The Productivity Puzzle and Misallocation: an Italian Perspective

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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. The Italian case can therefore offer useful insights to understand the global productivity slowdown. We find that resource misallocation has played a sizeable role in slowing down Italian productivity growth. If 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 across firms within sectors where technology is changing faster rather than between sectors with different speeds of technological change.

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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. Moreover, in 2016 in the US labor productivity growth fell into negative territory for the first time in the last three decades (Conference Board, 2016). 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 imperfections 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 firms, they lead to lower aggregate TFP than in an ideal situation of frictionless

[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 the results are very similar.

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) - henceforth HK - 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, HK call deviations from a situation in which TFPR is equalized "misallocation", and propose a simple way to measure its effect 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.

We then present a decomposition of misallocation into *within-* and *between-group* components, with firms grouped according to the sector, the geographical area and the size class. This analysis shows that the main source of misallocation comes from the within component: misallocation has mainly risen within sectors rather than between them, within geographical areas rather than between them, within different size classes rather than between them.

To shed light on this result, we consider the relationship at the sectoral level between the estimated within-sector component of misallocation and the sectoral speed of technological change. Following Griffith et al. (2004), we proxy the speed of technological change with the increase in sectoral R&D intensity (R&D expenditure over value added) in advanced countries over the period 1987-2007. The positive and significant correlation that we find entails that misallocation seems to have increased more in sectors where the world technological frontier has expanded faster. Once we account for the sectoral composition of Italian macro-regions and firm size classes, the implied "frontier shocks" are the strongest for Northern regions and big firms, thus matching the relatively higher increase in misallocation estimated for those classes of firms, which are traditionally the driving forces of the Italian economy.

Finally, we analyze a number of firm characteristics (i.e., 'markers') potentially associated with firms being inefficiently sized. In particular, we consider corporate ownership and management, finance, workforce composition, internationalization and innovation. We find that the firms that employ a larger share of graduates or invest more in intangible assets are inefficiently small and thus under-resourced. These are likely to be the firms keeping up with the technological frontier. On the contrary, the firms that have a large share of workers under the Italian wage supplementation scheme, that are family managed, or financially constrained, are inefficiently large and thus over-resourced. These firms are less likely to be keeping up with technological progress. We interpret this as evidence that rising within-industry misallocation is consistent with a heterogeneous ability of firms to respond to sectoral "frontier shocks" in the presence of sluggish reallocation of resources.

The broader message we draw from the above results 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 traditional, e.g. 'textile', into IT sectors would increase aggregate productivity less than ensuring that the most efficient firms within the textile sector are the ones that absorb more resources.

A concern with our quantification exercise relates to the caveats associated to measure of misallocation of HK. For instance Asker et al. (2014) argue that, in the presence of adjustment costs in investment ("time-to-build"), transitory idiosyncratic TFP shocks across firms naturally generate dispersion in productivity without this implying inefficiency. From a different angle, De Loecker and Goldberg (2014) and Haltiwanger (2016) argue that 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. Finally, Bils et al. (2017) stress the role of mismeasurement in the calculation of misallocation and propose a methodology to assess its impact. We show that our results are robust to these issues and that the caveats charcterising the HK concept of misallocation are unlikely to drive our results.

Our work relates to a number of studies that have used the framework of HK 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), Gamberoni et al. (2016) and Gopinath et al. (2017). Our paper is closer in spirit to Garcia-Santana et al. (2016), who analyze the patterns of misallocation for Spain, and to Gamberoni et al. (2016), who look at the evolution of misallocation across European countries.

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), Bandiera et al. (2015), Calligaris (2015), Daveri and Parisi (2015), Linarello and Petrella (2016) and Calligaris et al. (2016), Pellegrino and Zingales (2017) and Schivardi and Schmitz (2018). Our contribution is to focus more specifically on the role of resource misallocation and its impact on productivity.

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 analyzes the role of the increase in R&D intensity. Section 6 looks at idiosyncratic firm shocks and the cyclical behavior of misallocation. Section 7 estimates the impact of misallocation on aggregate

TFP. Section 8 discusses the robustness of our findings to the limitations of the Hsieh-Klenow framework. Section 9 discusses the markers of misallocated firms. Section 10 concludes.

2 Measuring misallocation

We follow HK in defining 'misallocation' as an inefficient allocation of productive factors (labor and capital) across firms with different TFPR (see the Appendix for details).[3] 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.

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').[4] 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

[3]The only quantitative results from HK 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 Appendix for additional details.

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

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.[5]

The extent misallocation in the economy can be measured in terms of aggregate TFPR dispersion as a weighted average of the sectoral misallocations, with the weights expressed in terms of sectoral value added (VA) shares with resepct to the total economy

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

where N_s is the number of firms in sector s and S is the number of sectors. This is the expression we use to measure aggregate misallocation for the economy.[6]

We are also interested in understanding the extent to which aggregate dispersion is driven by variations between and within geographical areas or firm size classes. 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

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

where G is the number of area/size groups. In (2) the overall TFPR variance is decomposed in two parts: a weighted average of the within-group squared deviations from the group mean, and a weighted average of the squared deviations of the group means from the overall mean. Specifically, the within-group component represents a weighted average of the group-specific variances, in turn expressed in terms of weighted averages of the variance within the sector-specific TFPR distributions in the group.

[5] 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).

[6] 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.

When the economy is considered a single area/size group (so that the number of groups is equal to one), the within-group component in 2 boils down to 1, that is to a simple within-sector component, consisting of a weighted average of the within-sector variances.

3 Data description

We use two main databases. The first - CERVED - covers the universe of incorporated companies, with information from firms' balance sheets that we use in Sections 4 and to study the evolution of aggregate misallocation. The second - INVIND - is a panel of representative Italian manufacturing firms with at least 50 employees, with more detailed information on firms' characteristics that we use in Section 9 to analyze the firm-level markers of misallocation. 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.[7]

CERVED accounts for 70% of manufacturing value added from national accounts and the trend rate follows very closely the national one. 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.

INVIND is the Bank of Italy's annual "Survey of Industrial and Service Firms". The survey contains detailed information on firm revenues, ownership, production factors, year of creation and number of employees since 1984. In order to analyse the firm-level features of misallocation, the INVIND data are matched with those from 'Centrale dei Bilanci', a representative sample with more detailed information on firms' characteristics. 'Centrale dei Bilanci' contains balance sheet data on around 30,000 Italian firms and is matched with 'Centrale dei Bilanci' using the tax identification number of firms. We drop observations pre–1987, in order to have a proper sample coverage, as well as those not matched. 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

[7]The total number of 3-digit sectors is 91. We also use a classification at 2-digit and 4-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.

manufacturing industries according to their global technological intensity, based on R&D expenditures respect to value added and production.[8]

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.[9] 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 evolution of misallocation, we divide the dataset into geographic and firm size cells. In particular, we group firms within each industry into four macro-areas: Northwest, Northeast, Center, South-Islands.[10] We also divide the firms in the dataset into four groups according to their size: 'micro', 'small', 'medium' and 'big'.[11] We report the summary statistics of the main variables divided by geographic area and 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

[8]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.

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

[10]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.

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

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 (1). 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.[12]

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 TFPR firms. When the comparison is made, instead, between 2007 and 2013 (see Figure 5), the difference in the share of low TFPR 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 6 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. Interestingly, misallocation stopped increasing after the global financial crisis. This is probably due to some cleansing effect of the crisis, as firms in the lowest percentiles of the productivity distribution are much more likely to exit the market after the crisis than in previous years.[13]

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 (2) in order to understand to what extent aggregate misallocation can be traced back to differences in terms of TFPR dispersion across the categories. In Figure 7 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 8 and 9).

[12] 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.

[13] Details available upon request.

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 10 we report the evolution 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 HK, TFPR is proportional to the 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 11 reports the patterns of MRPK and MRPL dispersion. Capital is the factor of production that experiences the sharpest increase in its marginal product's dispersion since the mid-1990s, although the 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.[14] This seems to suggest that the capital market is a very important source of misallocation in Italy.

5 Insights from regional and size patterns

To better understand the geographical distribution of misallocation, we report in Figure 12 the evolution of misallocation within macro-regions (i.e., the term $Var(TFPR)_g$ in Equation (2). We note that misallocation in the Northwest and the Center grew at a considerably higher rate, compared to the other areas; misallocation in the South was higher than in the rest of Italy at the beginning of the period but, being quite stable over time, ends up being lower than in the North at the end of the period.[15]. The same analysis can be carried out in terms of firm size categories (see Figure 13). This exercise shows that, while misallocation grew in all size classes, a steeper increase is reported for the big firms class, which faced the lowest degree of misallocation 1995 and turns to be the group with the highest level of misallocation towards the end of the period.

These results are surprising because firms in the Northwest region and bigger firms are traditionally more advanced and closer to the technological frontier. This suggests a possible explanation of raise of misallocation: 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, see Schivardi and Schmitz 2018). To explore this possibility we build on Griffith et al. (2004). As a proxy of shocks to the technology frontier by sector, we take the change of R&D intensity between the period

[14] 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.

[15] To save on space, we do not show the graphs of group-specific distributions, but they support this finding.

1993-2007 and 1987-1992. We measure R&D intensity as the share of R&D expenditure to value added at the 2-digit sectoral level in advanced countries other than Italy.[16] Figure 14 plots the correlation between the change of misallocation over our sample period and the change of R&D intensity described above. The correlation is positive and significative, such that an increase of one standard deviation of R&D intensity growth is associated with a 0.14 standard deviation increase of misallocation growth (statistically significant at the 1% level). Moreover, we compute the implied "frontier shocks" at the regional level, by taking the weighted average of the sectoral changes in R&D intensity. It turns out that the "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 region and size patterns of misallocation highlighted above. [17]

An implication of this result is that firms in the upper part of the TFPR distribution should be those that contribute more to the overall increase in misallocation. We find that the standard deviation of log TFPR is about 0.4 for firms in the top quartile of the TFPR distribution and it is increasing over time. Whereas, for firms in the 2nd and 3rd quartile misallocation 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. Therefore, the dispersion across the firms that are in the top quartile of the distribution is the one that contributes the most to the rise of aggregate misallocation.

