Productivity dynamics in Italy: learning and selection

Stefano De Santis [1], Jelena Reljic [2], Federico Tamagni [2]

Abstract

This paper investigates the sources of labour productivity dynamics in Italy between 2011 and 2018. Exploiting the FRAME-SBS dataset maintained by Istat, we apply productivity decomposition methods to assess the relative contribution of within-firm productivity ("learning" effect) and reallocation of market shares across firms ("market selection" effect) to aggregate productivity. While we cannot measure entry/exit dynamics and thus focus on incumbents, the comprehensive coverage of the Italian economy offered by the data enables us to perform a disaggregated analysis at the level of very narrowly defined industries (at 5-digit level, NACE Rev.2). This provides a significant contribution to the literature, as previous studies looked at aggregate economy or aggregate macro-sectors (e.g. total manufacturing). The general picture emerging from the analysis is that within-firm "learning" prevails over between-firm reallocation and allocative efficiency effects in shaping aggregate productivity dynamics. This finding is robust over time and across both manufacturing and service industries. In addition, allocative efficiency is generally stable and rather weak over the reference period, although somewhat stronger in manufacturing than in services.

Keywords: Productivity, decomposition, learning, reallocation.

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1 Italian National Institute of Statistics - Istat (sdesantis@istat.it).

2 Institute of Economics, Sant'Anna, School of Advanced Studies - Pisa, Italy (jelena.reljic@santannapisa.it; federico.tamagni@santannapisa.it).

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1. Introduction

The slowdown in productivity dynamics observed in advanced countries (Syverson, 2017) has recently revived the interest in productivity analysis and its drivers. Economic analysis of the micro-level sources of productivity typically follows two complementary research lines. On the one hand, one tries to identify the enhancing or hampering effect of firm-specific characteristics and capabilities, such as firm size, ownership type, managerial profiles and strategies, technological and innovation patterns, as well as their interplay with contextual or policy-related factors, such as product/labour market regulation, the role of credit and financial markets, innovation and industrial policies. On the other hand, the second strand of research seeks to explain aggregate (sector-wide or economy-wide) productivity patterns by looking at the relative contribution of learning effects due to within-firm productivity dynamics, vis-à-vis market selection or between-firms effects, arising from reallocation of market shares across heterogeneously productive firms.

A large number of studies have evaluated patterns and relative contribution of reallocation dynamics, using different methods to decompose productivity into within and between effects in various countries and time periods. Recent works, most notably from the US, provide suggestive evidence that they do play a role in the recent slowdown. To mention just a few, Foster *et al.* (2016) compare the 2008 financial crisis with earlier downturns and find that strength of productivity-enhancing reallocation fell rather than increase in the US, which is at odds with the “cleansing” hypothesis. Similarly, Decker *et al.* (2017) claim that productivity slowdown in the US can be partly explained by declining allocative efficiency.

This article examines learning *vs.* selection forces underlying the patterns of productivity in Italy between 2011 and 2018. The issue is the subject of long-lasting debate in the Italian case, as Italy has been underperforming in terms of aggregate productivity growth since the mid-nineties (Bugamelli *et al.*, 2020). Concerning the period under study, two studies provide a number of interesting empirical findings on Italy, both exploiting the Melitz and Polanec (2015) decomposition framework. First, Linarello and Petrella (2017) document an increase in allocative efficiency over the period 2005-2013 – occurring through productivity-enhancing reallocation from low-productivity to high-productivity firms as well as from the net entry effect –, coupled with a negative unweighted average firm-level productivity growth component. This adverse contribution of unweighted average productivities may reflect a polarised structure of the Italian economy (Costa *et al.*, 2020; Dosi *et al.* 2012), where a large number of micro/small low-productivity and innovation-laggards firms coexist with a small set of high-productivity firms featuring high technological and organisational capabilities. The second reference study for Italy, by Bugamelli *et al.* (2020), documents that the contribution of unweighted average productivity growth was negative for both aggregate manufacturing and aggregate services over the period 2007-2016. Instead, reallocation and net entry effects contributed positively to the aggregate productivity growth. Besides, they also find that less productive firms were downsizing during the period.

This paper adds to these existing studies by providing two main contributions. The first distinct feature of our work is that we perform decomposition analysis at a very narrow level of sectoral aggregation (at the 5-digit level, NACE Rev.2). This represents an important improvement not only vis-à-vis reference studies on Italy but vis-à-vis the literature on productivity decomposition more generally. In fact, as discussed in Bottazzi *et al.* (2010) and in Dosi *et al.* (2015), the higher level of sectoral aggregation employed in previous studies (from the aggregate economy to macro-sectors like services *vs.* manufacturing, or even more disaggregated by 2- or 3-digit industries) is likely mixing selection/reallocation effects occurring across firms active in quite diverse sub-markets, not actually competing among each other for market shares. The finer level of disaggregation we examine here, conversely, allows us to capture learning and selection effects across firms that are genuinely competing in the same product market. Put differently, as discussed for instance in Bugamelli *et al.* (2020), the components of the productivity decompositions summarise the average tendency in the sample over which those components are measured: within component represents the productivity increases or decreases of the average incumbent firm, while between component and allocative efficiency emerge as the balancing out of movements of market shares across differently productive incumbents, where shares are measured against all firms in the sample. If the reference sample is – say – aggregate manufacturing, patterns observed in average incumbent and market shares movements at this level surely do not adequately represent the underlying patterns occurring at more disaggregated levels, like in the 5-digit industries we focus on. It may well be that in disaggregated industries the within components increase (decrease), while the same component measured via the average incumbent in total manufacturing decreases (increases). As we shall see, our analysis of the components obtained separately for each 5-digit sector reveals substantial heterogeneity underlying the aggregate patterns, casting doubt that aggregate analysis is genuinely informative of the patterns unfolding in the country.

