European Commission

ISSN 2443-8022 (online)

Italy's Productivity Conundrum

A Study on Resource Misallocation in Italy

Sara Calligaris, Massimo Del Gatto, Fadi Hassan, Gianmarco I.P. Ottaviano and Fabiano Schivardi

DISCUSSION PAPER 030 | MAY 2016

EUROPEAN ECONOMY

Economic and Financial Affairs

Authorised for publication by Istvan Pal Szekely, Director for Economies of the Member States III.

Luxembourg: Publications Office of the European Union, 2016

KC-BD-16-030-EN-N (online)
ISBN 978-92-79-54432-3 (online)
doi:10.2765/970192 (online)

KC-BD-16-030-EN-C (print)
ISBN 978-92-79-54433-0 (print)
doi:10.2765/407175 (print)

European Commission

Directorate-General for Economic and Financial Affairs

Italy's Productivity Conundrum

A Study on Resource Misallocation in Italy

Sara Calligaris, Massimo Del Gatto, Fadi Hassan, Gianmarco I.P. Ottaviano and Fabiano Schivardi

Abstract

This paper provides a detailed analysis of the patterns of misallocation in Italy since the early 1990s. In particular, we show that the extent of misallocation has substantially increased since 1995, and that this increase can account for a large fraction of the Italian productivity slowdown since then.

We gather evidence on the evolution of firm level misallocation both within and between various categories of firms, in particular those based on geographic areas, industries, and firm size classes. We do so both for firms in manufacturing and for firms in non-manufacturing. Overall, looking at the distribution of firm productivity, we uncover a thickening of the left tail as the share of firms with low productivity has increased over the period. This implies not only a decrease in average firm productivity, but also an increase in its dispersion.

We show that the increase in misallocation has come mainly from higher dispersion of productivities within different firm size classes and geographical areas rather than between them. Crucially, we highlight that rising misallocation has hit firm categories that are traditionally the spearhead of the Italian economy such as firms in the Northwest and big firms. We also produce evidence that, while the 2008 crisis seems to have triggered, at least until 2013, a 'cleansing effect' of the least productive firms in the manufacturing sector as a whole, in non-manufacturing industries one observes the survival of firms with even lower productivities than they used to have.

Finally, we propose a novel methodology to assess which firm characteristics are more strongly associated with misallocation. In particular, we investigate the role of corporate ownership/control and governance, finance, workforce composition, internationalisation, cronyism and innovation. Together with the other findings already highlighted, the analysis of those 'markers' provides the ground for a policy-oriented discussion on how to tackle the Italian productivity slowdown.

JEL Classification: D22, D24, O11, O47.

Keywords: misallocation, TFP, productivity, Italy.

Report prepared for the Commission, Directorate General for Economic and Financial Affairs (DG ECFIN), under contract ECFIN/067/2015/705554.

Contact: Gianmarco I.P. Ottaviano, Centre for Economic Performance (CEP), Dept of Economics, London School of Economics, g.i.ottaviano@lse.ac.uk; Sara Calligaris, University of Rome Tor Vergata and EIEF; Massimo del Gatto, "G.d'Annunzio" University and CRENoS; Fadi Hassan, Trinity College Dublin and CEP; Fabiano Schivardi, Bocconi University, EIEF, and CEPR.

CONTENTS

1. INTRODUCTION 4

1.1 Productivity and its sources 4

1.2 Why productivity matters 5

1.3 Productivity in Italy against benchmark countries 5

1.4 Relevant global shocks since the 1990's 6

1.5 Relevant reforms in Italy since the 1990's 6

2. LITERATURE REVIEW 7

2.1 Methodological contributions 7

2.2 International studies 8

2.3 Studies with Italian focus 9

3. MEASURING MISALLOCATION 11

3.1 Data: CERVED 11

3.2 Methodological approach 12

3.3 Misallocation across different dimensions 15

3.3.1 Manufacturing sector 15

3.3.2 Non-manufacturing 23

3.4 The impact of misallocation to aggregate TFP 30

4. PRODUCTIVITY, MISALLOCATION, AND FIRM CHARACTERISTICS: METHODOLOGY 33

4.1 Firm relative productivity 33

4.2 Further analysis of the role of markers of misallocation 33

5. PRODUCTIVITY, MISALLOCATION, AND FIRM CHARACTERISTICS: FINDINGS 35

5.1 Data: INVIND and CB 35

5.2 Markers of misallocation 35

5.2.1 Corporate ownership/control and governance 36
5.2.2 Finance 36
5.2.3 Workforce composition 38
5.2.4 Internationalisation 40
5.2.5 Cronyism 41
5.2.6 Innovation 41
5.2.7 Cross-cutting results 41

6. CONCLUSIONS AND POLICY IMPLICATIONS 43

7. REFERENCES 45

8. ANNEX A 50

9. ANNEX B : TABLES 53

1. INTRODUCTION

"Italy is often regarded as the sleeping beauty of Europe, a country rich in talent and history, but suffering from a long lasting stagnation" (Hassan and Ottaviano, 2013). The broad consensus is that the beginning of such stagnation can be traced back to the 1990's and that faltering productivity growth lies at its root. This paper analyses the microeconomic aspects of this productivity slowdown. In particular, it emphasises a deteriorated allocation of resources among Italian firms and investigates the possible sources of this 'misallocation' problem. The final aim is to provide policy relevant insights on how to tackle the problem thereby contributing to the awakening of the "sleeping beauty".

The paper is organised in five sections. The rest of this section introduces the concepts of 'productivity' and 'misallocation' we use throughout the paper and highlights the relevance of productivity dynamics for understanding its slowdown. It then provides a very concise summary of the main global shocks and relevant reforms that may have affected Italian productivity since the 1990's. Section 2 provides a selective review of the relevant literature on 'misallocation' pinpointing key studies at both the national and international levels. Building on the methodological contributions surveyed in the previous section, Section 3 first operationalises the concept of 'misallocation' we use and details how we implement it empirically. It then discusses the evolution of 'misallocation' in Italy since the 1990's across regions, sectors and firm size classes. Section 4 develops a new methodology to identify firm characteristics ('markers') that are associated with 'misallocation'. This methodology is applied in Section 5 where we scan a rich set of economic and institutional characteristics. Section 6 concludes the paper summarising its main findings and distilling some policy implications.

1.1 PRODUCTIVITY AND ITS SOURCES

The concept of 'productivity' we use is "Total Factor Productivity" (henceforth simply TFP), which measures how efficiently given amounts of inputs are used. Clearly the economy's aggregate TFP is a weighted average of its firms' TFP (hence we will use 'aggregate TFP' and 'average TFP' interchangeably). As such it depends on their TFP along two dimensions.

On the one hand, given the amount of productive factors - like capital and labour - used by each firm, aggregate TFP grows when individual firm TFP grows thanks to the adoption of new technologies and better business practices. If firms are generally unable to take these opportunities, the economy's productive apparatus is exposed to obsolescence and senescence with a negative impact on aggregate TFP. On the other hand, in the presence of frictions in the markets for productive factors, aggregate TFP also depends on how those factors are allocated across firms.

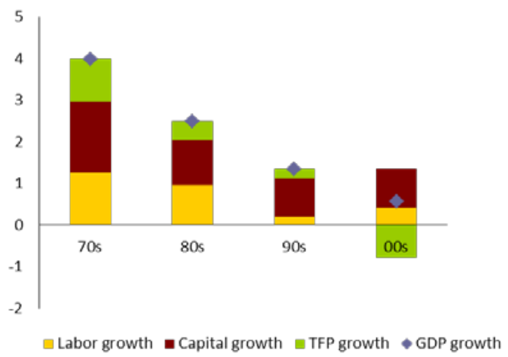
In particular, as long as market imperfections hamper the flow of factors from less productive firms (where factor returns are lower) to more productive firms (where factor returns are higher), they result in lower aggregate TFP compared to an ideal situation of frictionless factor markets. This distorted allocation of resources towards lower productivity firms is what we call 'misallocation' and, as we will discuss in greater detail in Section 3, it can be measured by the observed gaps ('wedges') in factor returns between firms.

Quantifying the impact that 'misallocation' has on aggregate Italian productivity and identifying the main firm characteristics associated with such misallocation is the aim of our analysis. In doing so, we will distinguish between characteristics potentially relevant for the allocation of capital (such as the involvements of firms with banks and financial markets) and those potentially relevant for the allocation of labour (such as the skill composition of the labour force and management practices).

1.2 WHY PRODUCTIVITY MATTERS

It is well understood that TFP is the main driver of long-run growth (see, e.g., Caselli, 2005). In fact a growth process based on increasing productivity and efficiency is more sustainable in the long run than a process based on the accumulation of the factor of productions – capital and labour – which are characterised by decreasing return to scale. It has also been shown that Italian firms tend to under-respond to TFP shocks because of frictions in the economy like the ability of managers to implement changes in a firm (Pozzi and Schivardi, 2015). **Figure 1.1** is quite emblematic of the relevance of TFP dynamics for aggregate growth. It shows a growth accounting decomposition for Italy in the past four decades. TFP growth shrank throughout the decades, turning negative in the 2000s (Hassan and Ottaviano, 2013). Accordingly, understanding the origin of such decline is crucial in order to design appropriate policies that can enhance future growth.

Figure 1.1: **Contribution to value added growth, Italy**

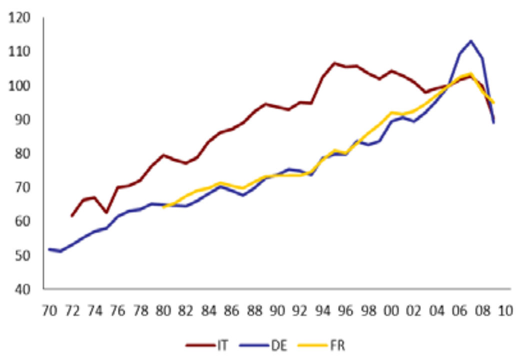


Source: LSE Enterprise

1.3 PRODUCTIVITY IN ITALY AGAINST BENCHMARK COUNTRIES

The TFP decline that we observe in Italy seems to be country specific. **Figure 1.2** shows the evolution of TFP for the manufacturing sector in Italy, France, and Germany. It reveals a clear slowdown in Italy since the middle of the 1990's, whereas in France and Germany TFP continued to grow up to the global financial crisis (Hassan and Ottaviano, 2013).

Figure 1.2: **TFP Manufacturing (2005 = 100)**



Source: LSE Enterprise

Recently a debate on the productivity slowdown of the United Kingdom, which occurred after the global financial crisis, has also emerged. In this respect, understanding the Italian case may provide useful methodological and policy guidance on how to tackle productivity issues in other countries.

1.4 RELEVANT GLOBAL SHOCKS SINCE THE 1990'S

The rise of globalisation and the revolution of ICT ('information and communications technology') are the two key global shocks that occurred in the 1990's. Moreover, the introduction of the euro is a relevant regional shock at the end of the decade that we also take into account.

These types of shocks caused a radical change of the competitive context in which firms operate. Italian firms, typically of smaller size than the European average, used to be particularly efficient in sectors with low technological intensity, low return to scale, and standardised products. It is likely that the Italian firms were not resilient to the shocks that occurred in the 1990's because: i) globalisation introduced new economic actors with lower production costs; ii) the euro prevented nominal devaluations that could have been used to help the adjustment; iii) the ICT revolution, which has been a key driver of recent TFP growth (Bloom et al., 2012b; Bloom et al., 2014), benefited larger firms that had sufficient scale for this type of technological investments.

1.5 RELEVANT REFORMS IN ITALY SINCE THE 1990'S

In the period under consideration, the Italian economy underwent important regulatory reforms in a number of areas, from the labour market to bankruptcy laws, from corporate governance to retail trade, from the social security to the school system. A complete description of the sequence of reforms, as well as an appraisal of their effects, is beyond the scope of this paper. The OECD has compiled a series of publications on these issues, and we refer the interested readers to them (see for example OECD, 2012).

Two such reforms might have played a particularly important role in the process of resources allocation. First, Italy underwent a large privatisation process. On the one hand, such process should have improved the efficiency of formerly publicly owned industrial companies or utilities. On the other hand, as for privatisation, this process may have shifted resources from industrial or services activities with a high level of productivity to services characterised by low competition, high rents and low productivity. This may have contributed to the productivity slowdown through the misallocation of resources between sectors rather than between firms within the same sector.

A second important sequence of reforms relates to the labour market, which was progressively made more flexible. On the one hand, higher flexibility should result in a better allocation of labour across sectors and firms. On the other, it has been argued that in Italy the reform has created a 'dual' labour market where some workers are highly protected while others highly 'flexible'. The consequent different labour efforts and behaviours may eventually lead to more labour misallocation and to a de-anchoring of wages from labour productivity (Manasse and Manfredi, 2014).

Quantifying econometrically the role of global shocks and Italian reforms for misallocation goes beyond the scope of this paper as it would require harmonised cross-country firm level data that are not readily available.

2. LITERATURE REVIEW

This section provides a selective overview of the relevant literature on misallocation. More specifically, the first subsection mentions the main methodological contributions to the quantification of misallocation; the second subsection surveys the papers that apply those methodologies to various countries and contexts; the third subsection reviews some studies aimed at understanding the Italian situation and the possible causes of the Italian productivity slowdown. As the literature on misallocation is evolving at a very rapid pace, this section has no aim of being comprehensive, but rather focuses on aspects that are central to our analysis.[1]

2.1 METHODOLOGICAL CONTRIBUTIONS

There is a wide literature on the inefficient allocation of resources across firms. Among them, the most relevant methodological contributions for our project are Hsieh and Klenow (2009) (HK, henceforth), Olley and Pakes (1996) (OP, henceforth) and Bartelsman, Haltiwanger and Scarpetta (2013).

The increasing interest in misallocation can largely be attributed to the contribution of HK, who provide an analytical framework to quantify the effects of misallocation on productivity. The basic intuition of HK is that, in a world where factors are allocated efficiently, the value of the marginal product of inputs should be equalised across firms. Dispersion in the marginal value product of inputs can then be seen as a measure of the extent of misallocation of factors of production. HK construct a model that, based on rather standard assumptions on technology (e.g. Cobb-Douglas with constant return to scale) and market structure (monopolistic competition with constant demand elasticity, assumed to be the same for all firms in the economy), allows to quantify the losses in productivity deriving from the fact that marginal value products are not equalised across firms. Under the assumptions of homogeneous technology and demand across firms, the only reason why marginal value products might not be equalised across them is the presence of distortions in the factor and/or product markets. As a consequence dispersion in marginal products is a measure of such distortions. They apply their framework to measure the impact of factors misallocation across manufacturing firms on aggregate TFP in China, India and the US. They find that misallocation is much more prominent in China and India than in the US, and that, if such countries had the same degree of allocative efficiency as the US economy, manufacturing TFP would grow by between 30 and 60%. HK propose a "summary" measure of the effects of dispersion in the marginal products, that is, TFP revenue (TFPR), which is a weighted average of the marginal revenue product of capital and labour. Dispersion in TFPR measures the total effect of misallocation on productivity. Other studies have focussed also separately on the marginal products of each input, which signal separately capital and labour misallocation. Asker, Collard-Wexler and De Loecker (2014) focus on capital misallocation. They criticise the HK model by showing that productivity volatility and investment adjustment costs can explain a large fraction of the dispersion of the marginal revenue product of capital. Under this condition, heterogeneity in the marginal revenue product of capital is not necessarily evidence of misallocation, but of an optimal response of firms conditional on productivity volatility and adjustment costs.

Olley and Pakes (1996) propose a decomposition of industry productivity into the unweighted average of firms' productivities and the sample covariance between productivity and size. The misallocation measure is provided by the covariance term: the more efficient the allocative process, the larger more productive firms should be. An application of the Olley and Pakes decomposition can be found in Bartelsman, Haltiwanger and Scarpetta (2013) who rely on the fact that heterogeneity in firm-level performance is accompanied by substantial heterogeneity in the size of firms and that the distributions of productivity and size of firms exhibit a positive correlation. We will come back to this paper in the next subsection.

[1] For a recent survey, see Restuccia and Rogerson (2013), as well as the papers in the same special issue of the Review of Economic Dynamics. The authors divide the literature on misallocation into "direct approach", which focuses on specific mechanisms that could result in resource misallocation, and "indirect approach", which focuses on the net effect of the entire bundle of underlying factors on misallocation without reference to a specific one. Another useful survey is Hopenhayn (2014).

2.2 INTERNATIONAL STUDIES

A number of authors have measured the size of overall distortions by applying the HK procedure to other countries and periods. Analyses based on the HK framework show that in recent years misallocation increased substantially in Spain (Garcia-Santana et al., 2016; Gopinath et al., 2015) and in Portugal (Dias et al., 2014), remained pretty constant in France (Bellone and Mallen-Pisano, 2013), while it declined in Germany (Crespo and Segura-Cayuela, 2014), Chile (Chen and Irarrazabal, 2014). In addition, comparing France, Italy, Germany and Spain, Crespo and Segura-Cayuela (2014) find that potential TFP gains from eliminating misallocation in Spain are larger than those in France but smaller than those in Germany and Italy. In parallel exercises, Brandt et al. (2013) consider the allocation of the Chinese economic activity across regions as well as between the public and the private sector; Ziebarth (2013) sets the HK exercise in a historical context by constructing a firm-level data set for manufacturing in the U.S. in the late 19th century; Bollard et al. (2013) study a much longer period for India than HK ranging from 1980 to 2004.

Using the OP covariance between TFP and/or labour productivity and market shares in the US and seven European countries, Bartelsman, Haltiwanger and Scarpetta (2013) find that the size/productivity relationship is stronger in more advanced economies and became stronger in Central and Eastern European countries, with misallocation remaining roughly constant in more advanced countries and decreasing in the transition ones. In their aforementioned study of Spain, together with the HK approach, Garcia-Santana et al. (2016) use also the OP covariance decomposition as a measure of misallocation obtaining largely consistent results.

In terms of specific channels that can give rise to misallocation of resources in the economy, the most studied aspect is arguably finance. In a seminal paper, Caballero et al. (2008) document that Japanese banks during the nineties directed credit toward "zombies" firm, that is, low productivity firms, keeping them artificially alive. This process depressed factors reallocation and productivity growth. Midrigan and Xu (2014) build a model of firm dynamics in the presence of financial frictions. They show that financial frictions affect productivity growth mostly by reducing entry and technology adoption. Gopinath et al. (2015) explain the low productivity growth in Italy and Spain by the decrease in the interest rates following the Euro adoption. They build a model in which, due to differences in net worth, some firms are financially constrained and cannot access capital markets, while others are not constrained and therefore can borrow. Following a decrease in the cost of capital (such as the one experienced by Spain and Italy after the Euro adoption) only firms that are not financially constrained can increase investment, which widens the wedge between the marginal product of capital of unconstrained and constrained firms. Moreover, as high net worth firms are not necessarily the most productive, capital is not allocated to the most productive firms. Caggese and Cunat (2013) study the interaction between financing constraints and export activity. Using firm level data for Italy, they show that credit constraints at the level of the firm reduce the productivity gains deriving from trade liberalisation, as constrained firms are less likely to enter the export market.

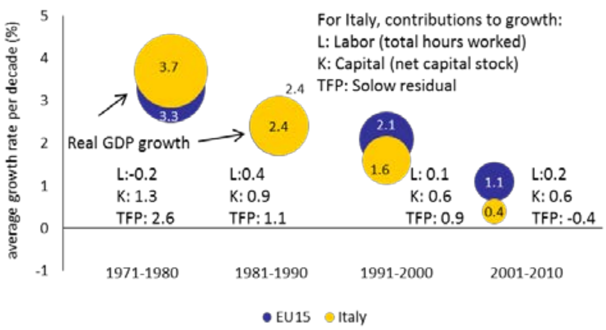
Another source of misallocation that can play a role in the Italian case is the allocation of talents. Hsieh et al. (2013) analyse the effects of race and gender discrimination on the misallocation on talents and, through this, on productivity. They conclude that 15 to 20 percent of growth in aggregate output per worker between 1960 and 2008 may be explained by the improved allocation of talent that follows a reduction in discrimination. Bloom et al. (2012a) document differences in the quality of managerial practices (and therefore in productivity) across firms with different ownership structures, showing that family run firms (as opposed to family owned, but managed by external managers) tend to be less effectively managed. Caselli and Gennaioli (2013) argue that, when the market of corporate control does not properly function, firms might remain family owned and managed even if the owners do not have the best skills to efficiently run the firm.

Some papers have also studied the effects of policies that distort the size distribution of firms. Guner et al. (2008) use a growth model with endogenous size distribution of firms to study the effects of size-contingent policies, such as firing costs applying only above a certain threshold. They document that such policies can have large effects on aggregate productivity. Bento and Restuccia (2015) show that average firm size increases with development. They construct a model in which size correlated distortions are more prevalent in poor countries, and show that such distortions can generate substantial productivity losses. Such distortions can be particularly relevant for the Italian productive structure, characterised by the prevalence of SMEs (Bartelsman et al., 2005).

2.3 STUDIES WITH ITALIAN FOCUS

The most striking feature of the recent developments in the Italian economy is the emergence of a marked productivity slowdown since the mid-nineties. Reports by the European Commission give an overall picture of sluggish Italian productivity (Country Report Italy 2015, Council Recommendation on the 2015 National Reform Programme of Italy, Macroeconomic Imbalances, Italy 2014). **Figure 2.1**, drawn from Lusinyan and Muir (2013), illustrates a growth accounting exercise for Italy and the EU15 countries. Two facts emerge clearly: the Italian slowdown starts in the nineties and becomes more pronounced in the 2000s; its main driver is the slowdown in TFP growth, which in the 2000s turns negative. This evidence has spurred a lively debate on the causes of the productivity slowdown, which we briefly summarise in this subsection. In this debate, the role of misallocation has been analysed only recently.

Figure 2.1: **Growth Accounting – Italy vs EU15**



Source: Lusinyan and Muir (2013)

An early line of interpretation, due among others to Faini and Sapir (2005), attributes the cause of the slowdown to the Italian model of specialisation, characterised by traditional sectors with low human-capital intensity and low technology. According to this view, the way out of the slowdown would be a change in the sectoral composition of the Italian productive system. This view has been challenged by a series of subsequent contributions. First of all, it has been shown that the productivity slowdown characterises all sectors and, if anything, tends to be stronger in high-tech sectors (Idee per la crescita, 2013). Moreover, cross-firm dispersion in the level of productivity is mainly accounted for by the within-sector rather than the between sector component (Bugamelli et al., 2010). Rather, an important role is represented by the firm size distribution. The Italian productive system is characterised by the prevalence of SMEs, which display a lower level of productivity when compared to large firms. De Nardis (2014) performs a productivity decomposition exercise that shows that the whole difference in productivity levels between Italy and Germany can be essentially explained by the difference in firm size distribution, while sectoral composition plays a smaller role. A similar result is obtained by Barba-Navaretti et al. (2010) when considering export performance. A related issue that has received growing attention is the role of corporate ownership and control. As in most European countries, family ownership is the predominant ownership mode; what is peculiar of Italian family firms is that they tend also to be controlled and closely managed by family members (Bugamelli et al., 2012). This might be a source of misallocation of talents, if the most appropriate managerial skills are not found within the family owning the firm.

The contributions that investigate specific channels of the productivity slowdown have focussed on these aspects. Pellegrino and Zingales (2014) find that labour productivity growth flattened due to small firms' inability to respond appropriately to the challenge of Chinese competition and to the failure of exploiting the ICT revolution. These failures, in turn, are shown to be due to the lack of meritocracy in managerial selection and promotion, as well as to familyism and cronyism. Daveri and Parisi (2015) argue that Italy's productivity slowdown can be explained by a 1997 labour market reform that introduced temporary employment contracts, producing a rightward shift to labour supply. In addition, managerial age appears to be either positively correlated or uncorrelated with productivity growth for non-innovative firms, but it is robustly negatively correlated with productivity growth for the innovative ones. Lippi and Schivardi (2014) and Bandiera et al. (2014) show that Italian family firms tend to select their managers more based on loyalty than capabilities and that they employ less power-incentive remuneration schemes with respect to other firms. Using cross-country data on OECD countries, Michelacci and Schivardi (2013) show that family firms tend to self-select into lower risk-lower returns projects, with negative consequences on productivity growth. Giordano et al. (2015a, 2015b) highlight the negative impact of public sector inefficiency. Firm size, ownership structure and labour market dualism are recognized by Bugamelli et al. (2012) as key drivers of the innovation gap that characterises the Italian productive system when compared to that of the other industrialised economies. Giordano et al (2015a) use differences in the degree of public sector efficiency at the local level and in the need for efficient public services across sectors to show that the inefficiency of the public sector is an important factor in hindering firms productivity. There is also some evidence that skill mismatch is a source of productivity losses in Italy. The OECD Survey on Adult Skills (PIAAC) shows that Italy is characterised both by a large share of under-skilled and of over-skilled workers with respect to the competencies required by their job. In addition, Italy seems to be the country in which a reduction of skill mismatch to the lowest cross-country level would be associated with the highest increase in the allocative efficiency with respect to the other countries (OECD, 2015). The reasons behind this skill mismatch can be attributed to the education system and/or the functioning of the labour market. Montanari et al. (2015) investigates the process of allocation of graduates in the Italian labour market. They show that the lack of adequate skills and experience is a major source of skill mismatch. At the same time, the widespread use of informal selection procedures among companies, particularity SMEs, as well the rigidities in the labour market, may also contribute to skill mismatch. On these issues, see also the Country Report on Italy 2016 (European Commission, 2016).

Our study contributes to this literature by quantifying the level of misallocation in Italy and by providing evidence of such misallocation. In fact, the role of misallocation has only recently been investigated in explaining the productivity slowdown. In recent work following the HK approach, Gopinath et al. (2015) find that between 1999 and 2008 in Italy (as well as in Portugal and Spain) the dispersion of the return to capital across firms increased significantly while the dispersion of the return to labour did not change significantly over time. They also find that the increasing dispersion of the return to capital was in some cases accompanied by significant productivity losses because some productive and high-return firms were constrained from increasing their investment. In a parallel work on Italy, Calligaris (2015) documents an increase in the extent of misallocation since the early 1990's that explains a large part of the productivity slowdown.

We innovate with respect to both Calligaris (2015) and Gopinath et al. (2015). Our accounting framework builds on Calligaris (2015). However, while Calligaris (2015) focuses only on manufacturing firms, we extend the analysis to non-manufacturing. In addition, we further investigate which firm characteristics or specific mechanisms could result in resource misallocation. Similarly, while measuring misallocation and relating it to credit frictions, also Gopinath et al. (2015) focus on manufacturing only and do not explore whether other firm characteristics are also associated with misallocation. Compared with Gopinath et al. (2015), there are also three additional differences. First, we use a dataset that covers a longer time span (since 1993 rather than 1999).[2] Second, in addition to documenting an increase in dispersion in productivity and marginal products, we apply the HK methodology to assess the productivity losses coming from misallocation. Third, we use another dataset that covers a representative sample of manufacturing firms and includes a large set of firms' characteristics, so that we can relate misallocation to a large set of potential markers.