6 Idiosyncratic shocks and the cyclical behaviour of misallocation

The raise of the dispersion of TFPR across firms that we highlight could be driven by an increase in the dispersion of idiosyncratic shocks that firms face. To investigate this issue we measure the idiosyncratic shocks to firms' TFPR following Gopinath et al. (2017). We assume that firms' productivity is the product of an aggregate effect, a permanent firm level effect, and an idiosyncratic transitory effect, which depends on past TFPR and an idiosyncratic shock. More specifically we consider:

$$\ln TFPR_{ist} = \gamma_i + \delta_{st} + \beta \ln TFPR_{ist-1} + u_{ist} \tag{3}$$

where γ_i captures the firm permanent component, δ_{st} is an industry-year fixed effect that denotes the aggregate component of firm productivity, and u_{ist} is the residual that captures the idiosyncratic shock that firms face.

In Figure 15 we show the dispersion of the residuals estimated from Equation 3. We find that there is no increase in the dispersion of idiosyncratic shocks between 1995 and 2000. This means that, at least initially, the raise in misallocation that we observe since

[16] 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.

[17] Interestingly, these results are unlikely to be linked to the raise of international competition. Firstly, as Griffith et al. (2004) show, import penetration has no significant effect on innovation. Secondly, we have looked at the effect of sectoral exposure to the raise of China after its access to the WTO, using an indicator similar to Autor. et al. 2014. We find no relation between sectoral exposure to China and increase in misallocation.

1995 is unlikely to be driven by a higher dispersion of firm-level shocks. Nonetheless, we see an increase in the dispersion of shocks in the period 2000-2002 and then in 2008-2009. The former is associated to a sharp slowdown in GDP growth (from 3.7% to 0.2%), the latter with the recession due to the global financial crisis.

Interestingly, there is no significant raise in the dispersion of idiosyncratic shocks after the European debt crisis of 2011, although the level of the dispersion remains higher than the pre-2008 period. Moreover, as we observed in Figure 6, the level of misallocation decreases slightly after the European debt crisis. This could be due to some cleansing effect that this crisis had. Figure 16 shows the exit rate of firms by TFPR decile: before the European crisis (i.e., before 2007), after the global financial crisis (i.e., after 2009) and after the European sovereign debt crisis (i.e., after 2012). The results show that, for firms in the lowest deciles, the exit rate increases significantly after the European crisis, but not after the global financial crisis. This provides suggestive evidence of some cleansing effect following the European crisis.

7 The impact of misallocation on aggregate productivity

The overarching message of the evidence presented in the previous sections 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.

Following 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 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:

$$\text{Gain}_t = \left(\frac{Y_t^*}{Y_t}\right) - 1 \tag{4}$$

Second, to understand how much aggregate productivity 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:

$$\text{Gain}_{t/95} = \left(\frac{Y_t^*/Y_t}{Y_{95}^*/Y_{95}}\right) - 1 \tag{5}$$

When applied to our data, equation (5) implies that, if misallocation had remained at its 1995 level, in 2013 aggregate productivity would have been 18% higher than its actual level (see Figure 17). Moreover, the effect of misallocation on productivity 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.[18]

From a size class (Figure 18) and geographical perspective (Figure 19), 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, productivity would have been 18% and 25% higher if misallocation in 2013 had stayed at its 1995 level.

8 Caveats of the Hsieh-Klenow framework: a robustness analysis

Even if the measure of misallocation of HK is extensively used in the literature, there are important caveats to keep in mind. For instance, the very idea of interpreting the entire observed dispersion of TFPR across firms as evidence of inefficiency is contentious. Asker et al. (2014) argue that, in the presence of adjustment costs in investment ("time-to-build"), transitory 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, HK 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. 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 average of the relative log-TFPR (i.e., $\ln \frac{TFPR_{sit}}{TFPR_{st}}$). For stationary series, the variance ratio approaches a limit. The output of this exercise is reported in Figure 20. 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.[19]

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

[18]The quantitative results of this exercise are sensitive to the values chosen for the elasticity of substitution σ between products sold by firms. In the baseline we set σ equal to 3 as in HK. 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 values of the elasticity deliver stronger gains: 12% with $\sigma = 2$, and 19% with $\sigma = 4$.

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

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. Melitz and Ottaviano (2008) show that in the case of linear demand, markup is increasing with size (the elasticity of demand is decresing with size). Therefore, if heterogenous markups drive dispersion, we should observe that TFPR increases with size. However, in Figure 21, where we report the average TFPR by size percentile, we find that there is no clear relation between TFPR and size.[20] Moreover, as Gopinath et al.(2017) stress, if markups drive dispersion, the effect should be symmetric for capital and labor and we should observe proportional increases in the dispersion of both MRPK and MRPL. As shown in Figure 11, this is not the case: dispersion increases more for capital.[21]

Finally, 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, 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 (i.e., $P_{si}Y_{si} = TFPR_{si}K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}$), the presence of measurement error introduces spurious correlation between firms' TFPR and input growth. Their suggested methodology consists of regressing revenue growth on input growth, revenue productivity and their interaction. While the interaction term is expected to be zero if the level of revenue productivity reflects true differences in marginal products, inverse negative correlation is expected when revenue productivity is a spurious indicator of true marginal products. This approach allows us to evaluate the fraction of observed TFPR dispersion reflecting the actual presence of distortions by estimating the following equation (under the assumption that the measurement error is additive with respect to the true revenues and inputs and orthogonal to the true marginal product):

$$\Delta VA_{si} = \Phi \ln \widetilde{TFPR}_{si} + \Psi \Delta Z_{si} + \Psi(1-\lambda) \ln \widetilde{TFPR}_{si} \Delta Z_{si} + D_s + \epsilon_{si,t}$$

where Δ denotes the annual growth rate from $t-1$ to t; Z_{si} is the composite input $K_{si}^{\alpha_s}(wL_{si}^{)}1-\alpha_s$; $\ln \widetilde{TFPR}_{si} = (\ln \widetilde{TFPR}_{si,t} + \ln \widetilde{TFPR}_{si,t-1})/2$, with $\ln \widetilde{TFPR}_{si,t} = \ln TFPR_{si,t} - \sum_{i=1}^{N_s} \frac{VA_{si,t}}{VA_{s,t}} \ln TFPR_{si,t}$; D_s is a sector dummy. The parameter λ indicates the fraction of observed misallocation (i.e. differences in TFPR) reflecting actual input misallocation. Our estimated value for this fraction is 0.54, suggesting that more than fifty per cent of our measured misallocation is not driven by measurement error and can thus be regarded as true misallocation.[22] 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.

[20] In Figure 21 we drop the top and the bottom percentile as a robustness to outliers. The variation of average ln TFPR across percentiles is low and it oscillates between 0.52 and 0.56.

[21] In ongoing work, Calligaris (2017) extend the analysis of this paper to allow for heterogeneous markups, finding that, if anything, measured misallocation actually increases.

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

9 Productivity, misallocation, and firm characteristics

In order 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 use data from INVIND, which is described in Section 3. In particular, we consider corporate ownership and management, finance, workforce composition, internationalization and innovation, relying on the following reduced form at the firm level:

$$\ln \frac{TFPR_{sit}}{\overline{TFPR}_{st}} = \beta_0 + \beta_1 X_{sit} + \delta_t + \gamma_s + \varepsilon_{sit}, \tag{6}$$

where i, s and t refer to firm, sector and year respectively; X_{sit} is the marker (or vector of markers) we want to analyze[23]; δ_t is a year dummy that captures common shocks to all firms in a given year; γ_s is a sector fixed effects controlling for time-invariant sector characteristics that can influence the effect of the marker on misallocation; ε_{sit} is the error term. This regression relates the a firm's relative TFPR 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_{sit} are characterized by higher (lower) relative TFPR. It is worth noting how this econometric specifications allows us to identify correlations, but not causation.

In equation (6) the main variable of interest is marker X. Its coefficient β_1 could be zero in two different scenarios. First, it would be zero if the aggregate allocation of resources were efficient (that is, if $TFPR_{is}/\overline{TFPR}_s = 1$ holds true for all firms). As we have seen, this is not the case in our data. Second, even if the allocation of resources were not efficient, β_1 would be zero if X 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 β_1 reveals that the marker increases misallocation.[24] In particular, larger (smaller) values of the marker are correlated to more misallocation for positive (negative) estimated β_1. In other words, if the estimated β_1 is positive, firms with relatively large X are inefficiently small and should absorb more resources; vice versa, if the estimated β_1 is negative, firms with relatively large X are inefficiently large and should downsize or exit the market.

Our benchmark specification is based on standard pooled OLS regression, always including sector and year dummies. In fact, with respect to our aim of investigating the markers of misallocation, the most appropriate specification does not include firm fixed effects. Indeed, 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.[25]

[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 β_1 were zero, if it is related to the dispersion of the residuals of equation (6). 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 misallocation. We omit these results for parsimony but they are available from the authors on request.

[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 using the OECD classification of manufacturing industries according to their global technological intensity (based on R&D expenditures with respect to value added). 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 (6). Moreover, following HK, we quantify the firm-level output and capital distortions ("wedges") and we use them as alternative dependent variables in (6).[26] 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. A positive and significant coefficient of the capital wedge on marker X 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 (6) 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, innovation, foreign exposure, and cronysm.[27]

9.1 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 TFPR 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 7).

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 7 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.

[26] HK show that, for firm i in sector s, the capital and output distortions ('wedges') can be computed as $\tau_{Ksi} = \alpha_s w L_{si} / [(1-\alpha_s)\ RK_{si}] - 1$ and $\tau_{Ysi} = 1 - \sigma w L_{si}\ / [(1-\sigma)(1-\alpha_s) P_{si} Y_{si}]$, respectively. w is wage, R is rental rate of capital, P_{is} is price of output and α_s is the capital share of firm expenditures.

[27] 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.