The second point of departure from the literature is more technical but nonetheless important. Since, as it is well known, different decompositions proposed in the literature entail alternative definitions of the components, in turn implying different measures and interpretations of the within *vs.* between/reallocation components (see Melitz and Polanec, 2015, for a detailed discussion), we want to test that our main conclusions are not driven by selecting one specific decomposition methodology. Therefore, while previous studies, in particular the abovementioned works on Italy, tend to focus on just one decomposition, we combine insights from three different decomposition methods proposed in the literature. In particular, we compare the relative weight of within vis-à-vis between and/or cross components from the dynamic decompositions developed by Griliches and Regev (1995) and by Foster, Haltiwanger and Krizan (2001), and also examine the relative weight of the covariance term from the static productivity decomposition proposed in Olley and Pakes (1996). This combination of techniques, besides testing the robustness of the results across methods, also allows us to provide evidence on both dynamic and static patterns of learning *vs.* reallocation.

The empirical analysis, and in particular its highly disaggregated level, takes advantage of access to a unique source of information on the Italian industrial system, the FRAME-SBS dataset, offering a comprehensive coverage of the population of Italian firms. Over the last couple of decades, the demand for high-quality firm-level micro-data has increased significantly, both for the purpose of measurement of economic phenomena and for policy reasons. In order to meet such demand, European statistical offices have accelerated the design and production of new datasets able to accurately capture heterogeneity and changes within productive systems, as well as factors underlying, *e.g.* the competitiveness and resilience of firms, competitive and backward segments, and profiles of growing or declining firms. In this context, Istat has undertaken a strategy of designing and implementing a new generation of micro-founded statistics, in which the microeconomic component plays a central role. This new approach has been based on the implementation of a twofold integrated strategy in statistical production, combining (*i*) massive use of administrative data for the construction of multidimensional statistical registers, with extensive possibilities to link individual data to additional administrative sources and direct surveys; and (*ii*) direct statistical surveys focussed on economic units with multi-purpose modules able to measure their organisational structures, behaviours and strategies, not detectable when using administrative sources only. The resulting new system of integrated data also guarantees consistency between the micro and macroeconomic perspectives lends solidity to micro-founded analyses of heterogeneity within various universes (*e.g.* economic units) in different dimensions (*e.g.* performance, geographical positioning, workforce utilisation, international openness, remunerations). The FRAME-SBS data, consisting in the annual replication of the Register System collecting information on firm balance sheets, is central in the new system and makes multi-level dynamic analyses possible.

For this work, we had access to FRAME-SBS data for the period 2011-2018. Our results document that, despite substantial variability across industries in terms of the relative weight of within *vs.* between/reallocation effects, the contribution of within-firm "learning" prevails over between-firm reallocation in shaping aggregate productivity dynamics over the reference period. Moreover, and notwithstanding large variability across 5-digit industries, static allocative efficiency is rather stable over time and in most industries is quite weak, although somewhat stronger across manufacturing sectors than across service industries.

Exploiting access to FRAME-SBS over the period 2011-2018, we document that, irrespectively of the decomposition method, within-firm "learning" prevails over between-firm reallocation in shaping aggregate productivity dynamics over the reference period. Moreover, efficient reallocation is stable over time and quite weak, although somewhat stronger across manufacturing sectors than across service industries.

The paper is organised as follows. In Section 2, we present the decomposition methods. Section 3 describes the data. We present and discuss our main findings in Section 4. Final remarks are drawn in the concluding Section 5.

2. Review of productivity decomposition methods

Various approaches have been put forward to break down aggregate productivity. All decompositions start with a common definition of aggregate productivity to be decomposed, defined as a weighted average of the productivity of all firms active in the same sector, in our case defined at the 5-digit level. Formally, indicating with t the year and j the sector, aggregate productivity is defined as:

$$\Pi_{j,t} = \sum_{i \in j} \omega_{i,t}\, \pi_{i,t} \tag{2.1.1}$$

where Π represents sectoral productivity, while π denotes firm-level productivity, and ω is the market share of each firm in industry j.

Needless to say, productivity can be measured in several ways. Studies typically adopt either single-factor or multi-factor indicators. We opt for labour productivity since total factor productivity necessitates strong assumptions about the undifferentiated nature of technology. Accordingly, we use employment shares as weights ω instead of output shares (Foster *et al.*, 2001).

Lacking information on "true" entry and exit, we focus on decomposing the contribution of incumbent firms. In general, the latter can be decomposed into (*i*) a 'learning component' or 'within-firm' effect, resulting solely from heterogeneity in individual firms' productivity, measured statically in a given year, or dynamically, as firms become more or less efficient over time; and (*ii*) one or more components capturing 'between-firm' or 'reallocation/selection' effects, resulting from the static or dynamic allocation of market shares among differently productive firms. We employ three productivity decompositions widely used in the literature, the two dynamic decompositions by Griliches and Regev (1995) and Foster, Haltiwanger and Krizan (2001), and the static decomposition by Olley and Pakes (1996).

Griliches and Regev (1995) method, hereafter GR, breaks down sectoral productivity growth of incumbent firms between two consecutive years, $\Delta\Pi_{j,t}$, into the following two components:

$$\Delta\Pi_{j,t}^{GR} = \underbrace{\sum_{i \in j} \overline{\omega}_i \left(\pi_{i,t} - \pi_{i,t-1}\right)}_{\text{within}} + \underbrace{\sum_{i \in j} \left(\omega_{i,t} - \omega_{i,t-1}\right)\left(\overline{\pi}_i - \overline{\Pi}_j\right)}_{\text{between}} \tag{2.1.2}$$

where a bar over a variable indicates the simple average of the variable over two consecutive periods (*e.g.* (ωit+ωit−1)/2; (πit+πit−1)/2; (Πjt+ Πjt−1)/2).