3. MEASURING MISALLOCATION

This section discusses in detail how we measure misallocation. In particular, we first introduce the data we use. We then explain the conceptual framework behind our measure of misallocation. Lastly, we discuss what our measure reveals for the evolution of Italian misallocation since the 1990's.

3.1 DATA: CERVED

We consider the Italian manufacturing and non-manufacturing (i.e. services, energy industries and construction firms) sectors recorded in the CERVED dataset, which accounts for the universe of limited companies ('società di capitali') in Italy. We group manufacturing firms into nine 2-digit sectors using the ATECO 2002 classification. The manufacturing sectors are 'Textile and leather', 'Paper', 'Chemicals', 'Minerals', 'Metals', 'Machinery', 'Vehicles', 'Food and tobacco', and 'Wood'.[3] As for non-manufacturing, we group firms at the 1-digit classification because a 2-digit classification[4] would be excessively detailed and would raise problems of low firms' numbers in some finer subdivisions. The service sectors we consider are 'Electricity, gas, water', 'Constructions', 'Wholesale and retail trade', 'Hotels and restaurants', 'Transport, storage, communication', 'Real estate', Health and Social work', 'Other services', 'Professional, scientific and technical activities', 'Support services'. We exclude 'financial intermediation' from our service sectors, as well as 'coke and petroleum products' and 'other manufacturing n.e.c.' from manufacturing. These sectors have peculiar behaviours, whose study lies outside the scope of this paper.

As we will discuss in Section 3.2, in order to compute firm-level measures of TFP, we need measures of output as well as of labour and capital inputs. Hence we measure the labour input using the cost of labour and the capital stock using the book value of fixed capital net of depreciation while we take firm value added as a measure of total output. These variables are deflated through sector-specific deflators (with base year 2007).

We clean the database from outliers by dropping all observations with negative values for real value added, cost of labour or capital stock. We are left with a pooled sample of 1,555,000 firm-year observations for manufacturing and 3,677,000 for non-manufacturing over the period 1993-2013. The average number of observations per firm is 12 for manufacturing and 10 for non-manufacturing.

To compute firm-level TFP we also need capital and labour shares at industry level. We compute the labour share by taking the industry mean of labour expenditure on value added measured at the firm level. We then set the capital share as one minus the computed labour share.

Tables 3.1 and **3.2** present sectoral descriptive statistics for average real value added, capital stock and cost of labour over the period of observation, both in absolute terms and in percentages with respect to the total. The tables reveal a higher difference in value added across sectors in non-manufacturing than in manufacturing, reflecting a higher degree of heterogeneity within non-manufacturing.

In manufacturing 'machinery', 'metals' and 'textile and leather' are the sectors with the largest numbers of firms and represent 62% of the total number of manufacturing firms. Real value added ranges from a mean of around 0.8m euros in 'wood' to around 4.4m euros in 'vehicles'. Variation in the average capital stock is sizable,

[2] Gopinath et al. (2015) use data from Amadeus, while we use data from CERVED. Both providers use information from the Chambers of Commerce as original sources.
[3] A further level of disaggregation is not advisable given the low number of firms that would characterise many sectors at three-digits.
[4] 1-Digit classification includes sectors like construction, hotels and restaurants, and whole and retail trade.

ranging from around 1m euros in 'textile and leather' to around 4.9m euros in 'vehicles'. The cost of labour varies notably too, ranging between 0.5m euros in 'wood' and 3.2m euros in 'vehicles'.

Looking at non-manufacturing, 'wholesale and retail trade' and 'constructions' are the most numerous sectors and represent 61% of our non-manufacturing sample. 'Health and social work', 'other services' and 'electricity and gas' are, instead, an extremely small fraction of non-manufacturing, less than 1%. Overall, both value added and the cost of labour are around half those in manufacturing, but also in this case they exhibit a sizable variation: value added ranges between 0.52m euros for 'hotel and restaurants' and 19.4m euros for 'electricity and gas', while the cost of labour ranges from 0.3m euros in 'real estate activities' to 5.6m euros in 'electricity and gas'. The capital stock is also on average lower for non-manufacturing than for manufacturing, with an average of 1.4m euros, excluding 'electricity and gas'.

In order to better understand the pattern of misallocation, we divide the dataset into geographic and firm size cells. In particular, we group firms *within each industry* into four main Italian macro-areas: Northwest, Northeast, Centre, South and Islands[5]. We also divide the firms in the dataset into four groups according to firm size: 'micro', 'small', 'medium' and 'big'[6]. We report the summary statistics of the main variables divided by geographic area and size, both in absolute terms and percentages, in **Table 3.3** (for manufacturing) and **Table 3.4** (for non-manufacturing). Around two thirds of manufacturing firms and half of non-manufacturing firms are located in the Northern areas of the country. In these areas, manufacturing firms' value added, capital stock and cost of labour are higher than the average. For non-manufacturing, instead, after the Northwest, the Centre is the region that exhibits value added and capital higher than the average. Looking at firm size, more than 88% of manufacturing firms and almost 95% of non-manufacturing firms are 'micro' or 'small', while only 2.2% of manufacturing firms and 1% of non-manufacturing firms are 'big'. However, 'micro' and 'small' firms account for only around 30% of total value added and input costs, whereas big firms account for around 45%.

In **Tables 3.5** and **3.6** we present the summary statistics of firms clustered by sector-area and by sector-size. For most of the industries in manufacturing, the majority of firms are located in the North. Moreover, practically all sectors are composed mainly by 'micro' and 'small' firms, with the majority of bigger manufacturing firms in concentrated in 'chemicals', 'food and tobacco' and 'vehicles industries'. The distribution of non-manufacturing firms is much more uniform over the country than in manufacturing. Furthermore, for non-manufacturing the percentage of 'micro' and 'small' firms is even higher than for manufacturing, and 'big' firms are nearly inexistent.

Tables 3.7 and **3.8** show the relevance of firm size by geographic area. In the Northwest more than half of the value added in the manufacturing and the non-manufacturing sectors comes from 'big' firms. 'Big' firms in the service sector are particularly relevant also in the Centre where they account for almost 60% of value added. Finally, **Tables 3.9** and **3.10** look at the distribution of value added by firm size across geographical areas. About 56% of value added produced by big firms in the manufacturing sector comes from the Northwest, this confirms a *strong overlap between the Northwest region and 'big' firms*.

3.2 METHODOLOGICAL APPROACH

Having discussed how firms in Italy are distributed across geographic areas, sectors and size classes, we now describe the conceptual framework within which we measure misallocation at the firm level.

[5] We use the ISTAT (National institute of Statistics) classification of macro-areas. "Northwest" includes the regions Liguria, Lombardy, Piedmont and Aosta Valley; "Northeast" includes Emilia-Romagna, Friuli-Venezia Giulia, Trentino-South Tyrol and Veneto; "Centre" includes Lazio, Marche, Tuscany and Umbria; "South and Islands" includes Abruzzi, Basilicata, Calabria, Campania, Molise, Apulia, Sicily and Sardinia.

[6] We use the European Commission classification of firms according to their turnover. "Micro" are firms with a turnover ≤2m Euros, "small" ≤10m Euros, "medium" ≤50m Euros, "big" >50m Euros. See http://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition/index_en.htm

As anticipated in the previous sections, we follow Hsieh and Klenow (2009) (HK) in defining 'misallocation' as the inefficient allocation of productive factors across firms with different TFP. Inefficiency is determined with respect to the ideal allocation of factors that would result in a world of frictionless factor markets where factors' owners – workers and owners of capital - were free to provide their services to the firms offering them the highest returns. In this ideal allocation, as long as firms face either decreasing returns or a downward sloping demand curve, the value of the marginal product of each factor is equalised across firms so that the factor's remuneration ('price') is the same for all firms. This is an allocative equilibrium as no factor owner has an incentive to change the allocation of her factor services. It is also a stable allocative equilibrium as any exogenous shock creating gaps in the value of a factor's marginal product across firms would trigger a reallocation of that factor from less to more productive firms until its remuneration is again equalised across all firms.

Shocks that can create such gaps are idiosyncratic shocks that increase the TFP of some firms *relative* to others. As firms with relatively higher TFP are able to offer relatively higher factor remunerations at the pre-shock allocation, they have the opportunity to expand by attracting additional factor services away from relatively less productive firms until convergence in the value of factors' marginal products restores the equalisation in factor remuneration across firms. In this respect, any observed gaps in the values of factors' marginal products across firms reveal a distorted allocation of factors across them. This inefficient allocation of resources is what we call 'misallocation' and its extent can be measured by the width of the observed gaps ('wedges') in the values of factors' marginal products between firms.

Notice that an increase in misallocation is not necessarily associated with a decrease in firm average TFP. The reason is that idiosyncratic shocks that increase the TFP of some firms, relative to others, can come in two types. Those that increase the weight of the right tail of the firm TFP distribution lead to higher dispersion (i.e. higher misallocation) but also higher average TFP. Shocks that, instead, increase the weight of the left tail of the firm TFP distribution (that is the productivity of the less productive firms) lead to higher dispersion (i.e. higher misallocation) but also lower average TFP. In other words, decreasing misallocation can be associated with either lower or higher average TFP in a given sector, depending on whether the latter is driven by (respectively) a decrease or an increase in the relative number of more productive firms. The problem with this approach is how to aggregate the gaps in the values of the marginal products of the different factors so as to obtain an overall measure of misallocation. As aggregation requires a weighting scheme, the solution requires some assumption on the underlying production structure. Following again HK, we assume that the production possibilities of a firm i in sector s can be represented by the constant-return-to-scale Cobb-Douglas production function $Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}$, where K_{si} and L_{si} are capital and labour inputs, α_s and $1-\alpha_s$ (ranging between 0 and 1) are their respective cost shares, and A_{si} is the firm's TFP measuring how much output the firm can obtain from given inputs. Under this assumption the value of TFP is proportional to a geometric average of the values of the marginal products of capital and labour with geometric weights α_s and $1-\alpha_s$ respectively. Accordingly, aggregate misallocation can be measured by looking at the gaps in the values of TFP between firms. In particular, it can be captured by dispersion of the distribution of those values. This dispersion has a direct impact on the sectoral TFP, as the latter can be expressed as a simple function of firm TFP and of the variance of the distribution of the value of TFP ('TFPR'). Specifically, as detailed in Annex, sectoral TFP is a weighted geometric average of firms' TFP with weights determined by firms' TFPR:

$$TFP_s = A_s = \left[\sum_{i=1}^{M_s} \left(A_{si} \frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} .$$

This can be rewritten as an unweighted geometric average of firms' TFP minus the variance of firms' TFPR:

$$\ln TFP_s = \frac{1}{\sigma-1}\ln\left(\sum_i A_{si}^{\sigma-1}\right) - \frac{\sigma}{2} var(\ln TFPR_{si})$$

The two terms on the right hand side correspond to the two dimensions along which aggregate TFP is determined by firms' productivities as discussed in Section 1.1. On the one hand, given the amount of productive factors - like capital and labour - used by each firm, aggregate TFP grows when individual firm TFP (the first term) grows thanks to the adoption of new technologies and better business practices. On the other hand, in the presence of frictions in the markets for productive factors, aggregate TFP also depends on how those factors are allocated across firms (the second term).

Formally, the value of TFP for firm *i* in sector *s* is defined as[7]:

$$TFPR_{si} = P_{si}A_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}. \qquad (3.1)$$

Note that this expression can be evaluated without econometric estimation as the value of output $P_{si}Y_{si}$, the capital stock K_{si} and the labour input L_{si} are directly observed while the capital share α_s can be obtained from $\alpha_s = 1 - \frac{w^L L_{si}}{P_{si}Y_{si}}$ (see previous section).

Once $TFPR_{is}$ has been evaluated for all firms in the sample, we can measure the aggregate misallocation in the economy as the variance of its distribution across firms. However, we are also interested in understanding the extent to which aggregate variance is driven by variations between sectors, geographical areas and firm size groups or by variations within them. For this reason, we classify firms not only in terms of the sector but also in terms of the geographical area and the size category they belong to.

Operationally, we use subscript *i* to index firms, subscript *s* to index sectors and subscript *g* to denote area/size groups. Accordingly, $TFPR_{gsi}$ will refer to the TFPR of firm *i* in sector *s* and area/size group *g* with N_{gs} counting the number of firms in that sector and area/size group. The aggregate TFPR dispersion in the economy can then be decomposed into within-group and between-group components as follows:

$$\text{Total}\,Var(TFPR) = \underbrace{\sum_{g=1}^{G}\frac{VA_g}{VA}\underbrace{\sum_{s=1}^{S}\frac{VA_{gs}}{VA_g}\underbrace{\sum_{i=1}^{N_{gs}}\frac{VA_{gsi}}{VA_{gs}}\left(TFPR_{gsi}-\overline{TFPR}_{gs}\right)^2}_{Var(TFPR)_{gs}}}_{Var(TFPR)_g}}_{WITHIN-GROUP} + \qquad (3.2)$$

$$+\underbrace{\sum_{g=1}^{G}\frac{VA_g}{VA}\sum_{s=1}^{S}\frac{VA_{gs}}{VA_g}\left(\overline{TFPR}_{gs}-\overline{TFPR}\right)^2}_{BETWEEN-GROUP}$$

[7] The output price Psi is allowed to differ across firms as HK assume that firms supply horizontally differentiated products under monopolistic competition.

where G is the number of area/size groups and S is the number of sectors. In (3.2) the overall TFPR variance is decomposed in two parts: a weighted average of the within-group squared deviations from the group mean, and a weighted average of the squared deviations of the group means from the overall mean. Specifically, the within-group component represents a weighted average of the group-specific variances, in turn expressed in terms of weighted averages of the variance within the sector-specific TFPR distributions within the group. The weights are calculated in terms of value added.

When the economy is considered a single area/size group (so that the number of groups is equal to one), the within-group component boils down to a simple within-sector component, consisting of a weighted average of the within-sector variances:

$$Var(TFPR) = \sum_{s=1}^{S} \frac{VA_{gs}}{VA_g} \underbrace{\sum_{i=1}^{N_s} \frac{VA_{si}}{VA_s} \left(TFPR_{si} - \overline{TFPR_s}\right)^2}_{Var(TFPR)_s}. \tag{3.3}$$

This is the expression we use to measure aggregate misallocation for the economy[8].

3.3 MISALLOCATION ACROSS DIFFERENT DIMENSIONS

We are now ready to apply our conceptual framework to the assessment of the patterns of misallocation in the Italian economy from 1993 to 2013.

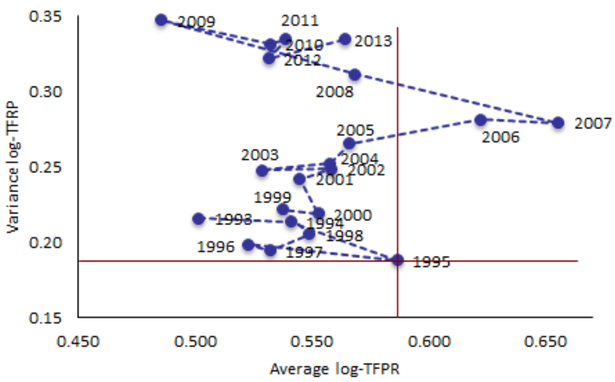
3.3.1 Manufacturing sector

We first investigate the misallocation pattern in the whole manufacturing sector by computing the TFPR variance as described in Equation (3.3). The output of this exercise is depicted in **Figure 3.1**, where we also report the average TFPR based on the same weighting scheme used for the variance. The figure shows that:

- A huge decline in average TFPR occurred in the mid-nineties, followed by a temporary recovery from 2005 to 2007 and a new fall associated with the economic crisis;
- Misallocation (as measured by the variance of TFPR) steadily and steeply increased, between 1995 and 2009 and slightly decreased, after its peak in 2009, until 2012.

[8] The same measure is used by HK (2009), although they do not weight across units (i.e. the shares VA_{si} / VA_s). Thus, compared to HK, our measure assigns more importance to the misallocation in large firms.

Figure 3.1: **Variance and Average TFPR - Aggregate pattern in manufacturing**



Source: LSE Enterprise

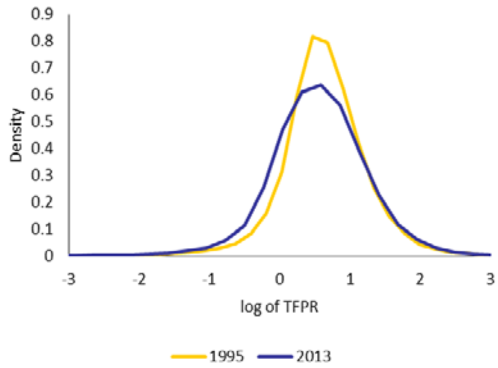
The order of magnitude of these trends can be read in **Table 3.11**, where we report the growth rate of the computed TFPR average and variance, using two-year averages in early and late periods. Looking at the different sub-periods, we see that:

- The drop in average TFPR associated with the economic crisis is substantial (-10.5%);
- Aggregate misallocation increased by almost 69% between 1995 and 2013 with most of the increase taking place in the first decade.

These results are mostly in line with the preliminary analysis in Section 2.3 (based on the EU-KLEMS data), where in **Figure 1.2** aggregate TFP starts declining in 1995. As in that figure, we also find here evidence of a recovery, which is however more substantial and brings average TFPR back to its 1995 level. Nevertheless, the recovery suddenly stopped in 2007 when the economic crisis hit the Italian economy.

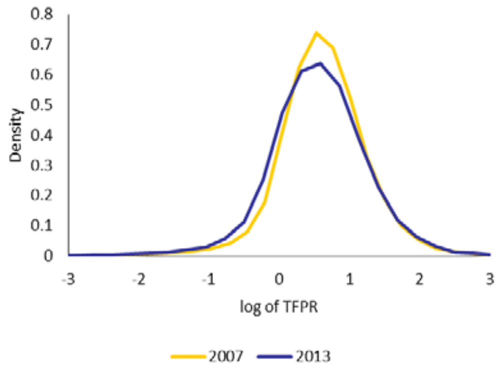
To better understand the firm-level dynamics behind the aggregate patterns displayed in **Figure 3.1**, we compare the firm-level distributions of TFPR in 1995 with that in 2013. This comparison, reported in **Figure 3.2**, shows quite clearly that the evolution of TFPR highlighted above (i.e. decreasing average and increasing variance) mainly occurred through a rising share of low productivity firms.

Figure 3.2: **Distribution of TFPR – Manufacturing (1995 vs 2013)**



Source: LSE Enterprise

Figure 3.3: **Distribution of TFPR – Manufacturing (2007 vs 2013)**

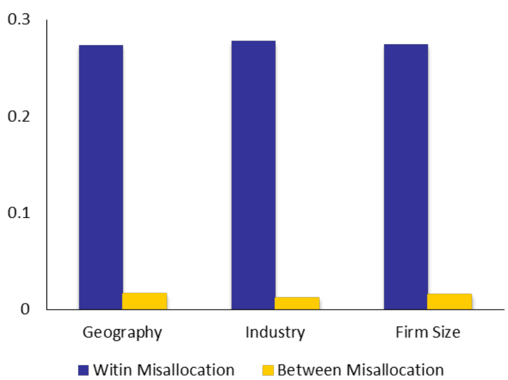


Source: LSE Enterprise

When the comparison is made, instead, between 2007 and 2013 (see **Figure 3.3**), the difference in the share of low productivity firms is much less pronounced. In fact, recalling what we have seen in **Figure 3.1,** 2007 represents a critical year for average TFPR but not for its variance as this keeps on growing until 2009. This suggests that the aggregate decrease in TFPR occurred in the last years compounds a secular increase in misallocation with a crisis-related fall in average firm productivity.

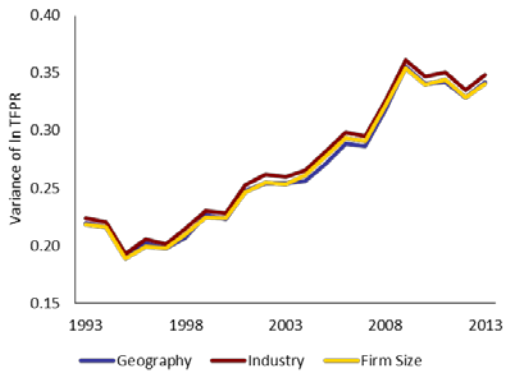
In principle, the increasing misallocation pattern documented in the aggregate might hide substantial differences across sectors, areas and firm size categories. However, before going into the details of each dimension, we implement the decomposition in Equation (3.2) in order to understand to what extent aggregate misallocation can be traced back to differences in terms of TFPR dispersion across the categories. In **Figure 3.4** we report the computed within and between components of aggregate TFPR variance for the three dimensions, along the whole period under consideration (1993-2013). The message is clear-cut as *the between component is always small compared with the within component* with only slight differences emerging across the three dimensions (see **Figure 3.5** and **Figure 3.6**). Moreover, since the between components start growing only after 2000, the increase in aggregate variance occurred between 1995 and 2000 is almost entirely driven by the within components.

Figure 3.4: **Misallocation within vs. between categories**



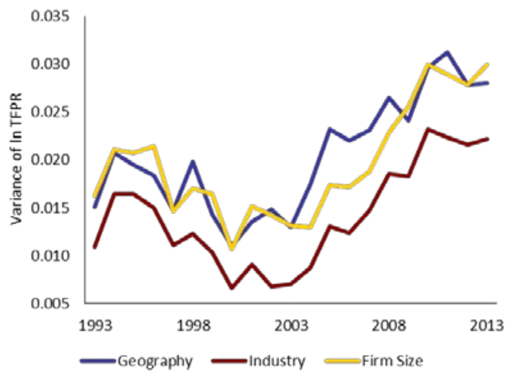
Source: LSE Enterprise

Figure 3.5: **Evolution of within misallocation by category**



Source: LSE Enterprise

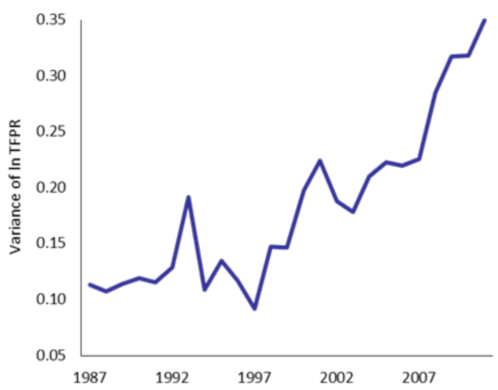
Figure 3.6: **Evolution of between misallocation by category**



Source: LSE Enterprise

In order to have some insight about the trend of misallocation before 1993, we use the INVIND database from the Bank of Italy, which covers the period 1987-2011. However, this more extended database, which we introduce more in details in Section 5, involves only manufacturing firms above 50 employees for the sectors six major manufacturing sectors: 'textile and leather', 'paper', 'chemicals', 'minerals', 'metals', 'machinery'. **Figure 3.7** shows that for this reduced subsample of firms, misallocation had a sharp increase in 1992 at the time of Italy's devaluation and exit from the EMU, but it then went back to the pre-crisis level and it basically remained stable between 1987 and 1997. This confirms that the rise of misallocation is a phenomenon that started in the mid-'90s and it was not a previously undergoing trend.

Figure 3.7**: Within misallocation by industry 1987-2011**



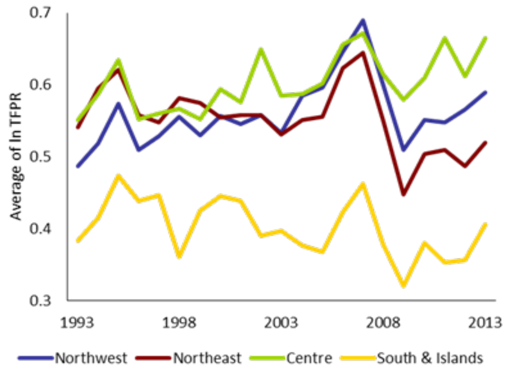
Source: LSE Enterprise

We now go back to our main database base, CERVED, which involves the universe of firms. To better understand the geographical distribution of the aggregate pattern, we report the evolution of misallocation within each macro-region - i.e. the term $Var(TFPR)_g$ - in **Figure 3.9** and the corresponding evolution of average TFPR in **Figure 3.8.** It is quite interesting to note that:

- TFPR in the South is on average always lower than in the rest of Italy;

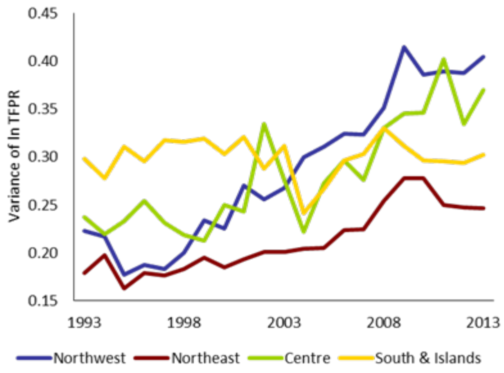
- Misallocation in the Northwest and the Centre grew at a considerably higher rate compared to the other areas;
- Misallocation in the South was higher than in the rest of Italy at the beginning of the period but, being quite stable over time, ends up being lower than in the North Italy at the end of the period.

