WORKING PAPER

THE ROLE OF SERVICES SECTORS FOR AGGREGATE PRODUCTIVITY: A FIRM-LEVEL ANATOMY OF A LARGE PANEL OF EUROPEAN FIRMS

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The role of services sectors for aggregate productivity: A firm-level anatomy of a large panel of European firms

Most recent version

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Abstract

This paper documents how the composition of value added per worker in Europe is distributed over manufacturing, services, and other industries based on a large panel of firm-level data. We show that a non-negligible part of value added is accounted for by services industries. We then explore how micro-data at the firm level can be used to analyse this important component of aggregate productivity growth. We further discuss and explore using our data whether semi-parametric estimators of total factor productivity that are commonly found in the literature and typically tailored towards manufacturing are fit for analysing firms services sectors.

Keywords: Productivity slowdown, firm-level data, services industries.
JEL Codes: E24, J24,

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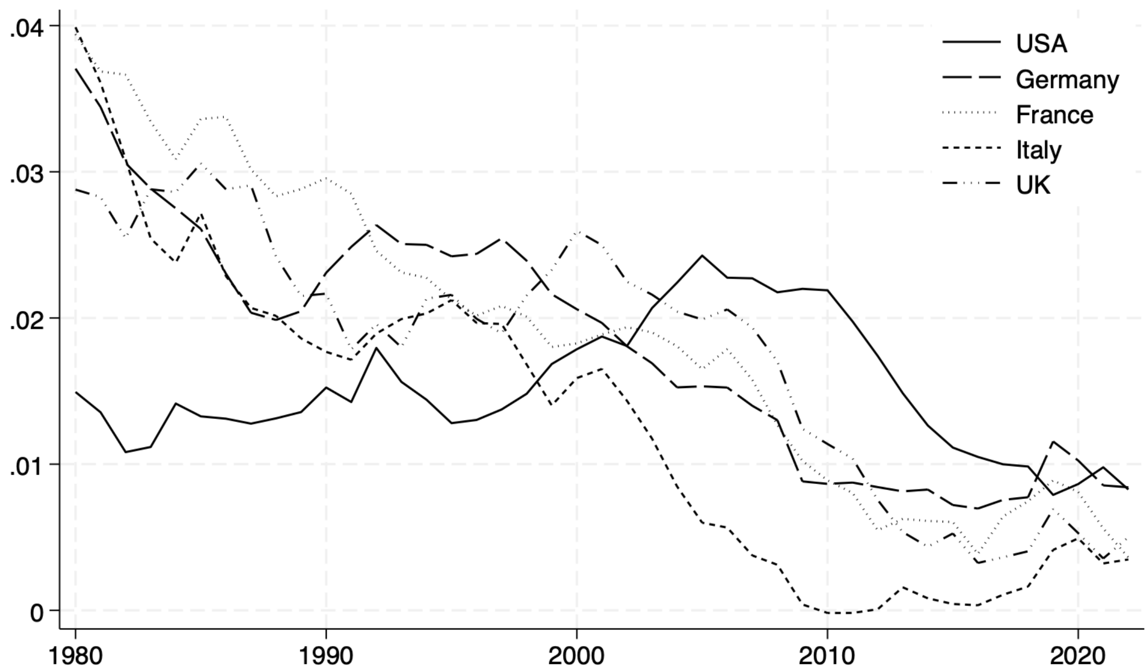
Figure 1: 10 year growth rates of aggregate labour productivity in selected countries. Source: Bergeaud et al. (2016)



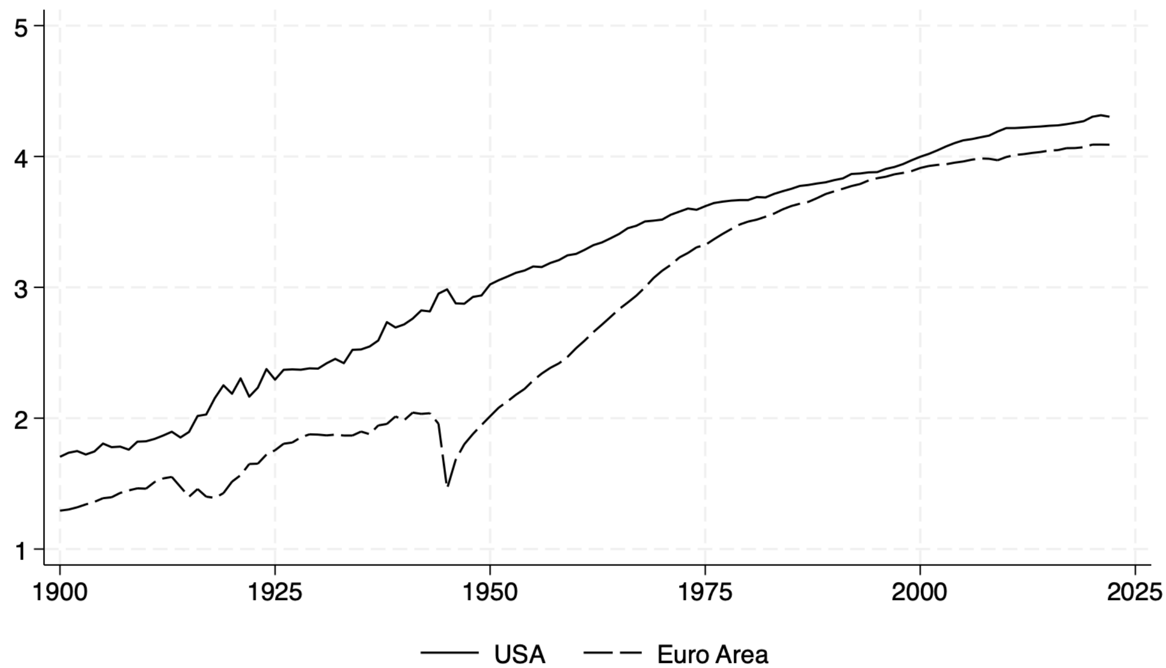
1 Introduction

Productivity growth is a key driver of long-term welfare and prosperity. Yet in recent decades, Western economies have seen a slowdown in productivity gains (Goldin et al., 2024; Bergeaud et al., 2017). Figure 1 shows this downward trend for four large European economies and the US. As can be seen from Figure 2, the more benign trend in the US has resulted in increasing gap in aggregate labour productivity between between the Euro area and the US after decades of catch-up. This productivity slowdown has become an important topic for academia and policymakers (see Draghi, 2024).

This paper documents the role of services firms for aggregate productivity in Europe. Western economies increasingly have become 'service economies' and the share of manufacturing in value-added continues to decline (Bernard et al., 2017). Figure 3 shows that in the European Union, by 2022, two-thirds of value added is generated by the business service sector. Aggregate productivity growth can be decomposed into different margins: the intensive margin, i.e. the contribution of productivity growth in incumbent firms, and two extensive margins, i.e. the contribution of entry and exit of firms to aggregate productivity growth. Figure 4 testifies of the importance of services with a share of 84.5% of entrants, 77.6% in incumbent observations, and 80.4% of exits.

The quantitative importance of services importance is at odds with the observation that

Figure 2: Aggregate labour productivity evolution in the USA and the Euro area. Source: Bergeaud et al. (2016)



the vast micro-economic firm-level literature on estimating TFP has been built on assumptions tailored to manufacturing (Olley and Pakes, 1996; Ackerberg et al., 2015; Gandhi et al., 2020). Total factor productivity (TFP), the efficiency with which firms transform inputs into outputs, is one of the key metrics in the productivity slowdown literature (see Andrews et al., 2016; Gordon and Sayed, 2020; Cette et al., 2024). TFP, however, is an unobservable metric and needs to be estimated. Also the macroeconomic analysis of the productivity slowdown, often does not account for sectoral heterogeneity (Restuccia, 2019; Ayerst et al., 2024).