The first term on the left-hand side of Equation 2.1.2 is the within-firm component, summing all the changes in firm-level productivities at constant market shares (equal to firms' average employment shares over the initial and final year). The within-component is therefore productivity-enhancing if individual firms increase their efficiency (learn, in evolutionary terms), keeping their input shares "fixed". The 'between-firm effect' in the second term on the right-hand side, instead, reflects over time changes in the distribution of employment shares among firms. It is productivity-enhancing if labour inputs tend to increase more in relatively more productive firms than in relatively less productive firms.

Foster, Haltiwanger, and Krizan (2001) decomposition, hereafter FHK, can be written formally as follows:

$$\Delta\Pi_{j,t}^{FHK} = \underbrace{\sum_{i\in j} \omega_{i,t-1}\left(\pi_{i,t} - \pi_{i,t-1}\right)}_{\text{within}} + \underbrace{\sum_{i\in j}\left(\omega_{i,t} - \omega_{i,t-1}\right)\left(\pi_{i,t-1} - \Pi_{j,t-1}\right)}_{\text{between}} + \underbrace{\sum_{i\in j}\left(\omega_{i,t} - \omega_{i,t-1}\right)\left(\pi_{i,t} - \pi_{i,t-1}\right)}_{\text{cross}} \qquad (2.1.3)$$

The within and between components in this framework are similar to the components of the GR decomposition, but they rely on different reference measures. Instead of taking averages of key variables (*i.e.* productivity and labour shares) over time, FHK take values in the initial period. Hence, the within-effect reflects changes in firm-level productivity, weighted by initial employment shares. The between-component accounts for changes in employment shares, weighted by the deviation of a firm's productivity from the average sectoral productivity in the initial year t-1. This leads to an additional third component that reflects simultaneous changes in employment shares and in productivity. This is usually referred to as a "cross" or covariance term, and it is productivity-enhancing (reducing) if firms increasing their employment shares are at the same time becoming more (less) efficient.

The Olley and Pakes (1996) decomposition is, instead, a static decomposition, which breaks down aggregate productivity in a given year t, without following productivity or market share changes over time. The OP decomposition is conceptually different from the abovementioned methods, meaning that their respective components are not easily comparable. Formally, one has

$$\Pi_{j,t}^{OP} = \overline{\Pi}_j + \underbrace{\sum_{i \in j} (\omega_{i,t} - \overline{\Omega}_j)(\pi_{i,t} - \overline{\Pi}_j)}_{\text{covariance term}} \tag{2.1.4}$$

where $\overline{\Pi}$ and $\overline{\Omega}_j$ are average productivity and average market share in sector j, respectively.

The first term is simply unweighted average productivity, and it thus reflects the hypothetical productivity level of sector j if all firms in the sector had the same employment shares. This is interpreted as a reference situation in the absence of market selection forces delivering reallocation of shares across firms. In this view, the deviation between such a benchmark and weighted productivity, given in the second term on the right-hand side of the equation, delivers a measure of allocative efficiency. Market selection/reallocation forces are efficient (inefficient) if this term is positive (negative), as this implies that more (less) productive firms have larger than average market shares. In other words, the higher the covariance term, and the more efficiently market forces operate in sector j.

3. Data

As mentioned, the empirical analysis takes advantage of the Italian microdata from the FRAME-SBS database maintained by Istat, reporting rich firm-level information on firms operating in non-agricultural and non-financial sectors between 2011 and 2018.

We run separate analyses by 5-digit sectors based on the NACE Rev. 2 classification of economic activities. Similarly to Linarello and Petrella (2017), we exclude from the analysis manufacturing of coke and petroleum products, construction, utilities, and services overlapping with the public sector. In addition, to ensure that a minimum number of firms is present in each 5-digit industry, which is essential to run meaningful statistical analysis, we restrict the analysis to the 5-digit sectors with more than twenty firms. We are left with more than 2.4 million firms operating annually in 613 industries – 280 within manufacturing and 333 within service.

The variables of our interest are employment figures and labour productivity. Employment is reported in FRAME-SBS as the number of full-time equivalent employees, while we compute labour productivity as the ratio between value added and employment. To avoid misleading comparisons over time, we compute real value added at constant 2015 prices, deflating firm-level nominal value added by the 2-digit sectoral production price indexes provided by Istat.

Table 3.1 reports some descriptive statistics of our sample. The total number of firms in the Italian economy has been increasing between 2013 to 2018. This growth has been concentrated in service sectors while a contrasting pattern emerges in manufacturing industries, where the number of firms has been steadily diminishing over the reference period. Namely, in 2018 there were 42,571 more firms in services and 29,305 firms less in manufacturing than in 2012. Moreover, we also observe a notable difference between manufacturing and services in terms of the average 5-digit NACE sectoral labour productivity levels. While the latter increased on average between 2012 and 2018 in both macro sectors, productivity levels have been relatively higher in manufacturing industries.

Table 3.1 - Descriptive statistics (a)

YEAR	Total			Manufacturing			Services		
	N	n		N	n		N	n	
2012	613	2,484,833	34,789.35	280	339,216	43,163.42	333	2,145,617	29,019.20
2013	613	2,418,302	35,441.69	280	323,969	44,714.48	333	2,094,333	29,150.45
2014	613	2,418,418	36,778.78	280	323,536	47,389.56	333	2,094,882	29,718.90
2015	613	2,430,713	38,642.65	280	320,346	50,397.88	333	2,110,367	30,908.64
2016	613	2,440,266	40,303.70	280	315,680	53,146.72	333	2,124,586	31,939.88
2017	613	2,482,292	41,604.49	280	317,857	54,495.13	333	2,164,435	33,157.28
2018	613	2,498,099	43,379.99	280	309,911	56,559.45	333	2,188,188	34,706.54

Source: Authors' elaboration
(a) "N" stands for the number of sectors, while "n" for the number of firms. Level of labour productivity is calculated as a ratio between value added at constant 2015 prices and the number of employees.