Figure 3.8: **Evolution of Average TFPR by geographic area**



Source: LSE Enterprise

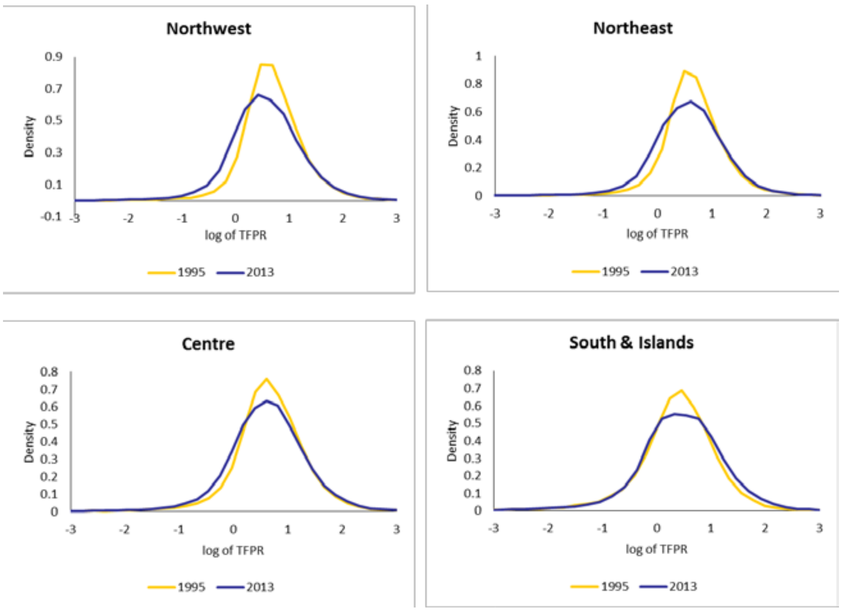
Figure 3.9: **Evolution of misallocation by geographic area**



Source: LSE Enterprise

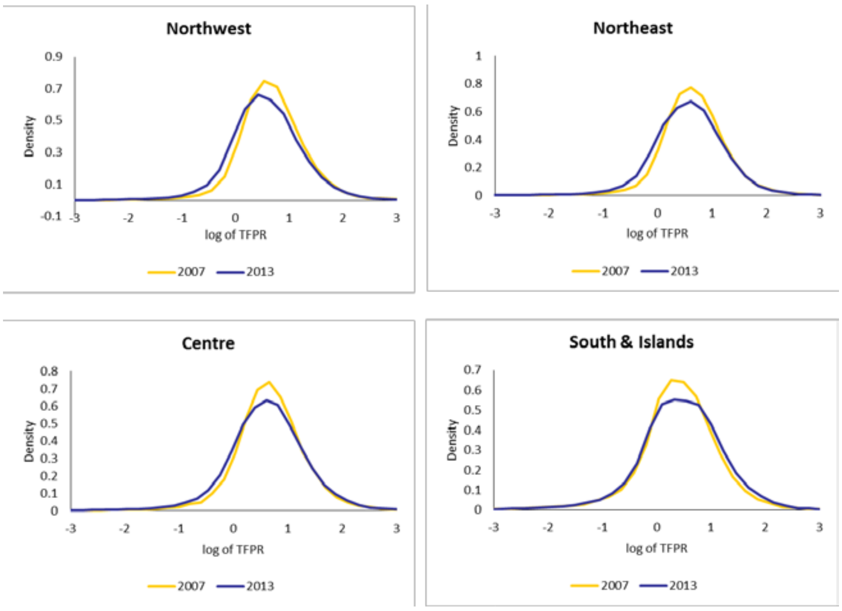
This evidence is confirmed by a graphical inspection of the group-specific distributions reported in **Figure 3.10** and **Figure 3.11**, where the increase in the share of less productive firms on the left tail occurred between 1995 and 2013 is more pronounced in the North, also after 2007.

Figure 3.10: **Distribution of TFPR by geographic area – Manufacturing (1995 vs 2013)**



Source: LSE Enterprise

Figure 3.11: **Distribution of TFPR by geographic area – Manufacturing (2007 vs 2013)**

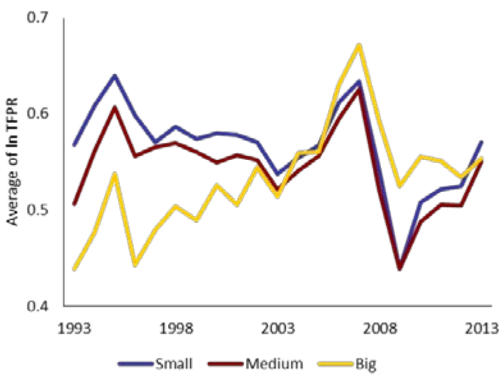


Source: LSE Enterprise

The same analysis can be carried out in terms of firm size categories (see **Figure 3.12** and **Figure 3.13**). While small and medium size groups behave quite similarly in the period under consideration, some specificity seems to characterise the TFPR patterns of big firms. In particular:

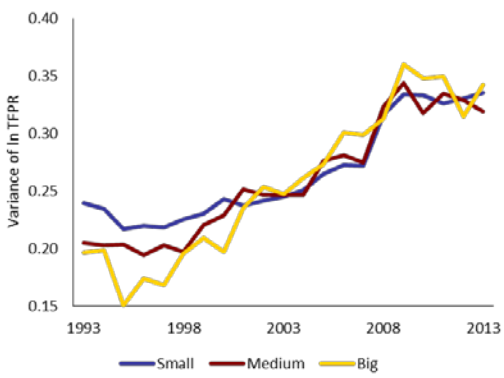
- Big firms were relatively less productive (lower TFPR) on average, at the beginning of the period;
- While the average TFPR of small and medium sized firms decreased between 1995 and 2011, the average TFPR of big firms increased progressively overcoming that of small and medium sized firms in the mid-2000s;
- Misallocation grew in all groups but grew more within the group of the bigger firms.

Figure 3.12: **Evolution of TFPR by firm size**



Source: LSE Enterprise

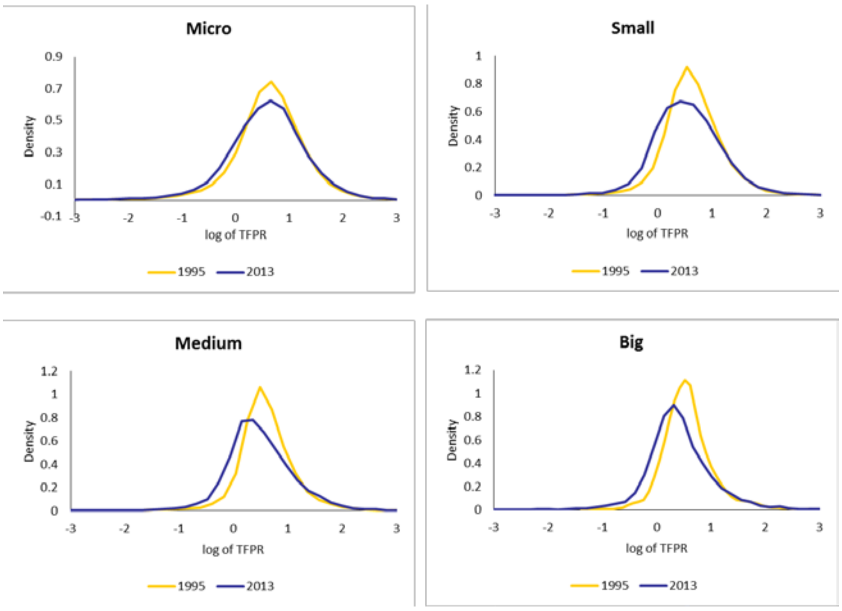
Figure 3.13: **Evolution of misallocation by firm size**



Source: LSE Enterprise

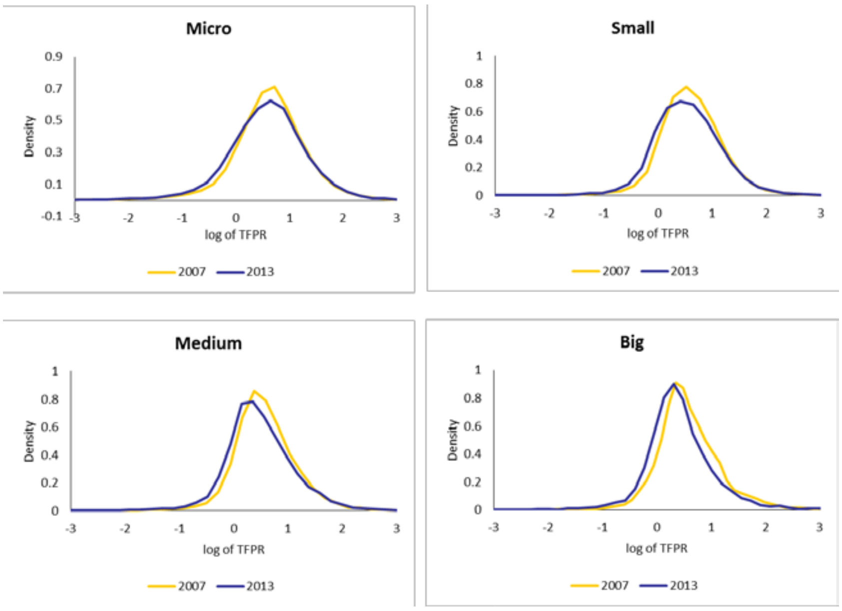
Considered together, these findings reveal that the widespread increase in misallocation that took place independently of firm size received a disproportionate contribution by the TFPR trajectory of big firms. This evidence is corroborated by **Figure 3.14** and **Figure 3.15**, where the leftward shift in the distributions of small and medium size firms is more evident but the distributions look more similar in terms of dispersion. Since the peak in terms of average TFPR within the group of large firms is in 2007, this difference would have been even more pronounced if one had plotted the 1995-2007 distributions instead of the 1993-2013 ones. The fact that both the misallocation and the average TFPR of big firms grew between 1995 and 2007 suggests the prominent role played by the more productive among the big firms: their TFPR increased relatively more than the less productive firms within the same group, and this would have required a disproportional increase in their share of capital and labour. Because such a resources reshuffling did not take place, misallocation grew.

Figure 3.14: **Distribution of TFPR by firm size – Manufacturing (1995 vs 2013)**



Source: LSE Enterprise

Figure 3.15: **Distribution of TFPR by firm size - Manufacturing (2007 vs 2013)**

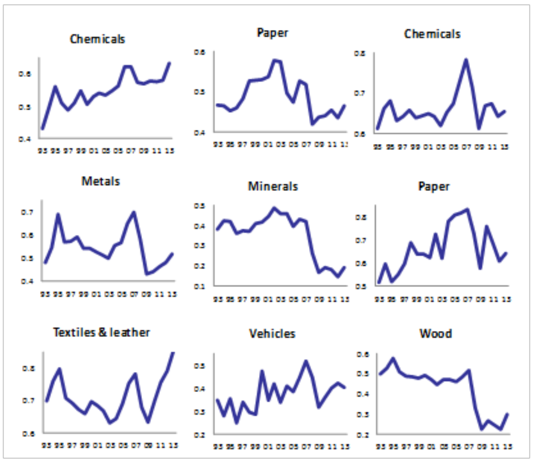


Source: LSE Enterprise

It has been often argued that the 'peculiar' specialisation of the Italian economy is one of the main factors responsible for the productivity slowdown (Faini and Sapir, 2005). To shed light on this aspect, we adopt a sectoral perspective and look at the evolution by industry of our computed TFPR mean and variance (the term Var $(TFPR)_s$ in equation (3.3)). Results are presented in **Figure 3.16** and **Figure 3.17.** Important differences in terms of sectoral dynamics seem to emerge. To better analyse them, we also report, in **Table 3.11**, the sectoral growth rates of both the TFPR average and the TFPR variance in different sub-periods (starting and ending with two-year averages to smooth over the business cycle). If we exclude the years after the crisis, and compare the 1995-1996 average with the 2005-2006 average, some key composition effects can be highlighted in the misallocation upsurge (and productivity slowdown) occurred in the 1990s:

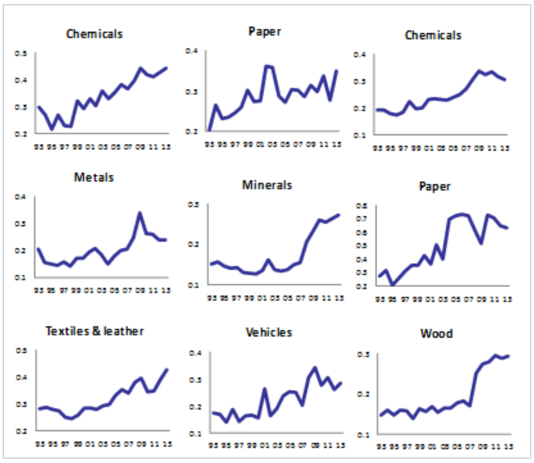
- Cross-industry heterogeneity in the misallocation patterns is substantial;
- The increase in misallocation in the first decade after 1995 is more pronounced in the 'paper', 'vehicles', 'chemicals' and 'machinery' industries;
- The increase in misallocation in 'paper', 'vehicles' and 'machinery' industries coincides, however, with rising average TFPR, and thus it is likely to be driven by the thickening of the right tail of the TFPR distribution;
- The average TFPR increase in industries such as 'paper', 'vehicles' and 'minerals', whose relative importance for the economy also increased (see the weights at the bottom of **Table 3.11**), arguably contrasted the general economy-wide downward tendency.

Figure 3.16: **Evolution of average TFPR by industry**



Source: LSE Enterprise

Figure 3.17: **Evolution of misallocation by industry**



Source: LSE Enterprise

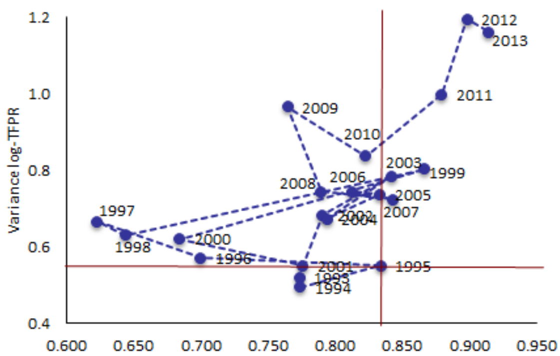
As a consequence of the economic crisis, average TFPR plummeted in all sectors but 'chemicals' and 'textiles', and all sectors experienced rising misallocation, with the exception of the 'paper' industry. Industries such as 'minerals' and 'wood', which were relatively less concerned by the increase in misallocation in the 1990's, are the most affected by the upsurge in misallocation in the years of the crisis.

It is finally worth noting how, *during the crisis, the industries in which misallocation grew the most are also the industries in which average TFPR decreased the most*. This suggests that the increase in misallocation in the years of the crisis is mainly driven by the thickening of the left tail of the TFPR distribution.

3.3.2 Non-manufacturing sector

When the foregoing analysis is applied to non-manufacturing, the misallocation and average productivity patterns appear more articulated (see **Figure 3.18 to 3-33**).

Figure 3.18: **Variance and Average TFPR - Aggregate pattern in non-manufacturing**

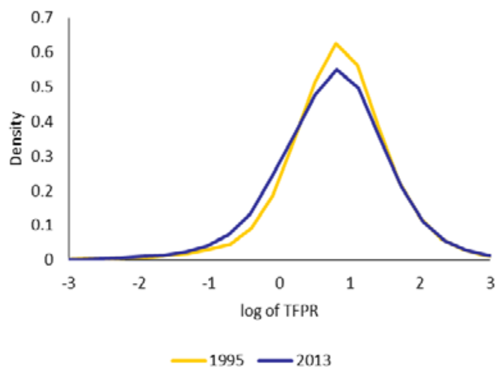


Source: LSE Enterprise

Starting with the aggregate figures (**Figure 3.18** and **Table 3.12**), although with more volatility than in manufacturing:

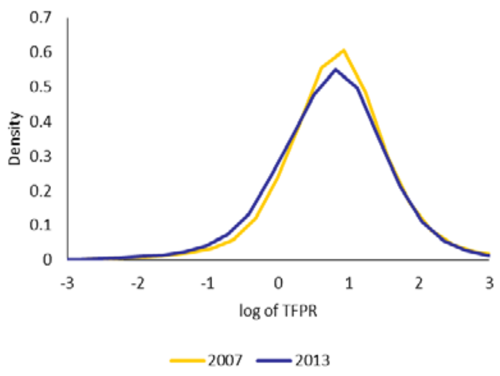
- A first period (1995-2006), characterised by increasing misallocation and oscillating average TFPR, can be separated from a second period, starting with the economic crisis, in which misallocation steadily and steeply increased;
- The overall (1995-2013) increase in misallocation (+52.4%) was larger, in magnitude, with respect to that occurred in manufacturing (+40.8%);
- Differently from manufacturing, there is an overall increase in terms of average TFPR over the period (+15.4%);
- Compared with the manufacturing sector, the fattening of the left tail of the TFPR distribution is less pervasive (**Figure 3.19** and **Figure 3.20**).

Figure 3.19: **Distribution of TFPR – Non-manufacturing (1995 vs 2013)**



Source: LSE Enterprise

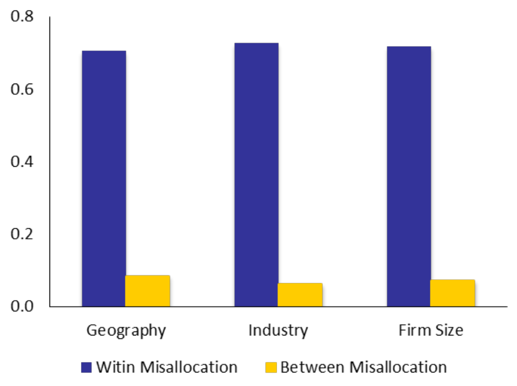
Figure 3.20: **Distribution of TFPR – Non-manufacturing (2007 vs 2013)**



Source: LSE Enterprise

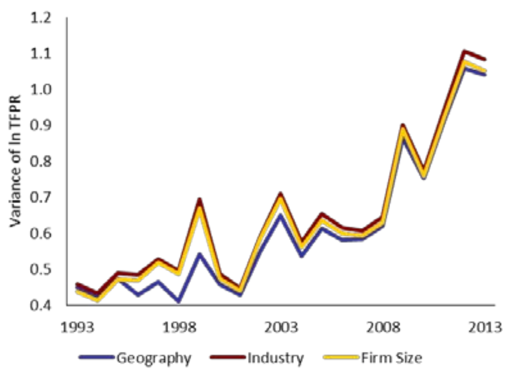
The decomposition of the overall misallocation in within and between components (**Figure 3.21, Figure 3.22** and **Figure 3.23)** reveals a higher relative importance for the within component and, notably, an upsurge in its relative importance that, after 2008, is mostly due to increasing misallocation in the Centre (**Figure 3.25**).

Figure 3.21: **Misallocation in non-manufacturing within vs between categories**



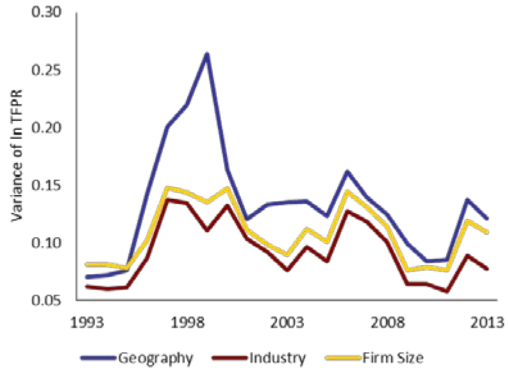
Source: LSE Enterprise

Figure 3.22: **Evolution of within misallocation in non-manufacturing by category**



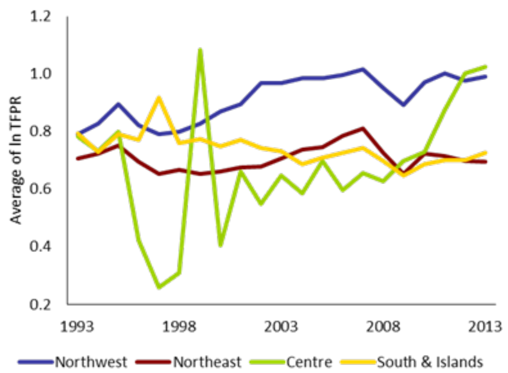
Source: LSE Enterprise

Figure 3.23: **Evolution of between misallocation in non-manufacturing by category**



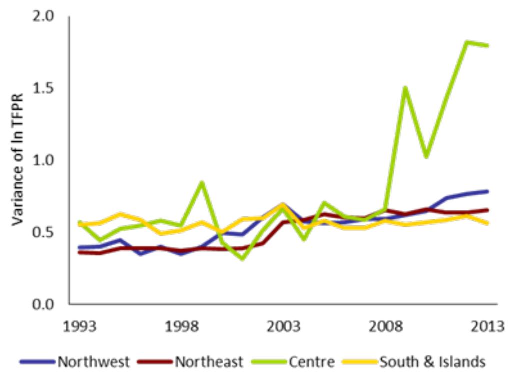
Source: LSE Enterprise

Figure 3.24: **Evolution of average TFPR in non-manufacturing by geographic area**



Source: LSE Enterprise

Figure 3.25: **Evolution of misallocation in non-manufacturing by geographic area**

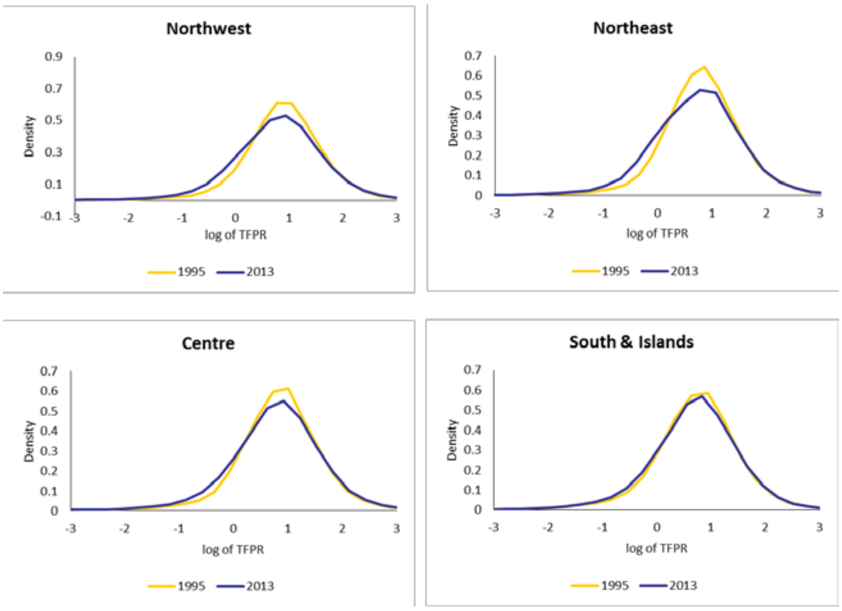


Source: LSE Enterprise

Compared with the differences across industries and firm size classes, the misallocation differences among geographic areas are relatively more important (**Figure 3.23**). This happens because:

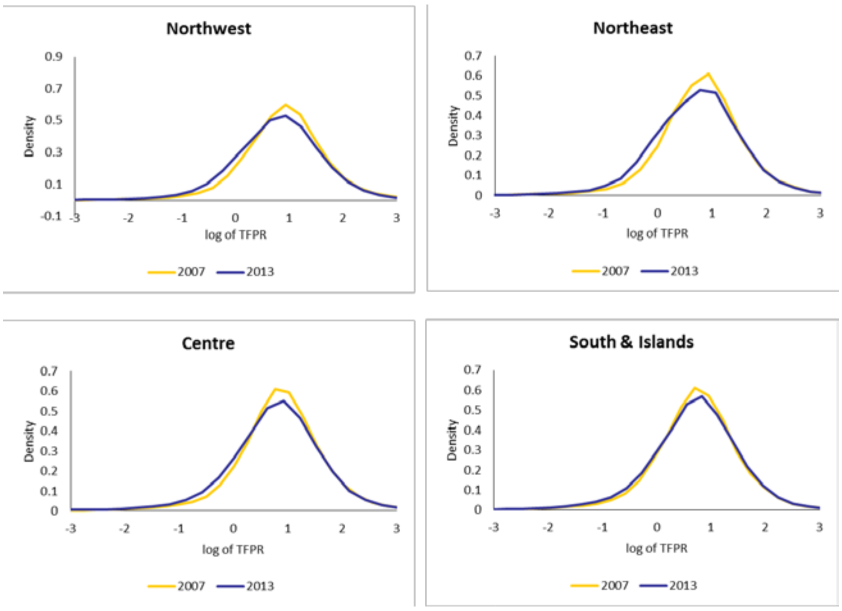
- Firms located in the Northwest were relatively more productive (higher TFPR), on average during the whole period under consideration (**Figure 3.24**);
- The economic crisis produced a steep increase in misallocation in the Centre (**Figure 3.25**)

Figure 3.26: **Distribution of TFPR by geographic area – Non-manufacturing (1995 vs 2013)**



Source: LSE Enterprise

Figure 3.27: **Distribution of TFPR by geographic area – Non-manufacturing (2007 vs 2013)**

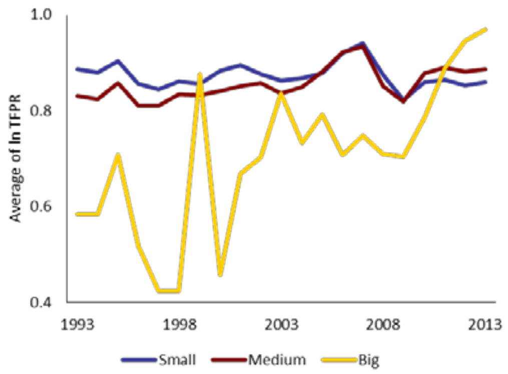


Source: LSE Enterprise

Regarding firm size:

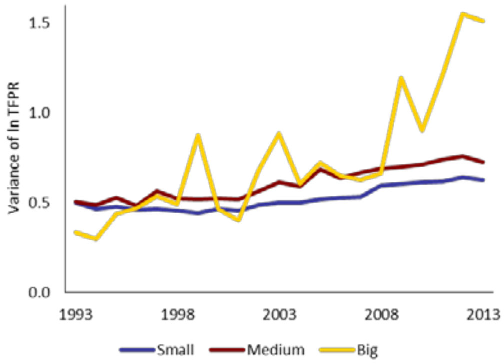
- Similarly to manufacturing, in non-manufacturing there is a *sharp increase in misallocation* starting in 1995;
- Also similarly to manufacturing, large firms started with a considerably lower average TFPR than small firms; however, differently from manufacturing, the TFPR gap seems to disappear only at the end of the period.