In this paper, we document the importance of services for aggregate productivity growth in Europe. We first describe the construction of our dataset covering 21 European countries that not only covers services, but the entire business economy in section 2.1. We further discuss our data cleaning steps and the coverage and respresentativenes of the resulting dataset. In section 3 we perform a micro-to-macro aggregation of labour productivity based on our firm-level data and show the importance of sectoral heterogeneity within services, affecting productivity measurement. Section 4 decomposes aggregate labour productivity growth into to the contribution of entrants, exiters, and incumbent firms. In section 5 we compare labour productivity with total factor productivity estimates obtained from existing semi-parametric production function estimators. Finally, Section 6 concludes.

Figure 3: Share of manufacturing vs. services in Europe. Source: World bank

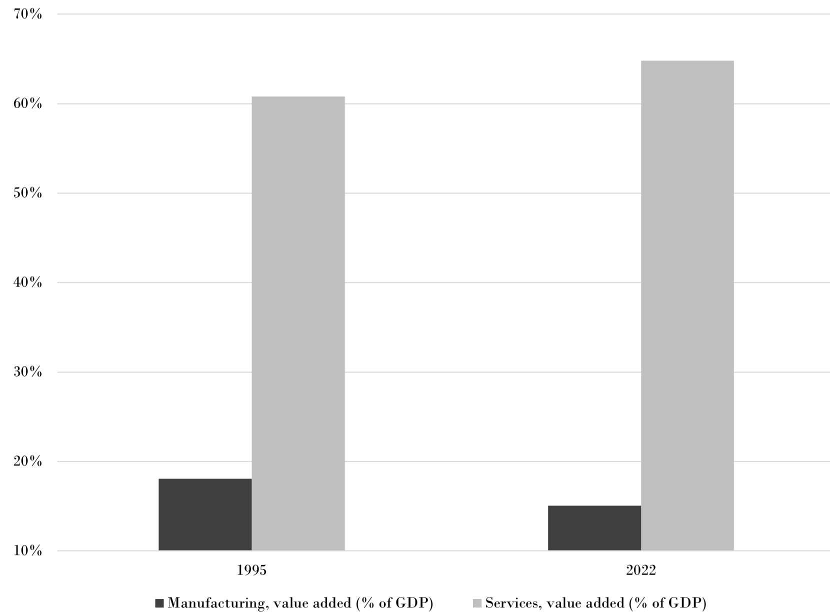
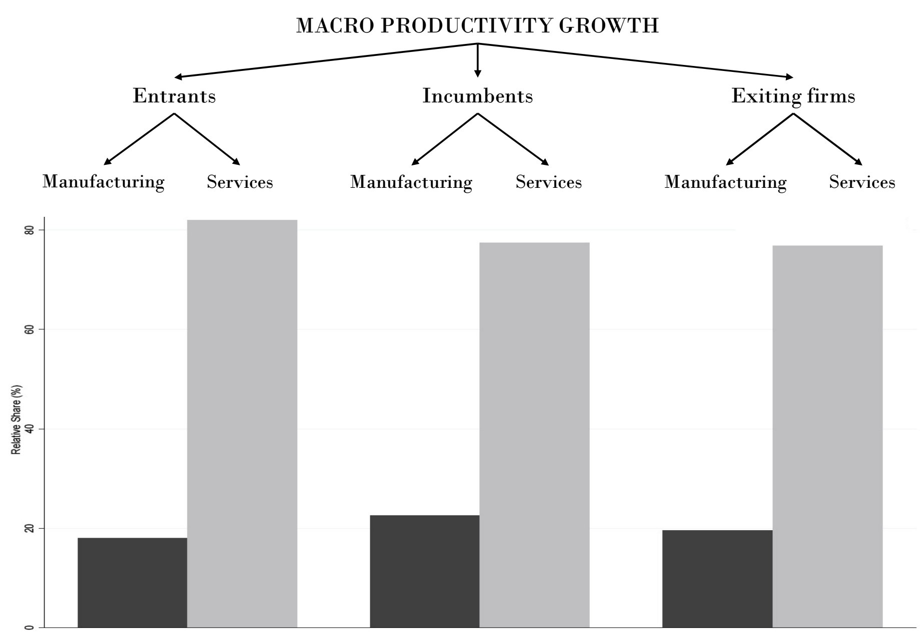


Figure 4: Productivity decomposition manufacturing vs. services. Source Orbis.



2 Data

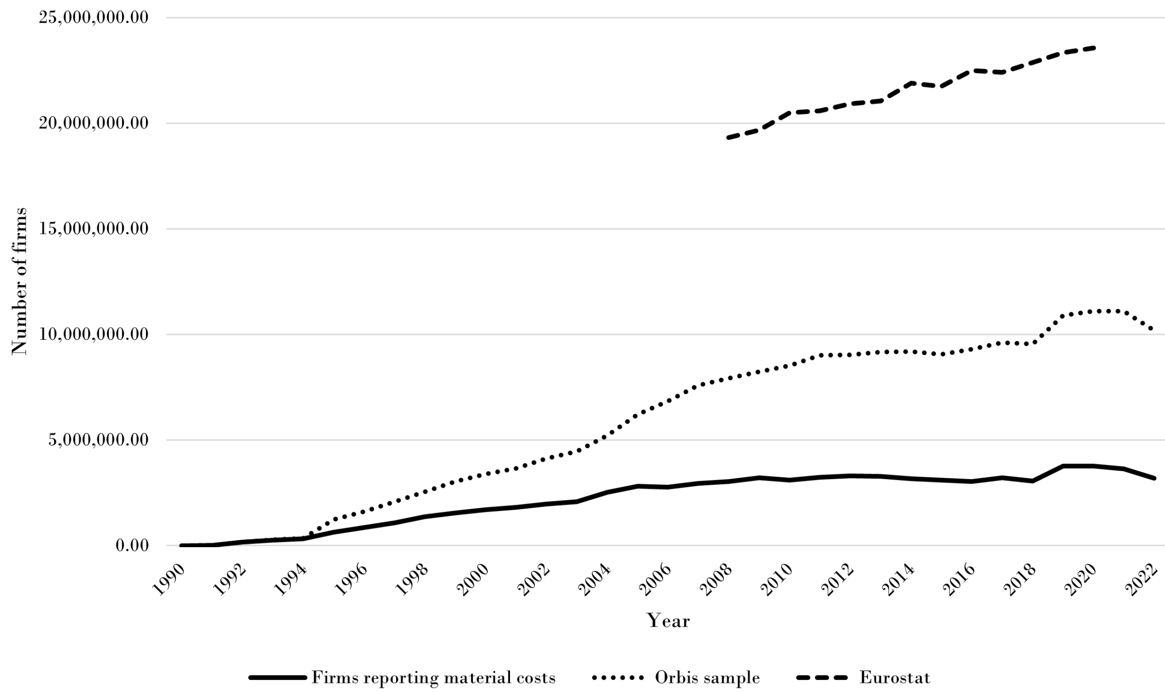
2.1 Data sources

Our research primarily relies on the Orbis database, a comprehensive pan-European database containing information on millions of companies in Europe. Developed by Bureau van Dijck, Orbis provides detailed financial, ownership, and corporate structure data for public and private companies across various industries and regions. It includes both public and private companies across various sectors and industries, providing a broad view of the global corporate landscape. Orbis offers a wide range of data fields and variables, including financial statements (income statements, balance sheets, cash flow statements), ownership information, corporate governance details, industry classifications (e.g., NACE codes), etc. We complement this firm-level database with the CompNet database, a dataset developed by the Competitiveness Research Network within the European Union, providing a harmonized and detailed collection of microeconomic indicators across a wide range of industries and countries. This database is built from the balance sheets and income statements of firms, offering data on various dimensions such as firm size, productivity, labour costs, and capital intensity. It is harmonized to ensure consistency and comparability across different EU member states, despite differences in national accounting standards and reporting practices. Furthermore, we will use publicly available datasets e.g. from Eurostat and the OECD for our research, mainly to check whether our firm-level dataset adequately captures the properties of the whole economy. The OECD database provides industry-level data, particularly focusing on industrial performance, productivity, and structural change across member countries. This dataset is useful for analyzing sectoral trends and economic performance. Other OECD databases will be employed to access macroeconomic indicators, productivity measures, and international trade statistics, offering a broad perspective on global economic conditions. Together, these data sources will provide a robust and comprehensive foundation for analyzing the interactions between firm-level dynamics and broader economic trends across different regions and sectors.