4. Decomposition results

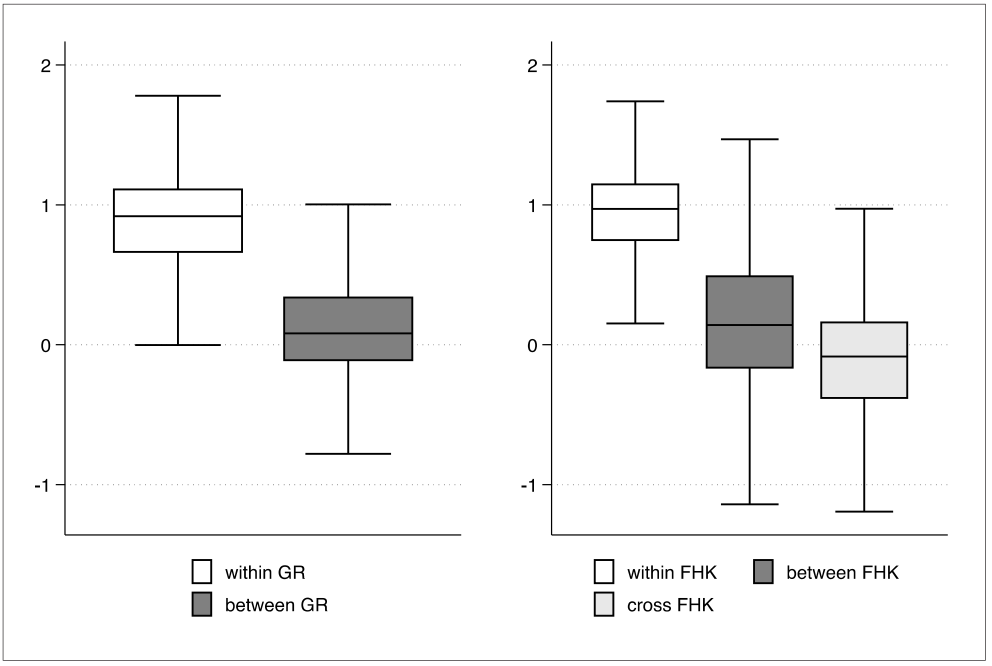
Decomposition analysis was run separately by year and 5-digit sector. We report a descriptive summary of results, primarily focussing on the extent of selection/efficient allocation. Accordingly, we focus on two main exercises. First, we compare within *vs.* between and/or cross components from the GR and FHK decompositions, allowing us to assess whether selection effects prevail over learning. Second, we study the covariance component of the OP decomposition to assess the strength of allocative efficiency. We highlight the main patterns emerging over time and across manufacturing *vs.* services.

Dynamic decompositions

We first summarise the empirical results of the GR and FHK decompositions. All reported values are expressed as percentage shares of the components in aggregate productivity changes, allowing us to assess their relative weight in productivity dynamics.

Figure 4.1 reports boxplots of the distribution of the relative weight of each component from the GR and the FHK decompositions, computed across the 5-digit sectors, pooled over time. Despite considerable cross-sectional variability, it turns out that both decomposition methods point to a relatively dominant role of the within-effect vis-à-vis the between-effect in shaping productivity dynamics in Italy. Indeed, the entire white box – spanning values between the 25th and the 75th percentile of the within-term components – is positioned above the boxes representing the distribution of the other components. This clearly suggests a relatively weak role of market selection forces.

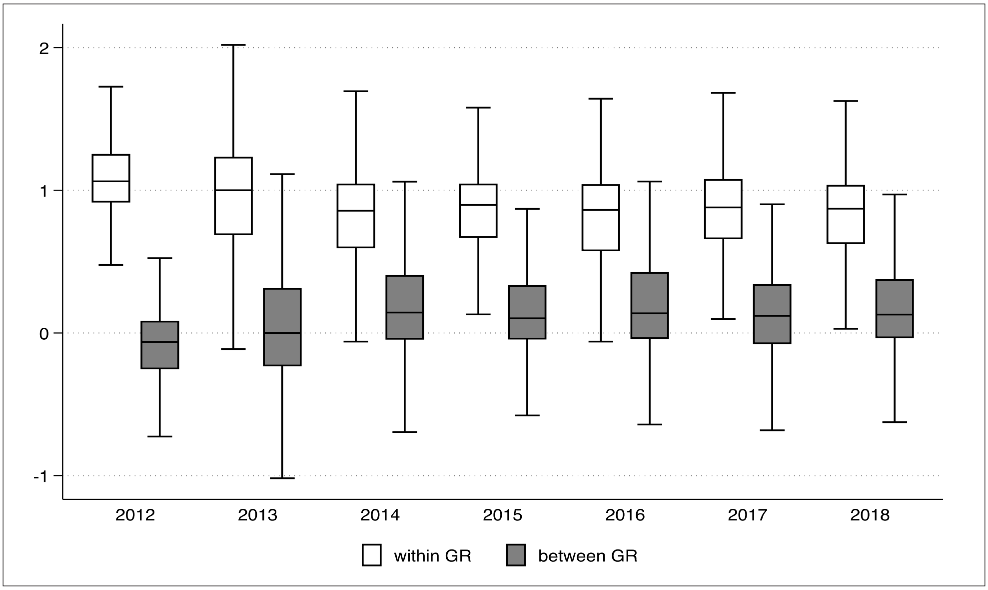
Figure 4.1 - Distribution of relative importance of components from the GR and FHK decompositions, computed by 5-digit industries and year, reported pooling across industries and time