Figure 3.28: **Evolution of Average TFPR in non-manufacturing by firm size**



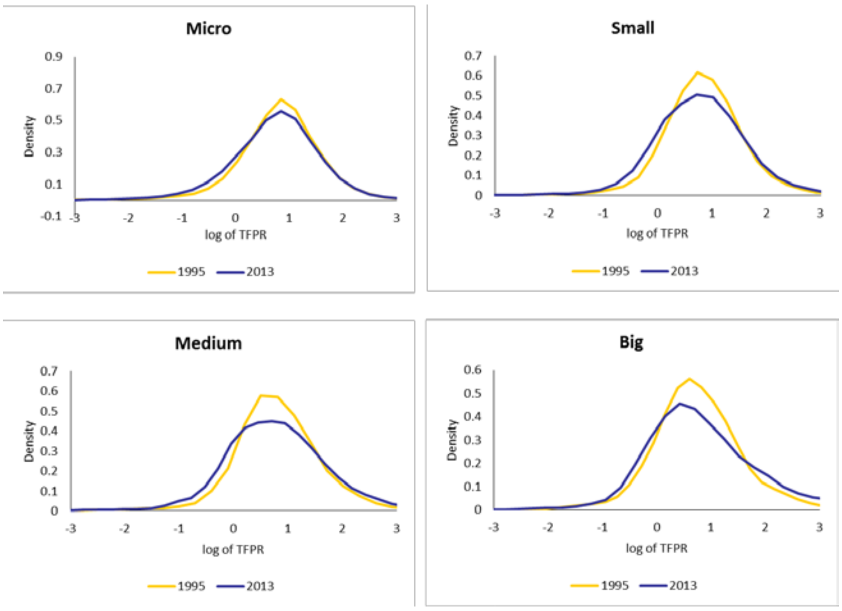
Source: LSE Enterprise

Figure 3.29: **Evolution of misallocation in non-manufacturing by firm size**



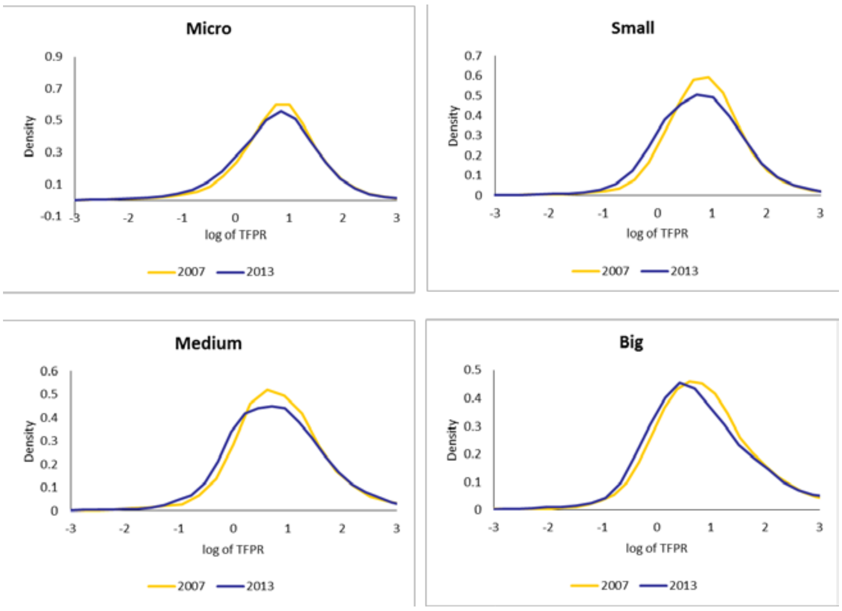
Source: LSE Enterprise

Figure 3.30: **Distribution of TFPR by firm size – Non-manufacturing (1995 vs 2013)**



Source: LSE Enterprise

Figure 3.31: **Distribution of TFPR by firm size – Non-manufacturing (2007 vs 2013)**

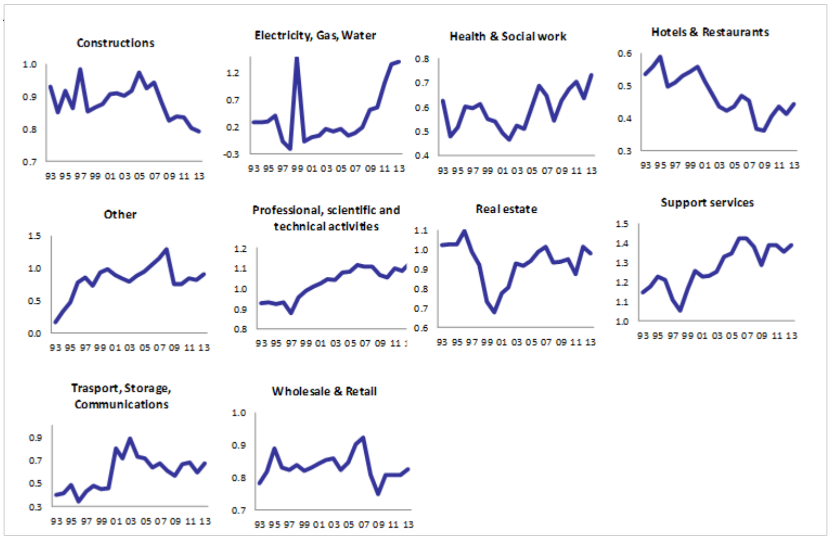


Source: LSE Enterprise

As for sectoral dynamics, the picture for non-manufacturing is much more nuanced than in manufacturing. Although substantial heterogeneity was also detected in the manufacturing sector, the non-manufacturing industries behave quite differently. **Figure 3.32** and **Table 3.12** show that:

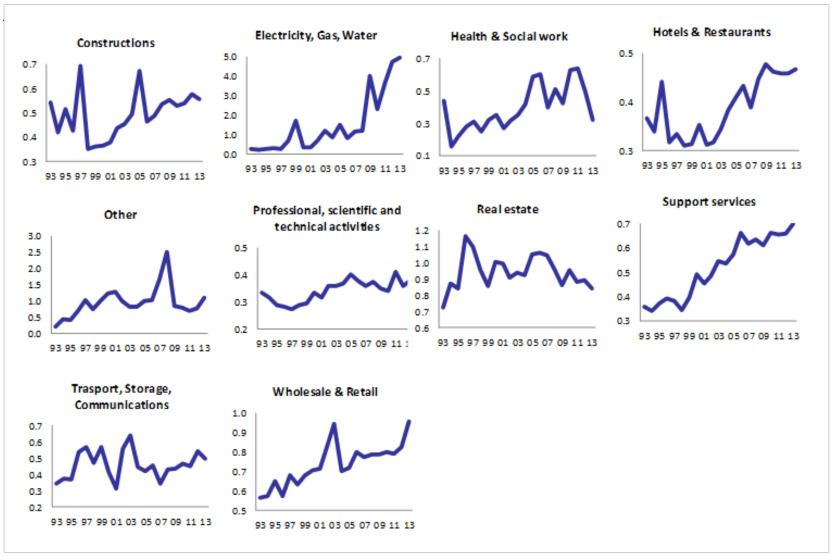
- An overall increase of average TFPR characterised most industries in the period considered;
- During the crisis, some sectors (namely, 'constructions' and 'wholesale & retail' in particular) experienced non negligible decreases in TFPR;
- The electricity/water/gas sector experienced a high increase in misallocation despite the energy sector officially being very liberalised and competitive. While this increase was already in act in the decade before the crisis, average TFPR, started rising only after 2007. A possible explanation could be that the high incentives for renewable energy, especially solar, that were put in place increased the dispersion between firms economically efficient but based on non-renewables and less efficient firms that provide renewable energy. Differently, market opening in the water sector is quite limited and to a very large extent operated by local state-owned enterprises.

Figure 3.32: **Evolution of average TFPR by industry**



Source: LSE Enterprise

Figure 3.33: **Evolution of misallocation by industry**



Source: LSE Enterprise

3.4 THE IMPACT OF MISALLOCATION TO AGGREGATE TFP

The overarching message sent by the battery of figures and tables just presented is that *overall the stagnation of Italian productivity since the 1990's has been accompanied by a steady increase in misallocation*. We now quantify the impact that the increase in misallocation had on aggregate TFP during our period of observation.

In particular, we want to understand how much aggregate TFP in 2013 would have changed if misallocation had remained constant at the 1995 level. In the wake of HK, we proceed as follows.

In each year t from 1995 to 2013 we evaluate the increase in aggregate output that could be achieved by completely eliminating misallocation (i.e. by reallocating productive factors so as to equalise their remunerations across all firms). In any given year, this increase is dictated by the ratio between the observed aggregate output level Y and the efficient aggregate output level Y^* in the absence of gaps in factor remunerations. In turn, the ratio Y/Y^* can be expressed as a weighted geometric average of the sectoral ratios of observed to efficient TFP levels A_s/A_s* across sectors with each sector's weight given by its share θ_s of aggregate output (value added)[9]:

$$\frac{Y}{Y^*} = \prod_{s=1}^{S}\left(\frac{A_s}{A_s^*}\right)^{\theta_s} = \prod_{s=1}^{S}\left[\sum_{i=1}^{N_s}\left(\frac{A_{si}}{A_s^*}\frac{TFPR_s}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{\theta_s}{\sigma-1}} \tag{3.4}$$

where N_s is the number of firms in sector s and σ is the elasticity of demand (which we set equal to 3 as in HK). Notice that equation (3.4) implies that the output ratio Y/Y^* equals the ratio of observed to efficient aggregate TFP levels $TFP/TFP^* = \prod_{s=1}^{S}(A_s)^{\theta_s}/\prod_{s=1}^{S}(A_s^*)^{\theta_s}$. We can, therefore, evaluate the percentage increase in aggregate productivity that could be achieved in any year t by completely eliminating misallocation as:

$$TFPGain_t = \frac{TFP_t^*}{TFP_t} - 1 = \left(\frac{Y_t}{Y_t^*}\right)^{-1} - 1 \tag{3.5}$$

Second, to understand how much aggregate TFP in year t would have changed if misallocation had remained constant at the 1995 level, we can look at the percentage relative change in the efficient-to-observed output ratios in the two years:

$$TFPGain_{t/95} = \frac{TFP_t^*/TFP_t}{TFP_{95}^*/TFP_{95}} - 1 = \left(\frac{Y_t/Y_t^*}{Y_{95}/Y_{95}^*}\right)^{-1} - 1 \tag{3.6}$$

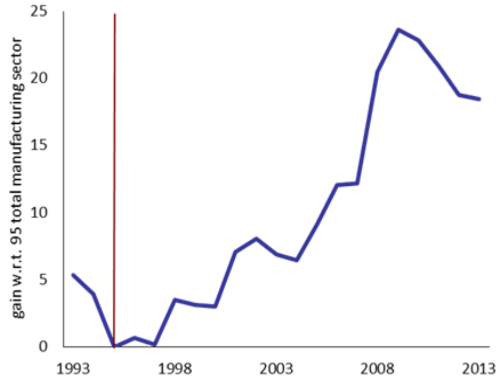
When applied to our data, equation (3.6) implies very large productivity gains if misallocation had remained at its 1995 level (**Figure 3.34**). For manufacturing we find that:

- If misallocation had remained at its 1995 level, in 2013 aggregate TFP would have been 18% higher than its actual level;
- The effect of misallocation on TFP picked in the aftermath of the global financial crisis leading to a 23% foregone productivity gain and weakened slightly after the Euro-debt crisis.

---

[9] Following HK, we assume that the sectoral share θ_s is constant over time, which is the case if one assumes that aggregate output is a Cobb-Douglas composite of sectoral outputs.

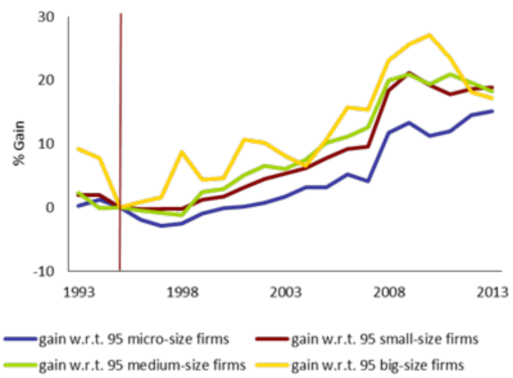
Figure 3.34: **Productivity gains if misallocation was kept at 1995 level - Manufacturing**



Source: LSE Enterprise

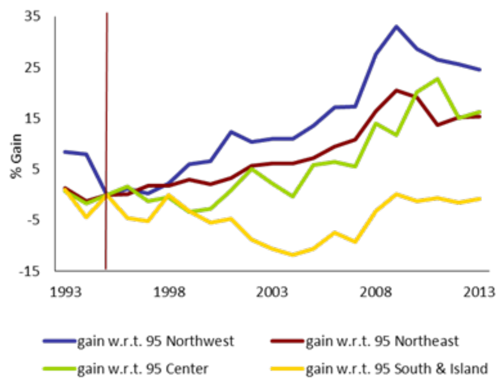
Looking at these effects by firm size and geographic areas (**Figure 3.35** and **Figure 3.36**), we see that misallocation among big firms and among firms of the Northwest are the major causes of the aggregate foregone TFP gains. In the cases of big firms and the Northwest TFP would have been 18% and 25% higher if misallocation in 2013 had stayed at its 1995 level.

Figure 3.35: **Productivity gains if misallocation was kept at 1995 level - Manufacturing, by size**



Source: LSE Enterprise

Figure 3.36: **Productivity gains if misallocation was kept at 1995 level - Manufacturing, by geographic area**



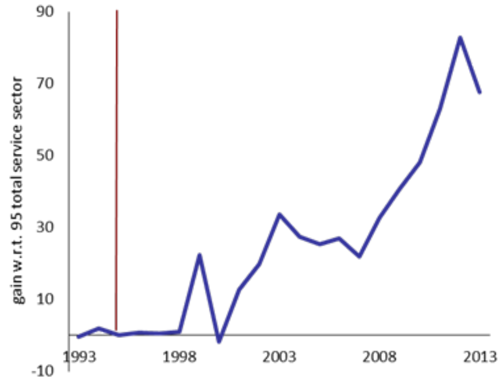
Source: LSE Enterprise

When the same methodology is applied to the service sector, foregone productivity gains are even larger as misallocation affects the service sector more severely (**Figure 3.37, Figure 3.38 and Figure 3.39**). In particular, we see that:

- Misallocation in non-manufacturing started to have severe consequences in terms of foregone productivity gains after 2000;
- The loss in productivity due to increased misallocation with respect to 1995 spiked after the global financial crisis, leading to an overall foregone TFP gain of 67% in 2013;
- Most of the adverse effect of misallocation on TFP is driven by big firms and by firms located in the Centre

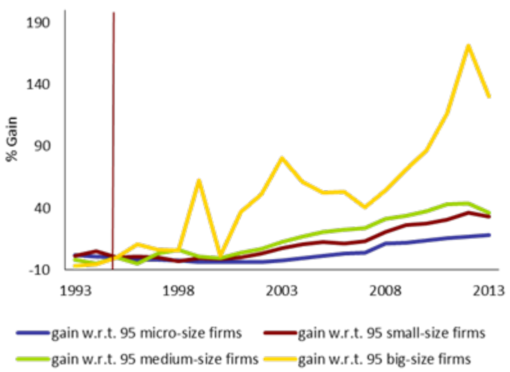
.

Figure 3.37: **Productivity gains if misallocation was kept at 1995 level - Manufacturing**



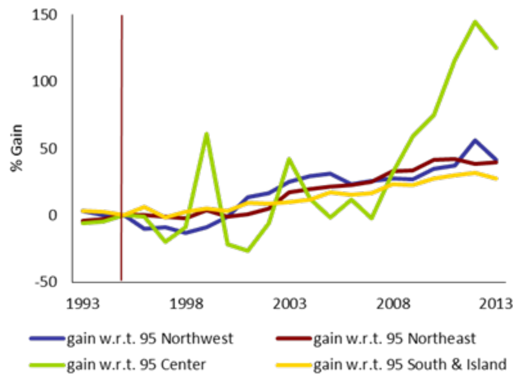
Source: LSE Enterprise

Figure 3.38: **Productivity gains if misallocation was kept at 1995 level – Non-manufacturing, by size**



Source: LSE Enterprise

Figure 3.39: **Productivity gains if misallocation was kept at 1995 level – Non-manufacturing, by geographic area**



Source: LSE Enterprise

To summarise, the detailed analysis covered in this Section 3 has revealed that:

a. The retrenchment of Italian aggregate productivity from 1995 to 2013 has been accompanied by a generalised increase in the misallocation of productive factors across firms;
b. The impact of increasing misallocation on the dismal evolution of Italian productivity is important: *if in 2013 misallocation had remained at its 1995 level, Italian productivity would have been 18% higher in manufacturing and a hefty 67% higher in non-manufacturing*;
c. Even after netting out the spike in the productivity penalty of misallocation associated with the crisis, the adverse effects of misallocation on Italian productivity in manufacturing and non-manufacturing remain sizeable;
d. These findings are consistent with a thickening of the left tail of the firm productivity distribution;
e. From a size class perspective, the observed patterns are mainly driven by misallocation across big firms in both manufacturing and non-manufacturing;
f. From a geographical perspective, they are mainly driven by firms in the Northwest for manufacturing, and by firms in the Centre for non-manufacturing.

4. PRODUCTIVITY, MISALLOCATION, AND FIRM CHARACTERISTICS: METHODOLOGY

In the previous section we have documented the important role played by rising misallocation across Italian firms in the dismal evolution of Italian productivity since the 1990's. We have also argued that the observed patterns are consistent with a thickening of the left tail of the firm productivity distribution such that the increase in misallocation is driven by the rising share of firms with below average productivity.

We now want to identify the firms' characteristics that are associated to higher misallocation and to higher average productivity. In order to do so we rely on reduced form regressions at the firm level. The econometric specifications that we rely on allow us to identify correlations, but not causation, of key firm characteristics with relative productivity and misallocation.

4.1 FIRM RELATIVE PRODUCTIVITY

To identify the main firm characteristics associated with higher relative firm productivity, we run the following regression:

$$\ln\frac{TFPR_{ist}}{TFPR_{st}} = \beta_0 + \beta_1 X_{ist} + \delta_t + \gamma_s + \varepsilon_{ist} \qquad (4.1)$$

where *i*, *s* and *t* refer to firm, sector and year respectively; X_{ist} is the marker (or vector of markers) we want to analyse[10]; δ_t is a year dummy that captures common shocks to all firms in a given year; γ_s is a sector fixed effects controlling for time-invariant sector characteristics that can influence the effect of the driver on misallocation; ε_{ist} is the error term.

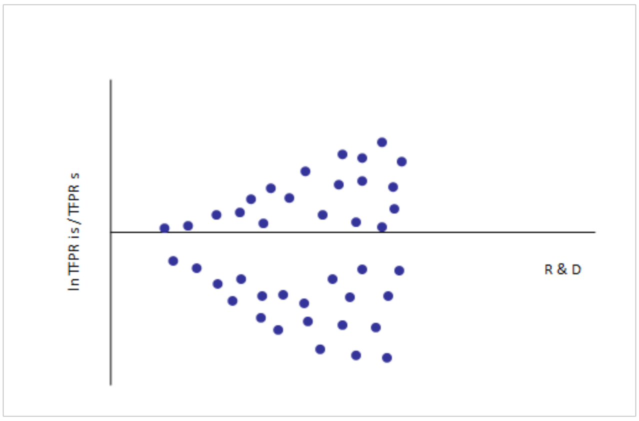
This regression relates a marker to the level of a firm's productivity. Thus, if our estimates point to $\beta_1 > (<)0$, we can conclude that firms with larger X_{ist} are characterised by higher (lower) relative TFPR.

4.2 FURTHER ANALYSIS OF THE ROLE OF MARKERS OF MISALLOCATION

Equation (4.1) allows us to determine the firms' characteristics that are associated to higher relative productivity. It also generates residuals that can be used to identify the covariates of misallocation. To see this, consider the thought experiment illustrated in **Figure 4.1**, where R&D expenditures are taken as the firm marker for innovation. In the figure, while there is no correlation between the marker and relative TFPR (i.e.$\beta_1 = 0$), higher R&D expenditures are associated with higher TFPR dispersion.

[10] For robustness, we also enter the markers with a squared term in order to allow for non-linearity.

Figure 4.1: **TFPR dispersion and R&D expenditures**



Source: LSE Enterprise

Accordingly, the correlation between markers and misallocation can be captured by the following regression of the square of the estimated residuals from equation (4.1) on the same markers and fixed effects:

$$\widehat{\varepsilon^2}_{ist} = \beta_0^{\varepsilon} + \beta_1^{\varepsilon} X_{ist} + \delta_t^{\varepsilon} + \gamma_s^{\varepsilon} + \epsilon_{ist} \qquad (4.2)$$

We will associate the notion of misallocation to the estimation of β_1^{ε}, and say that higher (lower) levels of X are associated to higher (lower) misallocation if β_1^{ε} is estimated to be positive (negative), in order to keep this analysis distinct from the misallocation effects associated with the (positive or negative) productivity effects of the marker.

Thus, we will interpret the results of the estimation of (4.1) and (4.2) as follows.

If our estimates point to

$$\beta_1 > (<)0 \text{ and } \beta_1^{\varepsilon} > (<)0,$$

then firms with larger X_{ist} are characterised by higher (lower) relative TFPR and higher (lower) misallocation.
We will run the econometric specifications (4.1) and (4.2) on various subsamples differing in terms of firm size class, geographic area, and industry technological intensity.

5. PRODUCTIVITY, MISALLOCATION, AND FIRM CHARACTERISTICS: FINDINGS

Unfortunately, the CERVED dataset we have used in Section 3 is not rich enough to be useful for the analysis of the relations between productivity, misallocation and firm characteristics. We have, therefore, to rely on a different dataset, which we have to introduce before presenting the corresponding results.

5.1 DATA: INVIND AND CB

The main dataset we use for the analysis of firm markers is the Bank of Italy's annual survey "Inquiry into manufacturing and service firms" (henceforth, INVIND). We focus on the open panel of representative Italian *manufacturing* firms with at least 50 employees[11]. The survey contains for each firm in the panel detailed information on revenues, ownership, production factors, year of creation and number of employees since 1984. Additional information is drawn from "Centrale dei Bilanci" (henceforth, CB), which contains balance sheet data on around 30,000 Italian firms. INVIND data are matched with those from CB using the tax identification number of each firm.

We group the manufacturing firms in INVIND into 2-digit sectors, using the ATECO 2002 classification of economic activities. Specifically, we focus on six major sectors: 'textile and leather', 'paper', 'chemicals', 'minerals', 'metals', 'machinery'. We drop observations pre-1987, in order to have a proper sample coverage, as well as those not matched with CB data. We are left with a pooled sample of 19,924 firm-year observations over the 25-year period 1987-2011, with an average of 11 observations per firm. We also divide our sample in low-tech and high-tech sectors using the OECD classification of manufacturing industries according to their global technological intensity, based on R&D expenditures respect to value added and production.[12]

We measure the labour input in terms of hours worked, whereas the capital stock is constructed using the perpetual inventory method. Value added is obtained from balance sheets data in CB. We have deflated both value added and capital using the deflator of current sales (base year 2007).

5.2 MARKERS OF MISALLOCATION

For each marker, we run regressions (4.1) and (4.2) with dependent variables labelled "rel_TFPR" and "mis" respectively. The independent variables ('markers') we use are listed in **Table 5.1** and we discuss them in the corresponding subsections.

Our benchmark specification is based on standard pooled OLS regression, always including sector and year dummies[13]. We have also run a number of different specifications, including additional controls, lagged

[11] From 2002 the survey was extended to service firms with at least 20 employees. However, these firms are given a shorter questionnaire, which excludes some of the key variables of our analysis. Moreover, we use data starting from 1987. Therefore, we focus exclusively on manufacturing firms with at least 50 employees.

[12] High-tech industries include firms that produce office, accounting and computing machines; radio, TV and communication equipment; aircraft and spacecraft; medical, precision and optical instruments; electrical machinery and apparatus n.e.c.; motor vehicles, trailers and semi trailers; chemicals excluding pharmaceuticals; rail-road equipment and transport equipment n.e.c.; and machinery and equipment n.e.c. Low-tech industries account for firms that work in building and repairing of ships and boats; rubber and plastic products; other non-metallic mineral products; basic metals and fabricated metal products; wood, pulp, paper; paper products; printing and publishing; food products; beverage and tobacco; textiles; and leather and footwear.

[13] With respect to our aim of investigating the markers of misallocation, the most appropriate specification does not include firm fixed effects. In fact, we are mainly interested in how cross-firm differences in the above dimensions of TFPR (TFPR levels and dispersion) are related to given firm characteristics. We are less concerned with the effects of the within-firm variation in those characteristics across time.

regressors, and firm effects. While the corresponding results are available upon request, for parsimony we provide here a synthetic description of the most robust and policy relevant findings based on the benchmark case.

5.2.1 Corporate ownership/control and governance

We construct an indicator (variable "controllo") of ownership type, distinguishing between firms controlled by an individual or a family, a conglomerate, a financial institution, the public sector or a foreign entity.

As Michelacci and Schivardi (2013) already found that family firms tend to choose activities with a lower risk/return profile compared to firms controlled by other entities, we expect family firms to have lower relative productivity, but also lower productivity dispersion than other firms. This is exactly what we find by regressing the relative TFPR on dummies for each ownership type, using family controlled firms as the reference group (**Tables 5.2A and 5.2B**). Specifically, we find that:

- Firms belonging to a group are more productive than family owned firms by around 5%, particularly in low-tech industries;
- Firms controlled by a foreign entity are more productive than family owned firms by around 6%;
- Government controlled firms are less productive than family owned firms by around 10%, and this is particularly true in the South and in low-tech industries;
- Firms controlled by a financial institution are not statistically different from family firms in terms of TFPR level;
- Misallocation in less pronounced in the category of family firms than in other firm categories, independently of the geographical area, the size class and the degree of technological intensity.

These findings imply that, keeping misallocation unchanged, aggregate productivity would increase if government controlled firms were privatised and acquired by families, but even more if both government controlled firms and family firms were acquired by private groups or foreign entities. On the other hand, keeping corporate ownership unchanged, aggregate productivity would increase if misallocation were reduced within all corporate ownership categories with the largest productivity gains coming from firms controlled by groups and foreign entities.

Unfortunately, the nature of our database prevents us from performing a robust analysis on other aspects of governance[14].

5.2.2 Finance

In the case of finance, we investigate the relevance of credit constraints, equity emissions and relational banking. We also explore the impact of the introduction of the euro on firms' financial characteristics.

a. Credit constraints

We define credit constrained firms as those that declared that they would have liked a higher level of debt (variable "Credit_constraint1", **Tables 5.3A and 5.3B**). We also use an alternative measure of credit constraint based on the willingness of having more credit even at higher interest rates (variable "Credit_constraint2", **Tables 5.4A and 5.4B**). Both measures enter the regression with a lag in order to mitigate endogeneity. In this

[14] Although the database is not representative in terms of young firms, we looked at the relationship between age and TFPR level or dispersion. We did not find any significant relationship when only linear terms are considered. Things seem to change substantially when we allow for a squared term. In that case, our regression results suggest that both the relative level and the dispersion of TFPR are U-shaped in age: they first decrease and then increase.

way we capture how being credit constrained at time t-1 is correlated to productivity and misallocation at time t. The results are similar in both cases. In particular, we find that:

- Firms that are credit constrained at time t-1 tend to have lower relative TFPR at time t. This effect is particularly pervasive in low-tech industries.
- No statistically significant relationship between being credit constrained and misallocation emerges.

Therefore, credit constraint is associated to significantly lower productivity, but not to significantly higher misallocation.

b. Equity

We look at the timing of equity emission by firm with respect to changes in productivity (**Tables 5.5A to 5.7B**). In particular, we look at the correlation between productivity at time t and equity emissions at time t-1, t, and t+1.The idea is to check when a firm tends to increase equity given its productivity pattern. We find that:

- Firms that have lower average productivity in a given year tend to issue more equity in the future, independently of geographical area, size class and technological intensity[15];
- Firms characterised by more equity issuance tend to misallocate more, in particular in low-tech industries; this relationship, however, disappears when the analysis is performed by size classes and by geographical area.

These findings suggest that equity issuance may be a relevant source of funding when firms are hit by a negative productivity shock.

c. Euro effect

One of the main arguments about the effect of the Euro on productivity and misallocation concerns the lower interest rates from which firms benefited after the currency union. The hypothesis is that the introduction of the Euro had a negative impact on Italian productivity because low productivity firms, rather than exiting the market, managed to survive thanks to cheaper credit, which allowed them to leverage. If this were the case, we should observe a significant increase in leverage for low productive firms after the introduction of the Euro.[16] We find (**Tables 5.8A and 5.8B**) that:

- Higher leverage is associated to lower TFPR;
- The interaction term between leverage and a time dummy for 1999 (when the parity across currencies was fixed) is not statistically significant. This means that after the introduction of the Euro the correlation between leverage and productivity did not get worse; whereas, according to the standard argument we should have expected a further deterioration.
- If we look at the interaction term in the regression with the squared residuals, we see that the introduction of the Euro is not associated to a significant effect of leveraged firms on misallocation.