2.2 Coverage

For our data cleaning procedure we refer to the procedure outlined in (Merlevede, 2015). We first restrict the observations from the Orbis database to the firms that report values for the variable 'Material costs'. 'Material costs' is a variable needed to calculate value-added and other derived productivity indicators. Figure 5 shows the number of firms in situated Europe and reported by Eurostat classified in the category "Total business economy; repair of computers, personal and household goods; except financial and insurance activities". We show the total number of observations that the Orbis database covers and the number of firms in the database that report a value for the variable 'material costs'. 35% - 40% of the firms reported by Eurostat are covered by Orbis and around roughly $1/10^{th}$ of the firms that are reported by Eurostat report

Figure 5: Number of firms reported in Eurostat - Orbis - Sample with material costs



a value for material costs in the Orbis database. For the lack of data availability in Orbis for earlier years, we restrict our the used sample to the years 1996 - 2022. Furthermore we drop the observations where firms don't report a value for operating revenue or turnover and we drop observations that report zero or no value for the number of employees.

2.3 Representativeness

The following section shows the representativeness of our data, with a particular focus on the services sector. The structure of different types of economic activities is described in the NACE (Nomenclature statistique des Activites economiques dans la Communaute Europeenne) NACE classification. NACE codes divide the business economy in broad types of activities indicated by letters ranging from B to N (NACE-1-digit level). Furthermore economic activity can be sub-divided in more specific activities on up to the NACE-4-digit level. We will compare our database with the aggregate business economy in order to ensure representativeness, with regards to sectors, years, firm size and geographical representativeness. For a lack of availability of the data, we exclude financial services and insurance activities from the analysis.

Sectoral representativeness Table 1 shows the distribution of firms over the different sectors on the NACE-1-digit level over the period 2011 - 2022, comparing our database from Orbis with the aggregate economic statistics from Eurostat. Table 1 shows that we match aggregate data fairly well when looking at the distribution of firms over over different economic sectors. Furthermore our distribution remains stable over time. Nonetheless, we have a slight over-representation of sectors classified as B: Mining and quarrying , C: Manufacturing. For services sectors: G: Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles also has a larger share in our database then in the aggregate economic statistics. Furthermore we have a slight under-representation of the other services sectors especially: M: Professional, scientific and technical activities is only 9-10% of observations in our database while being roughly 18% of the aggregate economy. More detailed figures on sectoral representativeness and the evolution over time can be found in Appendix A.

Firm size representativeness The Orbis database provides data on firms that are obliged to submit annual accounts. These are often bigger enterprises. Therefore it seems likely that there is a bias towards the large firms in our database. Table 2 shows the structure of enterprises in Eurostat and Orbis by size class over the different sectors on the NACE 1-digit level for 2019. Both in Eurostat and Orbis, the biggest share of firms in our economy are small firms with 0-9 persons employed. Larger firms are smaller shares. When we compare the firm-sizes for different sectors on the NACE-1-digit level in our sample with aggregate economic statistics from Eurostat, it shows that larger firms are overrepresented in our database.

3 Value added per worker and aggregate productivity dynamics based on micro-data

3.1 Aggregate labour productivity growth

In the following section, we aim to perform a macro-aggregation of micro data on firm-level productivity. We use value added per employee or labour productivity as our productivity indicator. We calculate the growth rate of real value added per employee (labour productivity) as the year-on-year difference between the sum of real value-added per employee weighted by the nominal value-added shares. The change in aggregate labour productivity, $\Delta\Phi_t$, over time is calculated as follows:

$$\Delta\Phi_t = \Phi_t - \Phi_{t-1} \tag{1}$$

$$\Phi_t = \sum_i s_{it}\phi_{it}. \tag{2}$$

$$s_{it} = \frac{VA_{it}}{\sum_i VA_{it}}. \tag{3}$$

Where Φ_t is the aggregate labour productivity at time t, defined as the weighted average of firm-level productivity. With s_{it} is the weight defined as the firm's share of nominal value

Table 1: Representativeness of data over NACE 1 aggregate sectors

	NACE Code											
	B	C	D	E	F	G	H	I	J	L	M	N
2011												
Orbis	0.28%	17.09%	0.34%	0.65%	16.24%	33.10%	4.79%	8.19%	3.56%	3.45%	8.25%	4.08%
Eurostat	0.09%	9.91%	0.31%	0.32%	14.92%	29.06%	5.38%	8.37%	3.75%	5.51%	17.00%	5.37%
2012												
Orbis	0.28%	17.17%	0.40%	0.69%	15.08%	32.80%	5.16%	7.90%	3.82%	3.65%	8.85%	4.21%
Eurostat	0.09%	9.64%	0.33%	0.33%	14.82%	28.66%	5.27%	8.27%	3.90%	5.92%	17.30%	5.46%
2013												
Orbis	0.27%	17.08%	0.40%	0.69%	14.65%	32.68%	5.33%	8.14%	3.89%	3.55%	9.00%	4.30%
Eurostat	0.09%	9.47%	0.37%	0.33%	14.63%	28.33%	5.22%	8.21%	4.09%	5.92%	17.71%	5.64%
2014												
Orbis	0.27%	16.82%	0.41%	0.68%	14.31%	32.55%	5.53%	8.38%	3.96%	3.48%	9.20%	4.41%
Eurostat	0.08%	9.25%	0.43%	0.33%	14.76%	27.58%	5.11%	8.22%	4.25%	6.00%	18.10%	5.88%
2015												
Orbis	0.27%	16.99%	0.42%	0.69%	14.15%	31.82%	5.80%	8.31%	4.12%	3.45%	9.44%	4.53%
Eurostat	0.09%	9.20%	0.45%	0.33%	14.59%	27.35%	5.15%	8.35%	4.33%	5.71%	18.43%	6.02%
2016												
Orbis	0.26%	16.85%	0.42%	0.70%	13.99%	31.46%	6.06%	8.56%	4.17%	3.39%	9.54%	4.60%
Eurostat	0.08%	8.98%	0.48%	0.33%	14.46%	26.88%	5.16%	8.36%	4.41%	6.07%	18.59%	6.20%
2017												
Orbis	0.25%	16.49%	0.41%	0.72%	13.89%	31.43%	6.14%	8.69%	4.25%	3.44%	9.66%	4.63%
Eurostat	0.08%	8.91%	0.45%	0.32%	14.49%	26.16%	5.25%	8.40%	4.63%	5.99%	18.96%	6.36%
2018												
Orbis	0.25%	16.62%	0.40%	0.72%	13.97%	31.07%	6.37%	8.71%	4.28%	3.27%	9.66%	4.67%
Eurostat	0.08%	8.99%	0.73%	0.34%	14.58%	25.63%	5.36%	8.27%	4.72%	5.70%	19.14%	6.47%
2019												
Orbis	0.23%	15.99%	0.38%	0.69%	14.73%	29.87%	6.29%	9.19%	4.43%	3.22%	10.15%	4.82%
Eurostat	0.07%	8.92%	0.75%	0.34%	14.85%	24.88%	5.44%	8.22%	4.87%	5.75%	19.25%	6.65%
2020												
Orbis	0.23%	15.78%	0.38%	0.69%	15.24%	29.62%	6.31%	8.94%	4.52%	3.20%	10.30%	4.79%
Eurostat	0.07%	8.89%	0.72%	0.34%	15.25%	24.51%	5.52%	7.94%	4.97%	5.81%	19.37%	6.61%
2021												
Orbis	0.23%	15.66%	0.39%	0.69%	15.66%	29.50%	6.36%	8.57%	4.55%	3.22%	10.43%	4.73%
Eurostat	0.07%	8.64%	0.70%	0.32%	15.22%	23.89%	5.63%	7.76%	5.22%	6.12%	19.56%	6.87%
2022												
Orbis	0.22%	15.42%	0.35%	0.67%	16.26%	28.77%	6.24%	8.67%	4.82%	3.21%	10.59%	4.77%
Eurostat	0.07%	8.48%	0.74%	0.32%	15.40%	23.02%	5.59%	7.71%	5.48%	6.15%	19.84%	7.20%