Source: Authors' elaboration

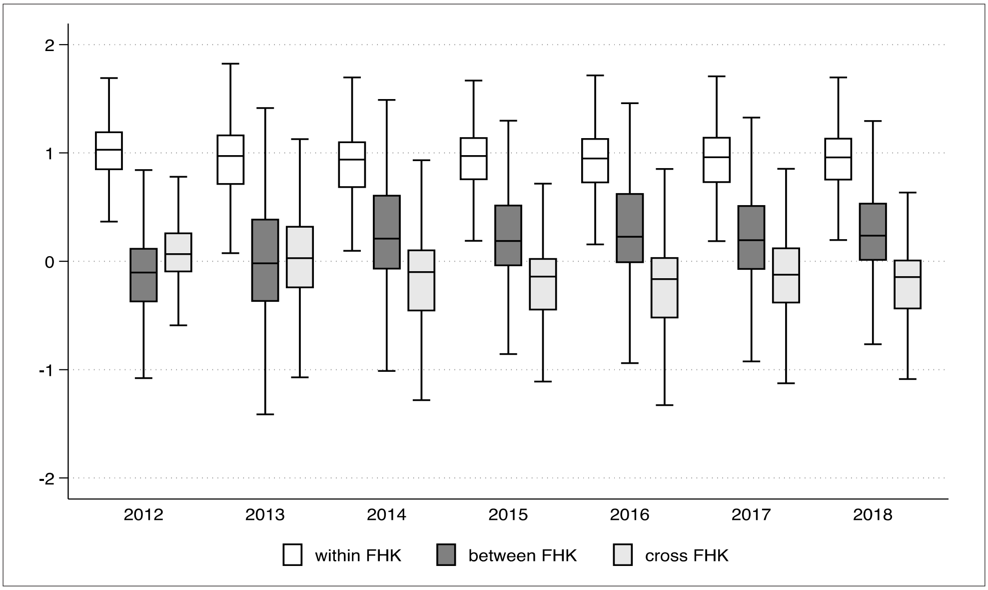
As patterns observed in Figure 4.1 may hinder some underlying time-related or business-cycle effect, we replicate the analysis splitting results by year. In particular, this allows us to capture whether the results presented above are characterised by significant changes in the pace of allocative efficiency over the reference period. Figure 4.2a reports the GR components. Both the within and the between components display notable stability over time, despite some variability between 2011 and 2013, which is marked by a slight increase in the strength of reallocation. This increase could be related to the sovereign debt crisis, which might have induced some downsizing among less productive firms. It is, in any case, marginal compared to the main pattern observed during the entire period. Results of the FHK decomposition, reported in Figure 4.2b, deliver a consistent picture. Again, the contribution of within-firm learning is larger than the contribution of the other components capturing reallocation of shares across firms in all years.

Figure 4.2*a* - Relative importance of components from the GR decomposition method, computed by 5-digit industries and year, break-down by year



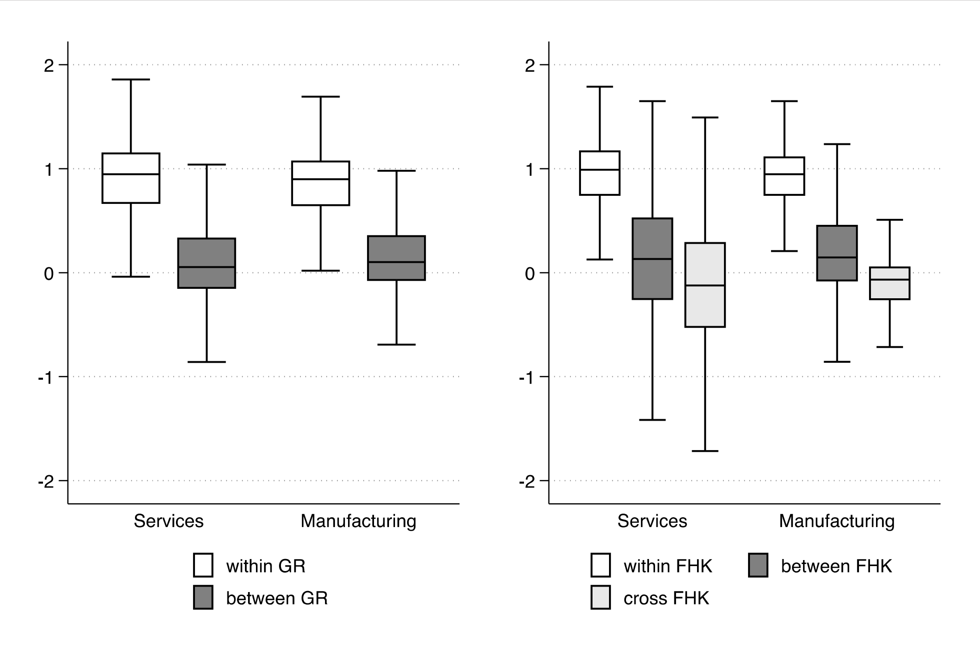
Source: Authors' elaboration

Figure 4.2*b* - Relative importance of components from the FHK decomposition, computed by 5-digit industry and year, break-down by year



Source: Authors' elaboration

Figure 4.3 - Relative importance of components from GR and FHK decompositions, computed by 5-digit industry and year, break-down of Manufacturing *vs.* Services