These effects refer to firms in the manufacturing sector with more than 50 employees. We cannot account for firms in the service and construction sectors, for which the increase in leverage could still matter. Unfortunately, INVIND covers firms in the service sector only since 2002, so we do not have observations before the introduction of the Euro.

[15] Note that the relationship with relative productivity at time t is always significant, independently of considering equity issuance at time t (**Tables 5.5A and 5.5B**), t-1 (**Tables 5.6A and 5.6B**) or t+1 (**Tables 5.7A and 5.7B**).
[16] Leverage is defined as debt over total assets. By looking at this variable we check if firms' debt increased disproportionally respect to total assets during the period of cheap credit that followed the introduction of the Euro.

d. Relational banking

We consider a firm as being involved in 'relational banking' if it declares that the principal reason for dealing with its main bank is "personal relationship and assistance". We observe (**Tables 5.9A and 5.9B**) that:

- Relational banking is significantly associated to low TFPR. This result holds true for both high- and low-tech firms, and is particularly pervasive in the North Italy and for large firms;
- No significant relationship emerges between relational banking and misallocation.

Thus, relational banking matters in our analysis because firms that undergo relational banking are systematically less productive. This suggests that relational banking might be a key motivation for low productive firms to choose a specific bank, perhaps because it grants more support in time of need. Hence, relational banking may be a drag on aggregate productivity because it diverts resources from more productive firms with weak banking connections to less productive firms with strong banking connections. However, we do not find a significant effect of relational banking on misallocation. This does not imply that banks do not misallocate capital, but that we cannot detect a significant difference in misallocation between firms that have relational banking from other firms.

5.2.3 Workforce composition

Misallocation is less likely to emerge when less productive firms are free to reduce (and more productive firms are free to increase) the amount of labour. In this perspective, by introducing more flexibility in the labour market, the reforms that the Italian economy underwent in the 1990s should have induced a better allocation of labour[17].

a. Wage Supplementation Scheme (Cassa Integrazione Guadagni - CIG)

Looking at how intensively firms resorted to the Wage Supplementation Scheme ("Cassa Integrazione Guadagni" - CIG) (variable "CIG_share" - hours of CIG over total hours worked) allows us to understand whether and how productivity and misallocation are affected by the possibility of temporarily reducing the cost of labour (without, however, reducing the number of workers).

The expected sign of these relationships depends on which type of firms is actually expected to benefit more from the CIG opportunities: if the less productive firms are thought of to be the most constrained, with respect to the chance to reduce labour, the expected sign is negative.

We find (**Tables 5.10A and 5.10B**) a strong and robust relationship with both the relative TFPR (variable "rel_TFPR") and its dispersion (variable "squared_resid"):

- Firms relying more on the CIG have lower relative TFPR;
- Misallocation is more pronounced within the group of firms relying more on the CIG;
- Both findings hold independently of geographical area, firm size class and technological intensity.

[17] Two major reforms of the labour market took place: the Treu Law and the Biagi Law. The former was introduced in 1997 (law 196/97) with the aim to make the Italian labour market more flexible. The main novelty of the Treu Law consisted in the introduction of temporary contracts and in the creation of Temporary Work Agencies (jobcentres were privatised and decentralised). The Treu Package also modified the discipline of fixed-term contracts, modified the regulation related to employment in the research sector and rose from 22 to 24 the age limit for apprenticeship contracts. The Biagi Law, introduced in 2003 (law 30/03), created new contractual forms and renovated some existing ones, mainly affecting the subordinated workers.

These findings support the idea that less productive firms are more likely to take advantage of the CIG and that, through the associated (temporary) reduction in labour costs, the CIG works against the reduction of the amount of labour used by low productivity firms, thereby fostering misallocation[18].

b. Temporary and foreign workers

To analyse the role of temporary workers and foreign workers, we construct the two variables "term_empl_share" and "foreign_empl_share". The former is expressed in terms of the ratio of the number of temporary employees to the total number of employees at the end of the year. The latter is, instead, measured as the ratio of the average number of foreign workers to the average number of workers in the year.

Depending on which type of firms actually benefited more from the two categories of workers, we might find an increasing share of temporary and/or foreign workers to be associated with either a decreasing misallocation (more productive firms making use of temporary and/or foreign workers relatively more than less productive firms) or an increasing misallocation (less productive firms resorting to temporary and/or foreign workers relatively more than more productive firms).

The regression results, starting from 1999 for temporary workers (**Tables 5.11A and 5.11B**) and from 2003 for foreign workers (**Tables 5.12A and 5.12B**), can be synthetized as follows:

- The intensity of use of temporary workers is associated with higher TFPR;
- There is no evidence of effectiveness of temporary contracts in reducing misallocation;
- A higher share of foreign workers seems to be associated with lower misallocation but has no impact on TFPR levels.

These findings support the idea that more productive firms are more likely to take the opportunity of resorting to temporary work. This result is in sharp contrast with Daveri and Parisi (2015), who find a negative correlation between a firm's share of workers in a temporary contract and its productivity. However, the different measure and the different time period (2001-2003 in their case) can explain the difference. Concerning misallocation, as far as temporary contracts are used to increase the amount of labour, they should result into lower misallocation (this seems to be the case for foreign workers). Instead, to the extent that temporary contracts are used to reduce the labour cost by substituting temporary worker to full time workers, no effect on misallocation is expected. The latter seems to be the case, according to our results.

c. Skill intensity

Lower skills are associated with lower (estimated) productivity if human capital is not controlled for in the estimation of productivity. Since TFPR does not account for human capital, our measured misallocation is overstated if more productive firms systematically use a higher share of high skilled workers and if high skills are systematically associated with higher wages. In this case, the firms considered more productive according to our TFPR measure face a higher cost of labour, so that they are in fact misallocating less, with respect to their 'true' MRPL, than what is suggested by our measure.

Moreover, a higher share of high skilled workers, in particular among white collars, might result in a higher propensity to engage in more risky activities, which in turn might result in higher productivity and higher misallocation.

[18] To go more into the details of these relationships, we build the variable "YearSwitch_CIG", taking value one in the year in which the firm starts resorting to CIG, and run contemporaneous and one-year lagged fixed effects regressions, finding that the decision to start with CIG is associated with a lower relative TFPR but it has no effect on misallocation.

We investigate these issues by looking at two measures of skill-intensity: the share of white collars holding a degree ("grad_share1", **Tables 5.13A and 5.13B**) and the share of blue collars holding a degree ("grad_share2", **Tables 5.14A and 5.14B**). We are able to observe these two variables only in 2010 and 2011, thereby being only able to run cross-section regressions separately for the two years and for the two years together. As expected, the corresponding results show that:

- Firms with a higher share of high skilled workers among white collars are more productive on average (this is particularly true for big firms and for low-tech firms) and tend to misallocate more (this is particularly true for medium-sized firms and for firms located in the Centre);
- No significant impact is found for the share of high skilled workers among blue collars, which seems to be uncorrelated with both TFPR levels and dispersion.

These findings seem to suggest that more productive firms systematically use a higher share of high skilled white collars. However, as skill intensity increases there is also a higher variance in the outcome of relative TFPR leading to an increase in misallocation.

5.2.4 Internationalisation

We use dichotomous variables indicating whether firms: i) belong to a foreign group ("foreign_group", **Tables 5.15A and 5.15B**); ii) are sub-contractors to foreign companies ("sub_foreign", **Tables 5.16A to 5.18B**); iii) delocalised part of the production process ("deloc", **Tables 5.19A and 5.20B**); iv) engaged in foreign direct investment (-"fdi", **Tables 5.21A and 5.23B**).

The regression results suggest that:

- Firms that belong to a foreign group are on average about 6% more productive than other firms;
- Firms that are sub-contractors to foreign companies tend to be less productive if they are located in the northwest of Italy, if they are big firms, or if they operate in a high-tech industry. These results hold for the cross sections in 2004 and 2007, but not for 2010, where the coefficient turns to be significantly negative for small firms and marginally positive for medium firms.
- No significant relationship emerges between misallocation and belonging or being sub-contractor to a foreign company.

As for the process of delocalisation, we find that:

- Delocalisation of production is uncorrelated with both productivity and misallocation;
- Firms that engage in FDI show mixed results according to the year of reference. The coefficient is positive for all years we have data for (2001, 2002, 2003), but it is significant only for 2001 when firms engaged in FDI turned to be 12% more productive than other firms.

Another stylized fact about productivity and internationalisation is the well-known higher productivity of the exporting firms, as compared to non-exporters. Given the nature of our sample, in which more than 80% of the firms export, we have to somehow take this evidence for granted. We have nonetheless considered the intensity of the export activity, measured in terms of the export share of revenues, finding traces of a positive relationship with productivity and a negative relationship with misallocation.[19]

[19] The variability in the data does not allow for a proper analysis of this issue. Given the low variability in the data, the relationship emerges only when controls are introduced for the export share in t-1 and t+1, or the nonlinearity in the relationship is taken into account.

5.2.5 Cronyism

Cronyism, expressed in terms of dependency on the public sector and interconnectedness with governmental institutions, is presented by Pellegrino and Zingales (2014) as the ultimate cause of the 'Italian disease'. Moreover, Giordano et al. (2015a) show that the efficiency of the public sector strongly affect private firms' labour productivity. With our data, we are able to measure the share of sales to the public sector in total firm's sales for the period 2009-2011 ("publ_adm_sales", **Tables 5.24A and 5.24B**). This enables us to run regressions restricted to this period.

The econometric results show that:

- A higher share of sales to the public sector is associated with a higher TFPR;
- A higher share of sales to the public sector is associated with less misallocation.

A possible explanation of these counterintuitive results, which are particularly true for large firms and for high-tech firms, is that working in the public sector gives higher returns and lower risk.

5.2.6 Innovation

Innovation is a fairly reasonable marker of both productivity and misallocation. The relationship can in principle go both ways. On the one hand, innovation can be thought of to foster productivity; on the other hand, more productive firms (e.g. Melitz, 2003) and/or firms with higher revenues (e.g. Bustos, 2011) can display a higher propensity to innovate. If the innovation choice is made in a dynamical contest, a positive relationship with misallocation can be expected (Asker, Collard-Wexler and De Loecker, 2014). To investigate the role of innovation, we consider the share of intangible assets (associated, essentially, with R&D, marketing and branding) on firms' total assets ("intangibles_share", **Tables 5.25A to 5.26B**). We find that:

- A higher share of intangible assets is associated with higher firm TFPR, both contemporaneously and in the immediate future; while this holds independently of geographical area and technological intensity, it does not hold for small firms;
- Misallocation is more pronounced within samples of firms with a higher share of intangible assets; this seems to be particularly true for big firms and for firms operating in low-tech industries.

While our database does not allow us to address innovation using alternative and more focused measures, this evidence is in line with literature results on the productivity effects of intangible assets, such as Battisti, Belloc and Del Gatto (2015), who find the latter in a positive relationship with both TFP and technology adoption, and seems to point to a key role of firms' innovation choices as markers of misallocation.

5.2.7 Cross-cutting results

We complete our investigation of the firm markers associated with relative productivity and misallocation by running regressions (4.1) and (4.2) on different subsets of our independent variables entered simultaneously (**Tables 5.27A and 5.27B**).

Three markers seem to be systematically associated with firm relative productivity: the intensity in the use of the wage supplementation scheme (CIG), the share of high-skill employees in white collars, and the share of intangibles in total assets. While higher reliance on the CIG is always associated with lower relative productivity, a higher share of high-skill employees in white collars and a higher share of intangibles in total assets are associated with higher relative productivity in the regressions not controlling for credit constraints. Two of these markers are also systematically associated with misallocation within the corresponding categories of firms. Specifically, while the share of intangibles in total assets is never significantly correlated with misallocation, higher reliance on the CIG and higher shares of high-skill employees in white collars are both associated with more misallocation in the regressions not controlling for credit constraints. We can, therefore, conclude that the key markers of low relative productivity for Italian firms are a strong reliance on the wage supplementation scheme, a small share of high-skill employees among white collars, and a limited share of intangibles in total assets. The key markers of high misallocation for Italian firms are again a strong reliance on the wage supplementation scheme but also a high share of high-skill employees among white collars. The share of intangibles in total assets has, instead, no bearing on misallocation.

These findings can be interpreted as two sides of the same coin. The share of high-skill employees among white collars drives firm technological and organisational innovation, which in turn increases firm productivity relative to competitors. In an efficient process of creative destruction labour should seamlessly flow from firms with falling relative productivity to firms with rising relative productivity thereby enhancing aggregate productivity. This process of efficient reallocation is impaired if firms with falling relative productivity can use the wage supplementation scheme to keep them afloat when faced not only with contingent problems (as in the original spirit of the CIG) but also with structural problems (as in the consolidated practice of the CIG).

6. CONCLUSIONS AND POLICY IMPLICATIONS

We have provided a detailed analysis of the patterns of misallocation in Italy since the early 1990s. In particular, we have shown that the extent of misallocation has substantially increased since 1995, and that this increase can account for a large fraction of the Italian productivity slowdown since then. Aggregate shocks like the acceleration of globalisation and the ICT revolution occurred in that period. This changed the optimality of the production structure and of the allocation of resources. Probably, the Italian economy has been unable to sufficiently adapt to such shocks and reallocate its resources accordingly.

We have gathered evidence on the evolution of firm level misallocation both between and within various categories of firms, in particular those based on geographic areas, industries, and firm size classes. We have done so both for firms in manufacturing and for firms in non-manufacturing. Overall, looking at the distribution of firm productivity, we have uncovered a thickening of the left tail as the share of firms with low productivity has increased over the period. This has implied not only a decrease in average firm productivity, but also an increase in its dispersion. We have interpreted this increased dispersion as an increase in the misallocation of production factors.

We have shown that the increase in misallocation has come mainly from higher dispersion of productivities *within* different size/area groups rather than *between* them. Crucially, we have highlighted that rising misallocation has hit firm categories that traditionally are the spearhead of the Italian economy such as firms in the Northwest and big firms. We have also produced evidence that, while the 2008 crisis seems to have triggered, at least until 2013, a 'cleansing effect' of the least productive firms in manufacturing sector as a whole, in non-manufacturing sector one observes the survival of firms with even lower productivities that they used to have. Finally, we have proposed a novel methodology to assess the firm characteristics that are more strongly associated with average productivity and misallocation. In particular, we have investigated the role of corporate ownership/control and governance, finance, workforce composition, internationalisation, cronyism and innovation. Together with the other findings already highlighted, the analysis of these 'markers' provides the ground for a policy-oriented discussion, to which we now turn.

The main policy implications we want to set out are the following:

- **"Within-misallocation" matters more than "between-misallocation"**: This implies that in order to raise productivity, Italy should not focus on policies aimed at switching resources between sectors, geographical areas and firm size classes; but rather on policies aimed at allocating capital and labour to the best performing firms within these categories. This means that Italy should focus less on moving capital and labour from, e.g., textile to electronics, than on facilitating the mobility of workers and capital towards the most productive firms within the textile sector. Similarly, Italy would benefit more from moving the factors of production to the most productive firms in the South rather than moving those same factors to the Northern part of the country. This represents both an opportunity and a challenge. An opportunity, because moving factors within sector or area is less costly than across them; but also a challenge, because it is harder to determine what prevents high-productivity firms from expanding and low-productivity firms from shrinking within the same sector or a geographical area. More generally, setting the framework conditions for the proper functioning of market-driven reallocations could be more effective than pursuing traditional industrial policies aimed at 'picking the winning sectors'.

- **There are a 'North issue' ('Questione Settentrionale') as well as a "Large firms' issue"**: The rise of misallocation and the subsequent decline of productivity in the traditional 'engines' of the Italian economy should be a source of major concern. The regional dimension indicates that misallocation has increased particularly in the Northwest, traditionally the core of the Italian productive system. And the size dimension suggests that the increase has been particularly strong among large firms. The two events are not unrelated, as the Northwest is where larger firms tend to be headquartered. Although we do not have an answer to what causes these trends, they clearly indicate that a lot of attention should be devoted to policies targeted at improving the efficiency of the allocative process within the category of large firms, such as labour market regulation and the system of public subsidies.

- **A larger share of firms survives despite low productivity levels**: The increase in misallocation is to a large extent due to the thickening of the left tail of the firm productivity distribution. This fact points to the inefficiency of the institutions and regulations that govern the process of firm restructuring. We see as particularly relevant: a) the regulation of firm bankruptcy procedures and the efficiency of the judicial system in reallocating the assets of distressed firms. These aspects have been subject to various reforms in the recent past, whose results should hopefully become apparent over the next years. Developments in this area should be closely monitored; b) the process of credit allocation by banks that might lead to 'zombie lending', whereby credit is extended to low productivity firms to keep them from going bankrupt; c) the diffusion of financial operators specialised in firm restructuring and turnaround, such a private equity firms. The market of private equity funds is still underdeveloped in Italy, possibly due to their regulation and to the constraints on firm restructuring.

- **The system of unemployment benefits needs to be reformed with more focus on the 'worker' than on the 'job'**: Our results clearly show that the Italian Wage Supplementation Scheme ('Cassa Integrazione Guadagni') is disproportionately used by low productivity firms and is associated with higher misallocation. The problem with this type of scheme is that it protects the job match between workers and firms even if it is no longer productive. This hinders the process of creative destruction that would lead to workers' reallocation towards more productive firms. This is especially the case whenever the scheme, rather than being used as a temporary safeguard as in its original spirit, is used on a more prolonged basis. In this respect, a universal unemployment benefit where unemployed workers receive a subsidy, without preserving the job, could lead to a lower misallocation of workers and higher productivity. This is the direction in which recent reforms included in the "Jobs Act" seem to be going.

- **Investments in intangible assets are important**: Our results show that firms with higher investment share in intangible fixed assets (such as R&D, branding, and marketing) have higher productivity. Public support to this type of investments can be an important incentive for firms to engage with such activities, which favour productivity growth. At the same time, the fact that firms with higher investment in intangible assets display a higher dispersion of productivity (in addition to higher average productivity) indicates that they might be particularly subject to reallocation constraints. For example, access to bank credit might be problematic for highly innovative, risky firms. Again, developing the non-banking component of the financial markets, such as venture capital and private equity, could help both increase the mean and decrease the dispersion of firm productivity and thus the extent of misallocation.

- **Graduates play a crucial role among white collars**: Our results show that firms with a higher number of graduates among their white-collars are more productive. Italy has a lower share of graduates than other European countries. Pro-active policies that encourage more tertiary education are warranted. At the same time, we have also found that productivity dispersion tends to be higher among firms with a higher share of highly educated people. This could be due to different reasons. One could be the same as the one already discussed in the case of intangible assets. Another reason could be that skill mismatches might be more likely among highly educated workers, because firms find it hard to fill positions requiring a high level of specific skills with the appropriate candidates. This calls into question both the 'production' of human capital through the school system and its 'deployment' to firms through formal placement networks.

7. REFERENCES

Asker, J., Collard-Wexler, A., De Loecker, J. (2014), "Dynamic Inputs and Resource (Mis)Allocation", *Journal of Political Economy*, 122(5): 1013-1063.

Bandiera, O., Guiso, L., Prat, A., Sadun, R. (2014), "Matching firms, managers and incentives", *Journal of Labor Economics*, 33(3): 623-681.

Barba-Navaretti, G., Bugamelli, M., Schivardi, F., Altomonte, C., Horgos, D., Maggioni, D. (2010), "The global operations of European firms", Second EFIGE Policy Report.

Bartelsman, E., Haltiwanger, J., Scarpetta, S. (2013), "Cross-Country Differences in Productivity: The Role of Allocation and Selection", *American Economic Review*, 103(1): 305-334.

Bartelsman, E., Scarpetta S., Schivardi F. (2005), "Comparative Analysis of Firm Demographics and Survival: Micro-level Evidence for the OECD countries", *Industrial and Corporate Change*, 14(3): 365-391.

Battisti, M., Belloc, F., Del Gatto, M. (2015), Unbundling Technology Adoption and TFP at the Firm Level: Do Intangibles Matter?, *Journal of Economics and Management Strategy*, 24(2): 386–410.

Bellone, F., Mallen-Pisano, J. (2013): "Is misallocation higher in France than in the United States*?*", GREDEG Working Paper, N. 38.

Bento, P., Restuccia, D. (2015), "Misallocation, Establishment Size, and Productivity", In 2015 Meeting Papers, No. 1391, Society for Economic Dynamics.

Bloom, N., Genakos, C., Sadun, R., Van Reenen, J. (2012), "Management practices across firms and countries", *The Academy of Management Perspectives*, 26(1): 12-33.

Bloom, N., Sadun, R., Van Reenen, J. (2012) "Americans Do IT Better: US Multinationals and the Productivity Miracle", *The American Economic Review*, 102(1): 167-201.

Bloom, N., Lemos, R., Sadun, R., Scur, D., Van Reenen, J. (2014), "JEEA-FBBVA Lecture 2013: The New Empirical Economics of Management", *Journal of the European Economic Association*, 12(4): 835-876.

Bollard, A., Klenow, P., Sharma, G. (2013), "India's Mysterious Manufacturing Miracle ", *Review of Economic Dynamics*, 16(1): 59-85.

Brandt, L., Tombe, T., Zhu, X. (2013), "Factor Market Distortions Across Time, Space, and Sectors in China ", *Review of Economic Dynamics*, 16(1): 39-58.

Bugamelli, M., Schivardi, F., Zizza, R. (2010), "The euro and firm restructuring", in *Europe and the euro*, A. Alesina and F. Giavazzi (editors), University of Chicago Press.

Bugamelli, M., Cannari, L., Lotti, F., Magri, S. (2012), "The innovation gap of Italy's production system: roots and possible solutions", Bank of Italy Occasional Paper, (121).

Bustos, P. (2011). "Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms", *American Economic Review*, 101: 304-340.

Caballero, R.J., Hoshi, T., Kashyap, A.K. 2008, "Zombie Lending and Depressed Restructuring in Japan", *American Economic Review*, 98(5): 1943-1977.

Caggese, A., Cuñat, V. (2013), "Financing constraints, firm dynamics, export decisions, and aggregate productivity", *Review of Economic Dynamics*, 16(1), 177-193.

Calligaris, S. (2015), "Misallocation and Total Factor Productivity in Italy: Evidence from Firm-Level Data", *Labour*, 29(4): 367-393.

Caselli, F. (2005). "Accounting for Cross-Country Income Differences", in *Handbook of Economic Growth*, P. Aghion and S.N. Durlauf (eds), North-Hollande.

Caselli, F., Gennaioli, N. (2013), "Dynastic management", *Economic Inquiry*, 51(1): 971-996.

Chen, K., Irarrazabal A. (2014): "The role of allocative efficiency in a decade of recovery", *Review of Economic Dynamics*, 18: 523-550.

Crespo, A., Segura-Cayela, R. (2014), "Understanding competitiveness", EUI Working Papers, 2.

Daveri, F., Parisi, M. L. (2015) "Experience, Innovation, and Productivity Empirical Evidence from Italy's Slowdown", *ILR Review*, 0019793915586971.

De Nardis, S. (2014), "Efficienza e specializzazione", Nomisma 9 October 2014.

Dias, D., Marques, C. R., Richmond, C. (2014), "Misallocation and productivity in the lead up to the Eurozone crisis", Banco de Portugal Working Paper, No. w201411.

European Commission (2015), "Country Report Italy 2015", SWD(2015) 31 final/2, http://ec.europa.eu/europe2020/pdf/csr2015/cr2015_italy_en.pdf

European Commission (2016), "Country Report Italy 2016", SWD(2016) 81 final, http://ec.europa.eu/europe2020/pdf/csr2016/cr2016_italy_en.pdf

European Commission (2015), "Recommendation for a Council recommendation on the 2015 National Reform Programme of Italy", COM(2015) 262 final, http://ec.europa.eu/europe2020/pdf/csr2015/csr2015_italy_en.pdf

European Commission (2014), "Macroeconomic Imbalances, Italy 2014", European Economy, Occasional Paper 182, http://ec.europa.eu/economy_finance/publications/occasional_paper/2014/pdf/ocp182_en.pdf

Faini, R., Sapir, A. (2005) "Un modello obsoleto? Crescita e specializzazione dell'economia italiana", *Oltre il declino,* Bologna: il Mulino, 19-77.

Forum Idee per la Crescita (2013), Fuori dalla crisi, Corriere della Sera.

Foster, L., Haltiwanger, J., Syverson, C. (2008), "Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?", *American Economic Review*, 98(1): 394-425.

Garcıa-Santana, M., Moral-Benito, E., Pijoan-Mas, J., Ramos, R. (2016), "Growing like Spain: 1995-2000", Banco de Espana Working Paper No. 1609.

Giordano, R., Lanaus, S., Tommasino, P., and Topalova, P. (2015a). "Does public sector inefficiency constrain firm productivity: evidence from Italian provinces", IMF Working Paper 15/168, Washington, D.C.

Giordano, R., Lanaus, S., Tommasino, P., and Topalova, P. (2015b). "Is the public sector holding back Italy's productivity?", VoxEu 04 August 2015.

Giordano, R., Tommasino, P. (2011). "Public sector efficiency and political culture," Economic Working Paper 786, Bank of Italy.

Gopinath, G., Kalemli-Ozcan, S., Karabarbounis, L., Villegas-Sanchez, C. (2015), "Capital Allocation and Productivity in South Europe", NBER Working Paper No 21453.

Guner, N., Ventura, G., Xu, Y. (2008), "Macroeconomic implications of size-dependent policies", *Review of Economic Dynamics*, 11(4):721-744.

Hassan, F., Ottaviano, G.I.P. (2013). "Productivity in Italy: the Great Unlearning", VoxEu 14 December 2013.

Hopenhayn, H. (2014), "Firms, misallocation, and aggregate productivity: A review", *Annual Review of. Economics*, 6(1): 735-770.

Hsieh, C., Klenow, P. (2009), "Misallocation and manufacturing TFP in China and India", *Quarterly Journal of Economics*, 124(4): 1403-1448.

Hsieh, C., Klenow, P. (2009), "Misallocation and manufacturing TFP in China and India Correction Appendix", Stanford University, unpublished.

Hsieh, C., Hurst, E., Jones, C. I., Klenow, P. (2013), "The allocation of talent and us economic growth", NBER Working Paper No. w18693.

Lippi, F., Schivardi, F. (2014), "Corporate Control and Executive Selection", *Quantitative Economics*, 5(2), 417-456.

Lusinyan, L., & Muir, D. (2013). Assessing the Macroeconomic Impact of Structural Reforms: The Case of Italy. *IMF, Working Paper No. 13/22* .