Reading these findings 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.[28]

9.2 Finance

We investigate in Table 8 the importance of credit constraints, equity emissions and relational banking. We also explore in Table 9 the impact of the introduction of the Euro on firms' financial characteristics.

Credit constraints

We define credit constrained firms as those that declared that they would have liked a higher level of debt (Table 8, Panel A). 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.[29] 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.[30] This implies that credit constrained firms are absorbing too many resources and should downsize (or exit the market), 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.

Equity

In Panel B we look at the relation of firms' relative TFPR and 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 $t+1$. 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

[28] 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. 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.

[29] Results available upon request

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

of funding when firms are hit by a negative productivity shock. This calls for further investigation about the allocative efficiency of different sources of external funding, such as equity, bonds, and bank credit.

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 Panel C 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.

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. 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.[31] We check if, after the introduction of the Euro, the correlation between TFPR and leverage has changed.

In Table 9, Column 1, we 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 assumption 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. Of course, this evidence is only suggestive and cannot be taken as causal. First, both TFPR and leverage are co-determined, so we are simply measuring the change in a correlation. Second, the result does not hold when we look at labor and capital wedges separately (Columns 2 and 3): not surprisingly, 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.

[31] 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.

9.3 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.[32] 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 consider: the Italian Wage Supplementation Scheme, which is the main instrument of labor hoarding that firms use, the shares of temporary and foreign workers that firms hire, the skill intensity among blue- and white-collars. Results are reported in Table 10.

Wage Supplementation Scheme (Cassa Integrazione Guadagni - CIG)

Firstly, we look at how intensively firms resorted to the Wage Supplementation Scheme ("Cassa Integrazione Guadagni" - CIG). This scheme allows distressed firms to hoard labor, so that workers suspend temporarily their job or reduce the hours of work and receive an income supplement from the government. The worker receives the benefit as long as he remains employed by the firm. We define the variable Wage Supplementation Scheme as hours paid by the supplementation scheme over total hours paid. The key characteristic of CIG is that it protects not only the worker, but also the specific job match between worker and firm. Thus, it 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.

Panel A of Table 10 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.

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.[33]

[32]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.

[33]To go more into the details of these relationships, we run contemporaneous and one-year lagged fixed

Temporary workers

Panel B analyzes the relation between temporary workers and misallocation. We define "Temporary employment share" as the ratio of the number of temporary employees to the total number of employees at the end of the year. 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.[34] 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.

Skill intensity

We consider two measures of skill-intensity: the share of white collars holding a degree (Panel C) and the share of blue collars holding a degree (Panel D). 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.[35]

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.[36] 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.

9.4 Internationalisation

We study the correlation of misallocation with two main dimensions of firms' internationalisation: delocalisation and foreign direct investment (FDI). In Table 11 we report in both cases no evidence of resource misallocation for firms engaging with these types of international activities with respect to those that do not (we use dummy variables). Notice that this result does not imply the absence of misallocation within those groups.

effects regressions, always finding that the decision to start using CIG is associated with lower relative TFPR.

[34]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.

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

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

However, this is an aspect that, given the low number of observations, we are not able to analyse.

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.[37]

9.5 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 et al., 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. While our database does not allow us to address innovation using alternative and more focused measures, relying on intangibles is consistent with Battisti et al. (2015), who show intangible assets to be positively associated with both TFP and technology adoption at the firm-level.

Table 12 shows that a higher share of intangible assets is associated with higher relative TFPR.[38] 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.

9.6 Combining markers: a short horse-race

We complete our investigation of the firm markers associated with 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. Although there might be concern of collinearity between the variables, cross-correlations are never above 0.27 (in absolute value).

[37] 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 when the nonlinearity in the relationship is taken into account. Results are available upon request.

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

Table 13 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 10. 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.

10 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 within 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.

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

References

[1] Altomonte, C., Aquilante, T. (2012). *The EU-EFIGE/Bruegel-unicredit dataset* (No. 753). `http://bruegel.org/2012/10/the-eu-efigebruegel-unicredit-dataset/`

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

[3] Bandiera, O., Prat, A., and R. Sadun, (2015), Managing the Family Firm: Evidence from CEOs at Work, CEPR Discussion Paper 10379.

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

[5] Battisti, M., Belloc, F., Del Gatto, M. (2015). Unbundling technology adoption and TFP at the firm level: do intangibles matter? *Journal of Economics & Management Strategy*, 24(2), 390-414.

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

[7] Bils, M., Klenow, P., and C. Ruane (2017), Misallocation or Mismeasurement?, Stanford University, mimeo.

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

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

[10] Broda, C., Weinstein, D.E. (2006), Globalization and the gains from variety, *Quarterly Journal of Economics*, 121(2): 541-585.

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

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

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

[14] Calligaris, S., 2017. The Role of Heterogeneous Markpus in Quantifying Misallocation: Evidence for Italy, mimeo, EIEF.

[15] Calligaris, S., Del Gatto, M., Hassan, F., Ottaviano, G.I.P., Schivardi, F. (2016). "Italy's Productivty Conundrum", European Commission Discussion Paper n. 030.

[16] Cette, G., Fernald, J.G.., and B. Mojon. (2016). The pre-Great Recession slowdown in productivity, *European Economic Review*,vol. 88, issue C, 3-20

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

[18] Choi, I., (2001), Unit root tests for panel data, *Journal of International Money and Finance*, vol. 20, issue 2, 249-272

[19] Cochrane, J.H., (1988). How big is the random walk in GNP?, *Journal of Political Economy*, vol. 96, 893920.

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

[21] Daveri, F., Parisi, M. L. (2015) Experience, Innovation, and Productivity Empirical Evidence from Italy's SlowdownILR Review, 68 (4): 889-915.

[22] De Loecker, J., and P. Goldberg (2014). Firm performance in a global market, *Annual Review of Economics* 6, 201-227.

[23] De Nardis, S. (2014), Efficienza e specializzazione, Nomisma 9 October 2014.

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

[25] Engel, C., (2000). Long-run PPP may not hold after all, *Journal of International Economics*, vol. 51, issue 2, 243-273.

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

[27] Fernald, J.G. (2014) Productivity and Potential Output Before, During, and After the Great Recession, Federal Reserve Bank of San Francisco, Working Paper 2014-15.

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

[29] Foster, L., Grim, C., Haltiwanger, J. and Wolf, Z. (2017) Macro and Micro Dynamics of Productivity: From Devilish Details to Insights. CES Working Paper 17-41R

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

[31] Gamberoni, E., Giordano, C. and P. Lopez-Garcia, 2016. "Capital and labour (mis)allocation in the euro area: some stylized facts and determinants," Working Paper Series 1981, European Central Bank.

[32] Gopinath, G., Kalemli-Ozcan, S., Karabarbounis, L., Villegas-Sanchez, C. (2017), Capital Allocation and Productivity in South Europe, *Quarterly Journal of Economics*, forthcoming.

[33] Griffith, R., Redding, S., and J. Van Reenen. (2004) Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries, *Review of Economics and Statistics*, vol. 86, issue 4, 883-895.

[34] Haltiwanger, D. (2016), Firm Dynamics and Productivity: TFPQ, TFPR, and Demand-Side Factors, *Economía* 17, 3-26.

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

[36] Head, K. and Mayer, T. (2014), Gravity Equations: Workhorse, Toolkit, and Cookbook. In Helpman, E., Rogoff, K., and Gopinath, G., editors, *Handbook of International Economics*, volume 4, pages 131-195. Elsevier.

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

[38] Im, K.S., Pesaran, M., and Y. Shon, (2003), Testing for unit roots in heterogeneous panels, *Journal of Econometrics*, vol. 115, issue 1, 53-74

[39] Linarello, A., Petrella, A. (2016), Productivity and Reallocation: evidence from the universe of Italian firms, Bank of Italy, Occasional Paper, n.353.

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

[41] Lusinyan, L. and Muir, D. (2013). Assessing the Macroeconomic Impact of Structural Reforms: The Case of taly. IMF, Working Paper No. 13/22.

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

[43] Melitz, M., Ottaviano, G.I.P. (2008). "Market Size, Trade, and Productivity", *Review of Economic Studies*, 75: 295-316.

[44] Pellegrino, B., Zingales, L. (2017) "Diagnosing the Italian disease", NBER Working Paper n. 23964.

[45] Sette, E., Schivardi, F. and G. Tabellini (2018). "Credit Misallocation During the European Financial Crisis", LUISS Working Paper no. 139.

[46] Schivardi, F., & Schmitz, T. (2012). "The ICT Revolution and Italys Two Lost Decades", LUSS WP series no. 138.

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

Table 1: **Summary statistics.**

	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: CERVED database. 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 by geographic area and size.**

	Value Added	Capital	Cost of labor	Obs.
Panel A: 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%
Panel B: by firm 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: CERVED database. Main variables expressed both in absolute values and in percentages of the total. Absolute values are expressed in thousand of 2007 Euros. Firms dived into four geographic areas and four firms sizes.

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

	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: CERVED database. Percentages of firms in each group. 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 firms in each geographic area, by size.**

	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: CERVED database. Value added shares of firms in each group. 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 firms in size class, by geographic area.**

	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: CERVED database. Value added shares of firms in each group. 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.

Note: The null hypothesis states that the estimated coefficient ϕ_{is} in the following autoregressive model is equal to zero for all firms: $\Delta \ln \frac{TFPR_{is,t}}{TFPR_{s,t}} = \phi_{is} \ln \frac{TFPR_{is,t-1}}{TFPR_{s,t-1}} + \mathbf{D'}_{is,t}\gamma_{is} + \epsilon_{is,t}$. $\mathbf{D}_{is,t}$ represents a firm fixed-effect in the standard cases and includes a linear time trend in the cases indicated with asterisk; $\epsilon_{is,t}$ is independently distributed normal for all i and t and is allowed to have heterogeneous variances across firms. The alternative hypothesis is that $\hat{\phi}_{is} \neq 0$ for a fraction of firms. We assume errors to be serially correlated. We let the routine chose the lag in the Im-Pesaran-Shin test, while we set the lag to one in the Fisher-type test.

