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Please cite as:

Calligaris, S., Del Gatto, M., Hassan, F., Ottaviano, G. I., & Schivardi, F. (2018). "The Productivity Puzzle and Misallocation: an Italian Perspective
Economic Policy, 33(96), 635-684.

https://doi.org/10.1093/epolic/eiy014

This is a PDF file of an unedited version of the manuscript that has been accepted for publication. The manuscript will undergo copyediting and typesetting before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content

*A replication package (data + STATA codes) for the linguistic index used in this paper, together with the full set of computed bilateral distance measures (geographical, linguistic and ethnic distances), can be downloaded from the first author's website.

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# The Productivity Puzzle and Misallocation: an Italian Perspective

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October 31, 2017

**Abstract**

Productivity has recently slowed down in many economies around the world. A crucial challenge in understanding what lies behind this "productivity puzzle" is the still short time span for which data can be analysed. An exception is Italy where productivity growth started to stagnate 25 years ago. Italy therefore offers an interesting case to investigate in search of broader lessons that may hold beyond local specificities. We find that resource misallocation has played a sizeable role in slowing down Italian productivity growth. If

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We thank Andrea Brandolini, Matteo Bugamelli, Sergio De Nardis, Lazaros Dimitriadis, Luigi Guiso, Silvia Fabiani, Francesca Lotti, Dino Pinelli, and Roberta Torre for useful comments and discussions. We thank the Directorate General for Economic and Financial Affairs (DG ECFIN) of the European Commission for financial support. The opinions expressed and arguments employed herein are those of the authors and do not necessarily reflect the official views of the OECD or of the governments of its member countries.

misallocation had remained at its 1995 level, in 2013 Italy's aggregate productivity would have been 18% higher than its actual level. Misallocation has mainly risen *within* sectors than *between* them, increasing more in sectors where the world technological frontier has expanded faster. Relative specialization in those sectors explains the patterns of misallocation across geographical areas and firm size classes. The broader message is that an important part of the explanation of the productivity puzzle may lie in the rising difficulty of reallocating resources between firms in sectors where technology is changing faster rather than between sectors with different speeds of technological change.

**Keywords:** Misallocation, TFP, Productivity, Productivity Puzzle, Italy.

**J.E.L. Classification:** D22, D24, O11, O47.

# 1 Introduction

In recent years, many advanced economies have experienced a serious productivity slowdown. As Figure 1 shows, in the US, the Eurozone and the UK total factor productivity is still below the pre-global financial crisis level. In 2016, US labor productivity growth fell into negative territory for the first time in the last three decades (Conference Board, 2016) and productivity has reached the headlines of global media, which have started focusing on "The productivity puzzle that baffles the world's economies".[1] These trends are particularly worrisome because productivity lies at the heart of long-term growth.

A crucial challenge in understanding what lies behind this productivity puzzle is the still short time span for which data can be analysed. As Fernald (2014) and Cette et al. (2016) point out, in some countries like the US, the productivity slowdown dates back a few years before the crisis. However, in Italy this is a much longer standing issue. Figure 2 shows a growth accounting decomposition for Italy over the past four decades and the results are quite emblematic. TFP growth shrank throughout the decades, becoming negative in the 2000s. Italy turned from being among the fastest growing EU economies into the "sleeping beauty of Europe", a country rich in talent and history but suffering from a long-lasting stagnation (Hassan and Ottaviano, 2013). TFP dynamics in the manufacturing sector, where measurement issues are less binding than in services, captures well the timing of the Italian decline. Figure 3 shows a dramatic slowdown in TFP growth since the mid-Nineties for Italy compared to France and Germany, where TFP continued to grow up to the global financial crisis.[2]

The relatively long time-series dimension that characterises the Italian productivity slowdown makes Italy a relevant case-study for analysing the key features of the productivity decline (and draw policy recommendations) that can be of general interest to other countries. We analyse the firm-level dimension of aggregate productivity and focus on the concept of resource "misalocation" and its impact on productivity. The "productivity" we refer to is Total Factor Productivity (henceforth, simply TFP), which measures how effectively given amounts of productive factors (capital and labor) are used. Clearly the economy's aggregate TFP depends on its firms' TFP. This happens along two dimensions. On the one hand, for given amounts of factors used by each firm, aggregate TFP grows when individual firm TFP grows, for example thanks to the adoption of better technologies and management practices. If market imper-

[1] The Financial Times, 29th May, 2016.

[2] In the paper we focus on firms in the manufacturing sector, because firm-level TFP measurement is less controversial than in services due to better accounting of the capital stock. We have run the same analysis also for firms in the service sector and comparable results are quite similar.

fections prevent firms from seizing these opportunities, the economy's productive apparatus is exposed to obsolescence and senescence with adverse effects on aggregate TFP.

On the other hand, for given individual firm-level TFP, aggregate TFP depends on how factors are allocated across firms. As long as market frictions "distort" the allocation of product demand and factor supply away from high TFP firms towards low TFP rivals, they lead to lower aggregate TFP than in an ideal situation of frictionless markets. Building on the distinction, introduced by Foster et al. (2008), between physical TFP (TFPQ or simply TFP, i.e., measured as the ability to generate physical output from given inputs) and revenue TFP (TFPR, i.e., measured as the ability to generate revenue from given inputs), Hsieh and Klenow (2009) construct a model of monopolistic competition in which, although firms can differ in their physical TFP, in the absence of frictions TFPR is the same for all firms. The idea behind this result is simple: with no frictions, the marginal revenue product of inputs should be equalized across firms as factors move from low to high marginal revenue product firms. As marginal revenue product equalization implies TFPR equalization, Hsieh and Klenow (2009) call deviations from a situation in which TFPR is equalized "misallocation", and propose a simple way to measure its consequences on aggregate TFP. This is also the definition of "misallocation" we adopt. It implies that the dispersion of TFPR across firms can be used to measure the extent of misallocation. It also implies that firms with a TFPR higher than the sectoral average are inefficiently small, while those with a TFPR below the sectoral average are inefficiently large. These are the two key implications of the misallocation literature that we use in this paper.

With these definitions in mind, we study the universe of Italian incorporated companies over the period 1993-2013 and find strong evidence of increased misallocation since 1995. If misallocation had remained at its 1995 level, in 2013 aggregate TFP would have been 18% higher than its current level. This would have translated into 1% higher GDP growth per-year, which would have helped to close the growth gap with France and Germany. The main source of misallocation comes from the *within* industry component rather than the *between* component: misallocation has mainly risen within sectors than between them, increasing more in sectors where the world technological frontier has expanded faster. Relative specialization in those sectors explains the patterns of misallocation across geographical areas and firm size classes with misallocation increasing particularly in the Northern regions and among big firms, which traditionally are the driving forces of the Italian economy. The broader message is that an important part of the explanation of the recent productivity puzzle may lie in a generally rising difficulty of reallocating resources between firms in sectors where technology is changing faster rather than between sectors with different speeds of technological change. This implies that moving factors of production from e.g. textile into IT would increase aggregate productivity less than ensuring that the most efficient firms within textile are the ones that absorb more resources.

In the wake of Griffith, Redding and Van Reenen (2004) we measure the speed of technological change in a sector by the average change of R&D intensity between 1987-1993 and 1994-2007 in advanced countries.[3] We find a positive and significant correlation between the increase in R&D intensity in advanced countries and the increase in misallocation in Italian sectors. Once we account for the sectoral composition of Italian regions and firm size classes, the implied "frontier shocks" are the strongest for Northern regions and big firms, thus matching the relative increase in misallocation across geographical areas and firm sizes.

The analysis of firm characteristics associated with firms being inefficiently sized sheds additional light on the relation between exposure to frontier shocks and misallocation within industries. In particular, we look at corporate ownership and management, finance, workforce composition, internationalization and innovation. We find that firms more likely to be keeping up with the technological frontier are inefficiently small and thus under-resourced. These are the firms that employ a larger share of graduates and invest more in intangible assets. On the contrary, firms less likely to be keeping up are inefficiently large and thus over-resourced. These are the firms that have a large share of workers under a wage supplementation scheme, that are family managed, and that are financially constrained. We interpret this as evidence that rising within-industry misallocation is consistent with an increase in the volatility of idiosyncratic shocks to firms due to their heterogeneous ability to respond to sectoral "frontier shocks" in the presence of sluggish reallocation of resources.

A concern with our quantification exercise relates to measurement error in firms' revenues and inputs. As Bils et al. (2017) point out, mismeasurement is likely to distort the misallocation analysis as a firm's TFPR is higher when revenues are overstated and/or inputs are understated: if, for example, the extent of revenue overstatement (input understatement) systematically grows (falls) with firms' true revenues (inputs), the dispersion of measured TFPR is unequivocally biased upward. Bils et al. (2017) suggest to tackle this issue by exploiting the fact that measurement error introduces spurious correlation between firms' TFPR and input growth. When we implement their suggested correction for this possible bias, we find that the fraction of observed misallocation reflecting sheer mismeasurement amounts to around 45% on

[3] R&D intensity is measured as the share of R&D expenditure over value added at the sectoral level. Data are from the ANBERD database of the OECD. We exclude Italy from the sample and, following Griffith, Redding and Van Reenen (2004), the countries that we consider are Canada, Denmark, Finland, France, Germany, Japan, Netherlands, Norway, Sweden, United Kingdom, and United States. Results hold also when we take R&D intensity in the US only.

average  This fraction is, however, relatively constant over our sample period, implying that, although the level of misallocation is affected by measurement error, its change through time is mostly unaffected.

Another potential sticking point concerns our reading of what we find in the data. The very idea of Hsieh and Klenow (2009) of interpreting the entire observed dispersion of TFPR across firms as evidence of inefficiency is contentious. Asker, Collard-Wexler and De Loecker (2014) argue that, in the presence of adjustment costs in investment ("time-to-build"), idiosyncratic TFP shocks across firms naturally generate dispersion of the marginal revenue product of capital (MRPK). In this case, as long as adjustment costs are determined by technological factors, the dispersion of MRPK is an efficient outcome and thus the observed gaps ("wedges") in MRPK should not be taken as evidence of any misallocation. In this respect, Hsieh and Klenow (2009) neglect the distinction between technology-driven adjustment costs, such as the natural time needed to build a new plant, and wasteful frictions, such as the bureaucratic procedures of authorisation that may delay the construction and activation of a new plant.

To explore whether time to build hides behind our findings, we explore the stationarity of firm TFPR relative to industry average, which should converge towards one over time if the adjustment process after a TFP shock is the main driver of TFPR dispersion. We first check the variance ratio statistics (Cochrane, 1988; Engel, 2000) finding that the variation in relative TFPR across firms tends to stabilise in a time horizon of around fifteen years, which is too long to be consistent with a dominant adjustment cost story. We then run a series of unit root tests (Choi, 2001; Im, Pesaran and Shin, 2003). We find relative TFPR to be stationary and not mean reverting. This also lends support to the conclusion that increasing time-to-build cannot be the key driver of what we see in the data.

From a different angle, De Loecker and Goldberg (2014) and Haltiwanger (2016) argue that a reduction in the observed wedges does not necessarily imply more market efficiency. For example, if firms had the same TFP but different initial market power due to demand characteristics, convergence of market power to the top would reduce TFPR dispersion but could be hardly considered an improvement in efficiency. While we adopt the Hsieh and Klenow (2009) interpretation for ease of comparison with the bulk of the literature on misallocation, it should nonetheless be remembered that the changing wedges in marginal revenue products and TFPR we observe in the data could also be partially due to changing market power across firms.

Our work relates to a number of studies that have used the framework of Hsieh and Klenow

(2009) to measure the extent of misallocation in various countries, such as Bellone and Mallen-Pisano (2013), Bollard et al. (2013), Ziebarth (2013), Chen and Irarrazabal (2014), Crespo and Segura-Cayuela (2014), Dias et al. (2014), Garcia-Santana et al. (2016), and Gopinath et al. (2017). Our paper is also related to studies that have analysed more specifically the issue of the Italian productivity slowdown since the 1990s, such as Faini and Sapir (2005), Barba-Navaretti et al. (2010), Bugamelli et al. (2010), Bugamelli et al. (2012), Lusinyan e Muir (2013), Michelacci and Schivardi (2013), De Nardis (2014), Lippi and Schivardi (2014), Pellegrino and Zingales (2014), Bandiera et al. (2015), Calligaris (2015), Daveri and Parisi (2015), Linarello and Petrella (2016) and Calligaris et al. (2016).

The rest of the paper is organized as follows. Section 2 introduces the methodological approach. Section 3 presents the main features of the database. Section 4 reports our aggregate findings on productivity and misallocation. Section 5 estimates the impact of misallocation on aggregate TFP. Section 6 discusses the markers of misallocated firms. Section 7 concludes.

# 2 Measuring misallocation

We follow Hsieh and Klenow (2009; henceforth HK) in defining 'misallocation' as an inefficient allocation of productive factors (labor and capital) across firms with different TFP.[4] Inefficiency is defined with respect to the ideal allocation of factors that would result in a world of frictionless product and factor markets where consumers are free to spend their income on the firms quoting the lowest prices and owners of productive factors are free to supply the firms offering the highest remunerations. In this ideal allocation the value of the marginal product ('marginal revenue product'; henceforth MRP) of each factor is equalized across firms so that the factor's remuneration is the same for all firms. This is an equilibrium as consumers have no incentive to change their spending decision, firms have no incentive to change their production decisions and factor owners have no incentive to change the provision of their services. It is also a stable equilibrium as any exogenous shock creating gaps in a factor's MRP across firms would trigger a reallocation of that factor from low to high MRP firms until its remuneration is again equalized across all firms.

[4]The only quantitative results from Hsieh and Klenow (2009) we will use are those on the computation of TFPR and factors' marginal revenue products. As these follow standard textbook definitions, we provide here only a qualitative discussion of the logic of the HK approach, referring interested readers to the original paper for additional details.

Shocks that can create such gaps are idiosyncratic shocks that increase the TFP of some firms relative to others. As firms with higher MRPs after the shocks are able to offer higher factor remunerations at the pre-shocks equilibrium allocation, they have the opportunity to expand their operations by attracting additional factor services away from less productive firms until convergence in factors' MRPs restores the equalisation of factor remuneration across firms in the new post-shocks equilibrium. In this respect, observed gaps in factors' MRPs across firms reveal 'distorted' factor allocation across them as factors are inefficiently used. This inefficient allocation of resources is what HK call 'misallocation' and its extent can be measured by the width of the observed gaps ('wedges') in factors' MRPs between firms. It implies that, though offering higher remunerations, more productive firms are not able to attract the factors they would need to grow and thus remain inefficiently small. Vice versa, though offering lower remunerations, less productive firms are inefficiently large.