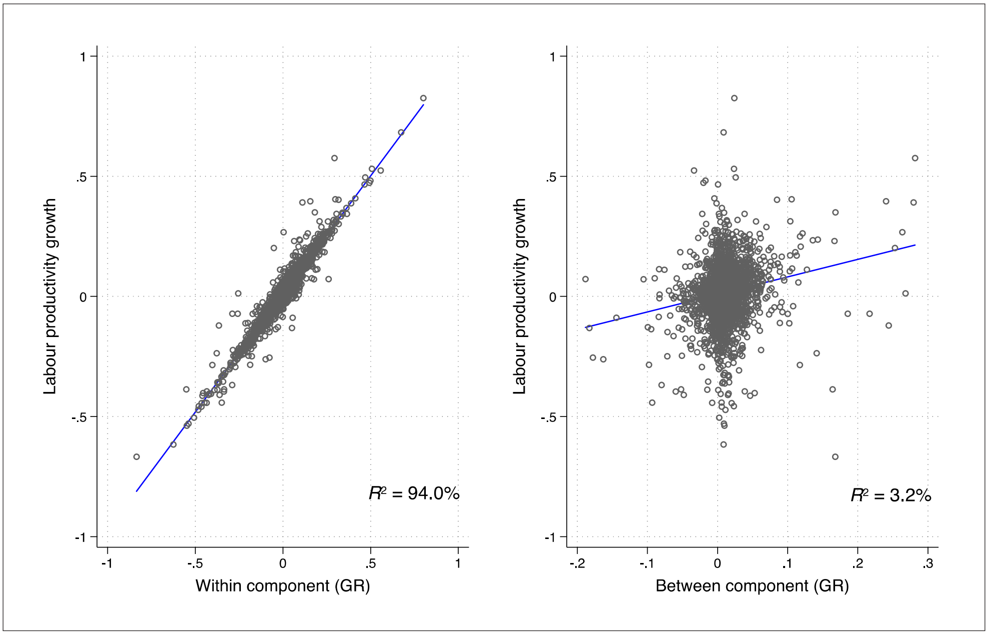
Source: Authors' elaboration

Next, we examine whether previous results hold when we break down the analysis by macro sector. Figure 4.3 reports the distribution of the relative contribution of the components, pooling across 5-digit industries in manufacturing and 5-digit industries in services. Results clearly reveal that our main findings do not stem from compositional effects across sectors. Indeed, the median value of the within-component is centred around 1 (*i.e.* 100%) for both manufacturing and services, once again corroborating that learning processes measured by changes in individual productivities account for a considerably greater percentage contribution to productivity growth than selection/reallocation effects. Moreover, the box plots referring to the other components are always positioned below the box plot of the within-term. Overall, we do not find support in data that market selection forces operate differently in manufacturing than in services. Interestingly, services are characterised by a higher degree of cross-sectoral heterogeneity in performance.

As a final exercise, exploiting all the industry-year observations allowed for by the data, we explore the relationship between productivity growth and the different components. Figures 4.4a and 4.4b report the results for the GR and the FHK decomposition, respectively. Two distinct patterns emerge. First, we observe a positive (and essentially linear) relationship between productivity growth and the within-firm components in the left-hand side graphs of both Figures. This suggests that sectors experiencing stronger and positive productivity growth are sectors where productivity growth is almost entirely driven by within-firm learning. Correspondingly, low or negative productivity growth is clearly related to a strong contribution of negative learning (de-learning) effects.

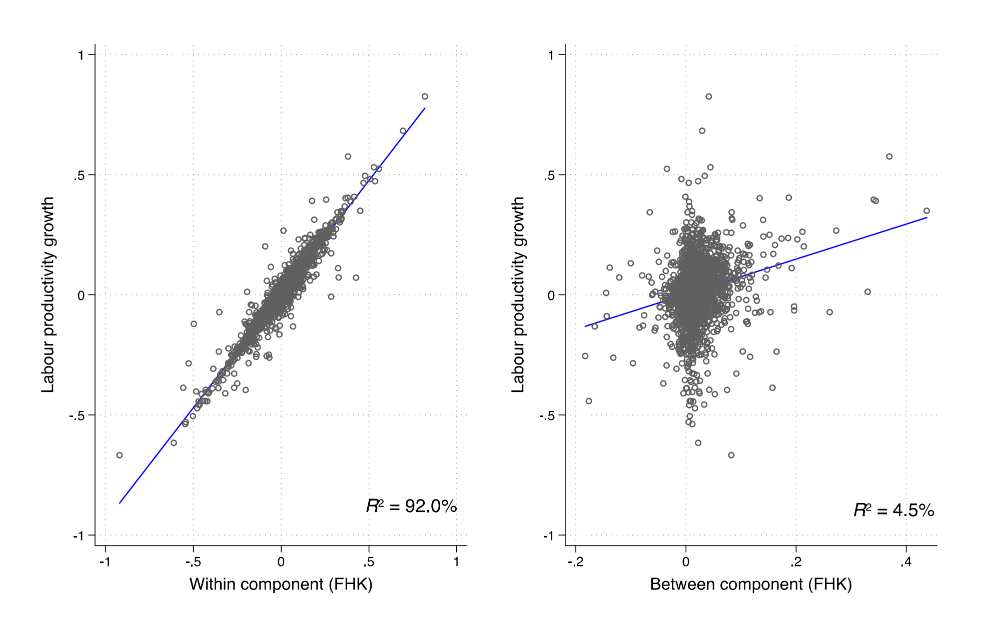
A second common pattern is that the between components display a much weaker association with productivity growth. In the right-hand side plots, indeed, although a linear fit of the data suggests a positively sloping relationship, we observe considerable cross-sectoral heterogeneity, quite more scattered data points and a very low explanatory power revealed by low R^2.