Macis, M., Schivardi, F. (2015), "Exports and wages: Rent sharing, workforce composition or returns to skills?", forthcoming.

Manasse, P., Manfredi T. (2014), "Wages, productivity and employment in Italy: Tales from a distorted labour market", VoxEu 19 April 2014.

Melitz, M. J. (2003), "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity", *Econometrica*, 71: 1695–1725.

Michelacci, C., Schivardi, F. (2013), "Does Idiosyncratic Business Risk Matter for Growth?", *Journal of the European Economic Association*, 11(2): 343-368.

Midrigan, V., Xu, Y. (2014), "Finance and misallocation: Evidence from Plant-Level Data", *American Economic Review*, 104(2): 422-458.

Montanari M., Pinelli, D., Torre, R. (2015), "From tertiary education to work in Italy: a difficult transition", ECFIN Country Focus, 12(5).

OECD (2013), OECD skills outlook 2013: First results from the survey of adult skills, OECD Publishing.

OECD (2015), The Future of Productivity, OECD Publishing.

Olley, G.S., Pakes, A. (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry", *Econometrica*, 64(6): 1263-1297.

OECD (2012), Reviews of Regulatory Reform – Italy 2009: Better Regulation to Strengthen Market Dynamics, OECD Publishing.

Pellegrino, B., Zingales, L. (2014) "Diagnosing the Italian disease", Unpublished manuscript.

Pozzi, A., Schivardi, F. (2015). "Demand or Productivity: What Determines Firm Growth?", Bocconi University, working paper.

Restuccia, D., Rogerson, R. (2013), "Misallocation and productivity", *Review of Economic Dynamics*, 16(1): 1-10.

Ziebarth, N. (2013), "Are China and India Backwards? Evidence from the 19th Century U.S. Census of Manufactures", *Review of Economic Dynamics*, 16(1): 86-99.

8. ANNEX A [20]

a. Definition of misallocation

From standard profit maximisation, we know that firms choose the amount of capital K and labour L by equalising the marginal revenue product (MRP) of each input to its marginal cost. While this process yields marginal revenue product of capital (MRPK) and marginal revenue product of labour (MRPL) equalisation across firms, when all firms face the same input cost, the presence of market distortions can drive 'wedges' between MRPK and MRPL across firms. In this case, we say that capital and labour are 'misallocated' across firms.

To see this, let us start with a standard Cobb-Douglas technology with sector-specific production coefficients

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \tag{A.1}$$

and follow Hsieh and Klenow (2009) (henceforth, HK) in denoting distortions that increase the marginal products of capital and labour by the same proportion ('output distortions') by τ_{si}^{Y} and distortions that raise the marginal product of capital relative to labour ('capital distortions') by τ_{si}^{K}. From the FOC of firm i, active in sector s, we have that

$$MRPK_{si} = P_{si} \frac{\partial \tilde{Y}_{si}}{\partial K_{si}} = \alpha_s P_{si} \frac{Y_{si}}{K_{si}} = \tilde{W}^{K} \tag{A.2}$$

and

$$MRPL_{si} = P_{si} \frac{\partial \tilde{Y}_{si}}{\partial K_{si}} = (1-\alpha_s) P_{si} \frac{Y_{si}}{L_{si}} = W^{L} \tag{A.3}$$

with $\tilde{Y}_{si} = (1-\tau_{si}^{Y})Y_{si}$ and $\tilde{W}^{K} = (1+\tau_{si}^{K})R$, where R and W^{L} refer to the rental and wage rates of capital and labour respectively.

If $\tau_{si}^{Y} = \tau_{si}^{K} = 0 \quad \forall i \in s$, firms face the same inputs costs and the MRP of the two inputs is equalised across them. In this case, capital and labour are efficiently allocated. When this happens, the within-sector distributions of MRPK and MRPL exhibit zero dispersion around the mean, as the average MRPK in sector s ($\overline{MRPK}_{s}$) equals $MRPK_{si} \quad \forall i \in s$ (and analogously for MRPL). No misallocation emerges in this case.

Note that the MRP equalisation condition holds independently of the way in which firms set P_{si}, that is, independently of market structure, the only condition being the absence of distortions in capital and labour markets.

b. A measure of misallocation

[20] See Hsieh and Klenow (2009) for further details.

Since the higher the dispersion the larger are the distortions, it would be relatively easy to investigate the presence, and the magnitude, of resource misallocation by looking at the within-industry dispersion of MRPK and MRPL. However, if one is interested in the aggregate effects of those distortions, more structure is needed.

To this aim, a useful strategy is suggested by HK, whose approach allow us to study the effect of misallocation on aggregate TFP. The intuition is quite simple and rests on the proportionality between firm TFP and MRP of inputs. In particular, using (A.1), it is possible to write firm i 's TFP as

$$TFP_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}. \tag{A.4}$$

As statistical information on either physical output Y_{si} or firm price P_{si} is hardly available (see. e.g., Foster et al., 2008), TFP is usually calculated/estimated on the basis of firms' revenues. In particular, by (A.4) we have

$$TFPR_{si} = P_{si} A_{si} = \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}. \tag{A.5}$$

While using $TFPR_{si}$ instead of TFP_{is} usually represents a shortcoming, this is not the case for the HK framework. The reason is that, under specific assumptions on market structure, $TFPR_{si}$ can be shown to be unaffected by firm-specific characteristics other than the distortions τ_{si}^{Y} and τ_{si}^{K} . In particular, if each sector s is monopolistically competitive, firms set prices according to the markup rule

$$P_{si} = \frac{\sigma}{\sigma-1} \beta_s (W^K)^{\alpha_s} (W^L)^{1-\alpha_s} \frac{(1+\tau_{si}^{K})^{\alpha_s}}{(1-\tau_{si}^{Y})} \frac{1}{A_{si}}. \tag{A.6}$$

where $\frac{\sigma}{\sigma-1}$ is the markup and $\beta_s = \alpha_s^{-\alpha_s} (1-\alpha_s)^{\alpha_s - 1}$ is the bundle of parameters associated with the Cobb-Douglas production function (A.1). Note that, apart from A_{si} , the only firm-specific terms in (A.6) are the distortions. When substituted into (A.5), the pricing rule in (A.6) yields

$$TFPR_{si} = \frac{\sigma}{\sigma-1} \beta_s (W^K)^{\alpha_s} (W^L)^{1-\alpha_s} \frac{(1+\tau_{si}^{K})^{\alpha_s}}{(1-\tau_{si}^{Y})}. \tag{A.7}$$

According to (A.7), also the cross-firm variability of $TFPR_{si}$ is not influenced by firm-specific characteristics other than τ_{si}^{K} and τ_{si}^{Y} (as the term A_{si} cancels out). Moreover, HK show that $TFPR_{si}$ is proportional to the weighted geometric average of $MRPK_{si}$ and $MRPL_{si}$ with weights given by the Cobb-Douglas parameters:

$$TFPR_{si} \propto (MRPK_{si})^{\alpha_s} (MRPL_{si})^{1-\alpha_s} \propto \frac{(1+\tau_{si}^{K})^{\alpha_s}}{(1-\tau_{si}^{Y})} \tag{A.8}$$

As a result, *the extent of misallocation can be studied by looking at the dispersion of the* $TFPR_{si}$ *distribution*, instead of the considering the distributions of $MRPK_{si}$ and $MRPL_{si}$.

c. Misallocation and aggregate TFP

The usefulness of this approach stems from the fact that it is relatively easy to sum up across firms and obtain a measure of the aggregate TFP loss due to misallocation. To see this, assume that the economy produces a single homogeneous final good Y by combining the output Y_s of the S manufacturing industries in a Cobb-Douglas fashion:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} = \prod_{s=1}^{S} \left(A_s K_s^{\alpha_s} L_s^{1-\alpha_s} \right)^{\theta_s} \qquad \text{with} \quad \sum \theta_s = 1 \tag{A.9}$$

where $K_s = \sum_i K_{si}$ and $L_s = \sum_i L_{si}$ are the total stocks of capital and labour used in sector s, the industry output Y_s is a CES aggregate of M_s horizontally differentiated products $Y_s = (\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma}{\sigma-1}}$ and the sectoral TFP is defined as

$$\text{TFP}_s = A_s = \left[\sum_{i=1}^{M_s} \left(A_{si} \frac{\overline{TFPR_s}}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{A.10}$$

with $\overline{TFPR_s}$ referring to the weighted geometric average of average MRPK and average MRPL in the sector (i.e. $\overline{TFPR_s} \propto (\overline{MRPK_s})^{\alpha_s} \propto (\overline{MRPL_s})^{1-\alpha_s}$).

According to (A.10), without misallocation, aggregate TFP would be a CES aggregation of individual TFP. Otherwise, a TFP loss will emerge in the aggregate.

The relationship between TFP_s and the dispersion of TFP_{si} can be made more explicit by assuming that the distributions of TFP and TFPR are jointly lognormally distributed. In this case, HK show that

$$\ln TFP_s = \frac{1}{\sigma-1} \ln\left(\sum_i A_{si}^{\sigma-1} \right) - \frac{\sigma}{2} var(\ln TFPR_{si}) \tag{A.11}$$

where $var(\cdot)$ denotes variance.

9. ANNEX B : TABLES

Table 3.1: **Summary statistics for manufacturing**

Manufacturing	**Value Added ('thousand EUR, 2007 prices)**	**Capital (thousand EUR, 2007 prices)**	**Cost of labour (thousand EUR, 2007 prices)**	**Observations (number)**
Textile and leather	1,265	969	802	249,000
(% of total)	*10.9%*	*8.9%*	*10.9%*	*16.0%*
Paper	1,342	1,410	834	127,000
(% of total)	*5.9%*	*6.6%*	*5.8%*	*8.2%*
Chemicals	2,990	3,138	1,769	138,000
(% of total)	*14.4%*	*16.0%*	*13.4%*	*8.9%*
Minerals	1,790	2,451	1,075	96,000
(% of total)	*6.0%*	*8.7%*	*5.7%*	*6.2%*
Metals	1,426	1,436	909	319,000
(% of total)	*15.8%*	*16.9%*	*15.9%*	*20.5%*
Machinery	2,092	1,276	1,398	390,000
(% of total)	*28.3%*	*18.3%*	*29.8%*	*25.1%*
Vehicles	4,405	4,884	3,177	51,800
(% of total)	*7.9%*	*9.3%*	*9.0%*	*3.3%*
Food and tobacco	1,994	2,693	1,102	137,000
(% of total)	*9.5%*	*13.6%*	*8.3%*	*8.8%*
Wood	807	1,109	520	46,800
(% of total)	*1.3%*	*1.9%*	*1.3%*	*3.0%*

Note: Main variables expressed both in absolute values and in percentages of the total. Absolute values are expressed in thousands of 2007 Euros.

Table 3.2: **Summary statistics for non-manufacturing**

Non-manufacturing	Value Added ('thousand EUR, 2007 prices)	Capital (thousand EUR, 2007 prices)	Cost of labour (thousand EUR, 2007 prices)	Observations (number)
Electricity, gas	19,400	61,000	5,618	16,700
(% of total)	*10.0%*	*21.8%*	*4.7%*	*0.5%*
Constructions	601	363	405	757,000
(% of total)	*14.0%*	*5.9%*	*15.4%*	*20.6%*
Wholesale and retail trade	588	515	377	1,470,000
(% of total)	*26.6%*	*16.2%*	*27.9%*	*40.0%*
Hotels and restaurants	522	1,033	373	305,000
(% of total)	*4.9%*	*6.7%*	*5.7%*	*8.3%*
Transport, storage and communication	2,546	6,191	1,454	312,000
(% of total)	*24.4%*	*41.3%*	*22.8%*	*8.5%*
Real estate activities	776	1,983	262	81,200
(% of total)	*1.9%*	*3.4%*	*1.1%*	*2.2%*
Professional, scientific and technical activities	824	265	604	256,000
(% of total)	*6.5%*	*1.5%*	*7.8%*	*7.0%*
Support service activities	815	306	617	468,000
(% of total)	*11.7%*	*3.1%*	*14.5%*	*12.7%*
Health and social work	608	882	432	2,743
(% of total)	*0.1%*	*0.1%*	*0.1%*	*0.1%*
Other services	615	992	413	4,943
(% of total)	*0.1%*	*0.1%*	*0.1%*	*0.1%*

Note: Main variables expressed both in absolute values and in percentages of the total. Absolute values are expressed in thousands of 2007 Euros.

Table 3.3: **Summary statistics for manufacturing, by geographic area and by size**

Manufacturing			Value Added ('thousand EUR, 2007 prices)	Capital (thousand EUR, 2007 prices)	Cost of labour (thousand EUR, 2007 prices)	Observations (number)
By geographic area	Northwest		2,438	2,175	1,559	592,000
		(% of total)	*50.1%*	*47.4%*	*50.5%*	*38.1%*
	Northeast		1,921	1,689	1,196	416,000
		(% of total)	*27.7%*	*25.8%*	*27.2%*	*26.8%*
	Centre		1,403	1,222	894	294,000
		(% of total)	*14.3%*	*13.2%*	*14.4%*	*18.9%*
	South and Islands		896	1,462	574	253,000
		(% of total)	*7.9%*	*13.6%*	*7.9%*	*16.3%*
By size	Micro		267	263	193	902,000
		(% of total)	*8.4%*	*8.7%*	*9.5%*	*58.0%*
	Small		1,224	1,117	816	471,000
		(% of total)	*20.0%*	*19.3%*	*21.0%*	*30.3%*
	Medium		4,950	4,613	3,105	148,000
		(% of total)	*25.5%*	*25.2%*	*25.2%*	*9.5%*
	Big		39,400	37,700	24,000	33,700
		(% of total)	*46.1%*	*46.8%*	*44.3%*	*2.2%*

Note: Main variables expressed both in absolute values and in percentages of the total. Absolute values are expressed in thousands of 2007 Euros. Manufacturing firms dived into four geographic areas and four firms' sizes.

Table 3.4: **Summary statistics for non-manufacturing, by geographic area and by size**

Non-manufacturing			Value Added ('thousand EUR, 2007 prices)	Capital (thousand EUR, 2007 prices)	Cost of labour (thousand EUR, 2007 prices)	Observations (number)
By geographic area	Northwest		1,277	1,433	736	1,110,000
		(% of total)	43.3%	33.9%	40.9%	30.2%
	Northeast		751	805	503	742,000
		(% of total)	17.1%	12.8%	18.7%	20.2%
	Centre		978	2,143	593	910,000
		(% of total)	27.3%	41.7%	27.1%	24.7%
	South and Islands		423	585	284	915,000
		(% of total)	11.9%	11.5%	13.0%	24.9%
By size	Micro		185	180	128	2,750,000
		(% of total)	15.7%	10.6%	17.7%	74.9%
	Small		884	780	600	727,000
		(% of total)	19.7%	12.1%	21.9%	19.8%
	Medium		3,418	3,556	2,296	162,000
		(% of total)	17.0%	12.3%	18.7%	4.4%
	Big		47,900	93,800	25,600	32,400
		(% of total)	47.6%	65.0%	41.7%	0.9%

Note: Main variables expressed both in absolute values and in percentages of the total. Absolute values are expressed in thousands of 2007 Euros. Non-manufacturing firms dived into four geographic areas and four firms' sizes.

Table 3.5: **Percentages of manufacturing firms in each sector, by geographic area and size**

Manufacturing	Northwest	Northeast	Centre	South & Islands	Micro	Small	Medium	Big	Total
Textile and leather									
(% of total)	4.6%	3.4%	5.1%	2.9%	9.2%	5.0%	1.5%	0.2%	16.0%
(% of the sector)	28.6%	21.0%	32.2%	18.2%	57.4%	31.5%	9.7%	1.4%	100%
Paper									
(% of total)	3.4%	1.8%	2.0%	1.1%	5.7%	1.9%	0.5%	0.1%	8.2%
(% of the sector)	41.1%	21.5%	24.6%	12.8%	69.7%	22.9%	6.2%	1.3%	100%
Chemicals									
(% of total)	4.3%	2.1%	1.3%	1.2%	4.2%	3.1%	1.2%	0.4%	8.9%
(% of the sector)	48.4%	23.9%	14.8%	12.9%	47.6%	34.6%	13.8%	4.1%	100%
Minerals									
(% of total)	1.3%	1.7%	1.4%	1.7%	3.5%	2.0%	0.5%	0.1%	6.2%
(% of the sector)	21.7%	27.7%	22.9%	27.8%	57.5%	32.0%	8.7%	1.8%	100%
Metals									
(% of total)	9.0%	5.7%	2.9%	3.0%	12.8%	5.9%	1.5%	0.3%	20.5%
(% of the sector)	43.6%	27.7%	14.0%	14.7%	62.4%	28.9%	7.1%	1.5%	100%
Machinery									
(% of total)	11.4%	8.0%	3.3%	2.3%	14.1%	7.9%	2.5%	0.5%	25.1%
(% of the sector)	45.6%	31.9%	13.3%	9.2%	56.4%	31.5%	9.9%	2.2%	100%
Vehicles									
(% of total)	1.3%	0.8%	0.6%	0.7%	1.8%	1.0%	0.4%	0.1%	3.3%
(% of the sector)	38.2%	22.8%	18.4%	20.5%	54.6%	28.9%	12.3%	4.2%	100%
Food and tobacco									
(% of total)	2.1%	2.3%	1.6%	2.8%	4.6%	2.7%	1.2%	0.3%	8.8%
(% of the sector)	24.2%	26.4%	17.8%	31.6%	52.0%	30.5%	13.6%	3.9%	100%
Wood									
(% of total)	0.7%	1.0%	0.6%	0.7%	2.0%	0.8%	0.2%	0.0%	3.0%
(% of the sector)	24.2%	33.3%	20.4%	22.2%	65.6%	28.2%	5.7%	0.5%	100%
Total	**38.1%**	**26.7%**	**18.9%**	**16.3%**	**58.0%**	**30.3%**	**9.5%**	**2.2%**	**100%**

Note: Percentages of firms in each group. Manufacturing firms dived into four geographic areas and four firms' sizes. For each sector, the first line reports the group percentage with respect to the whole manufacturing, while the second one the percentage with respect to the specific sector.

Table 3.6: **Percentages of non-manufacturing firms in each sector, by geographic area and size**

Manufacturing	Northwest	Northeast	Centre	South & Islands	Micro	Small	Medium	Big	Total
Electricity, gas									
(% of total)	0.2%	0.1%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%	0.5%
(% of the sector)	41.7%	21.3%	14.8%	22.2%	39.8%	29.7%	18.2%	12.2%	100%
Constructions									
(% of total)	5.2%	3.5%	5.2%	6.7%	16.0%	3.9%	0.6%	0.1%	20.6%
(% of the sector)	25.3%	17.2%	25.2%	32.3%	77.9%	19.1%	2.7%	0.4%	100%
Wholesale and retail trade									
(% of total)	12.1%	8.4%	9.6%	9.9%	25.8%	10.8%	2.8%	0.5%	40.0%
(% of the sector)	30.2%	21.0%	24.1%	24.7%	64.6%	27.1%	7.0%	1.3%	100%
Hotels and restaurants									
(% of total)	2.0%	1.7%	2.6%	2.0%	7.5%	0.7%	0.1%	0.0%	8.3%
(% of the sector)	24.5%	20.0%	31.3%	24.2%	90.8%	8.2%	0.9%	0.2%	100%
Transport, storage and communication									
(% of total)	2.5%	1.8%	2.0%	2.1%	6.1%	1.9%	0.4%	0.1%	8.5%
(% of the sector)	29.9%	21.1%	23.8%	25.2%	71.9%	21.9%	5.0%	1.1%	100%
Real estate activities									
(% of total)	0.7%	0.5%	0.7%	0.4%	1.9%	0.2%	0.0%	0.0%	2.2%
(% of the sector)	30.5%	21.1%	29.6%	18.8%	87.7%	9.6%	2.1%	0.6%	100%
Professional, scientific and technical activities									
(% of total)	2.5%	1.6%	1.6%	1.2%	6.2%	0.6%	0.1%	0.0%	7.0%
(% of the sector)	36.5%	22.7%	23.0%	17.8%	88.9%	8.8%	1.8%	0.4%	100%
Support service activities									
(% of total)	4.8%	2.6%	3.0%	2.4%	10.9%	1.5%	0.3%	0.1%	12.7%
(% of the sector)	37.6%	20.3%	23.2%	18.9%	85.8%	11.5%	2.2%	0.5%	100%
Health and social work									
(% of total)	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%
(% of the sector)	22.9%	29.7%	21.9%	25.6%	84.1%	15.3%	0.6%	0.0%	100%
Other services									
(% of total)	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%
(% of the sector)	20.2%	22.1%	29.7%	28.0%	86.3%	11.8%	1.9%	0.0%	100%
Total	**30.1%**	**20.2%**	**24.8%**	**24.9%**	**74.9%**	**19.8%**	**4.4%**	**0.9%**	**100%**

Note: Percentages of firms in each group. Non-manufacturing firms dived into four geographic areas and four firms' sizes. For each sector, the first line reports the group percentage with respect to the whole non-manufacturing, while the second one the percentage with respect to the specific sector.

Table 3.7: **Value added shares of manufacturing firms in each geographic area, by size**

Manufacturing	Micro	Small	Medium	Big	Total
Northwest	6.4%	17.5%	24.1%	52.0%	100.0%
Northeast	7.9%	21.7%	29.2%	41.2%	100.0%
Center	11.5%	21.7%	22.8%	44.0%	100.0%
South and Islands	18.3%	25.9%	25.2%	30.5%	100.0%

Note: Value added shares of firms in each group. Manufacturing firms dived into four geographic areas and four firms' sizes. For each geographic area, reported the group percentage with respect to the specific size class.

Table 3.8: **Value added shares of manufacturing firms in size class, by geographic area**

Manufacturing	Northwest	Northeast	Centre	South & Islands	Total
Micro	37.6%	26.0%	19.4%	17.0%	100.0%
Small	43.6%	30.5%	15.6%	10.3%	100.0%
Medium	47.2%	32.1%	12.8%	7.8%	100.0%
Big	56.1%	25.0%	13.7%	5.2%	100.0%

Note: Value added shares of firms in each group. Manufacturing firms dived into four geographic areas and four firms' sizes. For each size class, reported the group percentage with respect to each geographic area.

Table 3.9: **Value added shares of non-manufacturing firms in each geographic area, by size**

Non-manufacturing	Micro	Small	Medium	Big	Total
Northwest	11.5%	16.8%	17.0%	54.7%	100.0%
Northeast	19.1%	27.0%	23.0%	30.8%	100.0%
Center	13.8%	14.9%	12.1%	59.2%	100.0%
South and Islands	32.1%	29.6%	19.5%	18.7%	100.0%

Note: Value added shares of firms in each group. Non-manufacturing firms dived into four geographic areas and four firms' sizes. For each geographic area, reported the group percentage with respect to the specific size class.

Table 3.10: **Value added shares of non-manufacturing firms in size class, by geographic area**

Non-manufacturing	Northwest	Northeast	Center	South & Islands	Total
Micro	31.0%	20.7%	24.2%	24.1%	100.0%
Small	36.7%	23.9%	21.2%	18.1%	100.0%
Medium	42.9%	23.4%	19.8%	13.8%	100.0%
Big	49.0%	11.2%	34.5%	4.7%	100.0%

Note: Value added shares of firms in each group. Non-manufacturing firms dived into four geographic areas and four firms' sizes. For each size class, reported the group percentage with respect to each geographic area.