Table 2: Sectoral representativeness over size classes in 2019

	Size class				
	0-9 employees	10-19 employees	20-49 employees	50-249 employees	250+ employees
NACE code					
B					
Orbis	56.07%	19.27%	14.64%	7.72%	2.29%
Eurostat	77.10%	10.53%	7.29%	4.00%	1.08%
C					
Orbis	57.52%	16.90%	13.63%	9.60%	2.34%
Eurostat	83.02%	7.94%	5.12%	3.14%	0.79%
D					
Orbis	64.78%	10.42%	10.42%	10.53%	3.85%
Eurostat	96.92%	1.08%	0.92%	0.76%	0.33%
E					
Orbis	51.23%	15.66%	15.89%	13.69%	3.52%
Eurostat	79.53%	8.04%	6.62%	4.65%	1.15%
F					
Orbis	78.01%	12.16%	6.81%	2.70%	0.32%
Eurostat	93.22%	4.39%	1.78%	0.55%	0.05%
G					
Orbis	79.97%	10.37%	6.17%	2.91%	0.58%
Eurostat	93.41%	3.88%	1.86%	0.71%	0.13%
H					
Orbis	72.80%	12.10%	8.63%	5.23%	1.24%
Eurostat	90.76%	4.67%	3.01%	1.30%	0.26%
I					
Orbis	72.35%	16.60%	8.11%	2.60%	0.35%
Eurostat	88.93%	7.17%	3.00%	0.81%	0.09%
J					
Orbis	76.78%	10.15%	7.12%	4.84%	1.12%
Eurostat	94.25%	2.75%	1.79%	0.97%	0.24%
L					
Orbis	89.68%	5.53%	3.11%	1.49%	0.19%
Eurostat	98.24%	1.07%	0.47%	0.19%	0.03%
M					
Orbis	86.31%	6.96%	3.99%	2.23%	0.51%
Eurostat	96.91%	1.86%	0.85%	0.32%	0.06%
N					
Orbis	71.44%	11.14%	8.69%	6.65%	2.08%
Eurostat	92.50%	3.29%	2.36%	1.46%	0.39%

added in total nominal value added of firm i at time t, and ϕ_{it} is the labour productivity (real value-added per employee) of firm i at time t. Figure 6 shows the growth rate of value added per employee from 2008 until 2022. We see that labour productivity growth rates show both positive and negative values over this period, showing a negative growth rate in 2009 and the fluctuations in the period 2020-2022. On average labour productivity growth rates are small, and more than half of the years show negative growth rates. This indicates a slowdown of aggregate productivity growth which matches patterns observed in macro-economic data.

3.2 Contributions of underlying sectors

Aggregate labour productivity Φ_t, can be decomposed into contributions from underlying sectors. In the following section, we decompose aggregate labour productivity into the contributions of construction, manufacturing and services sectors. The aggregate real labour productivity equals the sum of the weighted contributions of real labour productivity from construction (C), manufacturing (M) and services (S). We rewrite this and identify $\widetilde{\Phi_{t_X}} = \sum_{i \in X} s_{it}\phi_{it}$ which represents the weighted contribution of a specific sector X to aggregate productivity.

$$\Phi_t = \sum_{i \in C} s_{it}\phi_{it} + \sum_{i \in M} s_{it}\phi_{it} + \sum_{i \in S} s_{it}\phi_{it} \tag{4}$$

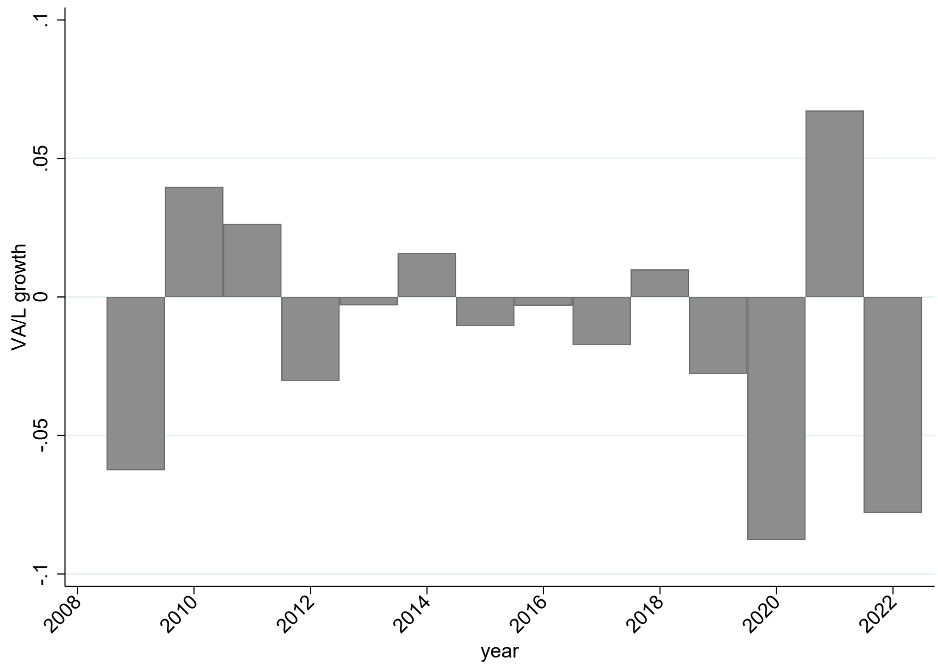
$$\Phi_t = \widetilde{\Phi_{t_C}} + \widetilde{\Phi_{t_M}} + \widetilde{\Phi_{t_S}} \tag{5}$$

Similarly, the growth rate of real aggregate labour productivity can also be decomposed into the sum of the contributions from the underlying sectors. Here we decompose again into the contribution from construction (C), manufacturing (M) and services sector (S).

$$\Delta\Phi_t = \Delta\widetilde{\Phi_C} + \Delta\widetilde{\Phi_M} + \Delta\widetilde{\Phi_S} \tag{6}$$

Figure 7 shows the weighted contributions of these three sectors to the aggregate *growth rate* of labour productivity. We notice that we only have small fluctuations in the aggregate growth rate of labour productivity: positive and negative growth rates remain smaller than 10% for aggregate growth. At the same time, the contributions of the three underlying sectors are larger and more volatile, but negative and positive growth patterns cancel each other out. For the three main industries, we notice positive growth rates of labour productivity in the construction sector in the last 10 years. Labour productivity in the manufacturing sector is showing negative growth rates, while in services we see a fluctuating pattern of positive and negative growth rates, especially over the last four years. Figure 8 shows the weighted contributions of manufacturing, construction and services to the aggregate value of labour productivity. Construction is the smallest sector in our dataset and as such provides the smallest contribution to aggregate labour productivity. Services on the other hand are making up the largest contribution, being the largest part of our economy. Manufacturing is situated in between the two other sectors.