The dispersions of marginal revenue products map into the dispersion of 'revenue TFP' (TFPR). Under the HK assumptions more dispersion of TFPR is, in turn, associated with more inefficient allocation and lower welfare ('misallocation').[5] If we use $TFPR_{si}$ to denote the TFPR of firm $i$ in sector $s$ and $\overline{TFPR}_s$ to denote the sectoral average, then $TFPR_{si}/\overline{TFPR}_s > 1$ implies that the firm is inefficiently small and should be allocated more inputs in order to be able to increase its output and decrease its price until $TFPR_{si}/\overline{TFPR}_s = 1$. Conversely, $TFPR_{si}/\overline{TFPR}_s < 1$ implies that the firm is inefficiently large and should be allocated less inputs in order to be able to decrease its output and increase its price until $TFPR_{si}/\overline{TFPR}_s = 1$. The dispersion of $TFPR_{si}$ around $\overline{TFPR}_s$ has a direct impact on sectoral TFP as the latter can be expressed in terms of the ideal level of sectoral TFP that would be achieved under the efficient allocation of resources minus the observed variance of firm TFPR in the actual allocation.[6]

Accordingly, sectoral misallocation can be measured in terms of sectoral TFPR dispersion as

$$Var(TFPR_s) = \sum_{i=1}^{N_s} \frac{VA_{si}}{VA_s} \left( TFPR_{si} - \overline{TFPR}_s \right)^2$$

where $VA$ is value added and $N_s$ is the number of firms in sector $s$. Analogously, overall

[5] As discussed in the Introduction, this is not necessarily the case when markups vary across firms (Asker, Collard-Wexler, De Loecker, 2014), or firms incur adjustment costs in reacting to idiosyncratic shocks (De Loecker and Goldberg, 2014; Haltiwanger, 2016).

[6] For our purposes it is conceptually crucial to measure TFPR based on cost shares as in HK rather from the residual of a firm-level production function estimation as in the productivity literature in IO (Foster et al., 2017).

misallocation in the economy can be measured in terms of aggregate TFPR dispersion as

$$Var(TFPR) = \sum_{s=1}^{S} \frac{VA_s}{VA} \left( TFPR_s - \overline{TFPR} \right)^2 .$$

where $S$ is the number of sectors. On the othet hand, we are interested not only in understanding the extent to which aggregate dispersion is driven by variations between and within sectors but also between and within geographical areas or firm size groups. Using $g$ to denote an area/size group, $TFPR_{gsi}$ will refer to the TFPR of firm $i$ in sector $s$ and area/size group $g$ and $N_{gs}$ to the number of firms in that sector and group. Aggregate TFPR dispersion in the economy can then be decomposed into within-group and between-group components as

$$\begin{aligned} Var(TFPR) = & \underbrace{\sum_{g=1}^{G} \frac{VA_g}{VA} \underbrace{\sum_{s=1}^{S} \frac{VA_{gs}}{VA_g} \underbrace{\sum_{i=1}^{N_{gs}} \frac{VA_{gsi}}{VA_{gs}} (TFPR_{gsi} - \overline{TFPR}_{gs})^2}_{(TFPR)_{gs}}}_{(TFPR)_g}}_{\text{WITHIN-GROUP}} + \\ & + \underbrace{\sum_{g=1}^{G} \frac{VA_g}{VA} \sum_{s=1}^{S} \frac{VA_{gs}}{VA_g} (\overline{TFPR}_{gs} - \overline{TFPR})^2}_{\text{BETWEEN-GROUP}}, \end{aligned} \tag{1}$$

where $G$ is the number of area/size groups. In (1) 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:

$$Var(TFPR) = \sum_{s=1}^{S} \frac{VA_s}{VA} \sum_{i=1}^{N_s} \frac{VA_{si}}{VA_s} (TFPR_{si} - \overline{TFPR}_s)^2. \tag{2}$$

This is the expression we use to measure aggregate misallocation for the economy.[7]

# 3 Data description

We use two main databases. The first covers the universe of incorporated companies (CERVED) with information from firms' balance sheets that we use to compute aggregate misallocation.[8] This database accounts for 70% of manufacturing value added from national accounts and the growth rate follows very closely the national one. Then, in order to analyse the firm-level features of misallocation, we rely on a representative sample of firms with more detailed information on firms' characteristics that we use to analyse firm-level misallocation (INVIND). We group manufacturing firms into 3-digit sectors using the ATECO 2002 classification, which allows us to distinguish detailed categories such as 'machines for producing mechanic energy', 'machines for agriculture', 'tooling machines', 'machines for general use', etc.[9]

In order to compute firm-level measures of TFPR as in HK, we need measures of output as well as of labor and capital inputs. We measure the labor input using the cost of labor and the capital stock using the book value of fixed capital net of depreciation, while we take firms' value added as a measure of the total revenue of the model as this does not consider intermediate inputs. All 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 labor or capital stock. We are left with a pooled sample of 1,740,000 firm-year observations for manufacturing over the period 1993–2013. The average number of observations per firm is 12. To compute firm-level TFPR we also need capital and labor shares at industry level. We compute the labor share by taking the industry mean of labor expenditure on value added measured at the firm level. We then set the capital share as one minus the computed labor share.

The second dataset is the main one we use for the analysis of firm-level misallocation is the Bank of Italy's annual "Survey of Industrial and Service Firms" (INVIND). We focus on

[7] 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 misallocation in larger firms.

[8] This database includes also micro enterprises with less than 10 employees.

[9] The total number of 3-digit sectors is 91. We also use a more aggregate classification at 2-digit and results hold. We exclude 'coke and petroleum products' and 'other manufacturing n.e.c.' from manufacturing. These sectors have peculiar behaviors, whose study lies outside the scope of this paper.

the open panel of representative Italian manufacturing firms with at least 50 employees. The survey contains detailed information on firm revenues, ownership, production factors, year of creation and number of employees since 1984. Additional information is drawn from "Centrale dei Bilanci" (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 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 divide the INVIND panel 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.[10]

Table 1 presents sectoral descriptive statistics from CERVED at 2-digits for average real value added, capital stock and cost of labor over the period of observation, both in absolute terms and in percentages with respect to the total.[11] The sectors '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 Euro in 'wood' to around 4.4m Euro in 'vehicles'. Variation in the average capital stock is sizable, ranging from around 1m Euro in 'textile and leather' to around 4.9m Euro in 'vehicles'. The cost of labor varies notably too, ranging between 0.5m Euro in 'wood' and 3.2m Euro in 'vehicles'.

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, Center, South and Islands.[12] We also divide the firms in the dataset into four groups according to firm size: 'micro', 'small', 'medium' and 'big'.[13] We report the summary statistics of the main variables divided by geographic area and

[10]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.

[11]We present the descriptive statistics for 2-digit sectors for ease of exposition, but the quantitative analysis is at 3-digit level.

[12]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; "Center" includes Lazio, Marche, Tuscany and Umbria; "South and Islands" includes Abruzzi, Basilicata, Calabria, Campania, Molise, Apulia, Sicily and Sardinia.

[13]We use the European Commission classification of firms according to their turnover. "Micro" are firms

size, both in absolute terms and percentages, in Table 2. Around two thirds of manufacturing firms are located in the Northern areas of the country. In these areas, manufacturing firms' value added, capital stock and cost of labor are higher than the average. Looking at firm size, more than 88% of manufacturing firms are 'micro' or 'small', while only 2.2% 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 Table 3 we present the summary statistics of firms clustered by sector-area and by sector-size. For most of the industries 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 concentrated in 'chemicals', 'food and tobacco' and 'vehicles industries'. Table 4 shows the relevance of firm size by geographic area. In the Northwest more than half of the value added in manufacturing comes from 'big' firms. Finally, Table 5 looks 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.

# 4 The patterns of aggregate misallocation

We first investigate the misallocation pattern in the manufacturing sector by computing the TFPR variance as described in Equation (2). The output of this exercise (in logs) is depicted in Figure 4, where we also report the average TFPR based on the same weighting scheme used for the variance. The figure shows that a large 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 with a drop of about -10.5%. Moreover, aggregate misallocation (as measured by the variance of TFPR) steadily and steeply increased between 1995 and 2009 and slightly decreased after its peak in 2009. However, aggregate misallocation increased by almost 69% between 1995 and 2013 with most of the increase taking place in the first decade.[14]

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.

[14] In order to have some insight about the trend of misallocation before 1993, we also use the INVIND database which starts in 1987–2011, but accounts for a more limited sample of firms above 50 employees. This longer database confirms that the rise of misallocation is a phenomenon that started in the mid-'90s and it was not a previously undergoing trend. In INVIND misallocation has a similar trend with respect to CERVED, although the raise starts a couple of years later in 1997 and is quantitatively stronger.

To better understand the firm-level dynamics behind the aggregate patterns displayed in Figure 4, we compare the firm-level distributions of TFPR in 1995 with that in 2013. This comparison, reported in Figure 5, 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. When the comparison is made, instead, between 2007 and 2013 (see Figure 6), the difference in the share of low productivity firms is much less pronounced. In fact, recalling what we have seen in Figure 4, 2007 represents a critical year for average TFPR but not for its variance as this grows until 2009. Figure 7 shows the evolution of aggregate misallocation, captured by the variance of TFPR over the full sample of firms per-year. We can see that misallocation raised sharply from 1995 to 2009, when it started a process of slow reversion. This suggests that the aggregate decrease in TFPR occurred in the last years compounds a long-run 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 (1) 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 8 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 Figures 9 and 10). 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. We wonder whether this pattern is driven by firms' entry and exit, so in Figure 11 we disentangle the pattern of within misallocation for firms that are always in our data set (balanced panel) and for the full sample that accounts also for entry and exit. Even if the level of misallocation is lower for the balanced panel, the trend of misallocation is qualitatively very similar in both samples. However, from a quantitative point of view, after 1995 misallocation increases more significantly for the balanced panel than for the full sample; this implies that if anything, the process of entry and exit is dampening the raise of misallocation, which is consistent with the findings of Linarello and Petrella (2016).

As shown by Hsieh and Klenow (2009), TFPR can be expressed as a geometric average of the marginal product of capital (MRPK) and labor (MRPL). Hence the dispersion of TFPR and our measure of misallocation are going to be proportional to MRPK and MRPL. Figure 12 looks at the patterns of MRPK and MRPL dispersion and it shows that capital is the factor of production that experiences the sharpest increase in its marginal product's dispersion since the mid-1990s, although this pattern has flattened out since the global financial crisis. To some extent the dispersion of MRPL increased too, but it does not show a striking trend.[15] This seems to suggest that the capital market is a very important source of misallocation in Italy.

A first source of concern is that capital may be subject to adjustment costs ("time-to-build") that can lead to a higher dispersion simply due to a technology-driven adjustment process, which would be an efficient outcome. In order to explore whether time to build can be a driver of our findings, we explore the stationarity of our firm-level misallocation measure $\ln\left(TFPR_{is}/\overline{TFPR}_s\right)$. The idea is that this ratio should converge towards one over time if the adjustment process after a TFP shock is the main driver of TFPR dispersion. Firstly, we consider the variance ratio statistics (Cochrane, 1988; Engel, 2000), defined as $Var(X_{t+k} - X_t)/Var(X_{t+1} - X_t)$, where $X$ denotes the relative log-TFPR averaged across sectors. For stationary series, the variance ratio approaches a limit. The output of this exercise is reported in Figure 13. The pattern suggests that the variation in firm-level misallocation tends to stabilise in a time horizon of around fifteen years, which is a too long period for being consistent with an adjustment cost story. We also run a series of unit root tests to investigate the mean reversion property of this ratio. Table 6 reports the the Im-Pesaran-Shin (Im et al., 2003) and the Fisher-type (Choi, 2001) tests for the presence of unit root. The null hypothesis is rejected in all cases, entailing the series to be stationary and firms' relative TFPR not being mean reverting.[16]

Another source of concern is related to measurement error in firms' revenues and inputs. As Bils et al. (2017) point out, this is likely to distort the misallocation analysis. In fact, as evident in Equation (**??**), a firm's TFPR is higher when revenues are overstated and/or inputs are understated: if, for example, the extent of revenue overstatement (input understatement) systematically grows (shrinks) with firms' true revenues (inputs), the dispersion of measured TFPR is unequivocally biased upward. Bils et al. (2017) suggest to tackle this issue by exploiting the intuition that, while without measurement error revenue growth solely depends on TFPR and input growth, the presence of measurement error introduces spurious correlation between firms' TFPR and input growth. Their suggested methodology allows us to evaluate the fraction of observed TFPR dispersion reflecting the actual presence of distortions. In our estimation based on Bils et al. (2017), this fraction amounts to 0.54, suggesting that more than fifty per cent of our measured misallocation is not driven by measurement error and can

[15] If we look at the change of the distribution of MRPK and MRPL between 1995 and 2013, we see that MRPK experienced a fattening of both tails and it kept a very similar mean; whereas, the distribution of MRPL experienced a clear leftward shift with a significant decrease of the mean. Results are available upon request.

[16] Analogous conclusions can be reached by carrying out the tests on the log-TFPR series.

thus be regarded as true misallocation.[17] More interesting for us, this fraction is relatively constant over time (if anything slightly increasing) over our sample period, suggesting that, although the level of misallocation has to be taken with caution, our discussion about the trend in misallocation is mostly unaffected by measurement error issues.

# 5 Insights from regional and size patterns

To better understand the geographical distribution of the aggregate pattern, we report the evolution of misallocation within macro-regions – i.e. the term $Var(TFPR)_g$ – in Figure 14.[18] We note that i) TFPR in the South is on average always lower than in the rest of Italy; ii) misallocation in the Northwest and the Center grew at a considerably higher rate compared to the other areas; and iii) 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 at the end of the period.[19]. The same analysis can be carried out in terms of firm size categories (see Figure 15) and an important highlight is that misallocation grew in all groups but it affected more heavily the bigger firms.