Figure 4.4*a* - Labour productivity growth *vs.* within and between components of the GR decomposition



Source: Authors' elaboration

Figure 4.4*b* - Labour productivity growth *vs.* within and between component of the FHK decomposition



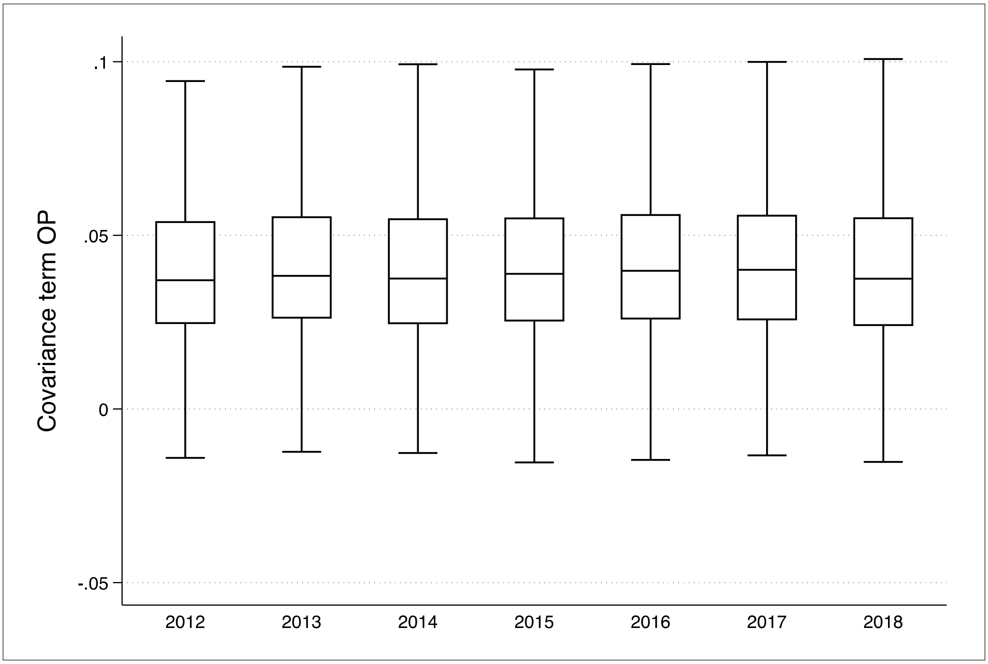
Source: Authors' elaboration

In summary, the general picture emerging from dynamic decomposition analysis is that within-firm learning prevails over between-firm reallocation in shaping aggregate productivity dynamics of Italian firms over the reference period. This overall confirms earlier findings at more aggregated levels of sectoral analysis. What we add here is perhaps that considerable heterogeneity across 5-digit sectors is hindered by aggregate results: the general tendency is that learning prevails, but sectoral specificities may matter.

The static OP decomposition

We now turn to the results of the OP decomposition. Figure 4.5 shows box plots of the distribution of the relative weight of the covariance measured across 5-digit industries, pooling by year. We find that allocative efficiency is productivity-enhancing for most of the 5-digit sectors, suggesting that more productive firms do generally enjoy higher than average employment shares. Nevertheless, market forces appear as quite weak. Indeed, the relative weight of the covariance term is quite low: median values are about 0.04 and even the largest values do not exceed 0.1. Moreover, these results are remarkably stable over time, both in the median and in distribution. This picture resonates with the minor role of reallocation in Europe documented in De Loecker and Eeckhout (2018) within a different literature stream examining markups instead of productivity. Instead, our findings are in contrast with productivity decomposition analysis for Italy by Linarello and Petrella (2017) and Bugamelli *et al.* (2020), who document some stronger role of allocative efficiency in fostering productivity that has been increasing over time. Our explanation for this discrepancy is that, as suggested above, disaggregating by 5-digit industries allows for a more detailed and precise characterisation of the components, avoiding mismeasuring the two reference benchmarks that are crucial in the definition of the components (unweighted productivity of the average incumbent and the average market shares). Differences in results vis-à-vis Linarello and Petrella (2017) may also, at least partly, reflect the more recent time period of our analysis (2011-2018 here *vs.* 2005-2013 in their paper). Of course, our results only apply to incumbents' productivity dynamics, as we cannot account for entry/exit as the other Italian studies do. However, this does not bias our conclusions: we decompose incumbents' productivity and judge allocative efficiency among them, while entry/exit data would allow us to benchmark incumbents against entrant and exiting firms.

Figure 4.5 - Distribution of the relative weight of the OP covariance term, computed by 5-digit industry and year, break down by year



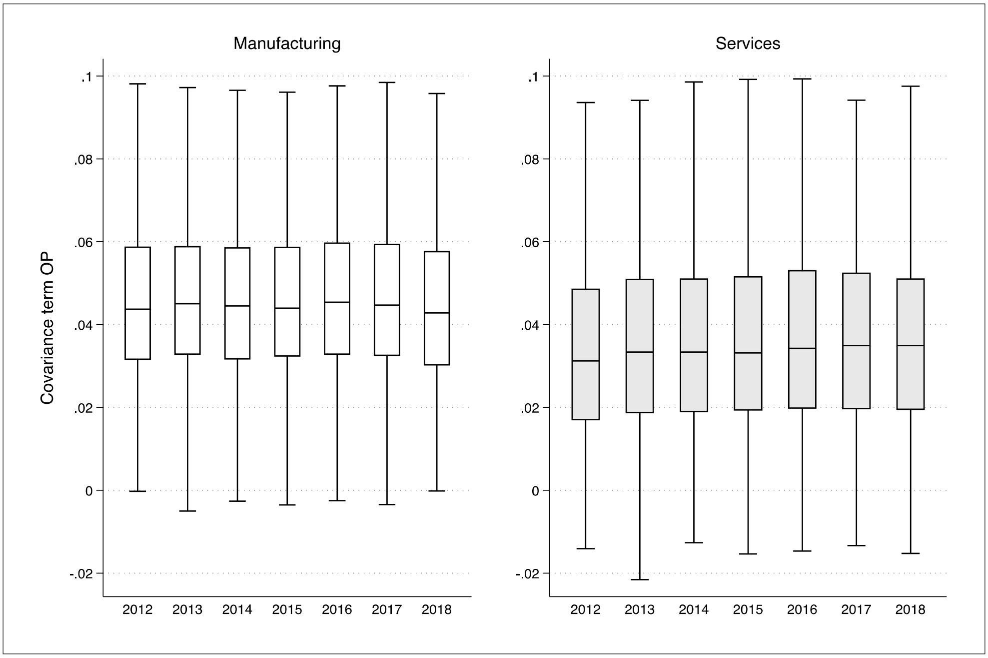
Source: Authors' elaboration

In Figure 4.6, we break down the analysis by macro sectors of activity, pooling together 5-digit industries within manufacturing and within services. The results reveal some dissimilarity across sectors. The covariance term displays stability between 2012 and 2018 in both macro-sectors, but manufacturing sectors feature relatively higher allocative efficiency than services. This is apparent by looking at median values, but also, more generally, by considering the lower positioning of the boxes referring to the central part (between the 25th and the 75th percentile) of the distribution of the covariance components in services.