Table 7: Firm-level 'markers' of misallocation: Ownership

	(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

Note: the table reports OLS regressions of relative TFPR, output and capital wedges on ownership dummies. Specifically, Family is a dummy equal to 1 if the firm is controlled by an individual or a family, Conglomerate is equal to 1 if controlled by a non-financial corporation, Financial Institution by a financial institution, Government by a public institution, Foreign by foreign entity. The sample includes manufacturing firms with at least 50 employees over the years 1987-2011. All regressions include year and two-digit sector fixed effects. Standard errors are clustered at the sectoral level. ***,**,* indicate significant at the 1, 5 and 10% respectively.

Table 8: Firm-level ‘markers’ of misallocation: Finance

	(1) Relative TFPR	(2) Output Wedge	(3) Capital Wedge
Panel A:			
Credit Constraint	-0.0657**	-0.0322**	-0.00445
	(0.0298)	(0.0157)	(0.0485)
Observations	1,188	1,188	1,188
R-squared	0.155	0.132	0.375
Panel B:			
Increased equity	-0.0629***	-0.0305***	0.000297
	(0.0151)	(0.00801)	(0.0276)
Observations	9,527	9,527	9,527
R-squared	0.035	0.076	0.255
Panel C:			
Relational banking	-0.0823**	-0.0202	-0.0273
	(0.0336)	(0.0257)	(0.0600)
Observations	774	774	774
R-squared	0.080	0.148	0.335

Note: the table reports OLS regressions of relative TFPR, output and capital wedges on indicators of financial conditions. Each panel report a separate set of regressions. Credit constraint is the lagged value of a dummy equal to 1 if the firm declared that, at the current borrowing conditions in terms of interest rate and collateral, the firm would prefer a higher level of debt from banks or other financial institutions. Increased equity is a dummy equal to 1 if the firm increased equity in the current year. Relational banging is a dummy equal to 1 if the firm declares that the principal reason for dealing with its main bank is “personal relationship and assistance”. The sample includes manufacturing firms with at least 50 employees over the years 1989-2011 in Panel A, 1998-2011 in Panel B and 2002 in Panel C. Regressions in Panel A and B include year and two-digit sector fixed effects; regression in Panel C includes two-digit sector fixed effects. Standard errors are clustered at the sectoral level. ***,**,* indicate significant at the 1, 5 and 10% respectively.

Table 9: Firm-level 'markers' of misallocation: Euro effect

	(1) Relative TFPR	(2) Output Wedge	(3) 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

Note: the table reports OLS regressions of relative TFPR, output and capital wedges on Leverage, defined as debt over total assets, Post, which is a dummy equal to 1 for years after 1999, and their interaction. The sample includes manufacturing firms with at least 50 employees over the years 1987-2007. All regressions include two-digit sector fixed effects. Standard errors are clustered at the sectoral level. ***,**,* indicate significant at the 1, 5 and 10% respectively.

Table 10: Firm-level ‘markers’ of misallocation: Workforce composition

	(1) Relative TFPR	(2) Output Wedge	(3) Capital Wedge
Panel A:			
Wage supplementation	-0.425***	-0.165***	-0.515***
	(0.0979)	(0.0432)	(0.0740)
Observations	19,078	19,078	19,078
R-squared	0.041	0.106	0.283
Panel B:			
Temporary employment, share	0.116**	-0.0398	0.597***
	(0.0565)	(0.0280)	(0.120)
Observations	11,825	11,825	11,825
R-squared	0.028	0.072	0.246
Panel C:			
Graduate share, white collars	0.359***	0.105***	-0.241*
	(0.0765)	(0.0308)	(0.133)
Observations	1,412	1,412	1,412
R-squared	0.080	0.152	0.279
Panel D:			
Graduate share, blue collar	-0.234	-0.159	-1.092*
	(0.421)	(0.412)	(0.571)
Observations	1,366	1,366	1,366
R-squared	0.059	0.143	0.278

Note: the table reports OLS regressions of relative TFPR, output and capital wedges on indicators of financial conditions. Each panel report a separate set of regressions. Wage supplementation is hours paid by the Government wage supplementation scheme over total hours worked. Temporary employment, share is the number of temporary employees over total number of employees. Graduate share, white collars is the number of graduate white collar over total number of white collar workers, and similarly for blue collar workers. The sample includes manufacturing firms with at least 50 employees over the years 1987-2011 in Panel A, 1999-2011 in Panel B, 2000 and 2010 in Panel C and in Panel D. Regressions in Panel A and B include year and two-digit sector fixed effects; regressions in Panel C and D include two-digit sector fixed effects. Standard errors are clustered at the sectoral level. ***,**,* indicate significant at the 1, 5 and 10% respectively.

Table 11: Firm-level 'markers' of misallocation: Internationalisation

	(1) Relative TFPR	(2) Output Wedge	(3) Capital Wedge
Panel A:			
Delocalisation	-0.00715	-0.000137	-0.0313
	(0.0386)	(0.0114)	(0.0709)
Observations	655	655	655
R-squared	0.109	0.203	0.295
Panel B:			
FDI	0.00640	-0.0137	0.0772
	(0.0585)	(0.0196)	(0.115)
Observations	201	201	201
R-squared	0.304	0.399	0.463

Note: the table reports OLS regressions of relative TFPR, output and capital wedges on indicators of Internationalization. Each panel report a separate set of regressions. Delocalization is a dummy equal to 1 if the firm delocalized part of its production activity. FDI is a dummy equal to 1 if the firm has engaged in FDI. The sample includes manufacturing firms with at least 50 employees. Panel A is a cross-section for the year 2011, and Panel B is a cross-section for 2003. All regressions include two-digit sector fixed effects. Standard errors are clustered at the sectoral level. ***,**,* indicate significant at the 1,5 and 10% respectively.

Table 12: Firm-level 'markers' of misallocation: Innovation

	(1) Relative TFPR	(2) Output Wedge	(3) 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

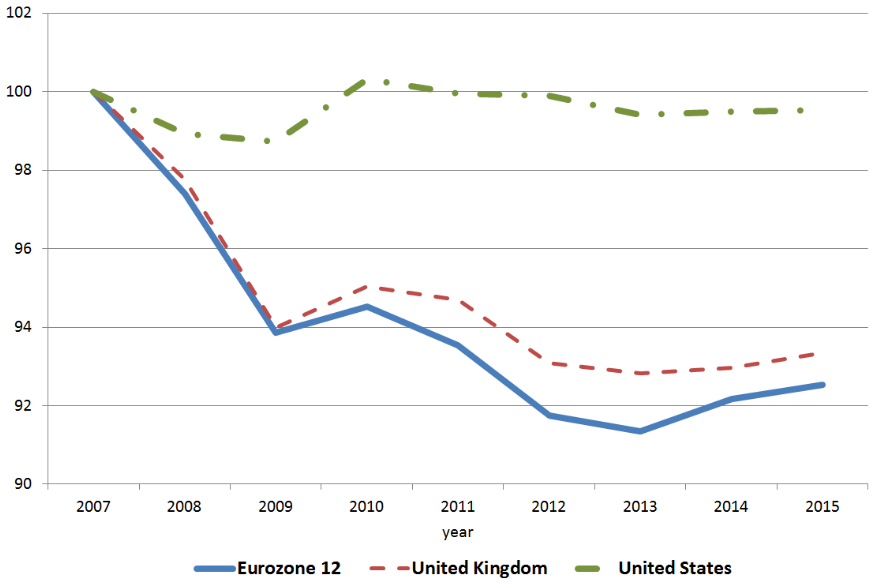
Note: the table reports OLS regressions of relative TFPR, output and capital wedges on the share of intangible assets over total assets. The sample includes manufacturing firms with at least 50 employees over the years 1999-2011. All regressions include year and two-digit sector fixed effects. Standard errors are clustered at the sectoral level. ***,**,* indicate significant at the 1,5 and 10% respectively.

Table 13: Firm-level 'markers' of misallocation: a short horse race

	(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)
Intangible assets share	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	-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

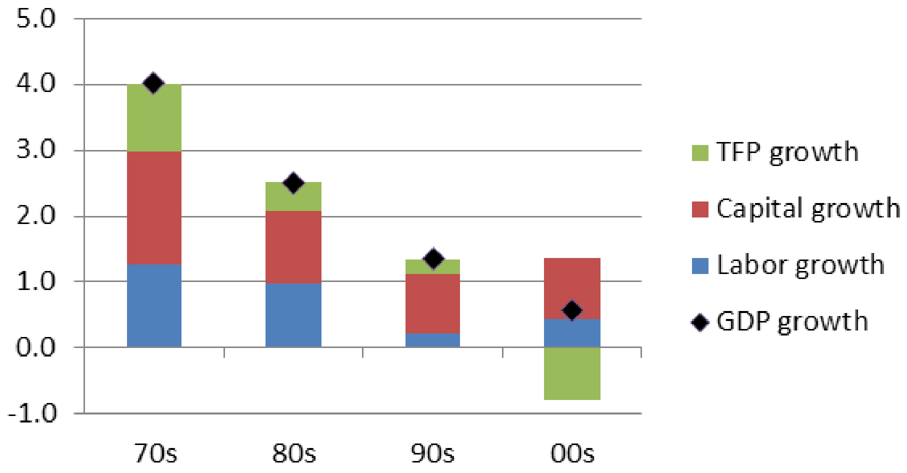
Note: the table reports OLS regressions of relative TFPR, output and capital wedges on a selected set of variables from the previous tables. Graduate share, white collars is the number of graduate white collar over total number of white collar workers, Intangible assets, share is the share of intangible assets over total assets, Family is a dummy equal to 1 if the firm is controlled by an individual or a family, Wage supplementation is hours paid by the Government wage supplementation scheme over total hours worked, Temporary employment, share is the number of temporary employees over total number of employees. The sample includes manufacturing firms with at least 50 employees over the years 2000 and 2010. All regressions include year and two-digit sector fixed effects. Standard errors are clustered at the sectoral level. ***,**,* indicate significant at the 1,5 and 10% respectively.