These results are puzzling because firms in the Northwest region and bigger firms are traditionally more advanced and closer to the technological frontier. However, this reveals important insights on the overall dynamics of misallocation. A possible explanation for the raise of misallocation is that, for given level of frictions, the shocks hitting firms have become more dispersed; this might be the result of a fast changing technological frontier (due for instance to the IT revolution). To explore this possibility we build on Griffith, Redding and Van Reenen (2004) and look at the average change of R&D intensity between 1987-1993 and 1994-2007 in advanced countries as a proxy of shocks to the technology frontier by sector. We measure R&D intensity as the share of R&D expenditure over value added at the sectoral level. The countries we consider are Canada, Denmark, Finland, France, Germany, Japan, Netherlands, Norway, Sweden, United Kingdom, and United States. Results hold also if we take R&D intensity in the United States only. Data are from the ANBERD database of the OECD.[20] Figure 16 shows

[17] Bils et al. (2017) find that this ratio is 0.23 for the US,

[18] The underlying is assumption is that within sector misallocation should be less problematic within macro regions than at the national level, as moving factors should have lower adjustments costs. This exercise allows us to understand the geographical distribution of misallocation.

[19] For ease of exposition we do not show the graphs of group-specific distributions, but they support this finding.

[20] This is measured as the share of R&D expenditure over value added at the sectoral level. Data are from the ANBERD database of the OECD.

that there is a positive and significant correlation between the increase in the R&D ratio in advanced countries and the increase in misallocation, such that an increase in R&D intensity by one standard deviation is associated with an increase in misallocation of 0.14 standard deviations (statistically significant at the 1% level). Moreover, once we account for the sectoral composition of regions (or firm size), it turns out that the implied "frontier shock" is higher in the Northwest (4.6%) and the Center (5.1%) and lower in the Northeast (3.1%) and the South (2.2%). This follows the ranking of the increase in misallocation by region highlighted above. The same result applies if we look at the implied shock by firm size.

An implication of this result is that firms in the upper part of the productivity distribution should be those that contribute more to the overall increase in misallocation. This is indeed the case, as shown by the contribution of each firm quartile to the overall increase of misallocation in our sample.[21] As we can see the top quartile is the one that contributes the most the rise of aggregate misallocation. The productivity thresholds of firms entry and exit do not exhibit a particular trend, but they are subject to standard year-to-year oscillation. On average, firms that enter a market are 20% more productive than the average firm in that sector, whereas firms that exit the market are 40% less productive than the average firm (Figure 17). This suggests that movements of the cut-off for firms entry and exit are unlikely to drive the rise of misallocation, which is actually the result of increased dispersion in the top quartile of the distribution.

# 6 The impact of misallocation on aggregate TFP

The overarching message sent by the battery of figures and tables presented in the previous section 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. First, in each year $t$ from 1995 to 2013 we evaluate the increase in aggregate output that could be achieved by completely eliminating

[21] The standard deviation of log-TFPR is about 0.4 for firms in the top quartile and it is increasing over time. For firms in the 2nd and 3rd quartile it is slightly increasing after the crisis, but its level is low (0.1). Finally for firms in the bottom quartile, the dispersion if higher (0.6), but it is stable up to the crisis and then decreases. The top and the bottom 1% of the distribution are trimmed from our sample

misallocation (i.e. by reallocating productive factors so as to equalize their remunerations across all firms). In any given year, within the HK framework that 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. We can, therefore, evaluate the percentage increase in aggregate productivity that could have been achieved in any year $t$ by completely eliminating misallocation as:

$$\% \text{ Gain}_{t/within} = \left(\frac{Y_t}{Y_t^*}\right)^{-1} - 1 \tag{3}$$

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:

$$\% \text{ Gain}_{t/95} = \left(\frac{Y_t/Y_t^*}{Y_{95}/Y_{95}^*}\right)^{-1} - 1 \tag{4}$$

When applied to our data, equation (4) implies that, if misallocation had remained at its 1995 level, in 2013 aggregate TFP would have been 18% higher than its actual level. Moreover, the effect of misallocation on TFP peaked in the aftermath of the global financial crisis leading to a 23% foregone productivity gain, but weakened slightly after the Euro-debt crisis. So, even after netting out the spike in the productivity penalty of misallocation associated with the crisis, the adverse effects of misallocation on Italian productivity remain sizeable.[22]

From a size class and geographical perspective, the observed patterns are mainly driven by misallocation across big firms and by firms in the Northwest. In fact, 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.

# 7 Productivity, misallocation, and firm characteristics

[22]The quantitative results of this exercise are sensitive to the values chosen for the elasticity of substitution $\sigma$ between products sold by firms. In the baseline we set $\sigma$ equal to 3 as in Hsieh and Klenow (2009). This is a conservative value also in light of Broda and Weinstein (2006) who find that for SITC-3 digits the average value of the elasticity of substitution after 1990 is about 4. Higher value of the elasticity deliver stronger gains. The gain would be to 12% with $\sigma$ equal to 2, and 19% with $\sigma$ equal to 4.

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 highlighted that the main source of misallocation comes from a *within* industry component, especially in sectors where the world technological frontier has expanded faster. Relative specialization in those sectors explains the patterns of misallocation across geographical areas and firm size classes: accounting for the sectoral composition of Italian regions and firm size classes implies that "frontier shocks" are the strongest for Northern regions and big firms. This matches the relative increase in misallocation across geographical areas and firm sizes.

To shed additional light on the relation between exposure to frontier shocks and misallocation within industries, we now investigate which firm characteristics ("markers") are associated with firms being inefficiently sized. We look in particular at corporate ownership and management, finance, workforce composition, internationalization and innovation. In doing so, we rely on reduced form regressions at the firm level. The econometric specifications that we implement allow us to identify correlations, but not causation, of key firm characteristics with a firm's TFPR relative to its sectoral average. In particular, we run the following regression:

$$\ln \frac{TFPR_{ist}}{\overline{TFPR}_{st}} = \beta_0 + \beta_1 X_{ist} + \delta_t + \gamma_s + \varepsilon_{ist}, \tag{5}$$

where $i$, $s$ and $t$ refer to firm, sector and year respectively; $X_{ist}$ is the marker (or vector of markers) we want to analyze[23]; $\delta_t$ is a year dummy that captures common shocks to all firms in a given year; $\gamma_s$ is a sector fixed effects controlling for time-invariant sector characteristics that can influence the effect of the marker on misallocation; $\varepsilon_{ist}$ is the error term. This regression relates the log-ratio of a firm's TFPR to the average TFPR of its sector with the chosen marker (or vector of markers). Thus, if our estimates point to $\beta_1 > (<)0$, we can conclude that firms with larger $X_{ist}$ are characterized by higher (lower) relative TFPR.

In equation (5) the main variable of interest is marker $X_{ist}$. Its coefficient $\beta_1$ could be zero in two different scenarios. First, it would be zero if the aggregate allocation of resources were efficient, as $TFPR_{is}/\overline{TFPR}_s = 1$ would hold for all firms. As we have already seen, this is not the case in our data. Second, even if the allocation of resources were not efficient, $\beta_1$ would be zero if $X_{ist}$ did not directly affect relative TFPR. As in the end only the second scenario is relevant, we can conclude that a non-zero estimate for $\beta_1$ reveals that the marker increases misallocation.[24] In particular, larger (smaller) values of the marker lead to more misallocation

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

[24] In Calligaris et al. (2016) we show that a marker could still be linked to misallocation even if $\beta_1$ were zero, if it is related to the dispersion of the residuals of equation (5). We have checked whether this is the case and found no evidence, which implies that $\beta_1 \neq 0$ is the necessary and sufficient condition for a marker to induce

for positive (negative) estimated $\beta_1$. In other words, if the estimated $\beta_1$ is positive, firms with relatively large $X_{ist}$ are inefficiently small; vice versa, if the estimated $\beta_1$ is negative, firms with relatively large $X_{sit}$ are inefficiently large.

Our benchmark specification is based on standard pooled OLS regression, always including sector and year dummies.[25] We have also run a number of different specifications, including additional controls, lagged regressors, and firm effects. Moreover, we have run these regressions by geographic area, firm size, and low- vs. high-tech sectors.[26] 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 with our aggregate sample.

For each marker, we run regression (5). Moreover, following HK, we infer the firm-level output and capital distortions ("wedges") and we use them as alternative dependent variables in (5).[27] There is a higher capital distortion when the ratio of labor compensation to the capital stock is high with respect to the one we would expect from the industry output elasticities relative to capital and labor. In order to interpret the regressions, it is important to keep in mind that capital and labor distortions are each other's mirror image, as a high labor distortion would show up as a low capital distortion. This implies that a positive and significant coefficient of the capital wedge on marker $X_{ist}$, reveals that $X$ is associated to higher capital distortion relative to labor (without implying that labor distortion is zero) so that capital compensation is too low relative to labor compensation, given the output elasticities of these two factors. A negative and significant coefficient means instead that firms characterised by marker $X$ tend to suffer from high labor distortion relative to capital, so that labor compensations are too low relative to capital. Similarly, the output wedge is large when the labor share is small given the industry elasticity of output with respect to labor.

Therefore, we run regression (5) using as dependent variable not only relative TFPR, but also the *output wedge* and the capital wedge. The independent variables ("markers") we use refer to a series of usual suspects that include various proxies for ownership, finance, labor force,

misallocation. We omit these results for parsimony but they are available from the authors on request.

[25]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 relative TFPR are related to given firm characteristics. We are less concerned with the effects of the within-firm variation in those characteristics across time.

[26]We use the OECD classification of manufacturing industries according to their global technological intensity, based on R&D expenditures with respect to value added.

[27]Hsieh and Klenow (2009) show that for firm $i$ in sector $s$ the capital and output distortions ('wedges') can be computed as $\tau_{Kis} = \alpha_s wL_{is}/\left[(1-\alpha_s)\ \ RK_{is}\right] - 1$ and $\tau_{Yis} = 1 - \sigma wL_{is}\ /\left[(1-\sigma)(1-\alpha_s)P_{is}Y_{is}\right]$.respectively, where $w$ is the wage, $R$ is the rental rate of capital, $P_{is}$ is price of output and $\alpha_s$ is the capital share of firm expenditures.

innovation, foreign exposure, and cronysm. The variables are listed in Table 7 and we discuss them in the corresponding subsections.[28]

### 7.1 Corporate ownership/control and governance

We construct an indicator 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 and thus to be inefficiently over-resourced with respect to 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 (Table 8).

Specifically, we find that firms controlled by either a financial institution, a group, or a foreign company have between 3% and 8% higher relative TFPR than family controlled firms (column 1). Differently, we do not find any statistical difference of relative TFPR between public and family controlled firms. This implies that for instance foreign controlled firms are too small and should be allocated more resources than family owned firms. Column 2 of Table 8 confirms this finding by showing that these types of firms suffer from higher output distortion with respect to family owned firms. Moreover, column 3 highlights that these firms specifically suffer from an additional distortion in terms of capital-labor ratio. In particular the negative coefficient implies that they suffer more strongly of labor distortions and they should increase the labor compensation with respect to capital, i.e. absorb a higher share of workers.

Reading these fundings through the lenses of the HK framework, they imply that aggregate productivity would likely increase if family firms and government controlled 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.[29]

[28] In order to check if our results are driven by the financial crisis, we run all regressions also up to 2008 only. Results are very similar qualitatively, quantitatively, and in terms of statistical significance. The only difference is for the regression on delocalisation, whose coefficient turns to be statistically significant, but very similar in magnitude.

[29] Although the database is not representative in terms of young firms, we looked at the relationship between age and relative TFPR. We did not find any significant relationship when only linear terms are considered.

## 7.2 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 constraint*

We define credit constrained firms as those that declared that they would have liked a higher level of debt (Table 9 ). We also use an alternative measure of credit constraint based on the willingness of having more credit even at higher interest rates, which delivers the same results.[30] Both measures enter the regression with a lag in order to mitigate endogeneity. In this way we capture how being credit constrained at time $t-1$ is correlated to TFPR and misallocation at time t.

In particular, we find that firms that are credit constrained at time $t-1$ tend to have lower relative TFPR at time $t$.[31] This implies that credit constrained firms are absorbing too many resources and should downsize, so in this sense the "right" firms seem to be financially constrained. Moreover, Column 2 shows that credit constrained firms are characterized by a negative and significant output distortion; this is equivalent to saying that these firms are actually receiving an implicit subsidy, so it would be more efficient if they exited the market. Finally, in credit-constrained firms the capital-labor ratio is not significantly distorted.

*b. Equity*

We look at the relation of firms' relative TFPR and distortions with the timing of their equity emissions. In particular, we look at the correlation between relative TFPR at time $t$ and equity emissions at time $t-1$, $t$, and $t+1$. In Table 10 we report results for time $t$ only, but there is virtually no difference with the other timings. We find that firms that have lower relative TFPR in a given year tend to issue more equity (either in the same year, the year after or the one before). This may suggest that equity issuance may be a relevant source of funding

Things seem to change substantially when we allow for a squared term. In that case, our regression results suggest that the relation between relative TFPR and age are U-shaped. Unfortunately, the nature of our database prevents us from performing a robust analysis of other aspects of governance.

[30] Results available upon request

[31] This effect is particularly pervasive in low-tech industries.

when firms are hit by a negative productivity shock, but at the same time it may also mean that equity buyers are not allocating capital efficiently as these firms are too large given the productivity they have and should absorb fewer resources.

*c. Euro effect*

An important issue about the effect of the Euro on productivity and misallocation relates to the interest rate convergence that characterised peripheral countries thanks to the common currency. The traditional argument, as in Gopinath et al. (2015) and Benigno and Fornaro (2014), is that the availability of cheaper funds led to a misallocation of capital towards low productive firms that rather than exiting the market increased their leverage. We do not provide a formal test of this hypothesis, but we look for observationally consistent facts. For instance, if this were the case, we should observe a significant increase in leverage for firms with lower relative TFPR after the introduction of the Euro.[32]

In Table 11 we can see that high leverage indeed characterizes lower TPFR firms. This relation becomes significantly stronger after national exchange rate parities were fixed to the Euro in 1999. This is consistent with the fact that the interest rate convergence that followed the introduction of the Euro led to a misallocation of credit to less productive firms that are disproportionately large given their productivity. Not surprisingly, we also observe that more leveraged firms are characterised by a misallocation of the capital-labor ratio as the share of capital is too large. However, this effect did not increase significantly after 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". In Table 12 we observe that relational banking is associate with lower relative TFPR, so that the firms that engage in relational banking are larger than what they should optimally be. 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.

[32]Leverage is defined as debt over total assets. By looking at this variable we check if firms' debt increased disproportionately with respect to total assets during the period of cheap credit that followed the introduction of the Euro.