Figure 6: Aggregate productivity growth rates



Following a similar logic, we can further decompose aggregate labour productivity growth into the contributions of the underlying sectors on the NACE 1-digit level. The aggregate values for labour productivity for sectors on the NACE-1-digit level can be found in Appendix B. Sectors C: Manufacturing, F: Construction and G: Wholesale and retail and repair of motor vehicles provide the largest contributions to aggregate labour productivity. Figure 9 shows the contributions of NACE 1-digit sectors to the *growth rate* of aggregate labour productivity. The largest sectors here have the most volatile growth patterns. The highest volatility in the growth rate of labour productivity can be found in the following sectors: Sector C: manufacturing, Sector F: construction, Sector G: Wholesale and retail and repair of motor vehicles and I: Food and accommodation. The other service sectors are providing smaller contributions to aggregate productivity and don't show a lot of variation in their growth patterns.

Figure 7: Aggregate productivity growth rates: contributions from construction, construction and services

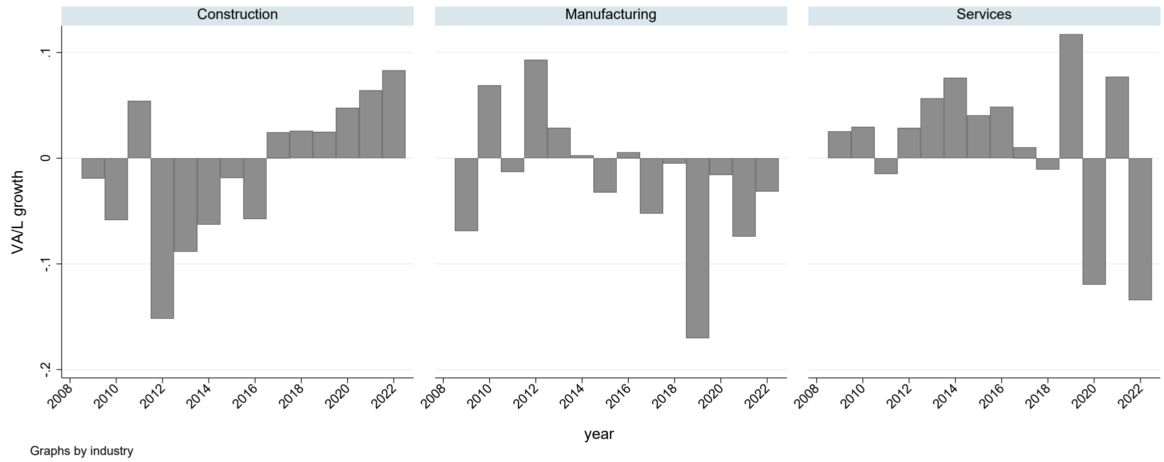


Figure 8: Aggregate labour productivity: contributions from manufacturing, construction and services

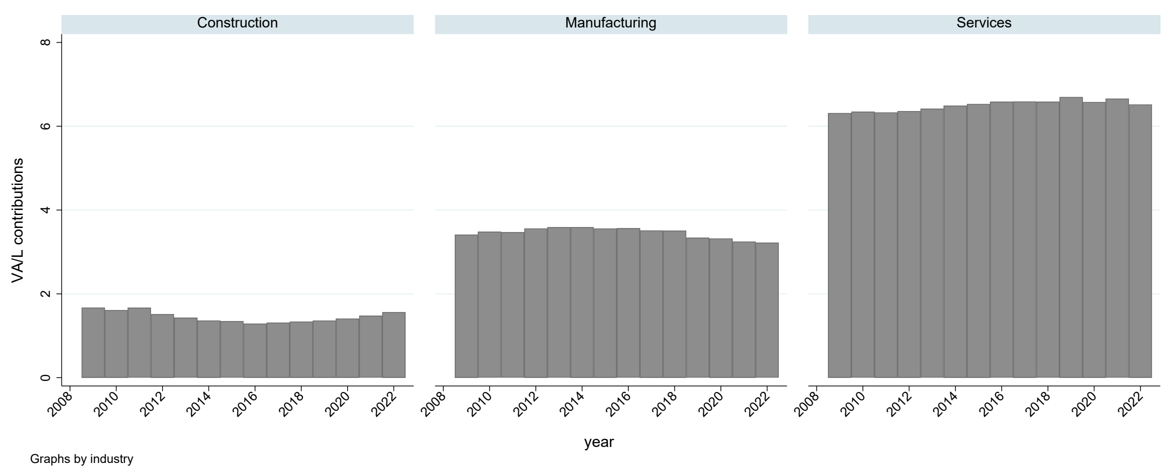
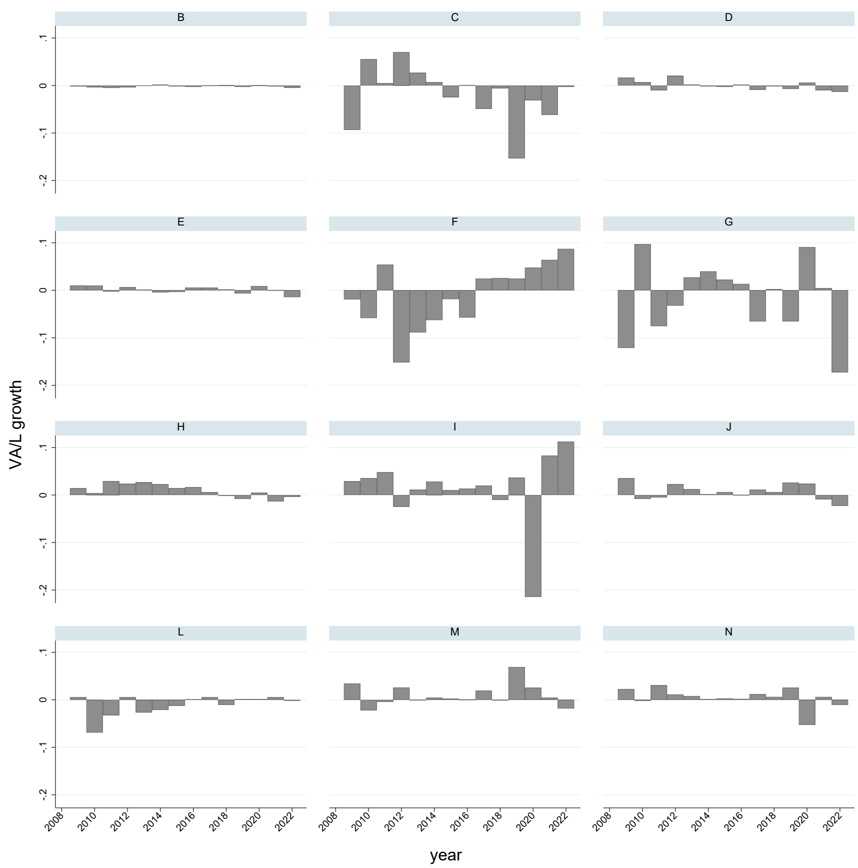


Figure 9: Aggregate productivity growth rates contributions from sectors on NACE-1-digit level