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



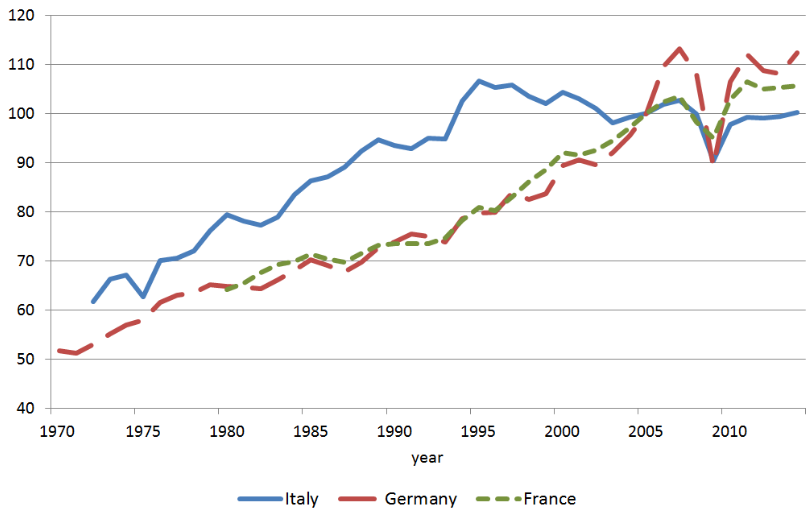
Source: Conference Board.

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



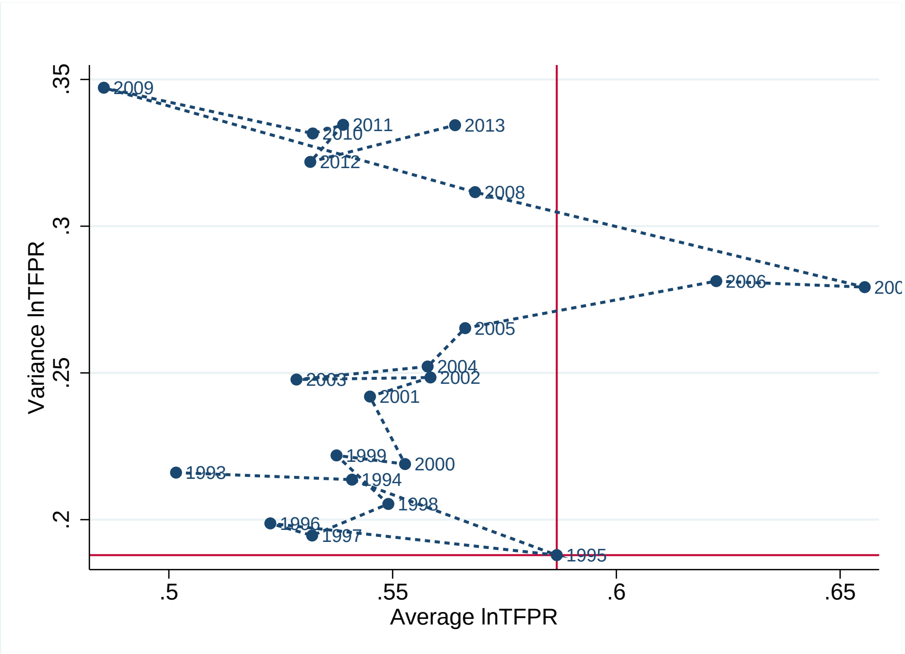
Source: EU-Klems.

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



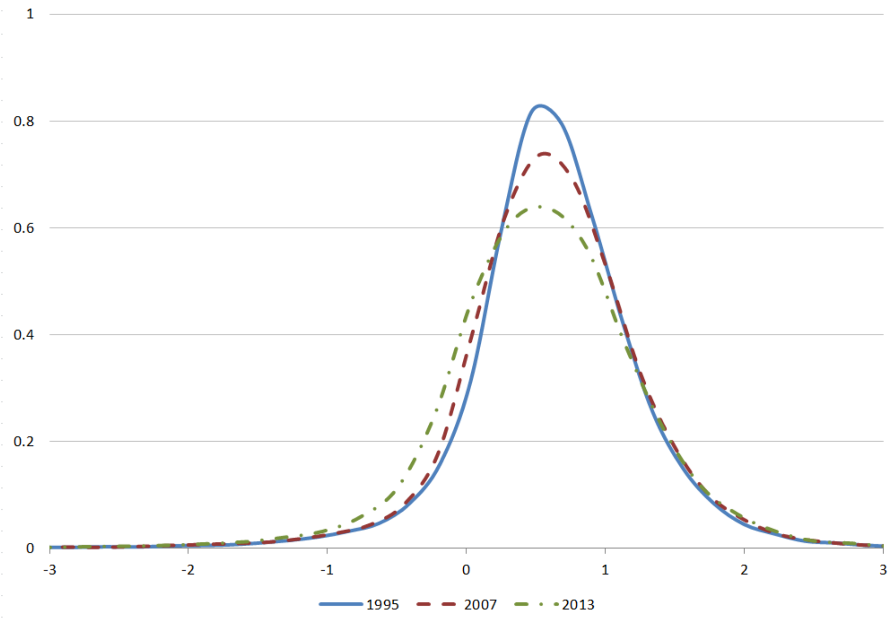
Source: Hassan and Ottaviano (2013).

Figure 4: **Evolution of TFPR average and variance (1993-2013)**



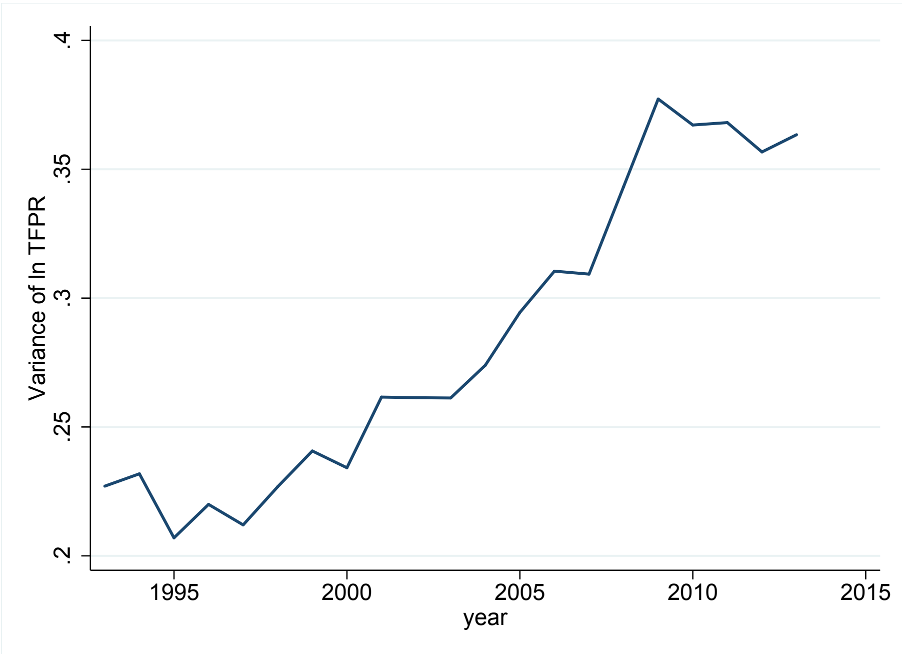
Source: CERVED.

Figure 5: **Distribution of TFPR, 1995, 2007 and 2013**



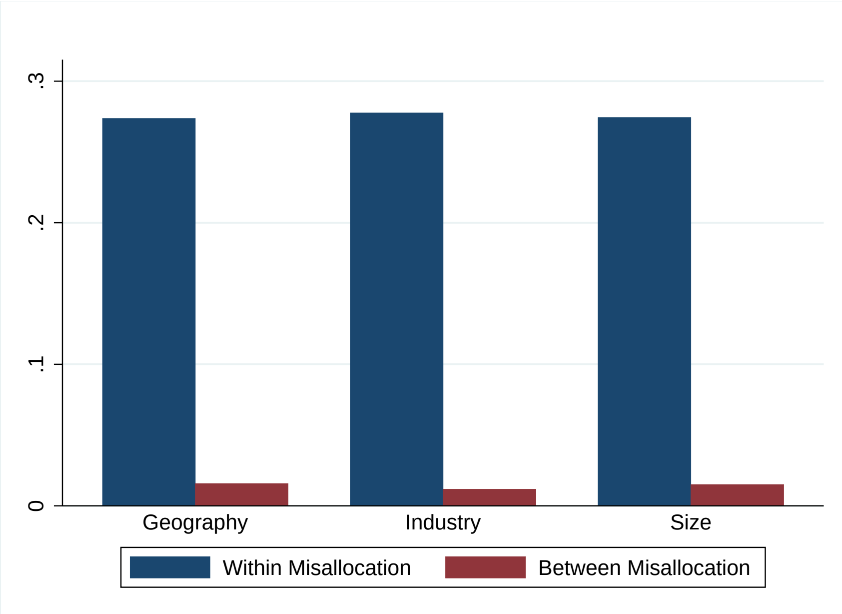
Source: CERVED.

Figure 6: **Evolution of aggregate misallocation, 1993-2013**



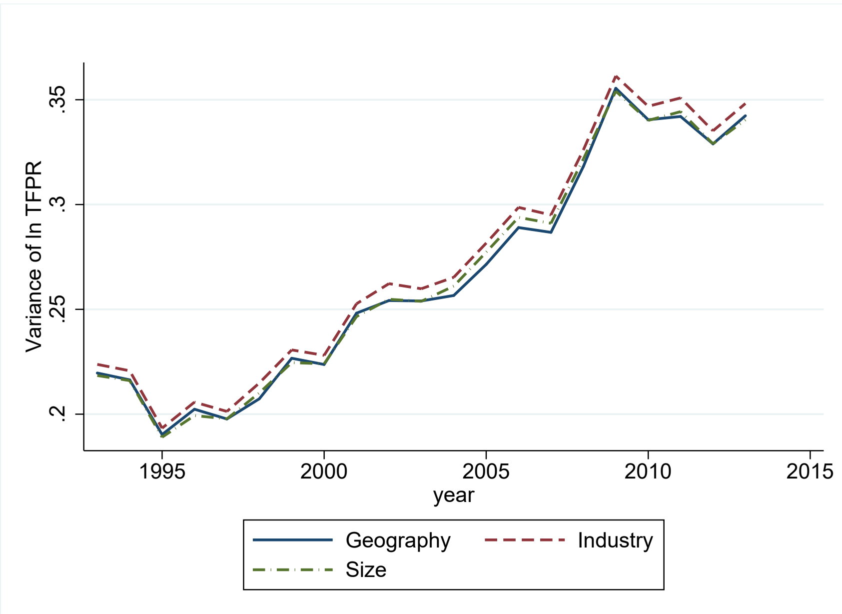
Source: CERVED.