## 7.3 Workforce composition

The functioning of the labor market is one of the structural features of the Italian economy that has been more extensively reformed since the 1990s.[33] 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 labor. In this perspective, by introducing more flexibility in the labor market, the reforms that the Italian economy underwent in the 1990s should have induced a better allocation of labor. In this section we analyse the relation between firms' workforce and misallocation from different perspectives. In particular we look at the Italian Wage Supplementation Scheme, which is the main instrument of labor hoarding that firms use. We also look at the shares of temporary and foreign workers that firms hire; and we analyse the role of skill intensity among both blue- and white-collars.

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

Firstly, we look at how intensively firms resorted to the Wage Supplementation Scheme ("Cassa Integrazione Guadagni" - CIG) (variable "CIG_share" - hours of CIG over total hours worked). When firms are in distress, they can use this scheme to hoard labor, so that workers suspend temporarily their job and receive a public benefit. The key characteristic of this scheme is that it protects not only the worker, but also the specific job match between worker and firm. This scheme can have either a positive or negative effect on misallocation, because it facilitates labor hoarding guaranteeing to firms and workers a useful buffer in downturns, but at the same time it might end up protecting a job match that would be more efficient to break. Our methodology allows us to understand in which direction productivity and misallocation are affected by this specific policy tool.

Table 13 shows that the firms that use the CIG more intensively are largely over-resourced and their size should be smaller than what it currently is. There is also a positive and significant correlation with output distortion implying that these firms are receiving an implicit subsidy, which is indeed the case. Finally, our results show that, as it might be expected, firms using the CIG suffer from a larger labor distortion relative to capital.

[33] Two major reforms of the labor market took place: the Treu Law and the Biagi Law. The former was introduced in 1997 (law 196/97) with the aim of making the Italian labor 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 (jobcenters were privatized and decentralized). 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 labor costs, the CIG works against the reduction of the amount of labor used by low productivity firms, thereby fostering misallocation especially on the labor side.[34]

*b. Temporary workers*

Table 14 and 15 analyze the association of temporary and foreign workers with our measures of misallocation. 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 a given year. Our sample begins from 1999 for temporary workers and from 2003 for foreign workers.

We find that firms that use a higher share of temporary workers have higher relative TFPR, so they are inefficiently under-resourced and their size should be larger than what it actually is.[35] At the same time, these firms suffer from a significantly stronger distortion on capital inputs relative to labor (while we do not find a significant association with output distortions). A possible explanation could be that more productive firms find stronger distortions in the capital market and, given the complementarity between capital and labor, they tend to respond favoring a higher share of temporary and more flexible workers.

As for foreign workers, we do not find that this marker is significantly associated with misallocation. The coefficient on relative productivity in Table 15 is not statistically different from zero. However, we find some positive and significant correlation with the capital distortion, which signals that firms relying more on foreign workers tend to suffer from stronger capital distortions relative to labor. Nevertheless, this does not result into broader misallocation.

*c. Skill intensity*

[34] To go more into the details of these relationships, we build the variable "YearSwitch_CI", 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 using CIG is associated with lower relative TFPR.

[35] These findings support the idea that higher TFPR 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 productivity measure and the different time period (2001–2003 in their case) may explain the difference.

We look at two measures of skill-intensity: the share of white collars holding a degree (Table 16) and the share of blue collars holding a degree (Table 17). We are able to observe these two variables only in 2010 and 2011, thereby we run a cross-section regression for the two years together.[36]

Firms with a higher share of high skilled workers among white collars have higher TFPR on average, hence they should be allocated more inputs to increase their size.[37] These firms suffer also from a large output distortion and from a relatively larger distortion for labor relative to capital, where the labor distortion could be related to both skilled and unskilled labor. However, if we look at the share of skilled workers among blue collars, we do not find any significant association with misallocation or output distortion, but only a marginally significant association with stronger distortions in labor input relative to capital.

## 7.4 Internationalization

We focus on two main dimensions of firms' internationalisation, delocalisation and foreign direct investment. In Table 18 we look at the correlation between misallocation and wether firms delocalized part of their production process, whereas in Table 19 we look at the correlation between FDI and misallocation. In both cases we do not find evidence of resource misallocation for firms engaging with these types of international activities with respect to those that do not. This does not imply, however, that within those groups there is nomisallocation, but given the low number of observations, we do not have enough power to analyse this aspect.

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 some evidence of a positive relationship with relative TFPR.[38]

[36] We also run the regressions for the two years separately and the results are similar.

[37] This result is particularly strong for big firms and for low-tech firms.

[38] 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.

## 7.5 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 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 dynamic context with adjustment costs for capital, 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.

Table 20 shows that a higher share of intangible assets is associated with higher relative TFPR.[39] This implies that firms that invest more in innovation tend to be under-resourced and should have larger size. Moreover, these firms tend to suffer from a larger distortion in the allocation of capital relative to labor. This is consistent with the view that credit provision to firms that innovate may play a key role in reducing misallocation.

While our database does not allow us to address innovation using alternative and more focused measures, this evidence is in line with recent studies on the productivity effects of intangible assets, such as Battisti, Belloc and Del Gatto (2015), who find that these assets are positively associated with both TFP and technology adoption, and suggest a key role of firms' innovation choices as markers of misallocation.

## 7.6 Combining markers: a short horse-race

We complete our investigation of the firm markers associated with relative productivity and misallocation by running the regressions on different subsets of independent variables entered simultaneously. This should give some guidance on the relative importance of these variables. More specifically, we look at the share of graduates among white collars, innovation, family ownership, reliance on the wage supplementation scheme (CIG), and the share of temporary employment. We focus on variables that are available over subsequent years and are consistently part of our panel and not just of some year-specific cross-section. There might be some concern of collinearity between the variables we consider. Hence, Table 21 looks at the cross-correlations

[39]We also enter the regressor with a lag and the results are very similar.

among these variables showing that correlations are never above 0.27 (in absolute value), which reveals a low degree of collinearity.

Table 22 summarises the main results. As some of the variables are dummies (i.e. "family ownership"), whereas the others are continuous variables, comparing the magnitude of the coefficients is difficult. Hence, we focus more on their relative statistical significance. The results show that the share of graduates among white collars and the use of the wage supplementation scheme (CIG) are the statistically most significant markers of misallocation, although of opposite sign (firms with a high share of graduates are too small and those using the CIG are too large). Family ownership and, to some extent, innovation are also two significant markers with opposite signs. However, the share of temporary workers loses significance with respect to the results presented in Table 14. In terms of output distortion, the most significant markers are again the share of graduates among white collars, which has a positive and significant coefficient (implying an implicit tax), and the use of CIG, which has a negative and significant coefficient (implying an implicit subsidy). Finally, in terms of the capital-labor ratio, innovative and family-owned firms are the ones with the strongest distortion in terms of capital, whereas firms with a higher share of white-collar graduates confirm to suffer from a significant distortion in terms of labor.

These findings, in particular the strong significance of the share of graduates among white collars and the CIG, can be interpreted as two sides of the same coin. The share of high-skill employees among white collars drives firm technological and organizational innovation, which in turn increases firm productivity relative to competitors. In an efficient process of creative destruction labor 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).

More generally, our findings on the importance of the different markers suggest that firms more likely to keep up with the technological frontier are inefficiently small and thus under-resourced. These are the firms that employ a larger share of graduates and invest more in intangible assets. On the contrary, firms less likely to keep up are inefficiently large and thus over-resourced. These are the firms that have a large share of workers under a wage supplementation scheme, that are family managed, and that are financially constrained. We interpret this pattern as evidence that rising within-industry misallocation is consistent with an increase in the volatility of idiosyncratic shocks to firms due to their heterogeneous ability to respond to sectoral "frontier shocks" in the presence of sluggish reallocation of resources.

# 8 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. We have shown that the increase in misallocation has mainly risen within than between sectors, increasing more witihin those in which the world technological frontier has expanded faster.

We have highlighted that rising misallocation has hit firm categories that traditionally are the spearhead of the Italian economy, in particular firms in the Northwest and big firms. We have argued that relative specialization in sectors where the world technological frontier has expanded faster helps explaining the patterns of misallocation across geographical areas and firm size classes. The broader lesson is that part of the explanation of the recent productivity puzzle in other advanced economies may lie in a generalised growing difficulty of reallocating resources between firms in sectors where technology has been changing faster rather than between sectors with different speeds of technological change.

We have shed additional light on the relation between exposure to "frontier shocks" and misallocation within industries by investigating which firm characteristics are associated with firms being inefficiently sized. We found evidence that inefficiently small under-resourced firms are those that, by employing a larger share of graduates and investing more in intangible assets, are more likely to be keeping up with the technological frontier. Vice versa, inefficiently over-resourced firms are those that, being featuring larger shares of workers under wage supplementation, more family managers and stricter financial constraints, are more likely to be falling behind the technological frontier. We have interpreted this pattern as evidence consistent with rising within-industry misallocation being associated with increasing volatility of idiosyncratic shocks to firms due to their heterogeneous ability to respond to sectoral "frontier shocks" in the presence of sluggish reallocation of resources.

Our findings provide the ground for a policy-oriented discussion, to which we now turn.

The main policy implications we highlight are the following:

- **"Within-misallocation" matters more than "between-misallocation"**: This implies that, in order to raise productivity, rather than trying to switch resources between sectors, geographical areas and firm size classes, policy intervention should aim at allocating capital and labor to the best performing firms within these categories. Policy intervention should therefore focus less on moving capital and labor 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, higher benefits would be reaped by moving the factors of production to the most productive firms within depressed geographical areas rather than moving them to more vibrant areas. 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 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/regions'.

- **There are a "North issue" as well as a "Large firm 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. These trends 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 labor market regulation, antitrust rules 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 increase in the share of firms that are inefficiently over-resourced. 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 specialized 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 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 less misallocation of workers and higher productivity. This is the direction in which recent reforms included in the Italian "Jobs Act" seem to be going.

- **Investments in intangible assets are important**: Our results show that firms with a higher investment share in intangible fixed assets (such as R&D, branding, and marketing) are more likely to be inefficiently under-resourced. Public support to firms engaging this type of investments can provide important incentives towards such productivity-enhancing activities; the recent Italian public program called "Industry 4.0" goes in that direction. Another example of reforms that could help along this dimension is the development of a non-banking component of the financial markets. In fact, venture capital and private equity could promote the access to credit by highly innovative, risky firms that would be otherwise credit constrained.

- **Graduates play a crucial role among white collars**: Our results show that firms with a higher number of graduates among their white-collars are inefficiently under-resourced. Italy has a lower share of graduates than other European countries. Pro-active policies that encourage more tertiary education are warranted. 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.

Beyond Italian specificities, several of these implications may apply more broadly to other advanced economies facing their own "productivity puzzles".

# 9 Tables

Table 1: **Summary statistics for manufacturing.**

| Manufacturing | Value Added | Capital | Cost of labor | Obs. |
|---|---|---|---|---|
| Textile and leather | 1,265 | 969 | 802 | 249,000 |
| | 10.92% | 8.86% | 10.91% | 16% |
| Paper | 1,342 | 1,410 | 834 | 127,000 |
| | 5.93% | 6.6% | 5.81% | 8.2% |
| Chemicals | 2,990 | 3,138 | 1,769 | 138,000 |
| | 14.36% | 15.96% | 13.38% | 8.9% |
| Minerals | 1,790 | 2,451 | 1,075 | 96,000 |
| | 5.97% | 8.65% | 5.65% | 6.2% |
| Metals | 1,426 | 1,436 | 909 | 319,000 |
| | 15.81% | 16.86% | 15.88% | 20.5% |
| Machinery | 2,092 | 1,276 | 1,398 | 390,000 |
| | 28.3% | 18.29% | 29.79% | 25.1% |
| Vehicles | 4,405 | 4,884 | 3,177 | 51,800 |
| | 7.93% | 9.31% | 9.01% | 3.3% |
| Food + tobacco | 1,994 | 2,693 | 1,102 | 137,000 |
| | 9.48% | 13.56% | 8.25% | 8.8% |
| Wood | 807 | 1,109 | 520 | 46,800 |
| | 1.31% | 1.91% | 1.33% | 3% |

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

Table 2: **Summary statistics for manufacturing, by geographic area and by size.**

| | **Manufacturing** | **Value Added** | **Capital** | **Cost of labor** | **Obs.** |
|---|---|---|---|---|---|
| **By geographic area** | Northwest | 2,438 | 2,175 | 1,559 | 592,000 |
| | | 50.1% | 47.35% | 50.49% | 38.1% |
| | Northeast | 1,921 | 1,689 | 1,196 | 416,000 |
| | | 27.71% | 25.81% | 27.19% | 26.8% |
| | Center | 1,403 | 1,222 | 894 | 294,000 |
| | | 14.3% | 13.2% | 14.36% | 18.9% |
| | South and Islands | 896 | 1,462 | 574 | 253,000 |
| | | 7.86% | 13.6% | 7.93% | 16.3% |
| **By size** | Micro | 267 | 263 | 193 | 902,000 |
| | | 8.37% | 8.73% | 9.51% | 58% |
| | Small | 1,224 | 1,117 | 816 | 471,000 |
| | | 20.01% | 19.34% | 21.01% | 30.3% |
| | Medium | 4,950 | 4,613 | 3,105 | 148,000 |
| | | 25.48% | 25.15% | 25.17% | 9.5% |
| | Big | 39,400 | 37,700 | 24,000 | 33,700 |
| | | 46.14% | 46.78% | 44.31% | 2.2% |