4 Decomposition of labour productivity

4.1 Theoretical framework: Melitz & Polanec (2015)

In the following paragraph, we make a decomposition of labour productivity growth into the contributions of entrants, incumbent firms and firms leaving the market. Following the theoretical framework by Melitz and Polanec (2015), let $s_{Gt} = \sum_{i \in G} s_{it}$ represent the aggregate market share of a group G of firms and define $\Phi_{Gt} = \sum_{i \in G} (s_{it}/s_{Gt})\, \varphi_{it}$ as that group's aggregate (average) productivity. We can then write aggregate productivity in each period as a function of the aggregate share and aggregate productivity of the three groups of firms (survivors, entrants, and exiters):

$$\Phi_1 = s_{S1}\Phi_{S1} + s_{X1}\Phi_{X1} = \Phi_{S1} + s_{X1}(\Phi_{X1} - \Phi_{S1}), \tag{7}$$

$$\Phi_2 = s_{S2}\Phi_{S2} + s_{E2}\Phi_{E2} = \Phi_{S2} + s_{E2}(\Phi_{E2} - \Phi_{S2}). \tag{8}$$

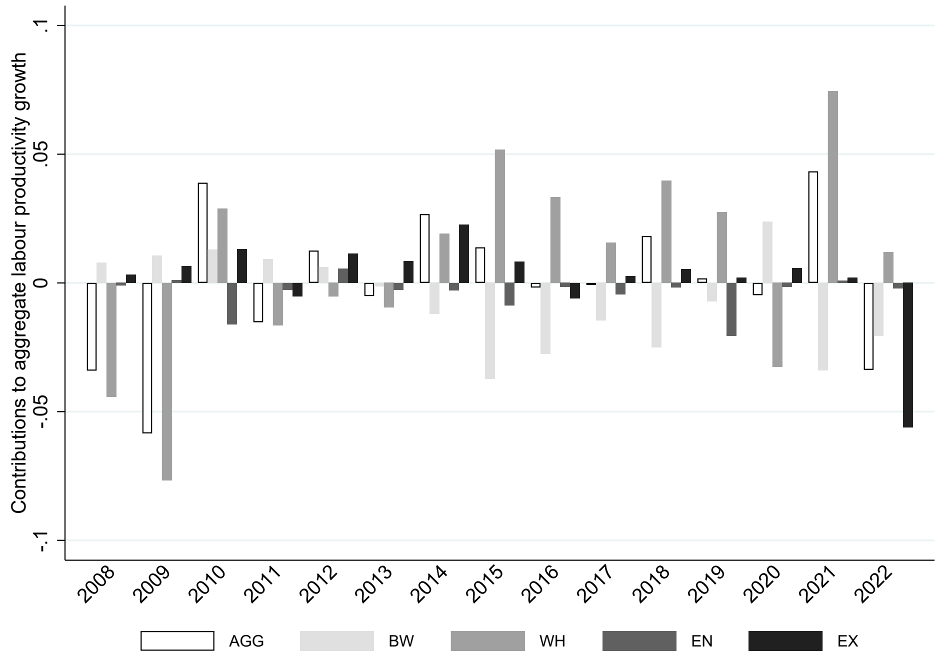
The decomposition features a contribution of firms that enter the market that increases with the aggregate productivity of entrants Φ_{E2}, a contribution of exit that increases with lower aggregate productivity of exiters Φ_{X1}, and a contribution of surviving firms that increases with the aggregate productivity difference $\Phi_{S2} - \Phi_{S1}$. All three also add up to the same aggregate productivity change $\Delta\Phi$. We then separately apply the Olley and Pakes (1996) decomposition to the contribution of the surviving firms dividing this contribution into an unweighted average productivity across all firms and a reallocation effect. The unweighted average component or the within-firm component provides a baseline measure of productivity by averaging the performance of all firms, regardless of their size or market share. The covariance term or the between firm effect captures the reallocation effect. This term measures the covariance between firm productivity and market share, reflecting how resources are distributed among firms.

$$\begin{aligned} \Delta\Phi &= (\Phi_{S2} - \Phi_{S1}) + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}) \\ &= \Delta\bar{\varphi}_S + \Delta\mathrm{cov}_S + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}). \end{aligned} \tag{9}$$

4.2 Data cleaning and nomenclature

In our sample, we make a distinction between entrants, survivors and exiting firms by first dropping all firms that have gaps in their observations from the dataset. When a firm is not observed in the previous year, the firm is classified as an 'entrant', when the firm is observed in the previous year it is a 'survivor' when the firm is not observed in the next year it is labeled an 'exiting firm'. This reclassification leads to slightly different growth patterns then the previous section. The productivity variable we will use as productivity indicator in our decomposition is real value added per employee or labour productivity. The weight variable is the share of nominal value added of a specific firm in total nominal value added in a certain year.

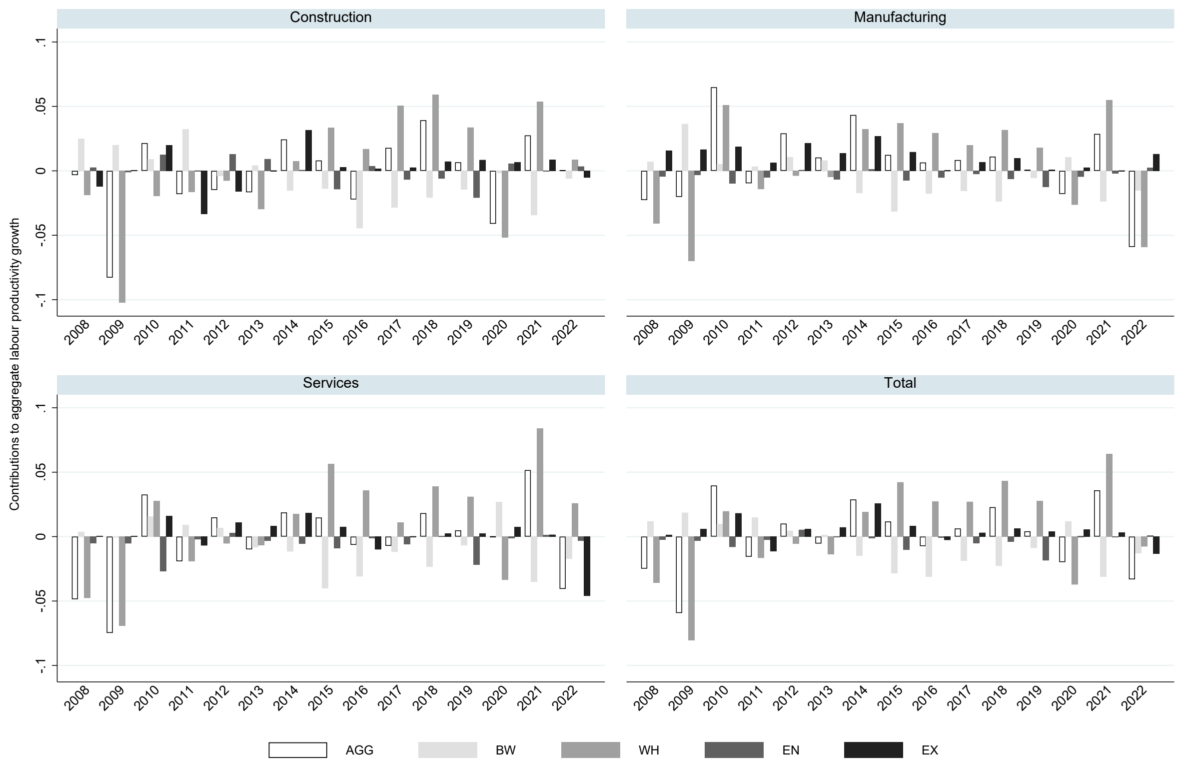
Figure 10: Mean values across all countries of contributions from entry, exit, between and within firm components to aggregate labour productivity growth



4.3 Contributions of entry, exit and incumbent firms

We decompose aggregate labour productivity growth into four components: the contribution of entrants 'EN' 'exiting firms 'EX' a between effect of surviving firms 'BW' capturing a reallocation of resources between firms and a within effect of surviving firms 'WH' where existing firms are becoming more productive. Figure 10 shows the four contributions to year-on-year labour productivity growth next to the aggregate productivity growth in our sample. Again the aggregate growth rates are small, and positive and negative growth rates appear over different years, not showing high and consistent growth patterns. Over different years the contributions of entry and exit remain relatively small as compared to the between and within firm contributions. The within-firm component is on average the largest contribution except for 2022 where firms leaving the market provide the largest contribution to aggregate productivity growth. The between firm component has for most observations the opposite sign as the within firm component. When existing firms become more productive, resources get redistributed from less productive firms, towards more productive firms or vice versa. Overall real labour productivity growth undergoes only small changes. It rises or falls less than 7% in the period 2008 to 2022.