Table 3.11: **Growth rates of TFPR average and TFPR variance (i.e misallocation) - Manufacturing**

1995-1996 vs 2005-2006		2007-2008 vs 2012-2013		1995-1996 vs 2012-2013	
Industry	**Misallocation**	**Industry**	**Misallocation**	**Industry**	**Misallocation**
Paper	212.5%	Minerals	48.4%	Paper	174.7%
Vehicles	54.7%	Wood	38.0%	Wood	89.0%
Chemicals	51.3%	Chemicals	14.1%	Minerals	86.5%
Machinery	38.3%	Textiles and leather	13.7%	Chemicals	79.5%
Metals	28.0%	Machinery	7.5%	Machinery	75.4%
Textiles and leather	23.5%	Vehicles	7.3%	Vehicles	67.2%
Food and tobacco	23.4%	Food and tobacco	6.7%	Metals	62.3%
Wood	17.0%	Metals	5.4%	Textiles and leather	47.4%
Minerals	-0.2%	Paper	-4.3%	Food and tobacco	34.3%
Total	*40.7%*	*Total*	*11.1%*	*Total*	*68.9%*
Industry	**Average TFPR**	**Industry**	**Average TFPR**	**Industry**	**Average TFPR**
Wood	-14.1%	Minerals	-50.0%	Wood	-56.8%
Textiles and leather	-4.4%	Wood	-43.1%	Minerals	-56.4%
Metals	-3.7%	Metals	-24.1%	Metals	-22.7%
Minerals	6.0%	Paper	-21.2%	Food and tobacco	-1.5%
Machinery	6.8%	Vehicles	-14.6%	Machinery	-1.2%
Food and tobacco	10.6%	Machinery	-13.3%	Textiles and leather	10.0%
Chemicals	11.0%	Food and tobacco	-4.2%	Chemicals	13.4%
Vehicles	37.7%	Chemicals	1.3%	Paper	18.9%
Paper	57.3%	Textiles and leather	13.8%	Vehicles	36.0%
Total	*7.1%*	*Total*	*-10.5%*	*Total*	*-1.2%*
Industry	**Weights**	**Industry**	**Weights**	**Industry**	**Weights**
Paper	20.0%	Food and tobacco	27.2%	Food and tobacco	20.1%
Metals	12.9%	Textiles and leather	16.9%	Metals	10.8%
Minerals	10.9%	Chemicals	6.4%	Chemicals	8.2%
Wood	10.6%	Machinery	-0.9%	Paper	7.0%
Chemicals	5.3%	Metals	-5.5%	Machinery	2.1%
Food and tobacco	-1.2%	Paper	-7.8%	Wood	-8.7%
Machinery	-1.3%	Wood	-14.9%	Vehicles	-18.6%
Vehicles	-7.1%	Vehicles	-18.4%	Textiles and leather	-19.3%
Textiles and leather	-26.0%	Minerals	-23.2%	Minerals	-23.2%

Table 3.12: **Growth rates of TFPR average and TFPR variance (i.e. misallocation) – Non-manufacturing**

1995-1996 vs 2005-2006		2007-2008 vs 2012-2013		1995-1996 vs 2012-2013	
Electricity, Gas, Water	346.3%	Electricity, Gas, Water	259.0%	Electricity, Gas, Water	1505.6%
Health & Social work	137.2%	Transport, storage and communication	28.7%	Health & Social work	126.1%
Other	80.6%	Health & Social work	25.5%	Support service activities	72.1%
Support service activities	61.9%	Hotels and restaurants	9.8%	Professional, scientific and technical activities	35.4%
Professional, scientific and technical activities	37.3%	Constructions	9.0%	Wholesale & Retail	32.1%
Wholesale & Retail	23.8%	Professional, scientific and technical activities	5.2%	Other	31.7%
Constructions	20.8%	Support service activities	5.0%	Hotels and restaurants	20.8%
Hotels and restaurants	10.8%	Wholesale & Retail	3.8%	Constructions	18.5%
Real estate	5.5%	Real estate	-11.6%	Transport, storage and communication	9.5%
Transport, storage and communication	-3.5%	Other	-64.9%	Real estate	-11.6%
Total	*32.1%*	*Total*	*49.4%*	*Total*	*95.7%*
Industry	**Average TFPR**	**Industry**	**Average TFPR**	**Industry**	**Average TFPR**
Electricity, Gas, Water	-70.8%	Other	-31.8%	Hotels and restaurants	-21.8%
Hotels and restaurants	-16.7%	Constructions	-10.4%	Real estate	-11.1%
Real estate	-9.0%	Wholesale & Retail	-6.8%	Constructions	-8.2%
Wholesale & Retail	1.4%	Real estate	-3.2%	Wholesale & Retail	-6.2%
Constructions	6.4%	Support service activities	-2.1%	Support service activities	12.6%
Support service activities	13.6%	Professional, scientific and technical activities	-1.5%	Professional, scientific and technical activities	17.8%
Health & Social work	15.0%	Transport, storage and communication	-0.5%	Health & Social work	19.9%
Professional, scientific and technical activities	18.3%	Hotels and restaurants	3.6%	Other	33.6%
Other	60.2%	Health & Social work	13.0%	Transport, storage and communication	52.7%
Transport, storage and communication	63.1%	Electricity, Gas, Water	744.9%	Electricity, Gas, Water	237.4%
Total	*7.3%*	*Total*	*8.8%*	*Total*	*15.8%*
Industry	**Weights**	**Industry**	**Weights**	**Industry**	**Weights**
Real estate	207.4%	Health & Social work	36.1%	Real estate	221.1%
Other	188.2%	Electricity, Gas, Water	25.0%	Other	142.5%
Health & Social work	75.4%	Professional, scientific and technical activities	9.9%	Health & Social work	123.2%
Electricity, Gas, Water	67.8%	Hotels and restaurants	8.8%	Electricity, Gas, Water	111.6%
Professional, scientific and technical activities	17.3%	Wholesale & Retail	4.3%	Professional, scientific and technical activities	29.8%
Transport, storage and communication	15.7%	Real estate	3.6%	Transport, storage and communication	1.4%
Support service activities	-4.2%	Support service activities	-1.3%	Support service activities	-0.3%
Wholesale & Retail	-15.5%	Transport, storage and communication	-7.8%	Wholesale & Retail	-10.5%
Constructions	-18.3%	Other	-15.0%	Hotels and restaurants	-14.7%
Hotels and restaurants	-23.6%	Constructions	-18.0%	Constructions	-33.1%

Table 5.1: **Description of main variables**

Variable	Description
credit_constraint1	desire to increase borrowing =1, 0 otherwise
credit_constraint2	desire to increase borrowing even paying higher rates =1, 0 otherwise
increase_equity	if increase of equity=1, 0 otherwise
leverage	leverage
post99	if year>1999=1, 0 otherwise
relational_banking	personal relations and support from the bank =1, 0 otherwise
CIG_share	hours of redundancy fund / hours worked
term_empl_share	temporary work/ Total employment
foreign_empl_share	average foreign employment/ average total employment
grad_share1	share of graduates among white collars
grad_share2	share of graduates among blue collars
foreign_group	if belongs to a foreign group =1, 0 otherwise
sub_foreign_04	if sub-contractor for a foreign company =1, 0 otherwise, year 2004
sub_foreign_07	if sub-contractor for a foreign company =1, 0 otherwise, year 2007
sub_foreign_10	if sub-contractor for a foreign company =1, 0 otherwise, year 2010
deloc_04	if firm delocalizes part of its activity =1, 0 otherwise, year 2004
deloc_11	if firm delocalizes part of its activity =1, 0 otherwise, year 2011
fdi01	if there are FDI =1, 0 otherwise, year 2001
fdi02	if there are FDI =1, 0 otherwise, year 2002
fdi03	if there are FDI =1, 0 otherwise, year 2003
public_adm_sales	Share of sales made with public administrations
intangibles_share	investments in intangibles/total investments
geographic area	4 geographic areas: Northwest (NW), Northeast (NE), Centre (Centre), South and Islands (South)
size	4 size classes: Micro, Small, Medium, Big

Table 5.2A: **Governance ("ownership type") - Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
Conglomerate	0.04**	-0.02	0.05	0.07*	0.05	-0.08*	-0.05***	0.04	0.05**	0.03
	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)	(0.02)	(0.03)	(0.02)	(0.03)
Financial Institution	-0.01	-0.04	-0.06	0.004	0.09*	-0.15***	-0.04	-0.01	-0.03	0.01
	(0.02)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)
Government	-0.11**	-0.07	-0.02	-0.07	-0.20**	-0.45**	-0.29***	-0.03	-0.18***	-0.07
	(0.04)	(0.06)	(0.08)	(0.1)	(0.09)	(0.18)	(0.06)	(0.05)	(0.05)	(0.06)
Foreign	0.06***	0.01	0.0007	0.12**	0.1	-0.27**	-0.04	0.04	0.03	0.06*
	(0.02)	(0.03)	(0.04)	(0.05)	(0.07)	(0.11)	(0.03)	(0.03)	(0.03)	(0.03)
Constant	-0.09***	-0.14***	0.06	-0.06	-0.22**	-0.05	-0.07*	0.07	-0.10***	-0.21***
	(0.03)	(0.04)	(0.07)	(0.06)	(0.09)	(0.05)	(0.04)	(0.06)	(0.03)	(0.07)
Obs.	18,074	7,198	4,318	3,877	2,681	2,107	8,410	7,509	10,796	7,276
R-squared	0.013	0.014	0.038	0.026	0.030	0.123	0.051	0.019	0.050	0.024
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.2B: **Governance ("ownership type") - Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
Conglomerate	0.11***	0.14***	0.12***	0.05*	0.07	0.16**	0.06***	0.12***	0.06***	0.18***
	(0.02)	(0.04)	(0.04)	(0.03)	(0.05)	(0.06)	(0.02)	(0.03)	(0.02)	(0.04)
Financial Institution	0.12***	0.14**	0.16**	0.06**	0.11*	0.14	0.09***	0.14***	0.12***	0.14***
	(0.03)	(0.05)	(0.08)	(0.03)	(0.07)	(0.09)	(0.03)	(0.05)	(0.04)	(0.04)
Government	0.29***	0.30***	0.06	0.24**	0.23*	0.88***	0.24***	0.20***	0.23***	0.35***
	(0.06)	(0.1)	(0.07)	(0.1)	(0.13)	(0.25)	(0.06)	(0.05)	(0.08)	(0.08)
Foreign	0.12***	0.10***	0.09*	0.134***	0.29**	0.6	0.09**	0.13***	0.11***	0.15***
	(0.03)	(0.03)	(0.06)	(0.05)	(0.14)	(0.37)	(0.04)	(0.03)	(0.03)	(0.04)
Constant	0.0495*	-0.04	0.24***	0.01	0.02	-0.03	0.08**	0.03	0.08***	-0.30***
	(0.03)	(0.04)	(0.07)	(0.05)	(0.08)	(0.05)	(0.04)	(0.05)	(0.03)	(0.08)
Obs.	18,074	7,198	4,318	3,877	2,681	2,107	8,410	7,509	10,796	7,276
R-squared	0.013	0.014	0.038	0.026	0.030	0.123	0.051	0.019	0.050	0.024
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.3A: **Finance ("credit_constraint1"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
credit_constraint1[t-1]	-0.08**	-0.10**	-0.05	-0.07	0.13	-0.01	-0.06	-0.1	-0.11***	-0.03
	(0.03)	(0.05)	(0.07)	(0.07)	(0.09)	(0.1)	(0.04)	(0.07)	(0.04)	(0.06)
Constant	-0.08	-0.02	-0.38***	-0.15	0.33*	-0.29*	-0.07	0.280*	-0.13	-0.02
	(0.08)	(0.1)	(0.13)	(0.22)	(0.19)	(0.17)	(0.11)	(0.17)	(0.09)	(0.17)
Obs.	1,234	475	241	292	226	188	642	401	758	476
R-squared	0.063	0.098	0.155	0.129	0.207	0.250	0.089	0.111	0.119	0.085
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
*, **, *** *indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.3B: **Finance ("credit_constraint1"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
credit_constraint1[t-1]	0.01	0.03	-0.08	0.06	-0.05	-0.05	-0.02	0.21*	0.004	0.03
	(0.05)	(0.04)	(0.09)	(0.1)	(0.06)	(0.07)	(0.04)	(0.12)	(0.04)	(0.1)
Constant	0.06	0.08	0.21*	0.01	-0.11	0.08	0.12**	-0.12	0.08*	-0.11*
	(0.05)	(0.06)	(0.12)	(0.14)	(0.07)	(0.07)	(0.05)	(0.15)	(0.04)	(0.07)
Obs.	1,234	475	241	292	226	188	642	401	758	476
R-squared	0.033	0.060	0.094	0.118	0.195	0.100	0.051	0.074	0.037	0.052
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
*, **, *** *indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.4A: **Finance ("credit_constraint2"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
credit_constraint2[t-1]	-0.12**	-0.09	-0.1	-0.14	0.12	0.04	-0.09*	-0.13	-0.14**	-0.1
	(0.05)	(0.07)	(0.09)	(0.12)	(0.11)	(0.19)	(0.05)	(0.13)	(0.06)	(0.08)
Constant	-0.25***	-0.24**	-0.09	-0.06	-0.84*	-0.41	-0.32***	-0.03	-0.28**	-0.11
		(0.11)	(0.41)	(0.22)	(0.42)	(0.26)	(0.12)	(0.17)	(0.12)	(0.17)
Obs.	543	195	101	133	114	80	295	167	330	213
R-squared	0.079	0.112	0.412	0.191	0.343	0.310	0.123	0.141	0.162	0.079
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.4B: **Finance ("credit_constraint2"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
credit_constraint2[t-1]	0.06	0.08	-0.05**	0.07	-0.03	-0.12	-0.0009	0.35	-0.004	0.12
		(0.07)	(0.02)	(0.13)	(0.06)	(0.1)	(0.03)	(0.23)	(0.06)	(0.12)
Constant	0.12	0.13**	0.26***	-0.09	0.50**	0.3	0.20***	-0.32	0.26***	-0.2
	(0.09)	(0.06)	(0.04)	(0.2)	(0.24)	(0.19)	(0.06)	(0.27)	(0.09)	(0.15)
Obs.	543	195	101	133	114	80	295	167	330	213
R-squared	0.050	0.082	0.473	0.178	0.314	0.254	0.078	0.164	0.070	0.101
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.5A: **Finance ("increase_equity at time t"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
increase_equity[t]	-0.08***	-0.11***	-0.01	-0.09**	-0.08*	-0.09*	-0.06**	-0.09***	-0.07***	-0.10***
	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.02)	(0.03)	(0.02)	(0.03)
Constant	-0.14***	-0.14*	0.01	-0.03	-0.50***	-0.58***	-0.16***	0.1	-0.16***	-0.11
	(0.05)	(0.08)	(0.1)	(0.09)	(0.14)	(0.19)	(0.05)	(0.08)	(0.05)	(0.13)
Obs.	9,961	3,238	2,507	2,430	1,786	951	4,872	4,113	6,164	3,792
R-squared	0.011	0.018	0.024	0.029	0.025	0.083	0.032	0.021	0.037	0.014
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.5B: **Finance ("increase_equity at time t"): Squared residual regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
increase_equity[t]	0.08**	0.07	0.04	0.06	0.06	-0.06	0.04	0.11*	0.09**	0.05
	(0.03)	(0.06)	(0.07)	(0.05)	(0.09)	(0.09)	(0.03)	(0.06)	(0.05)	(0.05)
Constant	0.17***	0.1	0.32**	0.07	0.2	0.40*	0.11***	0.09	0.12***	-0.03
	(0.06)	(0.13)	(0.14)	(0.06)	(0.13)	(0.22)	(0.04)	(0.07)	(0.04)	(0.16)
Obs.	9,961	3,238	2,507	2,430	1,786	951	4,872	4,113	6,164	3,792
R-squared	0.004	0.014	0.013	0.017	0.023	0.021	0.008	0.013	0.009	0.005
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.6A: **Finance ("increase_equity at time t-1"): Log relative TFPR regressions**

Dependent variable		Relative TFPR								
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Low tech	(10) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
increase_equity [t-1]	-0.07***	-0.10**	-0.01	-0.06	-0.04	-0.29***	-0.06**	-0.06*	-0.05*	-0.10**
	(0.02)	(0.04)	(0.05)	(0.04)	(0.05)	(0.1)	(0.03)	(0.04)	(0.03)	(0.04)
Constant	-0.15***	-0.13	0.07	-0.16	-0.40***	-0.26*	-0.18***	-0.01	-0.21***	-0.02
		(0.08)	(0.12)	(0.11)	(0.14)	(0.16)	(0.07)	(0.1)	(0.06)	(0.1)
Obs.	6,934	2,383	1,714	1,750	1,087	483	3,314	3,131	4,280	2,651
R-squared	0.014	0.028	0.030	0.031	0.028	0.120	0.039	0.024	0.046	0.017
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.6B: **Finance ("increase_equity at time t-1"): Squared residual regressions**

		Squared residuals								
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19) Low tech	(20) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
increase_equity[t-1]	0.09**	0.12	0.03	0.05	0.12**	0.27	0.04	0.1	0.09*	0.08
		(0.09)	(0.06)	(0.05)	(0.06)	(0.19)	(0.03)	(0.07)	(0.05)	(0.06)
Constant	0.17***	0.04	0.38**	0.14	0.13	-0.14	0.16***	0.19*	0.19***	-0.23**
	(0.06)	(0.08)	(0.16)	(0.11)	(0.11)	(0.16)	(0.06)	(0.1)	(0.07)	(0.09)
Obs.	6,934	2,383	1,714	1,750	1,087	483	3,314	3,131	4,280	2,651
R-squared	0.006	0.020	0.016	0.016	0.052	0.039	0.009	0.014	0.013	0.011
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.7A: **Finance ("increase_equity at time t+1"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Low tech	(10) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
increase_equity [t+1]	-0.07***	-0.10***	-0.01	-0.09**	-0.06	-0.18***	-0.05	-0.08**	-0.08***	-0.06*
	(0.02)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Constant	-0.06	-0.08	0.03	0.06	-0.30*	-0.07	-0.14**	0.09	-0.12**	0.02
	(0.05)	(0.06)	(0.11)	(0.08)	(0.16)	(0.14)	(0.06)	(0.08)	(0.05)	(0.12)
Obs.	7,196	2,494	1,781	1,790	1,131	545	3,526	3,122	4,410	2,784
R-squared	0.015	0.031	0.031	0.033	0.024	0.184	0.032	0.027	0.049	0.023
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.7B: **Finance ("increase_equity at time t+1"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19) Low tech	(20) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
increase_equity[t+1]	0.08*	0.08	0.15	0.02	0.06	-0.02	0.13*	0.04	0.14**	-0.01
	(0.04)	(0.05)	(0.16)	(0.04)	(0.05)	(0.03)	(0.08)	(0.04)	(0.06)	(0.03)
Constant	0.10***	-0.03	0.30***	0.02	0.17**	0.09	0.05	0.11**	0.07*	-0.24
	(0.03)	(0.05)	(0.1)	(0.05)	(0.09)	(0.07)	(0.04)	(0.05)	(0.04)	(0.15)
Obs.	7,196	2,494	1,781	1,790	1,131	545	3,526	3,122	4,410	2,784
R-squared	0.010	0.021	0.019	0.030	0.042	0.062	0.012	0.018	0.019	0.013
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.8A: **Finance ("euro effect"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Low tech	(10) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
leverage	-0.57***	-0.35***	-0.66***	-0.57***	-0.81***	-0.90***	-0.48***	-0.47***	- 0.57***	-0.51***
	(0.09)	(0.12)	(0.23)	(0.19)	(0.3)	(0.19)	(0.12)	(0.15)	(0.12)	(0.14)
post99	-0.03	-0.05	-0.08	0.14**	-0.08	-0.27***	-0.10**	-0.03	-0.01	-0.01
	(0.03)	(0.04)	(0.06)	(0.06)	(0.1)	(0.1)	(0.04)	(0.05)	(0.04)	(0.05)
leverage* post99	-0.22	-0.22	-0.16	-0.52*	0.13	-0.11	-0.2	-0.21	-0.24	-0.27
	(0.13)	(0.2)	(0.31)	(0.29)	(0.34)	(0.33)	(0.17)	(0.21)	(0.16)	(0.22)
Constant	-0.04	-0.12***	0.1	-0.05	-0.15	-0.04	-0.08**	0.13**	-0.05*	-0.25***
	(0.03)	(0.04)	(0.07)	(0.05)	(0.1)	(0.05)	(0.04)	(0.06)	(0.03)	(0.04)
Obs.	16,126	6,752	3,839	3,284	2,251	2,144	7,446	6,481	9,371	6,754
R-squared	0.026	0.022	0.057	0.050	0.033	0.124	0.052	0.029	0.074	0.036
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
*, **, *** *indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.8B: **Finance ("euro effect"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Mediu m	Big	Low tech	High tech
leverage	0.0004	-0.38*	0.58	-0.04	0.32	0.29	-0.09	-0.3	0.14	-0.2
	(0.16)	(0.23)	(0.42)	(0.18)	(0.38)	(0.28)	(0.09)	(0.29)	(0.16)	(0.33)
post99	0.11***	0.04	0.15*	0.09*	0.18	0.22*	0.09**	0.1	0.16***	0.08
	(0.04)	(0.05)	(0.08)	(0.05)	(0.14)	(0.13)	(0.04)	(0.06)	(0.04)	(0.07)
leverage* post99	0.19	0.43	-0.07	0.35	-0.36	0.12	-0.08	0.51	-0.06	0.55
	(0.23)	(0.32)	(0.64)	(0.31)	(0.53)	(0.79)	(0.16)	(0.38)	(0.26)	(0.45)
Constant	0.14***	0.10***	0.21**	0.11**	0.16*	-0.02	0.13***	0.26***	0.11***	-0.01
	(0.03)	(0.04)	(0.08)	(0.05)	(0.09)	(0.05)	(0.03)	(0.07)	(0.03)	(0.05)
Obs.	16,126	6,752	3,839	3,284	2,251	2,144	7,446	6,481	9,371	6,754
R-squared	0.005	0.011	0.014	0.017	0.022	0.018	0.011	0.012	0.005	0.006
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
*, **, *** *indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.9A: **Finance ("relational banking"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Low tech	(10) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
relational_banking	-0.13***	-0.17**	-0.15**	-0.12	-0.06	-0.05	-0.10**	-0.15**	-0.11**	-0.16**
	(0.04)	(0.07)	(0.06)	(0.08)	(0.12)	(0.1)	(0.05)	(0.06)	(0.05)	(0.07)
Constant	-0.10**	-0.13	0.03	0.03	-0.30***	-0.20**	-0.14***	0.04	-0.10**	0.003
	(0.04)	(0.08)	(0.07)	(0.07)	(0.09)	(0.09)	(0.04)	(0.09)	(0.04)	(0.08)
Obs.	801	244	221	190	146	87	415	295	502	299
R-squared	0.024	0.062	0.050	0.051	0.064	0.313	0.028	0.027	0.054	0.023
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.9B: **Finance ("relational banking"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19) Low tech	(20) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
relational_banking	0.02	-0.003	0.04	0.04	0.07	0.01	0.05	-0.06	0.01	0.02
	(0.05)	(0.11)	(0.08)	(0.11)	(0.09)	(0.05)	(0.07)	(0.06)	(0.06)	(0.1)
Constant	0.22***	0.27*	0.12***	0.14**	0.27***	0.11**	0.13***	0.41**	0.22***	0.30***
	(0.06)	(0.15)	(0.04)	(0.06)	(0.08)	(0.05)	(0.04)	(0.18)	(0.06)	(0.08)
Obs.	801	244	221	190	146	87	415	295	502	299
R-squared	0.004	0.005	0.012	0.026	0.040	0.348	0.016	0.025	0.005	0.004
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2002	2002	2002	2002	2002	2002	2002	2002	2002	2002

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.10A: **Workforce composition ("CIG_share"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
CIG_share	-0.54***	-0.64***	-0.67***	-0.87***	-0.28**	-0.25	-0.48***	-1.01***	-0.55***	-0.52**
	(0.12)	(0.16)	(0.17)	(0.13)	(0.14)	(0.16)	(0.13)	(0.26)	(0.12)	(0.22)
Constant	-0.05**	-0.12***	0.10*	-0.02	-0.19**	-0.09**	-0.09***	0.13**	-0.07**	-0.15*
	(0.03)	(0.03)	(0.06)	(0.05)	(0.09)	(0.04)	(0.03)	(0.06)	(0.03)	(0.08)
Obs.	19,797	8,007	4,701	4,159	2,930	2,433	9,144	8,162	11,700	8,096
R-squared	0.026	0.031	0.055	0.049	0.026	0.094	0.059	0.038	0.068	0.037
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.10B: **Workforce composition ("CIG_share"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
CIG_share	0.68***	0.48***	0.44*	0.36*	0.48***	0.60***	0.45***	0.65*	0.51***	0.91***
	(0.17)	(0.14)	(0.23)	(0.2)	(0.14)	(0.16)	(0.08)	(0.39)	(0.11)	(0.28)
Constant	0.11***	0.03	0.26***	0.07*	0.18**	-0.03	0.10***	0.19***	0.10***	-0.09
	(0.03)	(0.03)	(0.08)	(0.04)	(0.09)	(0.05)	(0.03)	(0.06)	(0.03)	(0.07)
Obs.	19,797	8,007	4,701	4,159	2,930	2,433	9,144	8,162	11,700	8,096
R-squared	0.013	0.014	0.012	0.019	0.029	0.031	0.019	0.012	0.013	0.015
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.11A: **Workforce composition (" term_empl_share"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
term_empl_share	0.19***	0.24	0.31*	0.23**	0.14	0.16	0.18**	0.45***	0.20**	0.21*
	(0.07)	(0.16)	(0.16)	(0.12)	(0.12)	(0.15)	(0.08)	(0.14)	(0.08)	(0.13)
Constant	-0.12***	-0.20***	0.02	-0.02	-0.31***	-0.28***	-0.15***	0.04	-0.13***	-0.07
	(0.03)	(0.04)	(0.08)	(0.05)	(0.07)	(0.06)	(0.03)	(0.05)	(0.03)	(0.07)
Obs.	12,400	4,297	2,994	2,845	2,264	1,200	5,933	5,237	7,533	4,859
R-squared	0.007	0.014	0.023	0.019	0.023	0.087	0.027	0.018	0.038	0.019
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.11B: **Workforce composition (" term_empl_share"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
term_empl_share	0.05	0.32	-0.16	-0.21**	-0.04	0.06	-0.05	0.07	0.11	-0.02
	(0.09)	(0.21)	(0.16)	(0.09)	(0.19)	(0.25)	(0.06)	(0.16)	(0.1)	(0.19)
Constant	0.23***	0.10**	0.46***	0.19***	0.20**	0.14	0.20***	0.20***	0.27***	-0.15**
	(0.04)	(0.04)	(0.15)	(0.05)	(0.1)	(0.1)	(0.04)	(0.05)	(0.05)	(0.07)
Obs.	12,400	4,297	2,994	2,845	2,264	1,200	5,933	5,237	7,533	4,859
R-squared	0.004	0.013	0.010	0.017	0.019	0.017	0.007	0.010	0.006	0.004
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.12A: **Workforce composition ("foreign_empl_share"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Low tech	(10) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
foreign_empl_share	-0.11	0.04	-0.67***	-0.37	0.5	0.90***	-0.04	-0.4	0.03	-0.16
	(0.15)	(0.28)	(0.24)	(0.35)	(0.36)	(0.31)	(0.18)	(0.29)	(0.17)	(0.34)
Constant	-0.12***	-0.21***	0.01	-0.01	-0.29***	-0.30***	-0.19***	0.05	-0.15***	-0.09
	(0.03)	(0.05)	(0.09)	(0.06)	(0.07)	(0.07)	(0.04)	(0.06)	(0.03)	(0.07)
Obs.	6,651	1,977	1,703	1,609	1,362	625	3,293	2,724	4,243	2,402
R-squared	0.013	0.017	0.030	0.043	0.023	0.093	0.033	0.019	0.042	0.010
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.12B: **Workforce composition ("foreign_empl_share"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19) Low tech	(20) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
foreign_empl_share	-0.54***	-0.85***	-0.31	-0.23	-0.3	0.27	-0.16	-1.19***	-0.27*	-1.05**
	(0.15)	(0.29)	(0.22)	(0.41)	(0.51)	(0.4)	(0.15)	(0.35)	(0.15)	(0.44)
Constant	0.26***	0.16***	0.49***	0.17***	0.21***	0.09	0.26***	0.24***	0.24***	-0.02
	(0.04)	(0.04)	(0.13)	(0.05)	(0.08)	(0.07)	(0.06)	(0.05)	(0.04)	(0.06)
Obs.	6,651	1,977	1,703	1,609	1,362	625	3,293	2,724	4,243	2,402
R-squared	0.006	0.019	0.014	0.015	0.028	0.029	0.009	0.012	0.007	0.013
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.13A: **Workforce composition ("grad_share1"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
grad_share1	0.42***	0.43	0.51***	0.62***	0.14	-0.19	0.02	0.67***	0.49***	0.19
	(0.1)	(0.27)	(0.13)	(0.15)	(0.16)	(0.43)	(0.1)	(0.17)	(0.11)	(0.15)
Constant	-0.17***	-0.25***	0.03	-0.04	-0.44***	-0.32***	-0.13***	-0.12**	-0.18***	-0.25***
	(0.03)	(0.04)	(0.08)	(0.05)	(0.07)	(0.07)	(0.03)	(0.06)	(0.03)	(0.06)
Obs.	1,476	515	347	337	277	167	702	602	910	564
R-squared	0.021	0.015	0.081	0.081	0.014	0.087	0.041	0.047	0.066	0.013
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.13B: **Workforce composition ("grad_share1"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
grad_share1	0.48***	1.10*	0.19	0.28**	0.23	1.97	0.18**	0.43	0.27**	0.60**
	(0.18)	(0.62)	(0.12)	(0.11)	(0.24)	(1.54)	(0.09)	(0.4)	(0.13)	(0.28)
Constant	0.14***	0.01	0.21***	0.11***	0.18**	0.1	0.13***	0.15*	0.17***	-0.13
	(0.03)	(0.06)	(0.06)	(0.03)	(0.08)	(0.09)	(0.02)	(0.08)	(0.02)	(0.08)
Obs.	1,476	515	347	337	277	167	702	602	910	564
R-squared	0.005	0.017	0.022	0.038	0.014	0.032	0.048	0.007	0.007	0.003
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.14A: **Workforce composition ("grad_share2"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Low tech	(10) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
grad_share2	0.05	-1.2	0.24	0.66	-1.15	-1.24	-0.66	0.03	1.82***	-1.43*
	(0.59)	(1.38)	(0.56)	(0.41)	(0.83)	(0.96)	(1.02)	(0.68)	(0.66)	(0.86)
Constant	-0.13***	-0.21***	0.09	0.01	-0.42***	-0.33***	-0.13***	-0.02	-0.14***	-0.20***
		(0.03)	(0.08)	(0.05)	(0.07)	(0.08)	(0.03)	(0.06)	(0.03)	(0.03)
Obs.	1,427	490	338	332	267	165	680	576	884	541
R-squared	0.007	0.016	0.050	0.036	0.013	0.086	0.047	0.013	0.052	0.023
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.14B: **Workforce composition ("grad_share2"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19) Low tech	(20) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
grad_share2	1.41	3.34	-0.61	0.37	-3.74	-4.46	1.14	1.46	-0.7	1.55
	(1.29)	(2.81)	(0.48)	(0.55)	(2.31)	(4.19)	(1.12)	(1.6)	(0.57)	(1.51)
Constant	0.19***	0.11***	0.25***	0.14***	0.22***	0.20**	0.14***	0.22***	0.20***	0
	(0.03)	(0.02)	(0.06)	(0.02)	(0.08)	(0.08)	(0.02)	(0.05)	(0.03)	(0.01)
Obs.	1,427	490	338	332	267	165	680	576	884	541
R-squared	0.004	0.045	0.020	0.036	0.017	0.024	0.049	0.019	0.007	0.003
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010	2000 and 2010