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

Table 3: **Percentages of manufacturing firms in each sector, by geographic area and size.**

| Manufacturing | Northwest | Northeast | Center | South & Islands | Micro | Small | Medium | Big | Tot. |
|---|---|---|---|---|---|---|---|---|---|
| Textile and leather | 4.6% | 3.4% | 5.1% | 2.9% | 9.2% | 5.0% | 1.5% | 0.2% | 16.0% |
| | 28.6% | 21.0% | 32.2% | 18.2% | 57.4% | 31.5% | 9.7% | 1.4% | 100% |
| Paper | 3.4% | 1.8% | 2.0% | 1.1% | 5.7% | 1.9% | 0.5% | 0.1% | 8.2% |
| | 41.1% | 21.5% | 24.6% | 12.8% | 69.7% | 22.9% | 6.2% | 1.3% | 100% |
| Chemicals | 4.3% | 2.1% | 1.3% | 1.2% | 4.2% | 3.1% | 1.2% | 0.4% | 8.9% |
| | 48.4% | 23.9% | 14.8% | 12.9% | 47.6% | 34.6% | 13.8% | 4.1% | 100% |
| Minerals | 1.3% | 1.7% | 1.4% | 1.7% | 3.5% | 2.0% | 0.5% | 0.1% | 6.2% |
| | 21.7% | 27.7% | 22.9% | 27.8% | 57.5% | 32.0% | 8.7% | 1.8% | 100% |
| Metals | 9.0% | 5.7% | 2.9% | 3.0% | 12.8% | 5.9% | 1.5% | 0.3% | 20.5% |
| | 43.6% | 27.7% | 14.0% | 14.7% | 62.4% | 28.9% | 7.1% | 1.5% | 100% |
| Machinery | 11.4% | 8.0% | 3.3% | 2.3% | 14.1% | 7.9% | 2.5% | 0.5% | 25.1% |
| | 45.6% | 31.9% | 13.3% | 9.2% | 56.4% | 31.5% | 9.9% | 2.2% | 100% |
| Vehicles | 1.3% | 0.8% | 0.6% | 0.7% | 1.8% | 1.0% | 0.4% | 0.1% | 3.3% |
| | 38.2% | 22.8% | 18.4% | 20.5% | 54.6% | 28.9% | 12.3% | 4.2% | 100% |
| Food and tobacco | 2.1% | 2.3% | 1.6% | 2.8% | 4.6% | 2.7% | 1.2% | 0.3% | 8.8% |
| | 24.2% | 26.4% | 17.8% | 31.6% | 52.0% | 30.5% | 13.6% | 3.9% | 100% |
| Wood | 0.7% | 1.0% | 0.6% | 0.7% | 2.0% | 0.8% | 0.2% | 0.0% | 3.0% |
| | 24.2% | 33.3% | 20.4% | 22.2% | 65.6% | 28.2% | 5.7% | 0.5% | 100% |
| Tot. | 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 4: **Value added shares of manufacturing firms in each geographic area, by size.**

| Manufacturing | Micro | Small | Medium | Big | Tot. |
|---|---|---|---|---|---|
| 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 & 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 5: **Value added shares of manufacturing firms in size class, by geographic area.**

| Manufacturing | Northwest | Northeast | Center | South & Islands | Tot. |
|---|---|---|---|---|---|
| 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 6: Unit root tests on relative TFPR

| **Test** | Statistic | p-value |
|---|---|---|
| **Im-Pesaran-Shin** | Statistic | p-value |
| W-t-bar (a) | -17.2958 | 0.0000 |
| W-t-bar (b) * | -63.9714 | 0.0000 |
| **Fisher-type, Augmented DickeyFuller (c)** | | |
| Inverse chi-squared(degrees of fr. 3476) | 5901.691 | 0.0000 |
| Inverse normal | -8.8742 | 0.0000 |
| Inverse logit t(degrees of fr. 8669) | -13.9079 | 0.0000 |
| Modified inv. chi-squared | 29.0925 | 0.0000 |
| **Fisher-type, Augmented DickeyFuller (c) *** | | |
| Inverse chi-squared(degrees of fr. 3476) | 6539.15 | 0.0000 |
| Inverse normal | -12.8297 | 0.0000 |
| Inverse logit t(degrees of fr. 8599) | -19.645 | 0.0000 |
| Modified inv. chi-squared | 36.7378 | 0.0000 |
| **Fisher-type, PhillipsPerron (d)** | | |
| Inverse chi-squared(degrees of fr. 3476) | 7465.222 | 0.0000 |
| Inverse normal | -21.5148 | 0.0000 |
| Inverse logit t(degrees of fr. 8639) | -29.4953 | 0.0000 |
| Modified inv. chi-squared | 47.8446 | 0.0000 |
| **Fisher-type, PhillipsPerron (d) *** | | |
| Inverse chi-squared(degrees of fr. 3476) | 8073.704 | 0.0000 |
| Inverse normal | -26.0377 | 0.0000 |
| Inverse logit t(degrees of fr. 8614) | -35.8587 | 0.0000 |
| Modified inv. chi-squared | 55.1425 | 0.0000 |

*Trend included

Serially correlated errors:
(a) 1.03 lags - chosen by AIC;
(b) 1.72 lags - chosen by AIC;
(c) 1 lag Augmented Dickey-Fuller;
(d) 1 lag Newey-West.

Table 7: **Description of main variables.**

| Variable | Description |
|---|---|
| control | 1 physical person, 2 holding, 3 Institution, 4 Public, 5 foreign |
| 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 |
| technological level | 2 technological Intensity classes: low or med-low, med-high or high |
| Year | Year in which the questionnaire was filled, from 1987 to 2011. |

Table 8: Ownership

| VARIABLES | (1) Relative TFPR | (2) Relative TFPR | (3) Output Wedge | (4) Output Wedge | (5) Capital Wedge | (6) Capital Wedge |
|---|---|---|---|---|---|---|
| Family | -0.0526*** | - | -0.0346*** | - | 0.209*** | - |
| | (0.0125) | | (0.00532) | | (0.0262) | |
| Conglomerate | | 0.0582*** | | 0.0417*** | | -0.219*** |
| | | (0.0147) | | (0.00593) | | (0.0291) |
| Financial Institution | | 0.0308* | | 0.0159* | | -0.133*** |
| | | (0.0183) | | (0.00812) | | (0.0368) |
| Government | | -0.0237 | | -0.0169 | | -0.250*** |
| | | (0.0326) | | (0.0160) | | (0.0547) |
| Foreign | | 0.0803*** | | 0.0498*** | | -0.238*** |
| | | (0.0176) | | (0.00681) | | (0.0369) |
| Constant | 0.107 | 0.0647 | 5.415*** | 5.388*** | 5.094*** | 5.299*** |
| | (0.221) | (0.219) | (0.0464) | (0.0456) | (0.465) | (0.469) |
| Observations | 17,420 | 17,420 | 17,420 | 17,420 | 17,420 | 17,420 |
| R-squared | 0.029 | 0.032 | 0.098 | 0.102 | 0.293 | 0.294 |
| Sector FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

Table 9: Credit constraints

| VARIABLES | (1) Relative TFPR | (2) Output Wedge | (3) Capital Wedge |
|---|---|---|---|
| credit constraint 1 [t-1] | -0.0657** | -0.0322** | -0.00445 |
| | (0.0298) | (0.0157) | (0.0485) |
| Constant | 0.658*** | 5.537*** | 6.516*** |
| | (0.0824) | (0.0381) | (0.152) |
| Observations | 1,188 | 1,188 | 1,188 |
| R-squared | 0.155 | 0.132 | 0.375 |
| Sector FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Table 10: Equity

| VARIABLES | (1) Relative TFPR | (2) Output Wedge | (3) Capital Wedge |
|---|---|---|---|
| Increased equity (at t) | -0.0629*** | -0.0305*** | 0.000297 |
| | (0.0151) | (0.00801) | (0.0276) |
| Constant | -0.147 | 5.258*** | 4.635*** |
| | (0.240) | (0.163) | (0.439) |
| Observations | 9,527 | 9,527 | 9,527 |
| R-squared | 0.035 | 0.076 | 0.255 |
| Sector FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Table 11: Leverage Euro

| VARIABLES | (1)<br>Relative TFPR | (2)<br>Output Wedge | (3)<br>Capital Wedge |
|---|---|---|---|
| leverage | -0.381*** | -0.0303 | -0.979*** |
| | (0.0663) | (0.0353) | (0.133) |
| post99 | -0.0206 | 0.105*** | -0.260*** |
| | (0.0240) | (0.0157) | (0.0430) |
| leverage*post99 | -0.197** | -0.0708 | 0.176 |
| | (0.0966) | (0.0460) | (0.175) |
| Constant | 0.0574*** | 5.468*** | 5.613*** |
| | (0.0201) | (0.0149) | (0.0352) |
| Observations | 15,633 | 15,633 | 15,633 |
| R-squared | 0.037 | 0.119 | 0.314 |
| Sector FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Table 12: Relational banking

| VARIABLES | (1)<br>Relative TFPR | (2)<br>Output Wedge | (3)<br>Capital Wedge |
|---|---|---|---|
| Relational banking | -0.0823** | -0.0202 | -0.0273 |
| | (0.0336) | (0.0257) | (0.0600) |
| Constant | -0.0183 | 5.388*** | 4.541*** |
| | (0.0619) | (0.0322) | (0.126) |
| Observations | 774 | 774 | 774 |
| R-squared | 0.080 | 0.148 | 0.335 |
| Sector FE | YES | YES | YES |
| Year FE | NO | NO | NO |

Table 13: Wage Supplementation Scheme

| VARIABLES | (1)<br>Relative TFPR | (2)<br>Output Wedge | (3)<br>Capital Wedge |
|---|---|---|---|
| Wag supplementation | -0.425*** | -0.165*** | -0.515*** |
| | (0.0979) | (0.0432) | (0.0740) |
| Constant | 0.0710 | 5.296*** | 5.310*** |
| | (0.178) | (0.121) | (0.394) |
| Observations | 19,078 | 19,078 | 19,078 |
| R-squared | 0.041 | 0.106 | 0.283 |
| Sector FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Table 14: Temporary employment, share of total workforce

| VARIABLES | (1)<br>Relative TFPR | (2)<br>Output Wedge | (3)<br>Capital Wedge |
|---|---|---|---|
| Temporary employment share | 0.116** | -0.0398 | 0.597*** |
| | (0.0565) | (0.0280) | (0.120) |
| Constant | -0.0687 | 5.384*** | 4.832*** |
| | (0.173) | (0.111) | (0.375) |
| Observations | 11,825 | 11,825 | 11,825 |
| R-squared | 0.028 | 0.072 | 0.246 |
| Sector FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Table 15: Foreign employment, share of total workforce

| VARIABLES | (1)<br>Relative TFPR | (2)<br>Output Wedge | (3)<br>Capital Wedge |
|---|---|---|---|
| Foreign empolyment share | 0.127 | -0.00505 | 0.705* |
| | (0.140) | (0.0513) | (0.366) |
| Constant | -0.116 | 5.352*** | 4.997*** |
| | (0.219) | (0.173) | (0.469) |
| Observations | 6,331 | 6,331 | 6,331 |
| R-squared | 0.037 | 0.073 | 0.238 |
| Sector FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Table 16: Share of graduates, white collars

| VARIABLES | (1)<br>Relative TFPR | (2)<br>Output Wedge | (3)<br>Capital Wedge |
|---|---|---|---|
| Graduate share, white collars | 0.359*** | 0.105*** | -0.241* |
| | (0.0765) | (0.0308) | (0.133) |
| Constant | -0.308 | 5.514*** | 5.039*** |
| | (0.332) | (0.0286) | (0.630) |
| Observations | 1,412 | 1,412 | 1,412 |
| R-squared | 0.080 | 0.152 | 0.279 |
| Sector FE | YES | YES | YES |
| Cross section Year | 2000 and 2010 | 2000 and 2010 | 2000 and 2010 |

Table 17: Share of graduates, blue collars

| VARIABLES | (1)<br>Relative TFPR | (2)<br>Output Wedge | (3)<br>Capital Wedge |
|---|---|---|---|
| Blue collar graduate | -0.234 | -0.159 | -1.092* |
| | (0.421) | (0.412) | (0.571) |
| Constant | -0.241 | 5.538*** | 5.062*** |
| | (0.377) | (0.0484) | (0.643) |
| Observations | 1,366 | 1,366 | 1,366 |
| R-squared | 0.059 | 0.143 | 0.278 |
| Sector FE | YES | YES | YES |
| Cross section Year | 2000 and 2010 | 2000 and 2010 | 2000 and 2010 |

Table 18: Delocalization

| VARIABLES | (1)<br>Relative TFPR | (2)<br>Output Wedge | (3)<br>Capital Wedge |
|---|---|---|---|
| Engage in delocalization | -0.00715 | -0.000137 | -0.0313 |
| | (0.0386) | (0.0114) | (0.0709) |
| Constant | -0.206 | 5.519*** | 4.921*** |
| | (0.457) | (0.0495) | (0.769) |
| Observations | 655 | 655 | 655 |
| R-squared | 0.109 | 0.203 | 0.295 |
| Sector FE | YES | YES | YES |
| Cross section Year | 2011 | 2011 | 2011 |

Table 19: FDI

| VARIABLES | (1)<br>Relative TFPR | (2)<br>Output Wedge | (3)<br>Capital Wedge |
|---|---|---|---|
| Engage in FDI | 0.00640 | -0.0137 | 0.0772 |
| | (0.0585) | (0.0196) | (0.115) |
| Constant | -0.181*** | 5.359*** | 4.387*** |
| | (0.0313) | (0.0250) | (0.222) |
| Observations | 201 | 201 | 201 |
| R-squared | 0.304 | 0.399 | 0.463 |
| Sector FE | YES | YES | YES |
| Cross section Year | 2003 | 2003 | 2003 |

Table 20: Innovation

| VARIABLES | (1)<br>Relative TFPR | (2)<br>Output Wedge | (3)<br>Capital Wedge |
|---|---|---|---|
| Intangible assets, share | 0.144*** | -0.00188 | 0.377*** |
| | (0.0381) | (0.0160) | (0.0688) |
| Constant | -0.0796 | 5.377*** | 4.849*** |
| | (0.176) | (0.110) | (0.398) |
| Observations | 11,689 | 11,689 | 11,689 |
| R-squared | 0.030 | 0.071 | 0.247 |
| Sector FE | YES | YES | YES |
| Year FE | YES | YES | YES |