Figure 11: Industry-by-industry decomposition of contributions of entry, exit and incumbents (mean values across all countries)



4.4 Manufacturing, construction and services

4.4.1 Industry-by-industry decomposition into entry, exit and incumbent firms

In this paragraph, we do an industry-by-industry decomposition of the growth rate of aggregate labour productivity into the contributions of entry, exit, between and within firm effects for the construction sector, the manufacturing sector and the services sector separately. Figure 11 shows the contributions. Aggregate growth rates vary by industry. Overall the within-firm contributions to the growth rates of the different industries are the largest, pointing at surviving firms that become more productive (with positive growth rates) or less productive (for negative growth rates). The between-firm component or the reallocation effect has in most of the years or most of the industries the opposite sign as compared to the within-firm contributions, pointing at reallocation gains or losses in the opposite direction as the within-firm level productivity growth or losses. The aggregate labour productivity growth on the sector level shows more volatility in the values of labour productivity growth then the aggregate productivity growth values. Services show the most pronounced negative growth rates in the period 2008-2009 and in 2022. In between small and fluctuating positive and negative growth rates can be witnessed.

4.4.2 Olley-Pakes decomposition: contributions of sectors to labour productivity

To analyze the sectoral contributions to aggregate labour productivity growth, we apply the Olley and Pakes (1996) decomposition to firms grouped by industry. This decomposition allows us to separate aggregate productivity into an unweighted mean productivity term which provides the baseline measure of firm productivity and a covariance term that captures the allocation of market shares across firms. First, we compute sectoral weights based on the total nominal value added within each industry and year. The weight of each firm within its industry is calculated by normalizing the firm's weight relative to the total weight of active firms in that industry-year. Next, we aggregate firm-level productivity within each industry by computing the weighted sum of firm productivity using the firms share of nominal value added in total value added as weights, yielding industry aggregate productivity. The industry mean productivity is then obtained as the simple average across all active firms, while the covariance between productivity and market share is computed to capture the extent to which more productive firms have higher nominal value-added shares. To examine productivity dynamics, we compute year-over-year differences for the unweighted mean productivity, covariance, and aggregate productivity of each industry.

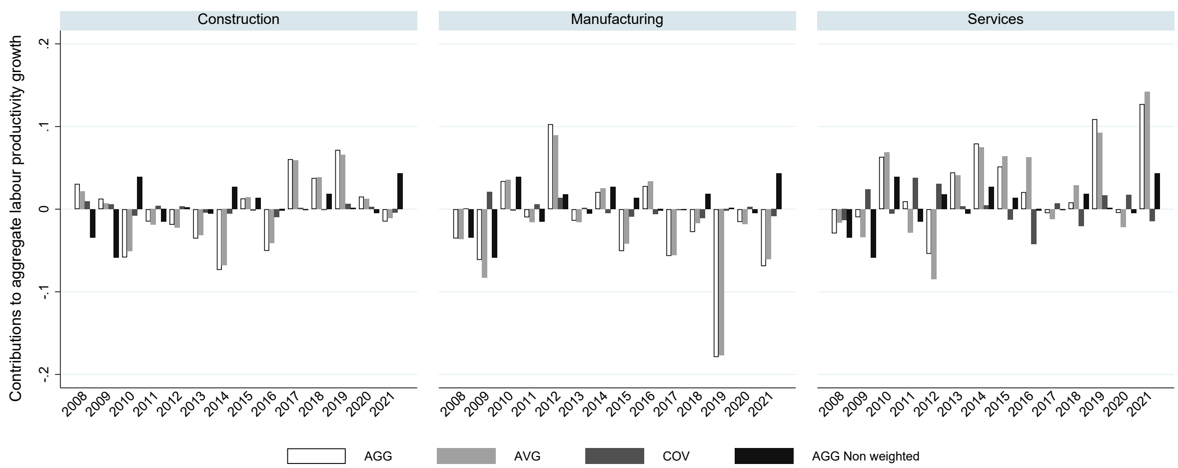
$$\Delta\Phi_{j,t} = \Delta\overline{\phi}_{j,t} + \Delta cov_{j,t} \tag{10}$$

Separate industry contributions to aggregate productivity at the economy-wide level are weighted by their industry size. We construct weighted productivity measures, including weighted aggregate productivity, weighted covariance, and weighted mean productivity. The corresponding year-over-year changes are computed to examine the evolution of different industry contributions to overall productivity dynamics. The equations formalizing the decomposition are described below. With Φ_t is aggregate productivity at time t, $\Phi_{j,t}$ is the productivity of sector j, and $w_{j,t}$ represents the weight of an industry j, based on the nominal value added share of a firm in total nominal value-added. An analogue approach is done to calculate the unweighted mean and covariance term. Figure 12 shows the results of the decomposition over three industries: construction, manufacturing and services. Services have the most volatile growth rate when looking at all years and within firm effects are contributing most to overall growth rates.

$$\Delta\Phi_t = \sum_{j\in J} w_{industry,t}\Delta\Phi_{industry,t} \tag{11}$$

$$\Phi_t = \sum_{j\in J} w_{,t}\Phi_{j,t} \tag{12}$$

Figure 12: Olley Pakes decomposition: Contributions of manufacturing, construction and services to labour productivity growth



4.4.3 Contributions of sectors to productivity of entrants, exiters and surviving firms

In this section, we analyze how different industries contribute to aggregate labour productivity (Φ) across three distinct groups of firms: entrants, incumbents (survivors), and exiters. For each of these groups, we decompose aggregate labour productivity into contributions from three broad sectors: manufacturing (M), construction (C), and services (S). Aggregate productivity for each group is computed as a weighted sum of sectoral productivity contributions, where the weights (s_{G_C}, s_{G_M}, and s_{G_S}) represent the sectoral shares in nominal value added for group G (entrants, incumbents, or exiters). The decomposition is formalized as follows:

$$\Phi_E = s_{E_C}\Phi_{E_{Construction}} + s_{E_M}\Phi_{E_{Manufacturing}} + s_{E_S}\Phi_{E_{Services}} \tag{13}$$

$$\Phi_S = s_{S_C}\Phi_{S_{Construction}} + s_{S_M}\Phi_{S_{Manufacturing}} + s_{S_S}\Phi_{S_{Services}} \tag{14}$$

$$\Phi_X = s_{X_C}\Phi_{X_{Construction}} + s_{X_M}\Phi_{X_{Manufacturing}} + s_{X_S}\Phi_{X_{Services}} \tag{15}$$

where Φ_E, Φ_S, Φ_X represent the aggregate productivity for entrants, incumbents (survivors), and exiters, respectively. The terms $\Phi_{E_{Industry}}, \Phi_{S_{Industry}}, \Phi_{X_{Industry}}$ denote productivity within each industry (construction, manufacturing, and services) for the respective group, while $s_{E_{Industry}}$, $s_{S_{Industry}}$, $s_{X_{Industry}}$ are the sectoral shares in value added for entrants, incumbents, and exiters. The aggregate productivity of entrants reflects the relative importance of construction, manufacturing, and services among newly established firms, while the aggregate productivity of exiters captures the productivity of firms leaving the market. Survivors contribute to aggre-

