangible_dummy	0.327***
	(0.008)
Constant	2.191***
	(0.035)
Regional dummies	Yes
Industry dummies	Yes
Observations	726,204

Clustered standard errors in parentheses; p-value < 0.01***, 0.05**, 0.10*

Table IV.25 Small firm survival

VARIABLES	s_var
Tr_mise	-0.049
	(0.067)
Intangible_dummy	0.295***
	(0.005)
Age	-0.003***
	(0.001)
Age2	0.000***
	(0.000)
Constant	2.150***
	(0.019)
Observations	2,077,330

Clustered standard errors in parentheses; p-value < 0.01***, 0.05**, 0.10*

Appendix 3.2. Distribution of untreated firms versus treated ones

Table IV.26 Distribution of untreated versus treated firms

Variable	Untreated		Treated		
	Mean	**SD**	**Mean**	**SD**	**P-value**
Center-North	0.7030	0.4569	0.7905	0.0102	0.000
Innovative industries	0.1579	0.3647	0.7797	0.4145	0.000

The t-test refers to the null hypothesis that two populations have the same mean

The geographical and sectoral distribution differ between treated and untreated firms

Appendix 3.3. description of the variables

Stk cap: total amounf of stock capital in '000 Euros.

Bank: total amount of bank debts in '000 Euros.

Workers: number of employees.

lnstkcapital: natural logarithm of the variable stock capital

lnbank: natural logarithm of the variable bank.

lnworkers: natural logarithm of the variable workers.

Start: binary variable. It is 1 if the firm is at most 5 years old and shows at most 5 m EUR in revenues; otherwise, it is 0.

Intangible_dummy: binary variable. It is 1 if the firm has at least 1,000 Euros of intangible assets; otherwise, it is 0.

Treatment: binary variable. It is 1 if the firm is listed in the special register by 'MISE' as an 'innovative startup'; otherwise, it is 0.

Post-treatment: binary variable. It is 1 if the firm used to be listed in the special register by 'MiSE' as an 'innovative startup'; otherwise, it is 0.

Treatment2013: binary variable. It is 1 if the firm is listed in the special register by 'MISE' as an 'innovative startup ' in 2013; otherwise, it is 0.

Treatment2014: binary variable. It is 1 if the firm is listed in the special register by 'MiSE' as an 'innovative startup ' in 2014; otherwise, it is 0.

Treatment2015: binary variable. It is 1 if the firm is listed in the special register by 'MiSE' as an 'innovative startup ' in 2015; otherwise, it is 0.

Treatmentnorth: binary variable. It is 1 if the firm is listed in the special register by 'MiSE' and is located in Center or Norhtern Italy; otherwise, it is 0.

Treatmentsouth: binary variable. It t is 1 if the firm is listed in the special register by 'MiSE' and is located in Southern Italy; otherwise, it is 0.

Mills: value of Mills' ratio.

VA: value-added in '000 Euros.

ln(VA): natural logarithm of the variable value-added.

VA/wrk: value-added in '000 Euros divided by number of workers.

ln(VA/wrk): natural logarithm of the variable value-added per worker.

ever_mise: binary variable. It is 1 if the firm is or used to be listed in the special register by 'MISE' as an 'innovative startup'; otherwise, it is 0.

Age: the age of the firm in years, namely the difference between the observation year and the year of foundation.

Age2: it is the squared value of age.

Year dummy: binary variable, which changes among the years.

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This thesis contains at least one error.