Table 21: Correlations

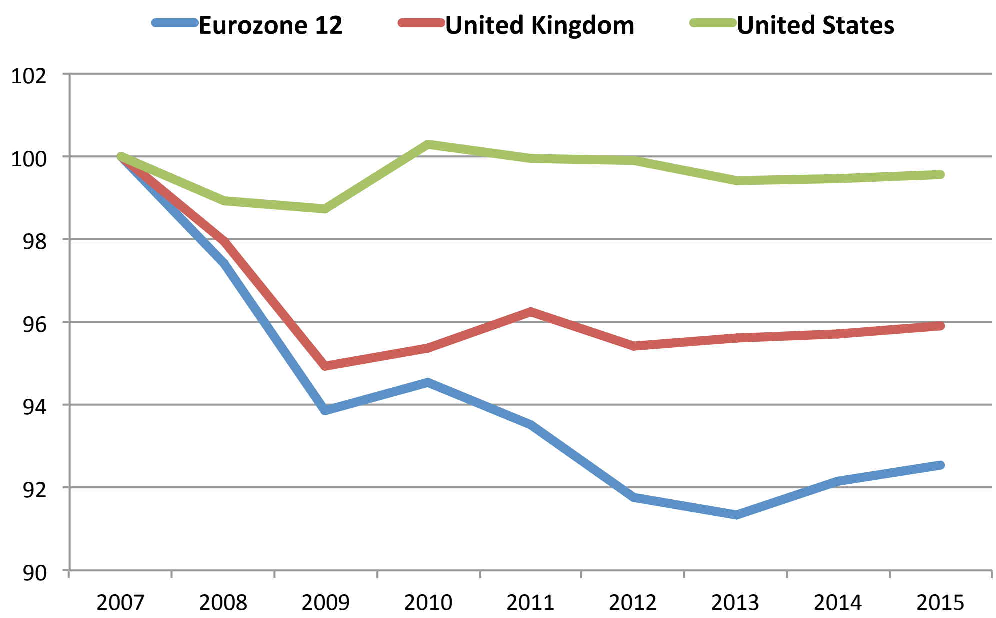
| | Wage suppl. | Graduates sh. white collars | Innovation | Family ownership | Credit constr. (t-1) | Temporary empl. sh |
|---|---|---|---|---|---|---|
| Wage supplementation | 1 | | | | | |
| Graduates share, white collars | -0.15 | 1 | | | | |
| Innovation | 0.14 | 0.22 | 1 | | | |
| Family ownership | -0.11 | -0.08 | 0.07 | 1 | | |
| Credit constraint (t-1) | 0.24 | -0.15 | 0.02 | -0.27 | 1 | |
| Temporary employment, share | -0.20 | 0.06 | -0.07 | 0.18 | -0.13 | 1 |

Table 22: All together

| VARIABLES | (1) Relative TFPR | (2) Relative TFPR | (3) Output Wedge | (4) Output Wedge | (5) Capital Wedge | (6) Capital Wedge |
|---|---|---|---|---|---|---|
| Graduate share, white collars | 0.350*** | 0.313*** | 0.0854** | 0.0747** | -0.229* | -0.269** |
| | (0.0746) | (0.0736) | (0.0336) | (0.0353) | (0.128) | (0.129) |
| Innovation | 0.0855 | 0.139* | -0.0265 | -0.00886 | 0.571*** | 0.609*** |
| | (0.0753) | (0.0720) | (0.0351) | (0.0348) | (0.143) | (0.141) |
| Family ownership | -0.0527** | -0.0619** | -0.0154 | -0.0182 | 0.179*** | 0.169*** |
| | (0.0247) | (0.0243) | (0.0128) | (0.0127) | (0.0491) | (0.0488) |
| Wage supplementation | | -0.782*** | | -0.279*** | | -0.393 |
| | | (0.141) | | (0.0784) | | (0.244) |
| Temporary employment, share | | 0.169 | | 0.0179 | | 0.423* |
| | | (0.130) | | (0.0436) | | (0.233) |
| Constant | -0.00547 | 0.0228 | 5.537*** | 5.554*** | 5.331*** | 5.286*** |
| | (0.377) | (0.306) | (0.0390) | (0.0215) | (0.742) | (0.712) |
| Observations | 1,290 | 1,289 | 1,290 | 1,289 | 1,290 | 1,289 |
| R-squared | 0.101 | 0.131 | 0.158 | 0.170 | 0.315 | 0.319 |
| Sector FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

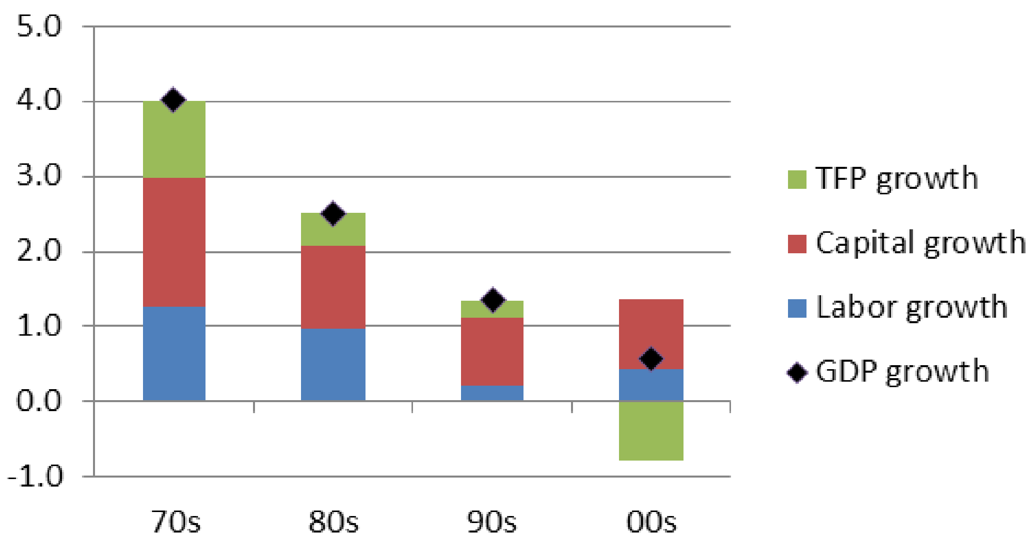
# 10 Figures

Figure 1: **TFP pattern since the global financial crisis (2007=100)**



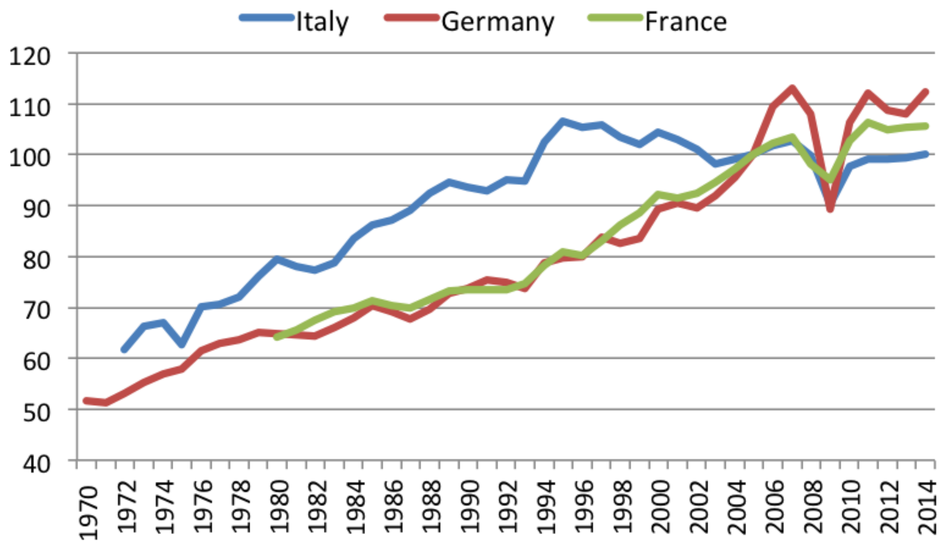

Data: Conference Board

Figure 2: **Contribution to value added growth, Italy**



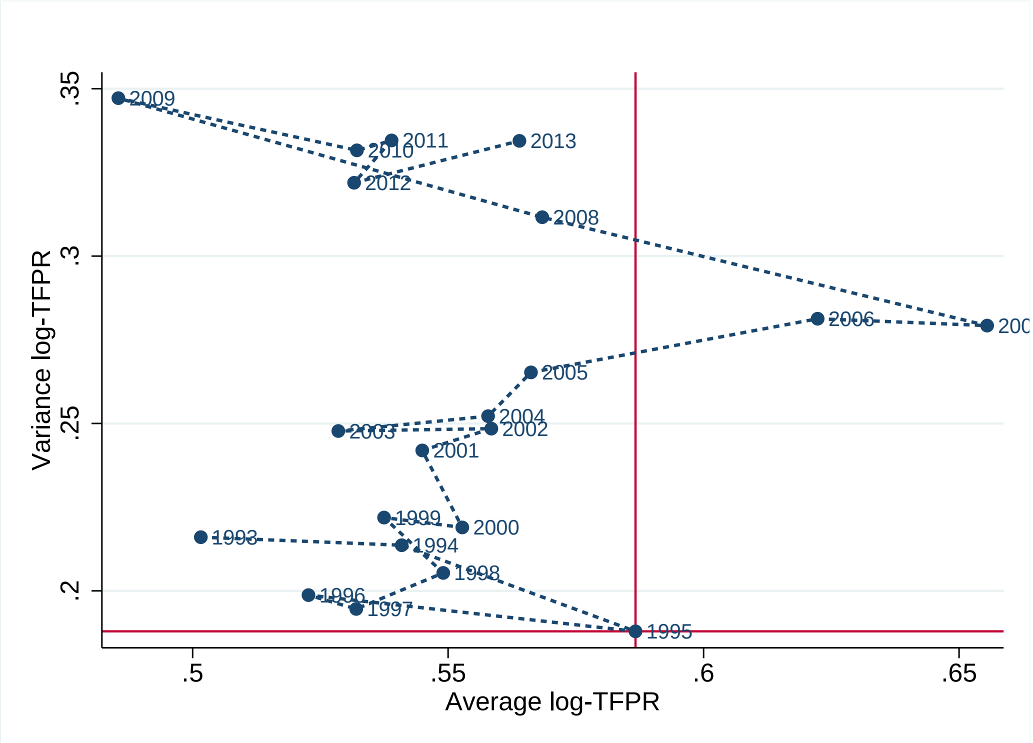

Data: EU-Klems

Figure 3: **TFP in manufacturing for Italy, Germany and France (2005=100)**



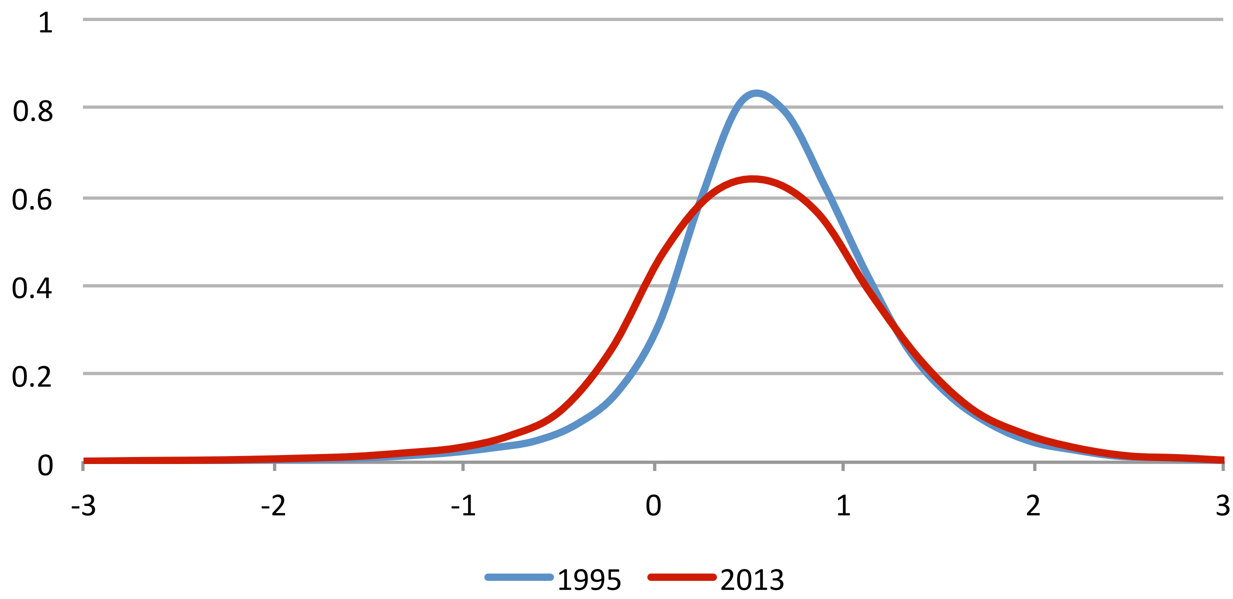

Source: Hassan and Ottaviano (2013)