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.15A: **Workforce composition ("foreign_group"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
foreign_group	0.06**	0.07	-0.0001	0.08	0.13	-0.29	0.08*	0.01	0.04	0.07
	(0.03)	(0.05)	(0.05)	(0.06)	(0.08)	(0.3)	(0.04)	(0.04)	(0.03)	(0.04)
Constant	-0.06	-0.23***	0.16	0.09	-0.30**	-0.15	-0.19***	0.07	-0.06	-0.09
	(0.04)	(0.05)	(0.1)	(0.06)	(0.13)	(0.15)	(0.05)	(0.06)	(0.04)	(0.08)
Obs.	8,391	3,130	2,290	1,841	1,130	260	3,254	4,862	4,667	3,719
R-squared	0.007	0.017	0.031	0.030	0.022	0.094	0.031	0.020	0.031	0.027
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.15B: **Workforce composition ("foreign_group"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
foreign_group	0.02	0.05	-0.05	0.03	0.13	1.43	0.01	0.05	-0.01	0.06
	(0.04)	(0.06)	(0.05)	(0.06)	(0.18)	(1.05)	(0.04)	(0.04)	(0.03)	(0.06)
Constant	0.17***	0.02	0.44***	-0.004	0.13	-0.12	0.16***	0.16***	0.20***	-0.26***
	(0.05)	(0.04)	(0.13)	(0.04)	(0.12)	(0.19)	(0.05)	(0.06)	(0.05)	(0.08)
Obs.	8,391	3,130	2,290	1,841	1,130	260	3,254	4,862	4,667	3,719
R-squared	0.005	0.016	0.013	0.015	0.031	0.131	0.013	0.012	0.008	0.007
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.16A: **Workforce composition ("sub_foreign_04"): Log relative TFPR regressions**

Dependent variable		Relative TFPR								
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
sub_foreign_04	-0.002	-0.005***	1.82E-05	0.0001	8.49E-05	0.003	-0.001	-0.003*	0.001	-0.005***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)
Constant	-0.246**	-0.034	-0.308***	-0.153	-0.504***	-0.711***	-0.139	-0.256***	-0.354***	0.089
	(0.1)	(0.142)	(0.097)	(0.237)	(0.162)	(0.204)	(0.162)	(0.091)	(0.09)	(0.174)
Obs.	136	49	32	27	28	9	66	61	81	55
R-squared	0.059	0.268	0.097	0.112	0.137	0.268	0.056	0.139	0.132	0.151
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.16B: **Workforce composition ("sub_foreign_04"): Squared residuals regressions**

		Squared residuals								
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
sub_foreign_04	0.0003	0.0015	0.0004	0.0013	-0.0008	-0.0006	0.0001	0.0006	0.0008	-0.0003
	(0.0008)	(0.0014)	(0.0009)	(0.0019)	(0.0009)	(0.001)	(0.0009)	(0.0012)	(0.0008)	(0.0013)
Constant	0.148*	-0.0709	0.0016	0.214*	0.0828**	0.046	0.223*	-0.0124	0.104*	0.231**
	(0.0828)	(0.103)	(0.0325)	(0.12)	(0.0367)	(0.043)	(0.114)	(0.0574)	(0.0536)	(0.107)
Obs.	136	49	32	27	28	9	66	61	81	55
R-squared	0.050	0.114	0.179	0.133	0.164	0.294	0.072	0.087	0.057	0.035
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.17A: **Workforce composition ("sub_foreign_07"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
sub_ foreign_07	-0.0015	-0.0047***	0.0008	0.0003	-0.0008	0.0045	4.69e-05	-0.0031**	0.0013	-0.0040***
	(0.001)	(0.0014)	(0.0014)	(0.0031)	(0.0023)	(0.0027)	(0.0015)	(0.0014)	(0.0011)	(0.0015)
Constant	-0.255***	-0.0265	-0.424***	-0.164	-0.495***	-0.764***	-0.181	-0.245**	-0.373***	0.121
		(0.115)	(0.109)	(0.249)	(0.162)	(0.165)	(0.141)	(0.11)	(0.0772)	(0.15)
Obs.	152	59	37	28	28	10	72	70	86	66
R-squared	0.053	0.241	0.129	0.173	0.141	0.463	0.045	0.112	0.200	0.143
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.17B: **Workforce composition ("sub_foreign_07"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
sub_foreign_07	0.0001	0.0012	-0.0001	0.0015	-0.0018	-0.0008	-0.0001	0.0003	0.0006	-0.0002
	(0.0008)	(0.0011)	(0.0008)	(0.0018)	(0.0014)	(0.001)	(0.0008)	(0.0012)	(0.0007)	(0.0011)
Constant	0.147**	-0.0476	0.0356	0.198	0.0936**	0.0472	0.195*	0.0406	0.0920**	0.239***
	(0.0728)	(0.0749)	(0.0259)	(0.123)	(0.0379)	(0.0432)	(0.1)	(0.059)	(0.0427)	(0.0877)
Obs.	152	59	37	28	28	10	72	70	86	66
R-squared	0.054	0.119	0.128	0.143	0.217	0.360	0.059	0.087	0.055	0.038
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2007	2007	2007	2007	2007	2007	2007	2007	2007	2007

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.18A: **Workforce composition ("sub_foreign_10"): Log relative TFPR regressions**

Dependent variable		Relative TFPR								
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
sub_foreign_10	-0.002	-0.009	0.004	-0.001	-0.002	-0.0220***	0.00324*	-0.005	0.003	-0.006
	(0.002)	(0.007)	(0.005)	(0.003)	(0.003)	(0.001)	(0.002)	(0.004)	(0.002)	(0.003)
Constant	-0.368*	-1.747	-1.104**	-0.08	-0.486	-0.305***	-0.577***	-0.111	-0.663***	-0.122
	(0.201)	(1.298)	(0.421)	(0.204)	(0.312)	(0.026)	(0.211)	(0.403)	(0.213)	(0.075)
Obs.	104	28	30	29	17	10	48	46	63	41
R-squared	0.152	0.340	0.199	0.048	0.272	0.832	0.232	0.365	0.249	0.229
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2010	2010	2010	2010	2010	2010	2010	2010	2010	2010

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.18B: **Workforce composition ("sub_foreign_10"): Squared residuals regressions**

		Squared residuals								
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
sub_foreign_10	0.006	0.01	0.005	0.0002	0.001	0.0001	-0.001	0.01	0.002	0.002
	(0.004)	(0.008)	(0.004)	(0.002)	(0.001)	(0.0002)	(0.001)	(0.006)	(0.002)	(0.004)
Constant	-0.231	3.685**	-0.425	0.014	0.146	0.0007***	0.251*	-0.85	0.013	-0.048
	(0.297)	(1.758)	(0.351)	(0.133)	(0.141)	(9.30e-10)	(0.144)	(0.578)	(0.176)	(0.079)
Obs.	104	28	30	29	17	10	48	46	63	41
R-squared	0.242	0.542	0.220	0.142	0.396	0.315	0.132	0.527	0.367	0.096
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2010	2010	2010	2010	2010	2010	2010	2010	2010	2010

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.19A: **Internationalisation ("deloc_04"): Log relative TFPR regressions**

Dependent variable		Relative TFPR								
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
deloc_04	0.012	-0.128	0.087	0.069	0.009	0.013	-0.002	-0.068	0.039	-0.024
	(0.042)	(0.087)	(0.062)	(0.087)	(0.171)	(0.109)	(0.046)	(0.086)	(0.054)	(0.068)
Constant	-0.110**	-0.087	-0.067	-0.053	-0.275**	-0.270***	-0.158***	0.124	-0.124***	-0.074
	(0.043)	(0.08)	(0.094)	(0.072)	(0.11)	(0.099)	(0.053)	(0.094)	(0.045)	(0.11)
Obs.	749	232	212	198	107	73	377	299	454	295
R-squared	0.010	0.023	0.063	0.057	0.066	0.163	0.036	0.025	0.052	0.003
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.19B: **Internationalisation ("deloc_04"): Squared residuals regressions**

		Squared residuals								
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
deloc_04	0.11	0.26	0.08	-0.09	0.34*	-0.04	0.01	0.19	0.18	0.005
	(0.10)	(0.27)	(0.08)	(0.14)	(0.19)	(0.07)	(0.03)	(0.24)	(0.15)	(0.12)
Constant	0.14**	0.002	0.20***	0.193***	-0.02	0.15***	0.18***	0.05	0.1	0.52***
	(0.06)	(0.16)	(0.08)	(0.06)	(0.10)	(0.05)	(0.04)	(0.19)	(0.08)	(0.16)
Obs.	749	232	212	198	107	73	377	299	454	295
R-squared	0.005	0.019	0.014	0.016	0.187	0.110	0.023	0.013	0.015	0.010
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2004	2004	2004	2004	2004	2004	2004	2004	2004	2004

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.20A: **Internationalisation ("deloc_11"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
deloc_11	-0.07	-0.12	0.02	-0.13	-0.07	-1.13	-0.09	-0.11	-0.03	-0.1
	(0.05)	(0.08)	(0.08)	(0.09)	(0.15)	(0.81)	(0.06)	(0.07)	(0.05)	(0.09)
Constant	-0.14**	-0.14**	-0.19	0.12	-0.56*	-0.38*	-0.11*	-0.05	-0.15***	-0.10*
		(0.07)	(0.13)	(0.10)	(0.3)	(0.21)	(0.06)	(0.11)	(0.06)	(0.06)
Obs.	695	250	165	168	112	35	311	349	450	244
R-squared	0.021	0.026	0.069	0.046	0.076	0.539	0.057	0.017	0.060	0.008
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.20B: **Internationalisation ("deloc_11"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
deloc_11	0.04	0.15	-0.10	-0.09	0.11	1.17**	-0.06	-0.06	-0.03	0.14
	(0.07)	(0.15)	(0.11)	(0.09)	(0.19)	(0.48)	(0.05)	(0.12)	(0.07)	(0.15)
Constant	0.25***	0.08	0.28***	0.21***	0.74	0.26**	0.17***	0.41**	0.29***	-0.02
	(0.07)	(0.07)	(0.08)	(0.06)	(0.48)	(0.1)	(0.03)	(0.18)	(0.07)	(0.05)
Obs.	695	250	165	168	112	35	311	349	450	244
R-squared	0.004	0.023	0.023	0.020	0.104	0.685	0.016	0.003	0.008	0.015
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.21A: **Internationalisation ("fdi01"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Low tech	(10) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
fdi01	0.12*	0.06	0.16	0.16	-0.95	(omitted)	0.08	0.14	0.14	0.08
	(0.07)	(0.11)	(0.13)	(0.13)	(0.86)		(0.08)	(0.11)	(0.08)	(0.12)
Constant	-0.09	-0.19*	0.2	-0.08	0.08		-0.29***	0.03	-0.09	-0.49
	(0.08)	(0.1)	(0.26)	(0.15)	(0.23)		(0.07)	(0.12)	(0.08)	
Obs.	190	77	72	34	7	3	80	107	98	92
R-squared	0.039	0.052	0.094	0.156	0.569		0.120	0.063	0.129	0.129
Sector FE	YES	YES	YES	YES	YES		YES	YES	YES	YES
Cross section Year	2003	2003	2003	2003	2003		2003	2003	2003	2003

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.21B: **Internationalisation ("fdi01"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19) Low tech	(20) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
fdi01	0.17*	0.10*	0.21	0.06	0	(omitted)	-0.05	0.25	0.07	0.2
	(0.1)	(0.05)	(0.25)	(0.06)	(0)		(0.05)	(0.16)	(0.05)	(0.2)
Constant	0.16**	0.14***	0.24	0.07	0.03***		0.07**	0.18*	0.20***	0
	(0.06)	(0.05)	(0.21)	(0.07)	(0)		(0.03)	(0.1)	(0.05)	(0)
Obs.	190	77	72	34	7	3	80	107	98	92
R-squared	0.042	0.121	0.044	0.358	1.000		0.081	0.055	0.125	0.024
Sector FE	YES	YES	YES	YES	YES		YES	YES	YES	YES
Cross section Year	2003	2003	2003	2003	2003		2003	2003	2003	2003

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.22A: **Internationalisation ("fdi02"): Log relative TFPR regressions**

Dependent variable		Relative TFPR								
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
fdi02	-0.01	0.08	-0.22*	0.16	-0.59	-0.1	-0.07	0.01	0.01	-0.07
	(0.06)	(0.11)	(0.12)	(0.12)	(0.47)		(0.08)	(0.09)	(0.08)	(0.1)
Constant	-0.04	-0.20**	0.41	-0.08	0.19	0.4	-0.22***	0.07	-0.04	-0.43***
		(0.1)	(0.25)	(0.15)	(0.24)		(0.08)	(0.13)	(0.09)	(0.1)
Obs.	194	77	73	35	9	3	81	110	98	96
R-squared	0.020	0.049	0.100	0.157	0.425	1.000	0.124	0.041	0.107	0.121
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.22B: **Internationalisation ("fdi02"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
fdi02	0.09	0.06	0.13	0.05	-0.04	0	-0.01	0.1	-0.04	0.16
	(0.08)	(0.05)	(0.17)	(0.05)	(0.04)		(0.05)	(0.12)	(0.06)	(0.15)
Constant	0.18**	0.15***	0.22	0.07	0.06	0	0.06*	0.24**	0.26***	-0.16
	(0.08)	(0.05)	(0.21)	(0.07)	(0.04)		(0.04)	(0.12)	(0.08)	(0.15)
Obs.	194	77	73	35	9	3	81	110	98	96
R-squared	0.028	0.073	0.033	0.355	0.944	1.000	0.051	0.026	0.098	0.020
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2003	2003	2003	2003	2003	2003	2003	2003	2003	2003

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.23A: **Internationalisation ("fdi03"): Log relative TFPR regressions**

Dependent variable		Relative TFPR								
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Low tech	(10) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
fdi03	0.02	0.10	-0.08	0.08	-0.45	(omitted)	-0.03	0.01	0.04	0.004
	(0.06)	(0.09)	(0.11)	(0.14)	(0.54)		(0.07)	(0.08)	(0.07)	(0.09)
Constant	-0.08	-0.26***	0.28	-0.04	0.29		-0.25***	0.06	-0.08	-0.50***
	(0.08)	(0.09)	(0.23)	(0.17)	(0.49)		(0.07)	(0.13)	(0.08)	(0.09)
Obs.	204	80	78	36	10	3	86	115	102	102
R-squared	0.022	0.089	0.062	0.142	0.301		0.120	0.033	0.113	0.105
Sector FE	YES	YES	YES	YES	YES		YES	YES	YES	YES
Cross section Year	2003	2003	2003	2003	2003		2003	2003	2003	2003

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.23B: **Internationalisation ("fdi03"): Squared residuals regressions**

		Squared residuals								
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19) Low tech	(20) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
fdi03	0.07	0.06	0.12	0.04	-0.05	(omitted)	-0.08*	0.12	0.03	0.09
	(0.07)	(0.04)	(0.17)	(0.06)	(0.04)		(0.04)	(0.1)	(0.05)	(0.13)
Constant	0.18***	0.12***	0.29	0.09	0.14***		0.08***	0.22**	0.21***	-0.09
	(0.07)	(0.03)	(0.19)	(0.08)	(0.04)		(0.03)	(0.1)	(0.06)	(0.13)
Obs.	204	80	78	36	10	3	86	115	102	102
R-squared	0.024	0.085	0.037	0.336	0.953		0.097	0.029	0.091	0.008
Sector FE	YES	YES	YES	YES	YES		YES	YES	YES	YES
Cross section Year	2003	2003	2003	2003	2003		2003	2003	2003	2003

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.24A: **Cronyism ("publ_adm_sales"): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
public_adm_sales	0.40***	0.50***	0.59***	0.36**	0.22	0.12	0.35**	0.41***	0.19	0.51***
	(0.09)	(0.16)	(0.12)	(0.17)	(0.23)	(0.4)	(0.14)	(0.13)	(0.14)	(0.11)
Constant	-0.14***	-0.27***	0.05	0.03	-0.39***	-0.55***	-0.15***	-0.01	-0.14***	-0.12**
	(0.04)	(0.05)	(0.10)	(0.06)	(0.12)	(0.10)	(0.05)	(0.06)	(0.04)	(0.06)
Obs.	2,320	810	518	558	434	195	1,092	1,032	1,504	811
R-squared	0.024	0.022	0.083	0.052	0.023	0.099	0.079	0.014	0.053	0.030
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.24B: **Cronyism ("publ_adm_sales"): Squared residuals regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big	Low tech	High tech
public_adm_sales	-0.13**	-0.18	-0.13	-0.23	0.06	-0.24	0.01	-0.24**	-0.02	-0.29**
	(0.07)	(0.13)	(0.09)	(0.17)	(0.12)	(0.31)	(0.09)	(0.12)	(0.11)	(0.12)
Constant	0.26***	0.17***	0.32***	0.20***	0.36**	0.23***	0.18***	0.29***	0.27***	0.03***
	(0.03)	(0.03)	(0.06)	(0.03)	(0.17)	(0.06)	(0.02)	(0.07)	(0.03)	(0.005)
Obs.	2,320	810	518	558	434	195	1,092	1,032	1,504	811
R-squared	0.006	0.021	0.010	0.022	0.020	0.033	0.013	0.009	0.005	0.022
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cross section Year	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011	2009/ 2011

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.25A: **Innovation ("intangibles_share" at time t): Log relative TFPR regressions**

Dependent variable		Relative TFPR								
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Low tech	(10) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
Intangible share[t]	0.33***	0.42***	0.28***	0.29***	0.15	0.01	0.16***	0.59***	0.31***	0.31***
	(0.05)	(0.1)	(0.1)	(0.1)	(0.11)	(0.12)	(0.05)	(0.09)	(0.07)	(0.09)
Constant	-0.16***	-0.24***	-0.01	-0.05	-0.33***	-0.28***	-0.16***	-0.04	-0.17***	-0.1
	(0.03)	(0.04)	(0.08)	(0.06)	(0.07)	(0.06)	(0.03)	(0.06)	(0.03)	(0.08)
Obs.	12,246	4,274	2,982	2,810	2,180	1,150	5,848	5,219	7,421	4,818
R-squared	0.015	0.029	0.028	0.024	0.026	0.087	0.031	0.038	0.046	0.025
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.25B: **Innovation ("intangibles_share" at time t): Squared residuals regressions**

		Squared residuals								
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19) Low tech	(20) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
Intangible share[t]	0.32***	0.40***	0.42**	0.18	0.16	0.31	0.13	0.34**	0.32***	0.29*
	(0.09)	(0.15)	(0.21)	(0.13)	(0.14)	(0.22)	(0.08)	(0.14)	(0.09)	(0.15)
Constant	0.18***	0.08*	0.38**	0.14***	0.15	0.1	0.18***	0.16***	0.23***	-0.16**
	(0.04)	(0.05)	(0.15)	(0.06)	(0.09)	(0.09)	(0.04)	(0.05)	(0.05)	(0.08)
Obs.	12,246	4,274	2,982	2,810	2,180	1,150	5,848	5,219	7,421	4,818
R-squared	0.006	0.015	0.014	0.016	0.021	0.019	0.008	0.011	0.009	0.006
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.26A: **Innovation ("intangibles_share" at time t-1): Log relative TFPR regressions**

Dependent variable	Relative TFPR									
	Full sample	By geographic area				By size			By technological intensity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Low tech	(10) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
Intangible share[t-1]	0.48***	0.49***	0.38***	0.51***	0.40***	0.23	0.29***	0.65***	0.46***	0.45***
	-0.06	-0.11	-0.10	-0.11	-0.14	-0.19	-0.05	-0.10	-0.07	-0.09
Constant	-0.18***	-0.24***	-0.05	-0.05	-0.38***	-0.35***	-0.16***	-0.08	-0.18***	-0.08
		-0.04	-0.09	-0.06	-0.08	-0.08	-0.03	-0.06	-0.04	-0.07
Obs.	8,220	3,012	1,958	1,941	1,309	591	3,833	3,790	4,933	3,284
R-squared	0.027	0.041	0.041	0.042	0.038	0.107	0.045	0.046	0.062	0.036
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.26B: **Innovation ("intangibles_share" at time t-1): Squared residual regressions**

	Squared residuals									
	Full sample	By geographic area				By size			By technological intensity	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19) Low tech	(20) High tech
Variables	ALL	NW	NE	Centre	South	Small	Medium	Big		
Intangible share[t-1]	0.14**	0.2	0.11	0.06	0.12	-0.05	-0.05	0.22**	0.16**	0.07
	(0.07)	(0.13)	(0.17)	(0.07)	(0.14)	(0.38)	(0.05)	(0.1)	(0.07)	(0.11)
Constant	0.21***	0.10**	0.49**	0.08**	0.18**	0.05	0.17***	0.18***	0.27***	-0.23***
	(0.06)	(0.05)	(0.24)	(0.03)	(0.07)	(0.09)	(0.05)	(0.05)	(0.08)	(0.08)
Obs.	8,220	3,012	1,958	1,941	1,309	591	3,833	3,790	4,933	3,284
R-squared	0.005	0.014	0.014	0.016	0.046	0.035	0.007	0.010	0.010	0.008
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.27A: **Log relative TFPR on various regressors together**

Dependent variable	Relative TFPR				
	(1)	(2)	(3)	(4)	(5)
Variables	Full 1	Full 2	Full 3	Full 4	Full 5
CIG_share	-0.53**	-0.53**	-0.92**	-0.53**	-0.91**
	(0.25)	(0.25)	(0.36)	(0.25)	(0.42)
grad_share1	0.40***	0.39***	-0.57**	0.40***	-0.57**
	(0.09)	(0.1)	(0.24)	(0.09)	(0.26)
intangible_share	0.21**	0.29***	0.41	0.22**	0.39
	(0.1)	(0.1)	(0.32)	(0.1)	(0.36)
Conglomerate		0.01			0.04
		(0.04)			(0.13)
Financial Institution		0.01			0.14
		(0.05)			(0.13)
Government		-0.02			-0.06
		(0.09)			(0.2)
Foreign		0.05			0.12
		(0.05)			(0.14)
credit_constraint1[t-1]			-0.01		-0.03
			(0.1)		(0.11)
term_empl_share				0.14	0.08
				(0.18)	(0.26)
Constant		-0.16***	-0.30**	-0.16***	-0.37**
	(0.03)	(0.04)	(0.12)	(0.03)	(0.16)
Obs.	1,438	1,347	81	1,438	77
R-squared	0.052	0.054	0.269	0.053	0.281
Sector FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

Table 5.27B: **Squared residuals from the previous regression on various regressors together**

	Squared residuals				
	(6)	(7)	(8)	(9)	(10)
Variables	Full 1	Full 2	Full 3	Full 4	Full 5
CIG_share	0.72***	0.64***	-0.15	0.74***	-0.08
	(0.2)	(0.2)	(0.15)	(0.2)	(0.17)
grad_share1	0.42**	0.32*	-0.21**	0.40**	-0.16
	(0.18)	(0.19)	(0.1)	(0.17)	(0.13)
intangible_share	0.02	-0.07	0.19	0.03	0.16
	(0.2)	(0.19)	(0.15)	(0.2)	(0.17)
Conglomerate		0.17*			-0.04
		(0.1)			(0.06)
Financial Institution		0.12			-0.11*
		(0.11)			(0.06)
Government		-0.03			-0.21**
		(0.08)			(0.08)
Foreign		0.18			-0.07
		(0.17)			(0.06)
credit_constraint1[t-1]			0.04		0.08*
			(0.05)		(0.05)
term_empl_share				0.68	0.11
				(0.55)	(0.15)
Constant	0.10*	0.04	0.04	0.05	0.07
	(0.05)	(0.06)	(0.05)	(0.04)	(0.06)
Obs.	1,438	1,347	81	1,438	77
R-squared	0.008	0.010	0.149	0.010	0.230
Sector FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note: Standard errors are reported in parentheses.
, **, * indicates significance at the 90%, 95%, and 99% level, respectively.*

EUROPEAN ECONOMY DISCUSSION PAPERS

European Economy Discussion Papers can be accessed and downloaded free of charge from the following address:
http://ec.europa.eu/economy_finance/publications/eedp/index_en.htm

Titles published before July 2015 under the Economic Papers series can be accessed and downloaded free of charge from:
http://ec.europa.eu/economy_finance/publications/economic_paper/index_en.htm

Alternatively, hard copies may be ordered via the “Print-on-demand” service offered by the EU Bookshop: http://bookshop.europa.eu.

HOW TO OBTAIN EU PUBLICATIONS

Free publications:

- one copy:
  via EU Bookshop (http://bookshop.europa.eu);

- more than one copy or posters/maps:
  - from the European Union's representations (http://ec.europa.eu/represent_en.htm);
  - from the delegations in non-EU countries (http://eeas.europa.eu/delegations/index_en.htm);
  - by contacting the Europe Direct service (http://europa.eu/europedirect/index_en.htm) or calling 00 800 6 7 8 9 10 11 (freephone number from anywhere in the EU) (*).

(*) The information given is free, as are most calls (though some operators, phone boxes or hotels may charge you).

Priced publications:

- via EU Bookshop (http://bookshop.europa.eu).

KC-BD-16-030-EN-N

Publications Office

ISBN 978-92-79-54432-3