Figure 7: **Misallocation, within vs. between categories**



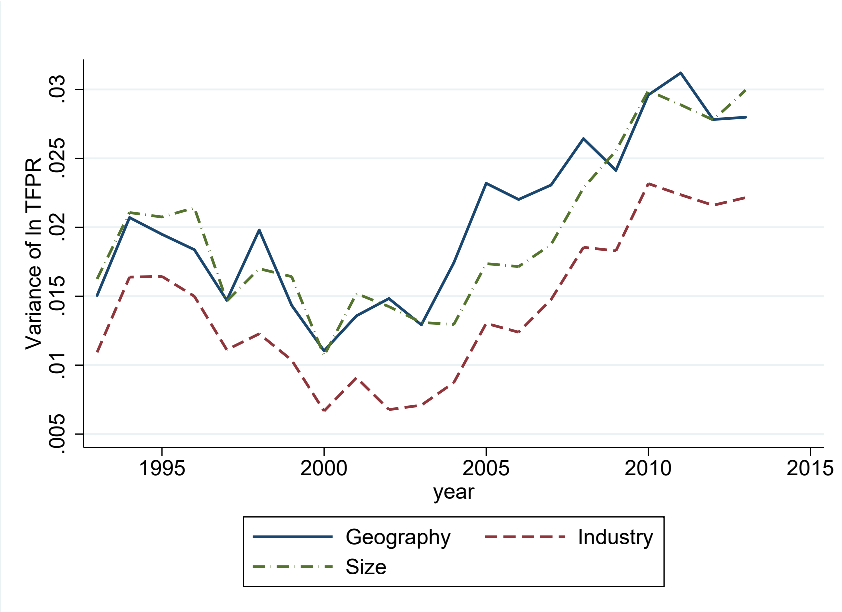
Source: CERVED. The figure reports a decomposition exercise of the dispersion of ln TFPR within and between each of the three categories (geographic area, industry and size class). The values are computed over the whole 1993–2013 period.

Figure 8: **Evolution of within-misallocation by category**



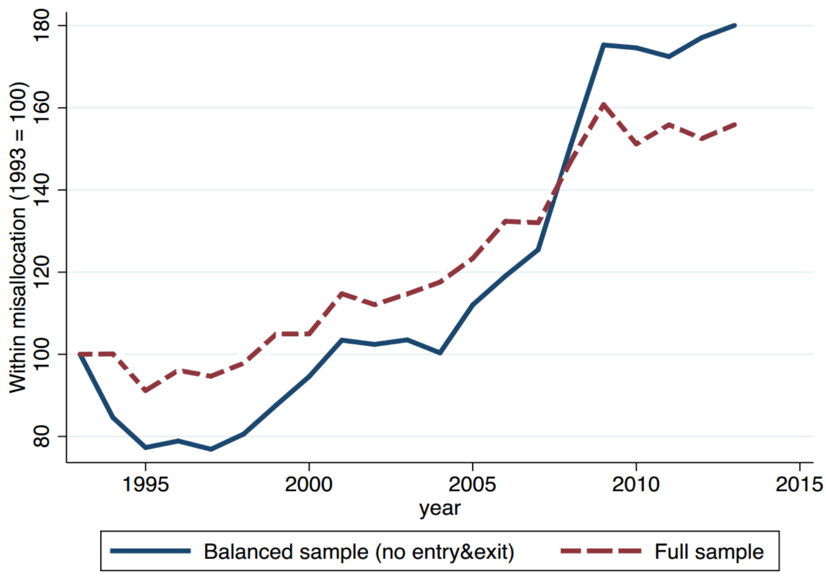
Source: CERVED. The figure reports the evolution of the within component of the variance of ln TFPR, by category.

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



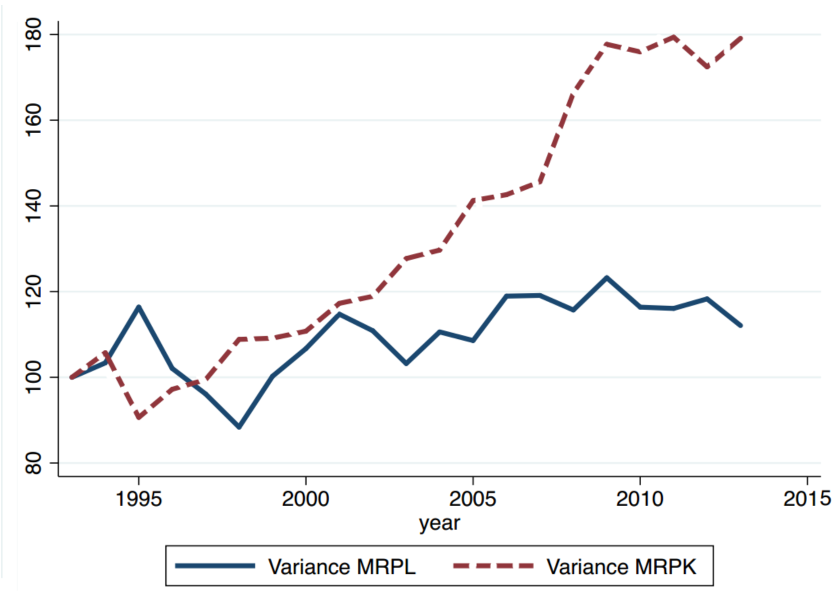
Source: CERVED. The figure reports the evolution of the between component of the variance of ln TFPR, by category.

Figure 10: **Evolution of misallocation, balanced vs. full-sample (1993=100)**



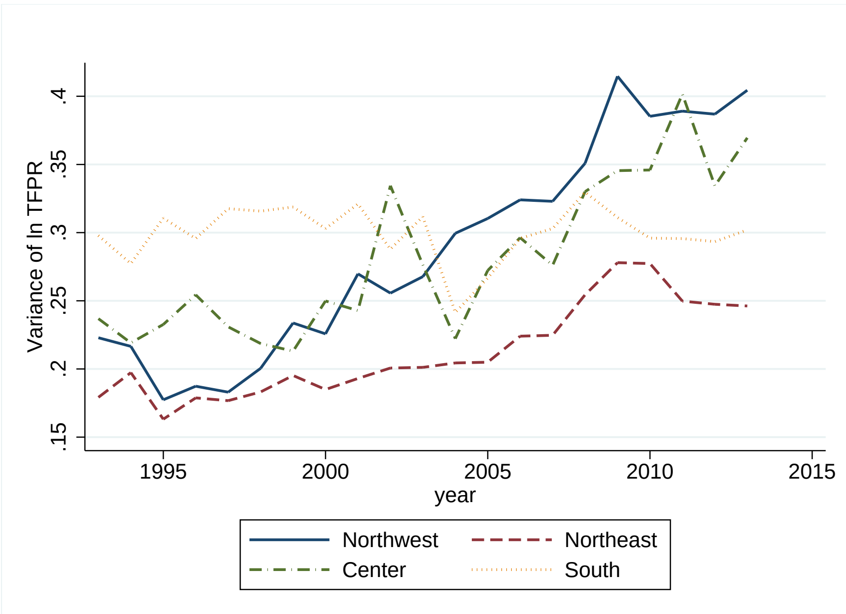
Source: CERVED.

Figure 11: **Evolution of misallocation, marginal product of capital and labor (1993=100)**



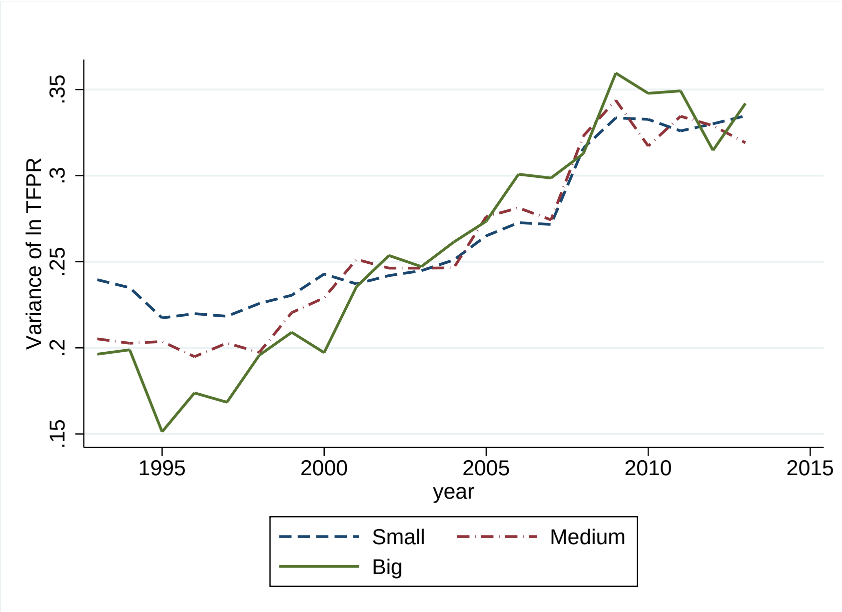
Source: CERVED.