Figure 4: **Variance and average TFPR**



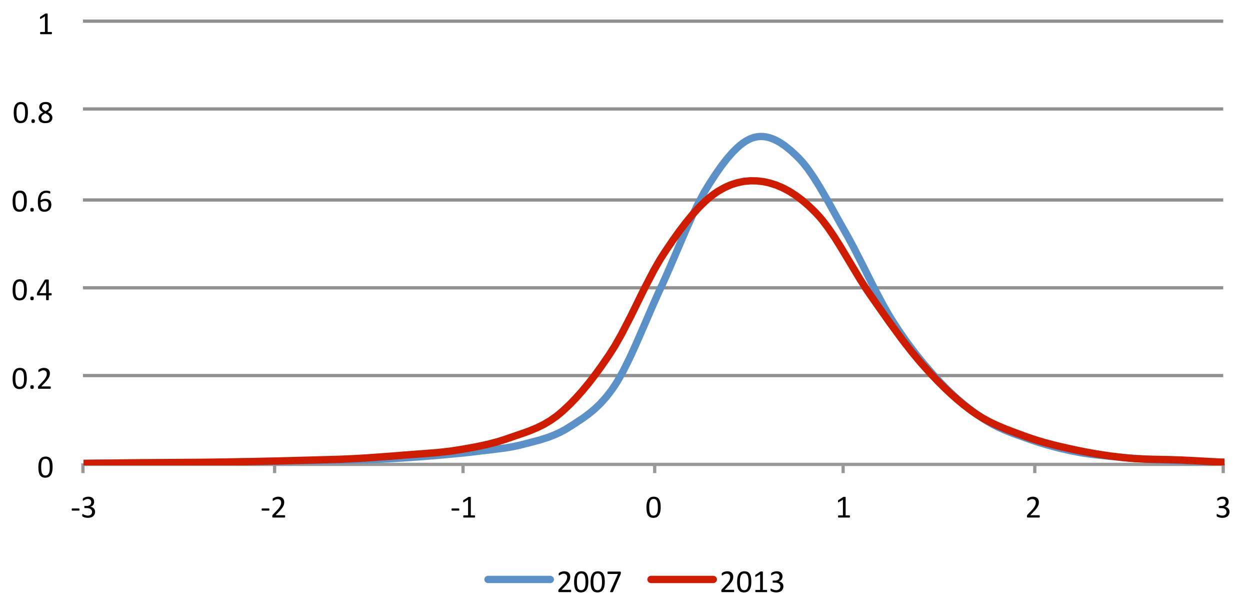

Data: CERVED

Figure 5: **Distribution TFPR, 1995 and 2013**



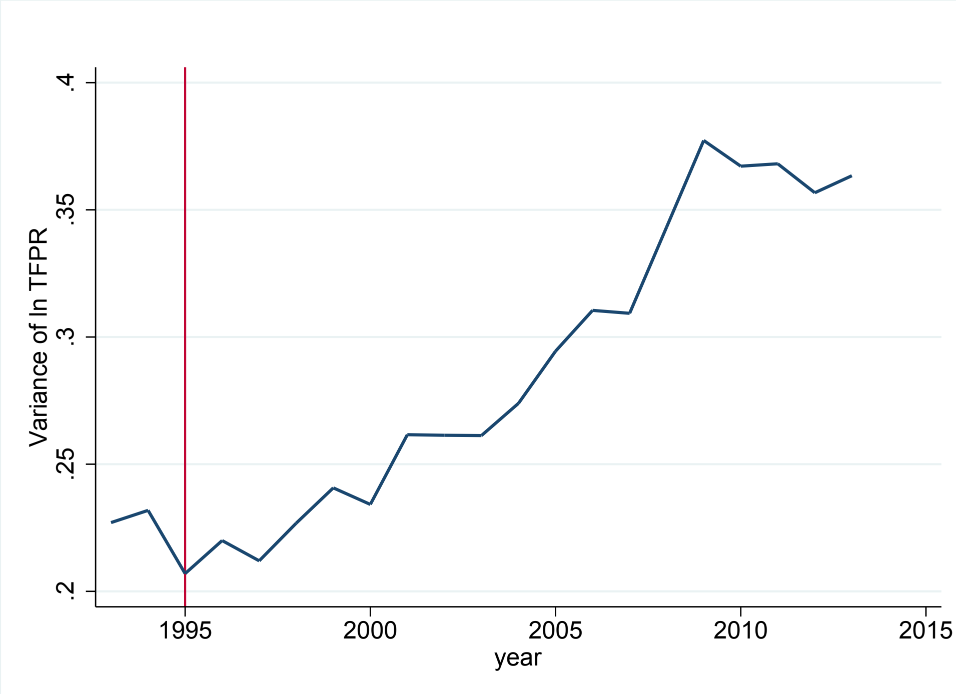

Data: CERVED

Figure 6: **Distribution TFPR, 2007 and 2013**



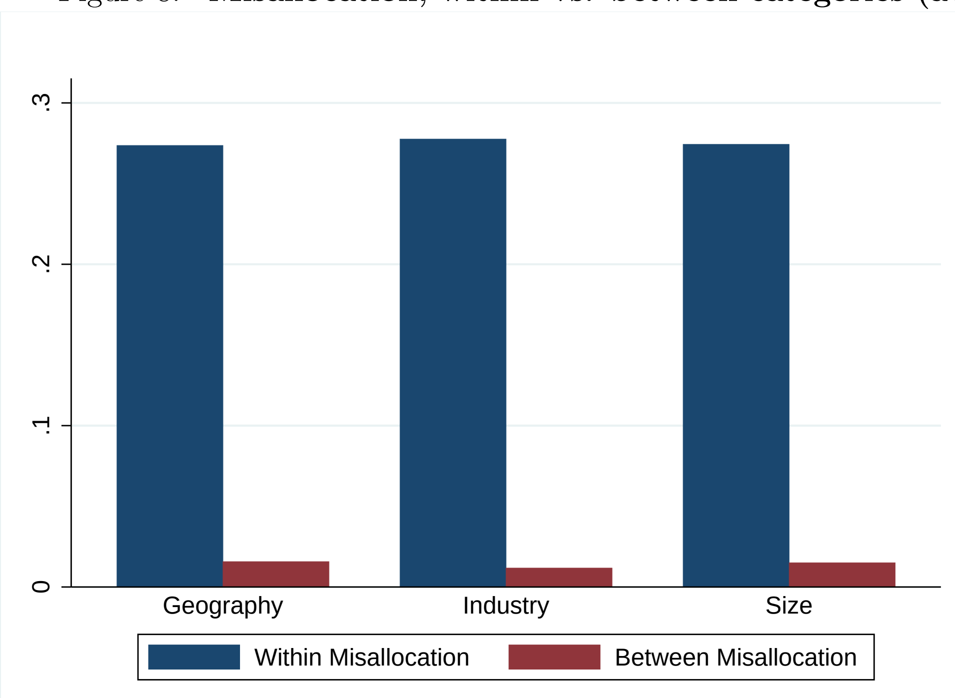

Data: CERVED

Figure 7: **Evolution of aggregate misallocation, 1993-2013**



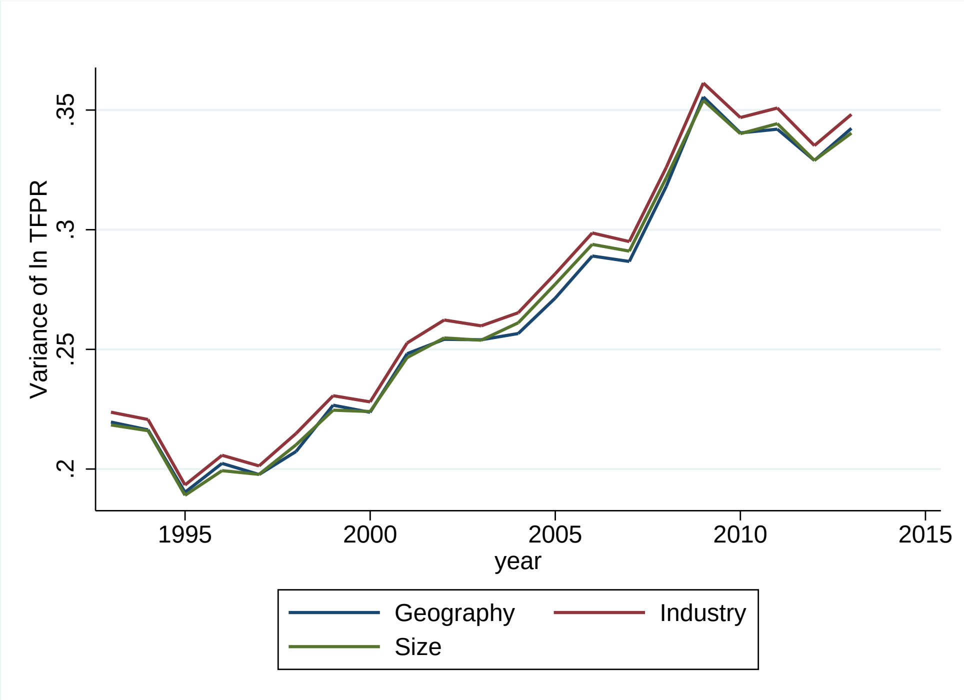

Data: CERVED

Figure 8: **Misallocation, within vs. between categories (average 1993-2013)**



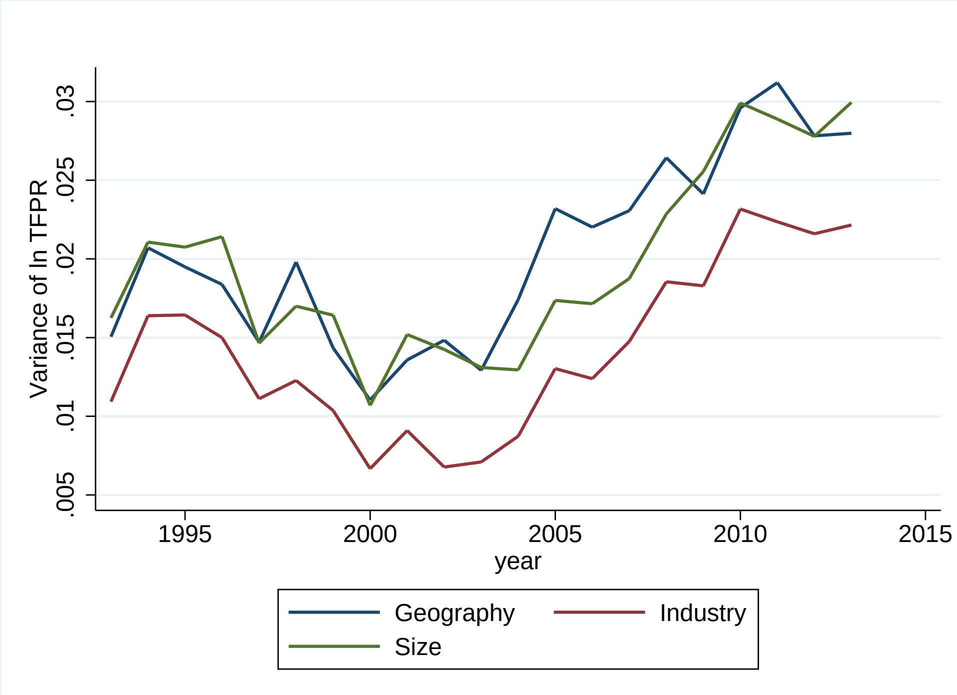

Data: CERVED

Figure 9: **Evolution of within-misallocation by category**



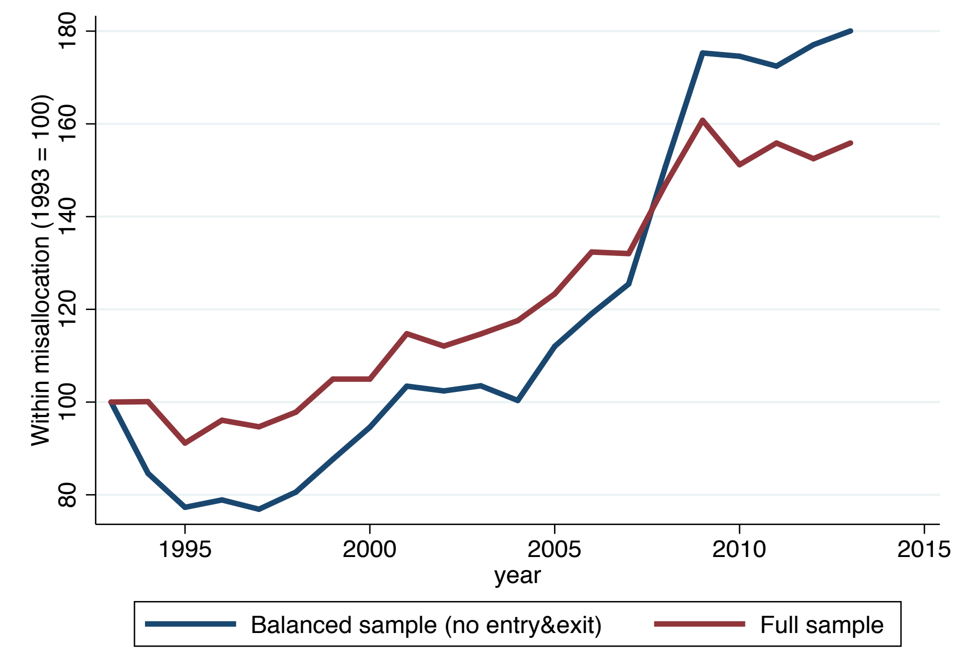

Data: CERVED

Figure 10: **Evolution of between-misallocation by category**



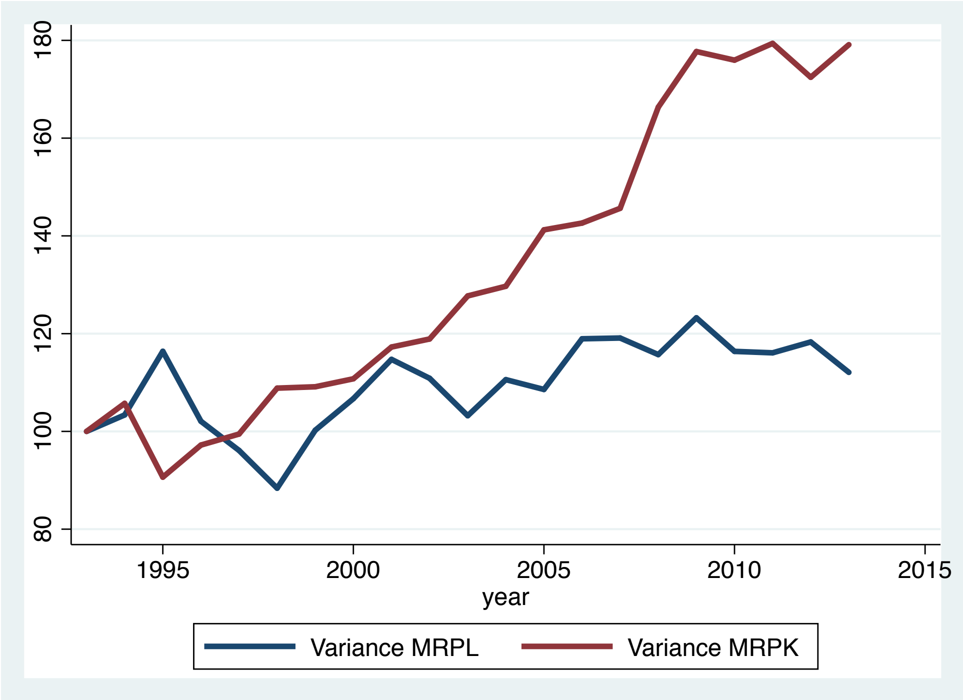

Data: CERVED

Figure 11: **Evolution of misallocation, balanced vs. full-sample**




Data: CERVED

Figure 12: **Evolution of misallocation, marginal product of capital and labor**




Data: CERVED

Figure 13: **Variance Ratio of relative TFPR**