To mention some paradigmatic examples of sectoral patterns, "Manufacturing of beer" (NACE 11050), "Rental and leasing of cars and light motor vehicles" (NACE 77110) and "Manufacture of plaster products for construction purposes" (23620), exhibit among the highest relative weights of allocative efficiency productivity over the reference period. Namely, in these

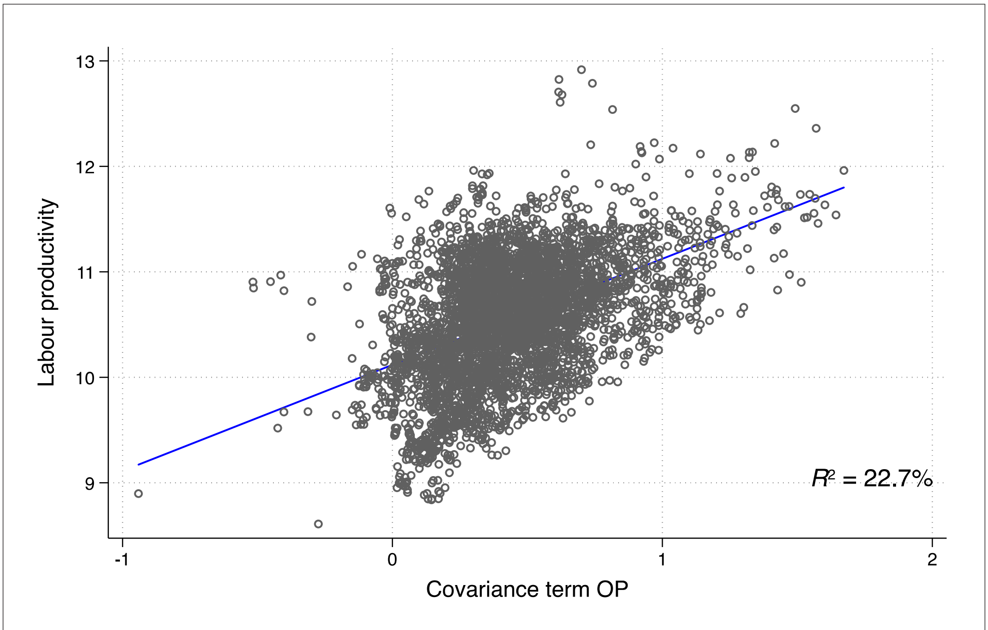
5-digit industries, aggregate productivity is around 13% higher than what it would have been if employment shares were evenly distributed across firms. On the other extreme, "Service activities incidental to land transportation" (NACE 52214) and "Security systems service activities" (NACE 80200) are both characterised by strongly negative allocative efficiency. Their actual productivity level is around 3% lower than what it would have been if employment shares were equally distributed among firms.

Figure 4.6 - Relative weight of the OP covariance term, computed by 5-digit industry and year, break-down of manufacturing *vs.* services



Source: Authors' elaboration

Figure 4.7 - Labour productivity *vs.* covariance term from the OP decomposition



Source: Authors' elaboration

Finally, we examine the simple correlation between sectoral productivity and the covariance term, addressing to what extent higher allocative efficiency is in fact positively associated with higher productivity. In Figure 4.7, we plot this relationship, exploiting all the sector-year observations in our data. The linear fit indicates that, as one could expect, there is a positive association between the two. However, the relationship does not appear as strong as the one observed in the previous section relating productivity growth and within-effects. Moreover, the R^2 suggests that the covariance term explains only about 23% of labour productivity total variance.

Final remarks

By exploiting access to the Istat FRAME-SBS data covering more than 2.4 million Italian firms operating in manufacturing and services, we examined the relative importance of learning vis-à-vis efficiency of reallocation/market selection processes underlying productivity dynamics over the period 2011-18. Taking together results from static and dynamic decompositions of productivity by disaggregated 5-digit sectors, we find robust evidence that within-firm learning plays a predominant role. Instead, selection forces appear as generally weak, considering that reallocation of labour inputs across firms contribute relatively little to aggregate productivity performance. This picture is consistent across sectors and rather stable over time.

As we cannot account for entry/exit effects, our main findings signal that Italy has not been able to improve its allocative efficiency across incumbents over the last decade. Notwithstanding two decades of "structural" labour market reforms towards more flexibilisation (see Cirillo *et al.*, 2017 for a review), which promised to achieve greater productivity-enhancing allocative efficiency, the relative magnitude of the reallocation of labour inputs from less to more productive firms is low and continues to play a minor role. One interpretation could be that labour market deregulation and stagnant wages allowed a number of relatively low-productivity firms to survive in the market via cost factors by reducing incentives toward much-needed investments in new technologies, organisational capabilities and labour skills (see Kleinknecht, 2020 for a critical review). This is in line with studies documenting the emergence of a dichotomy between "the best" *vs.* "the rest" in many OECD countries (Andrews *et al.*, 2016). In the Italian case, our findings resonate the emergence of a "neo-dualism" in the Italian productive system (Dosi *et al.* 2012; Dosi *et al.* 2019; Costa *et al.*, 2020), featuring the co-existence of a small group of high-productivity and technologically advanced leading firms whose traction on the economy is hampered severely by a large group of small, low-productivity and non-innovative laggard firms.

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