Figure 12: **Misallocation by geographic area**



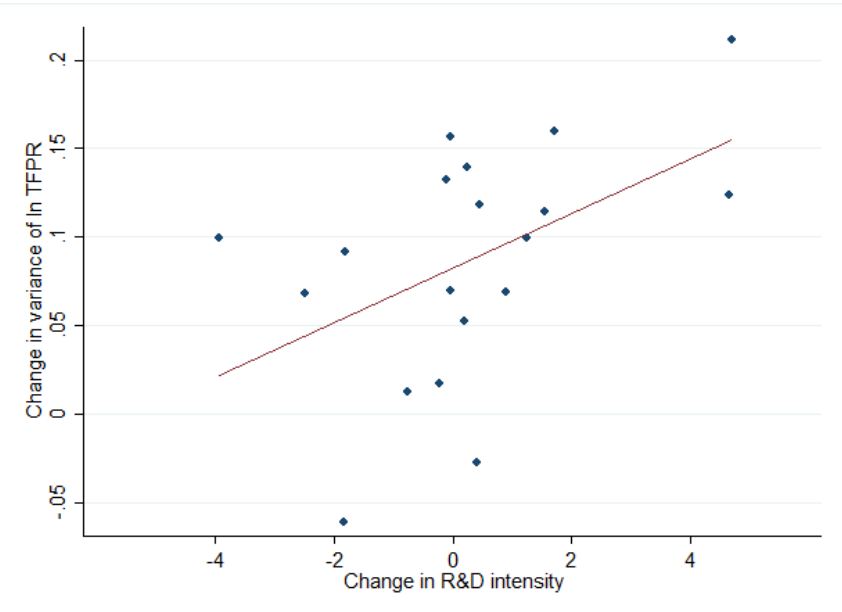
Source: CERVED.

Figure 13: **Misallocation by firm size**



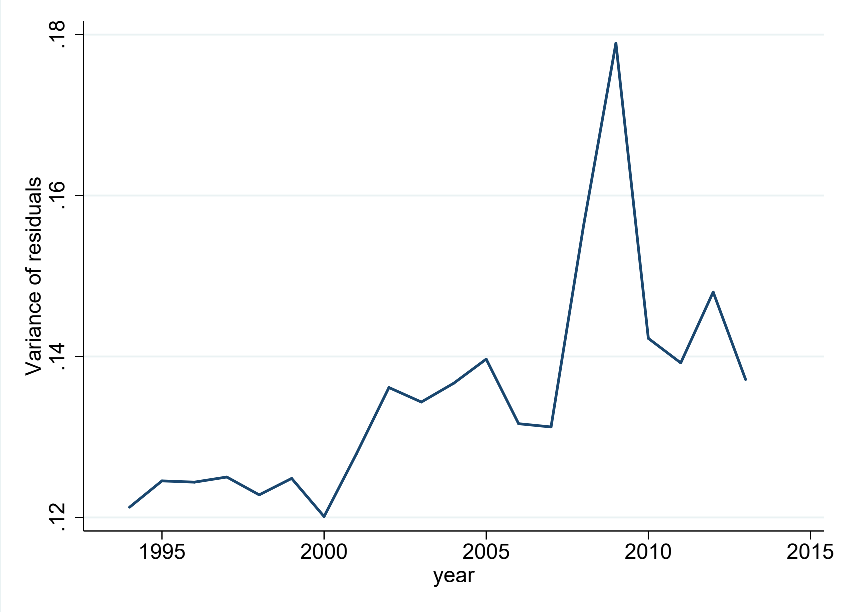
Source: CERVED.

Figure 14: **Change in R&D intensity and misallocation at the sectoral level**



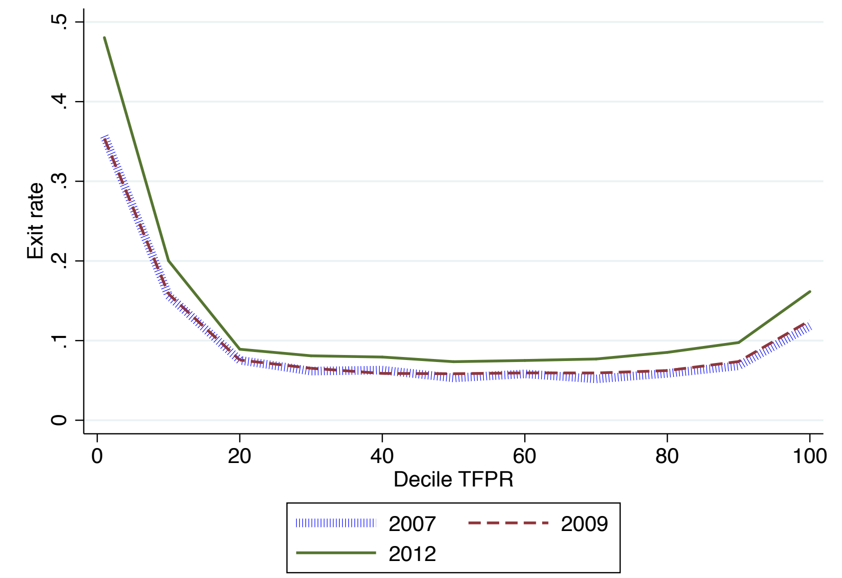
Source: CERVED and OECD. The figure reports the correlation between the change of misallocation and R&D intensity at the 2-digit sectoral level. The change in misallocation is computed between 2013 and 1993. The change in research intensity is measured by taking the difference between the period 1993-2007 and 1987-1992. R&D intensity is measured as the share of R&D expenditure on value added.

Figure 15: **Dispersion of idiosyncratic productivity shocks**



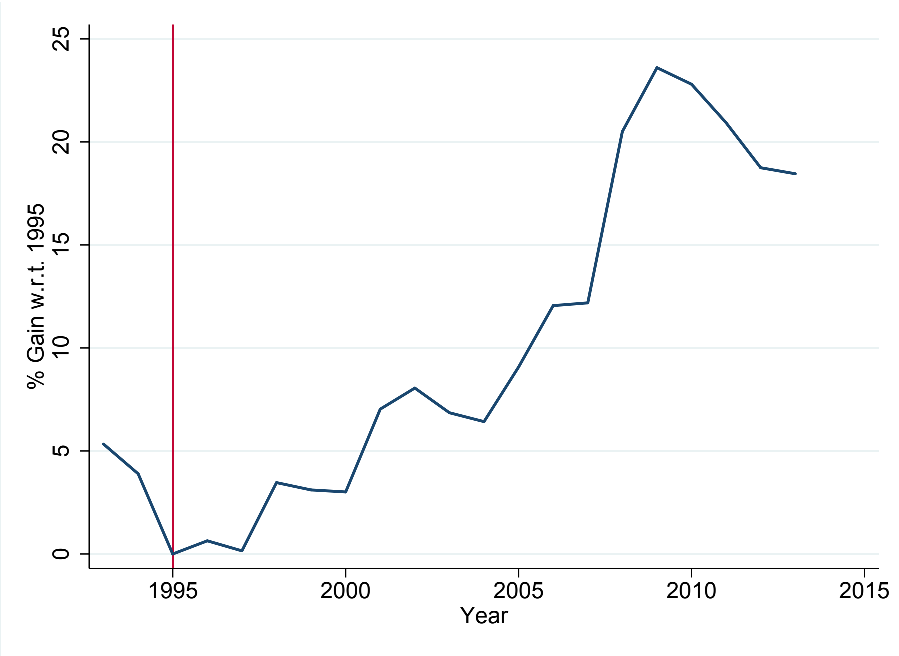
Source: CERVED. The figure reports the evolution of the dispersion of idiosyncratic productivity shocks, constructed as the residuals of a regression of TFPR on firm fixed effects, sector-year fixed effects and lagged TFPR. See the main text for the details.

Figure 16: **Exit rate by productivity decile**



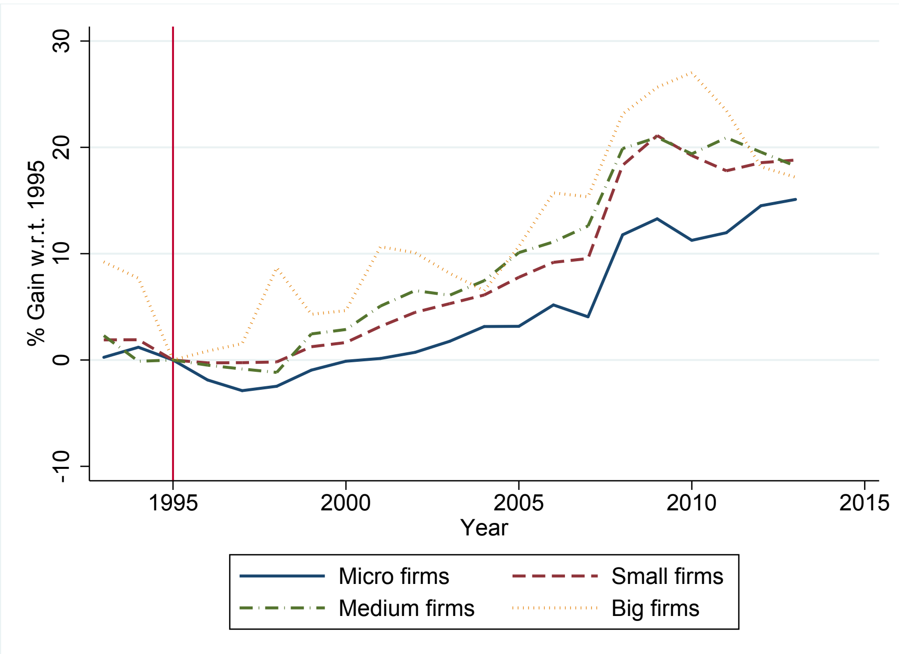
Source: CERVED. The figure shows the share of firms that exit the market for each decile of firms' productivity in specific years.