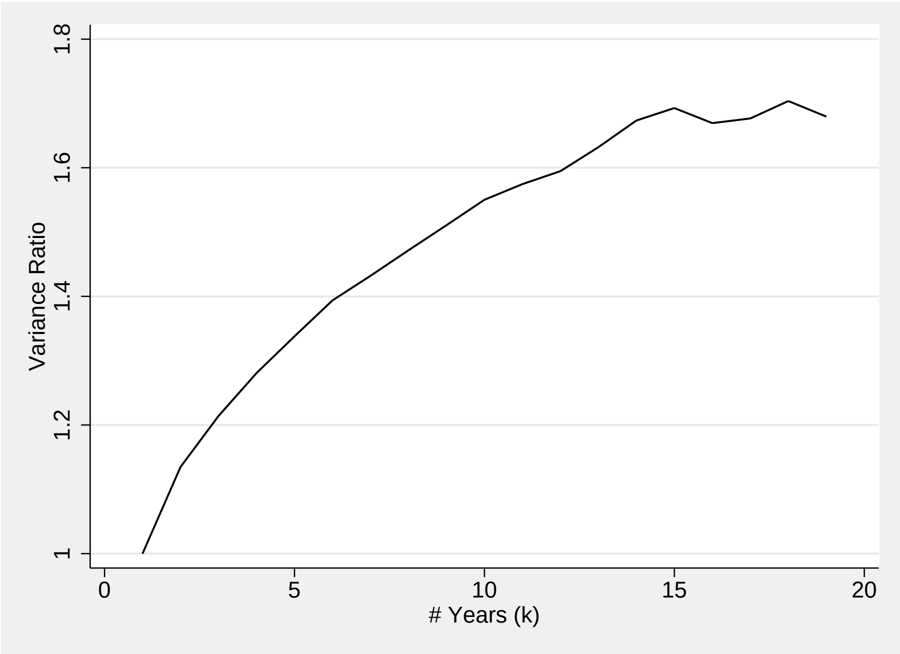
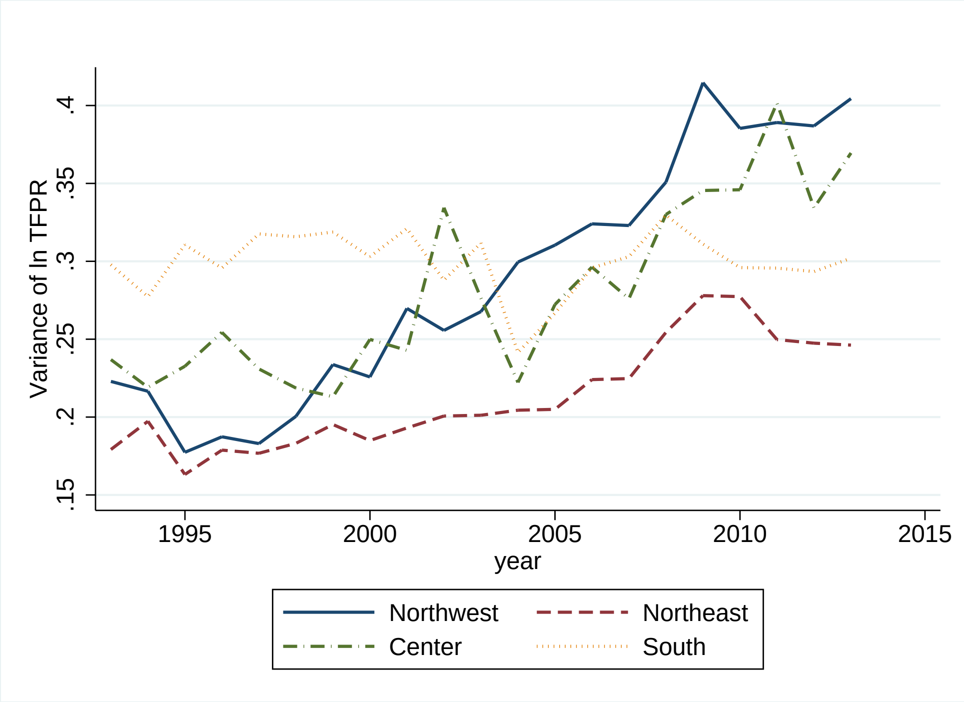


Figure 14: **Evolution of misallocation by geographic area**

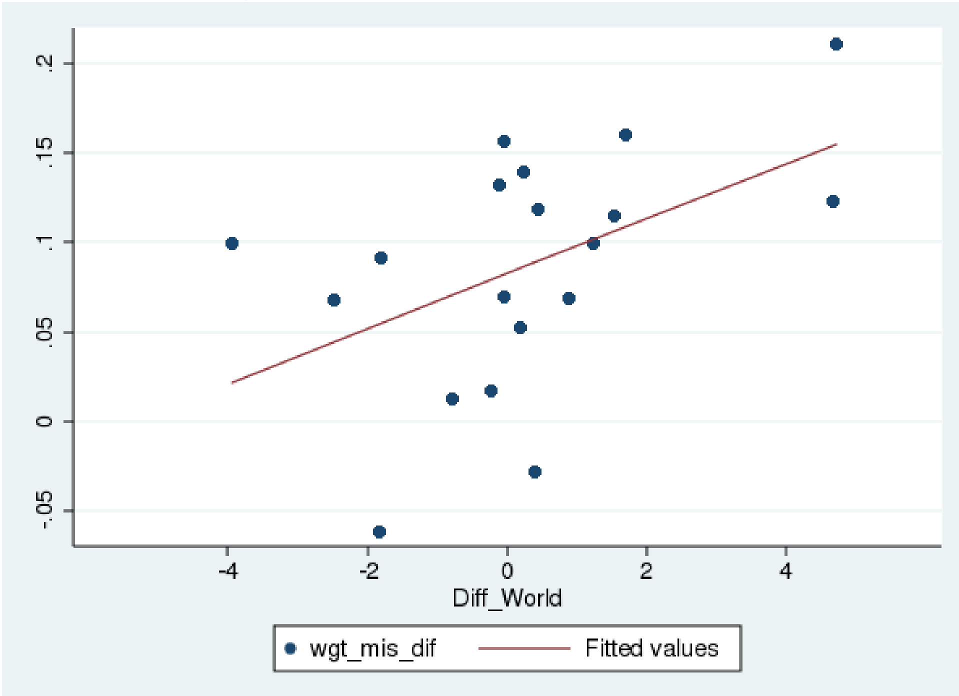



Data: CERVED

Figure 15: **Evolution of misallocation by firm size**

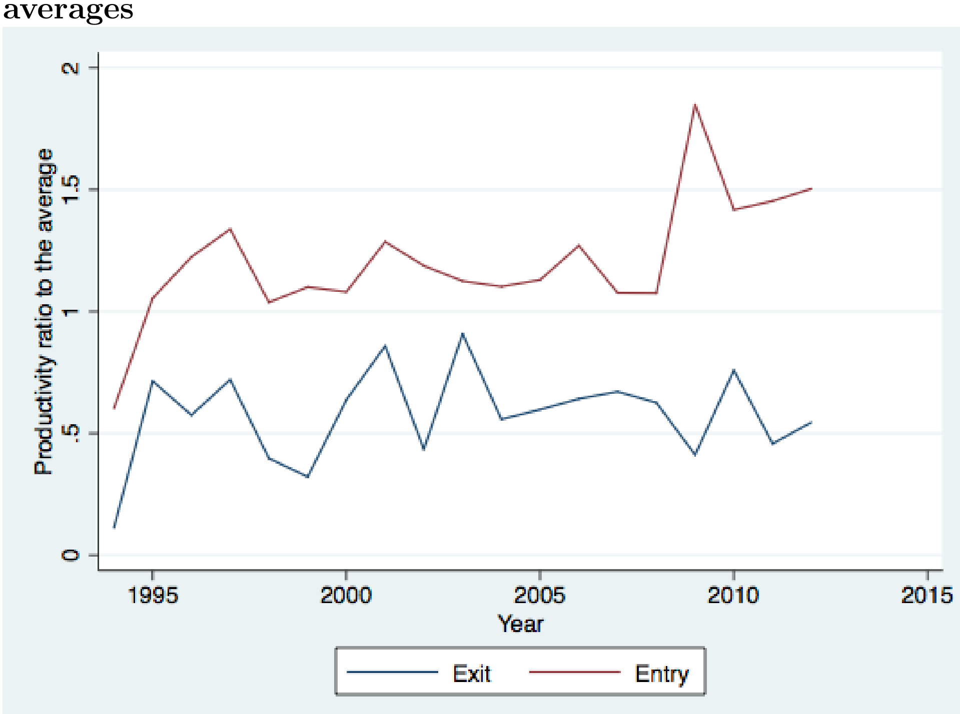

Data: CERVED

Figure 16: **Sector misallocation and World RD intensity**



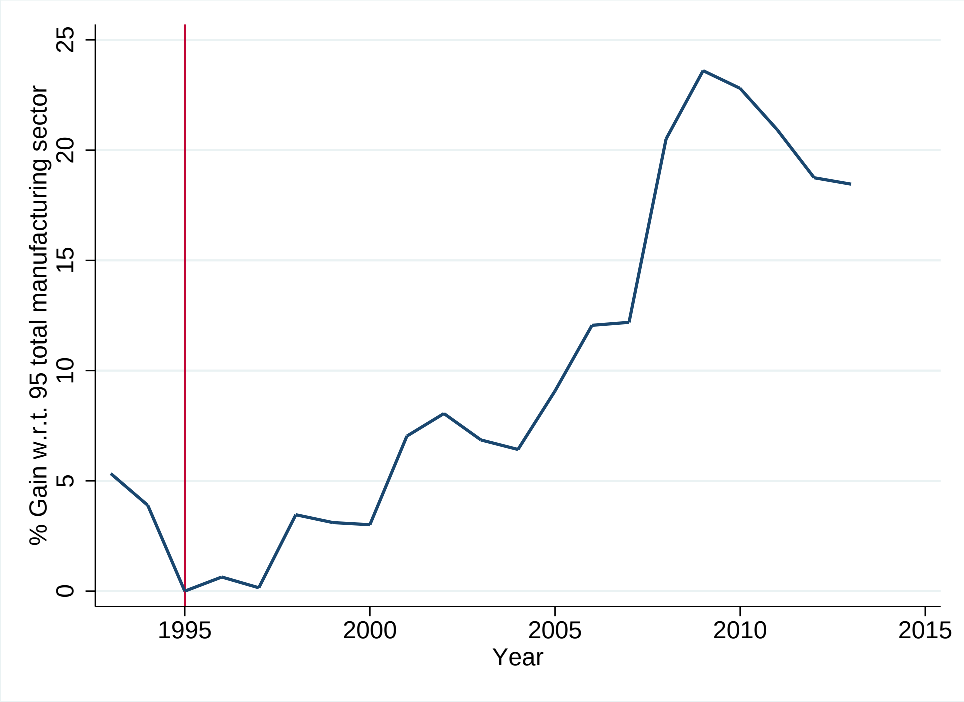

Data: CERVED and OECD

Figure 17: **Productivity ratio of firms' entry and exit with respect to sectoral averages**



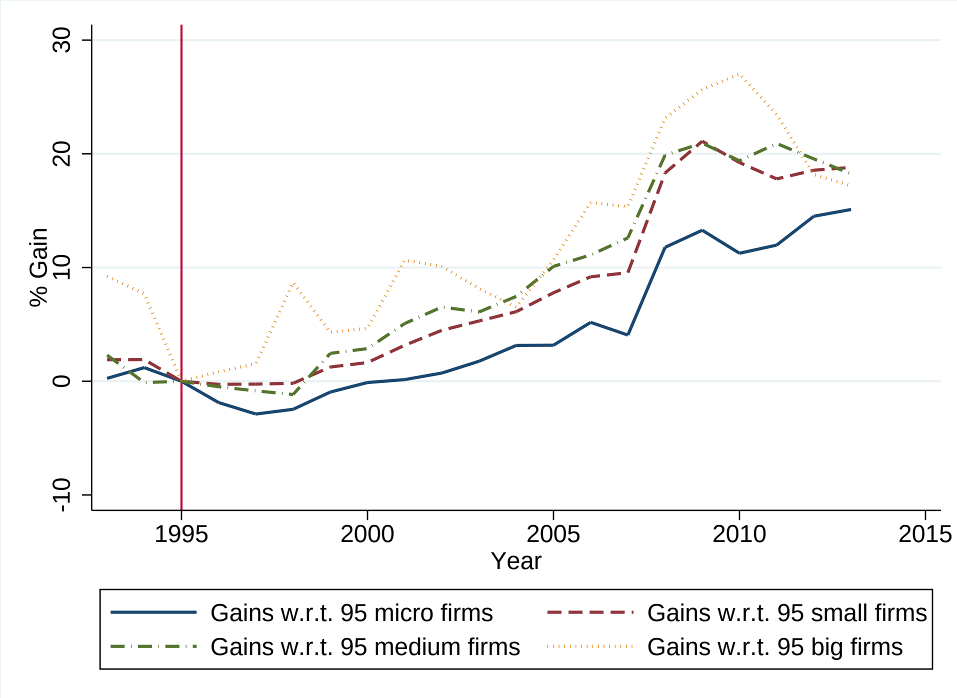

Data: CERVED and OECD

Figure 18: **TFP gains from equalising TFP dispersion to its 1995 value**



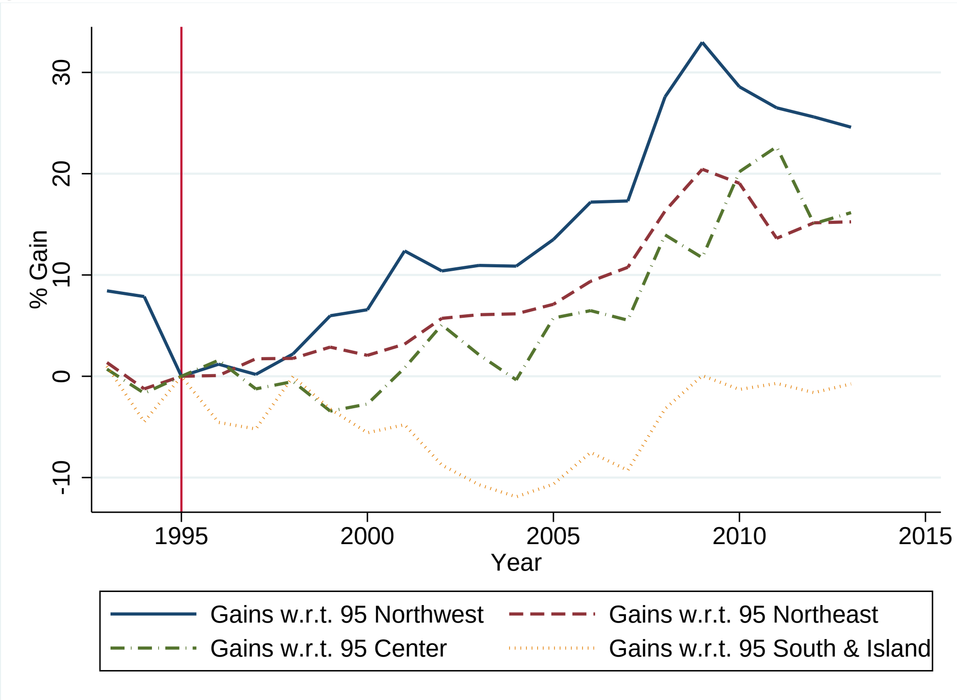

Data: CERVED

Figure 19: **TFP gains from equalising TFP dispersion to its 1995 value, by firm size**




Data: CERVED

Figure 20: **TFP gains from equalising TFP dispersion to its 1995 value, by geographic area**




Data: CERVED

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