Figure 17: **Productivity gains from equalising TFPR dispersion to its 1995 value, manufacturing**



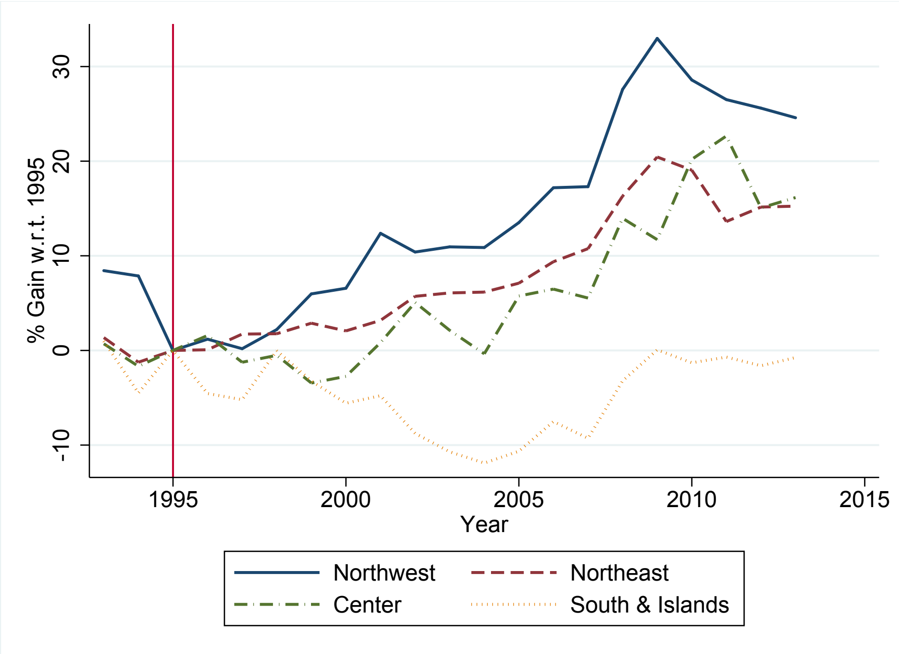
Source: CERVED.

Figure 18: **Productivity gains from equalising TFPR dispersion to its 1995 value, by firm size**



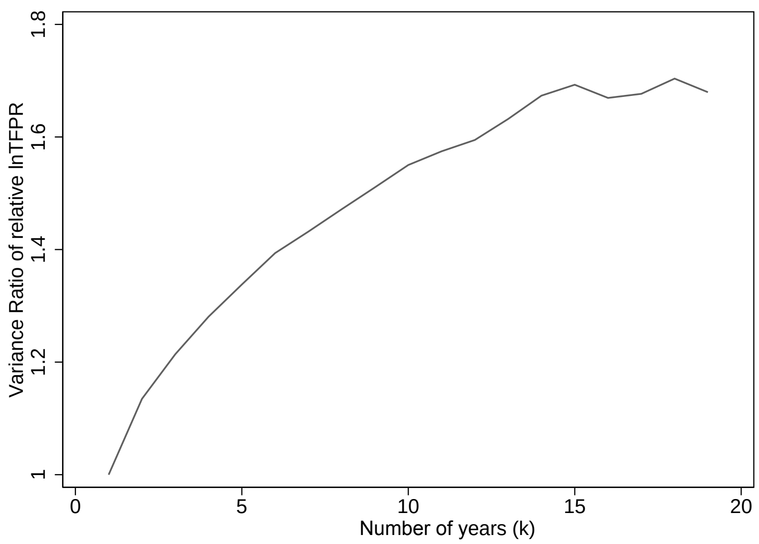
Source: CERVED.

Figure 19: **Productivity gains from equalising TFPR dispersion to its 1995 value, by geographic area**



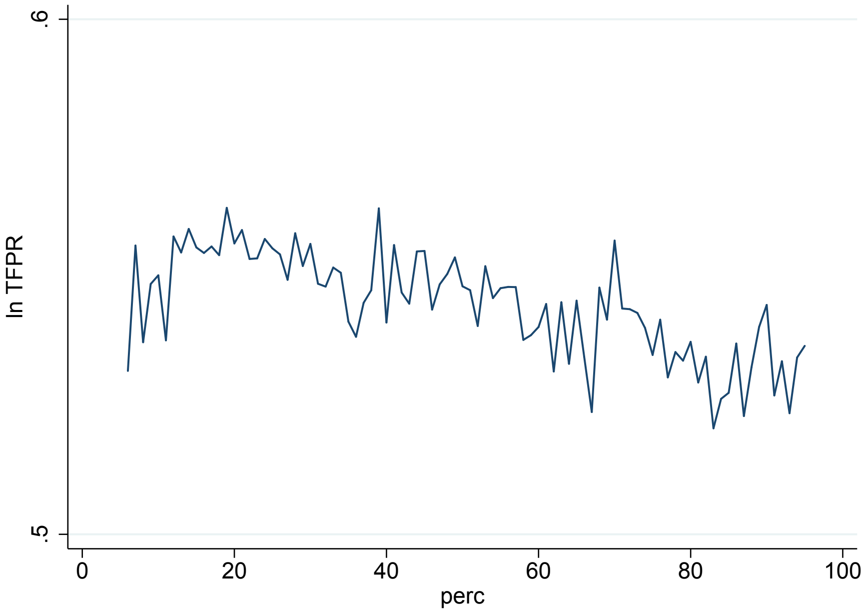
Source: CERVED.

Figure 20: **Variance Ratio Statistics (stationarity of relative TFPR)**



Source: CERVED. Variance Ratio of relative lnTFPR defined as $Var(X_{t+k} - X_t)/Var(X_{t+1} - X_t)$, with X denoting the average value of $\ln \frac{TFPR_{sit}}{TFPR_{st}}$.

Figure 21: **Ln TFPR by the percentile of firm size**



Source: CERVED.

Appendix

A Defining Misallocation (Hsieh and Klenow, 2009)

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

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

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}, \tag{7}$$

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

$$MRPK_{si} = P_{si} \frac{\partial \widetilde{Y}_{si}}{\partial K_{si}} = \alpha_s P_{si} \frac{Y_{si}}{K_{si}} = \widetilde{W}^{K} \tag{8}$$

and

$$MRPL_{si} = P_{si} \frac{\partial \widetilde{Y}_{si}}{\partial L_{si}} = (1-\alpha_s) P_{si} \frac{Y_{si}}{L_{si}} = W^{L} \tag{9}$$

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

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

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

A.1 A measure of misallocation

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

To this aim, a useful strategy is suggested by HK, whose approach allow us to study the effect of misallocation on aggregate TFP. The intuition is quite simple and rests on the proportionality between firm TFP and MRP of inputs. In particular, using (7), it is possible to write firm i's TFP as

$$TFP_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}. \tag{10}$$

As statistical information on either physical output Y_{si} or firm price P_{si} is hardly available (see. e.g., Foster et al., 2008), TFP is usually calculated/estimated on the basis of firms' revenues. In particular, by (10) we have

$$TFPR_{si} = P_{si}A_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}. \tag{11}$$

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

$$P_{si} = \frac{\sigma}{\sigma-1}\beta_s(W^K)^{\alpha_s}(W^L)^{1-\alpha_s}\frac{(1+\tau_{si}^K)^{\alpha_s}}{(1-\tau_{si}^Y)}\frac{1}{A_{si}}, \tag{12}$$

where $\frac{\sigma}{\sigma-1}$ is the markup and $\beta_s = \alpha_s^{-\alpha_s}(1-\alpha_s)^{\alpha_s-1}$ is the bundle of parameters associated with the Cobb-Douglas production function (7). Note that, apart from A_{si}, the only firm-specific terms in (12) are the distortions. When substituted into (11), the pricing rule in (12) yields

$$TFPR_{si} = \frac{\sigma}{\sigma-1}\beta_s(W^K)^{\alpha_s}(W^L)^{1-\alpha_s}\frac{(1+\tau_{si}^K)^{\alpha_s}}{(1-\tau_{si}^Y)}. \tag{13}$$

According to (13), also the cross-firm variability of $TFPR_{si}$ is not influenced by firm-specific characteristics other than τ_{si}^K and τ_{si}^Y (as the term A_{si} cancels out). Moreover, HK show that it is proportional to the weighted geometric average of $MRPK_{si}$ and $MRPL_{si}$, with weights given by the Cobb-Douglas parameters:

$$TFPR_{si} \propto (MRPK_{si})^{\alpha_s}(MRPL_{si})^{1-\alpha_s} \propto \frac{(1+\tau_{si}^K)^{\alpha_s}}{(1-\tau_{si}^Y)}. \tag{14}$$

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

A.2 Misallocation, aggregate TFP and aggregate gains from eliminating misallocation

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

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} = \prod_{s=1}^{S}\left(A_sK_s^{\alpha_s}L_s^{1-\alpha_s}\right)^{\theta_s}, \quad \text{with} \quad \sum_{s=1}^{S}\theta_s = 1 \tag{15}$$

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

$$A_s = \left[\sum_{i=1}^{M_s}\left(A_{si}\frac{\overline{TFPR}_s}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}, \tag{16}$$

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

According to (16), without misallocation, aggregate TFP is a CES aggregation of individual TFP. Otherwise, a TFP loss will emerge in the aggregate.

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

$$\ln TFP_s = \frac{1}{\sigma-1}\ln\left(\sum_i A_{si}^{\sigma-1}\right) - \frac{\sigma}{2}var(\ln TFPR_{si}). \tag{17}$$

Finally, the ratio Y/Y^* can be expressed as a weighted geometric average of the sectoral ratios of observed to efficient TFP levels A_s/A_s^* across sectors, with each sector's weight given by its share θ_s of aggregate output (value added):[39]

$$\frac{Y}{Y^*} = \prod_{s=1}^{S}\left(\frac{A_s}{A_s^*}\right)^{\theta_s} = \prod_{s=1}^{S}\left[\sum_{i=1}^{N_s}\left(\frac{A_{si}}{A_s^*}\frac{\overline{TFPR}_s}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{\theta_s}{\sigma-1}}, \tag{18}$$

where N_s is the number of firms in sector s and σ is the elasticity of demand (which we set equal to 3 as in HK). Notice that equation (18) implies that the output ratio Y/Y^* equals the ratio of observed to efficient aggregate TFP levels $TFP/TFP^* = \prod_{s=1}^{S}(A_s)^{\theta_s}/\prod_{s=1}^{S}(A_s^*)^{\theta_s}$.

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