Figure 13: Sectoral contributions of construction, manufacturing, and services to aggregate labour productivity of entrants (mean values over countries)

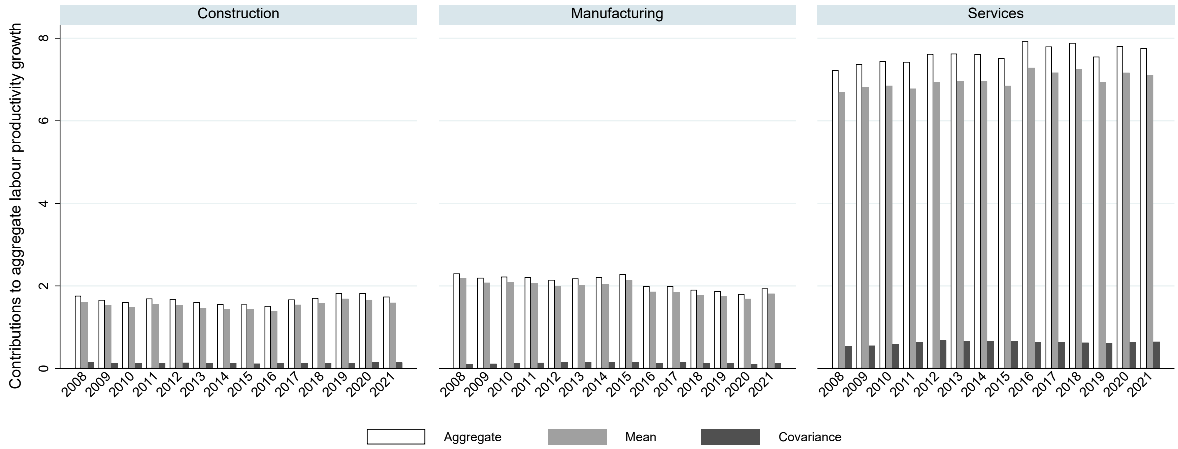
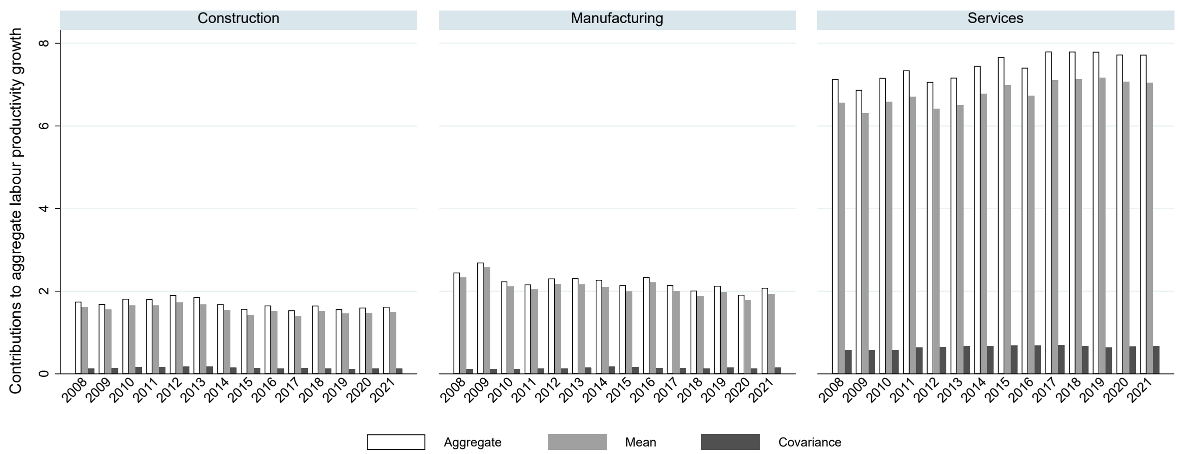
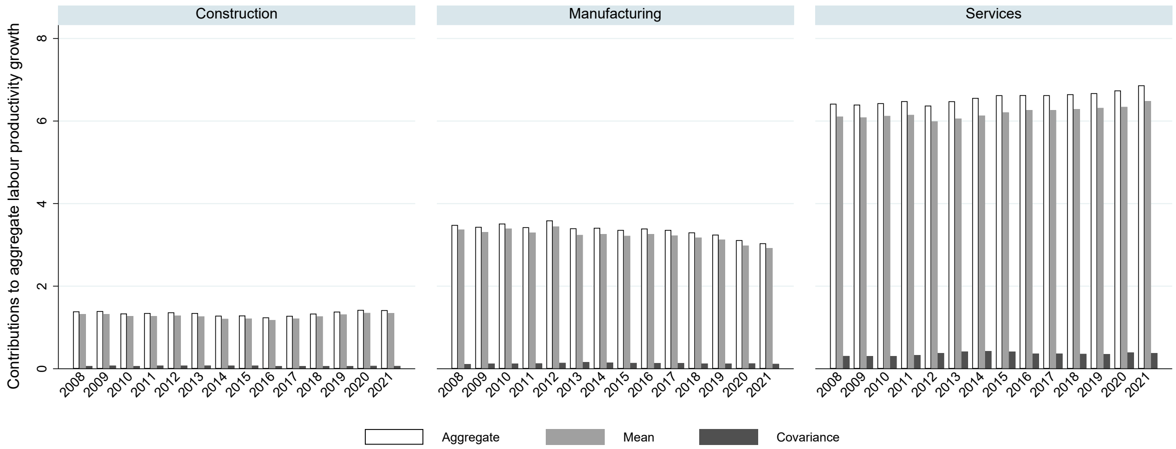


Figure 14: Sectoral contributions of construction, manufacturing, and services to aggregate labour productivity of exiting firms (mean values over countries)



gate productivity by representing ongoing operations in the economy. Figure 13, Figure 14, and Figure 15 show the sectoral contributions of construction, manufacturing and services to aggregate productivity of entrants, exiters and incumbent firms respectively, for each aggregate productivity value, services industries are providing the largest contribution to aggregate labour productivity. This is then followed by the manufacturing sector, while construction provides the smallest contribution. Furthermore, the contribution of entrants, exiters and incumbent firms to aggregate labour productivity can be decomposed in a value for mean productivity and a covariance term. The covariance or the reallocation effect between firms provides a smaller contribution to aggregate labour productivity than the average unweighted firm productivity for all three industries and for the three categories: entrants, exiters and incumbent firms.

Figure 15: Sectoral contributions of construction, manufacturing, and services to aggregate labour productivity of incumbent firms (mean values over countries)



4.5 Further sectoral heterogeneity: contributions of underlying sectors to aggregate labour productivity in services

As shown in the previous section, services contribute most to the aggregate labour productivity levels of entrants, exiters and incumbent firms. We now further divide into the contributions of the underlying sectors on the NACE 1-digit level to the aggregate productivity entrants exiters and incumbent firms in services. Figure 16, Figure 17 and Figure 18 show the contributions of NACE-1-digit sectors to aggregate labour productivity of services. Firms classified as G: Wholesale, retail and repair of motor vehicles are providing the largest contributions to labour productivity in services, although their share is declining while the other service sectors are gaining importance. For entrants and exiting firms, the levels of aggregate productivity are more volatile than for incumbent firms. The labour productivity of incumbent firms shows the least volatility while entrants and exiting firms have more volatile productivity values throughout the years. For all years and categories, the within-firm component contributes most to aggregate productivity, while the between-firm component or the covariance is much smaller, pointing at the existing firms becoming more productive and only limited reallocation between firms.

Figure 16: Sectoral contributions to labour productivity in services labour productivity of entrants (mean values over countries)

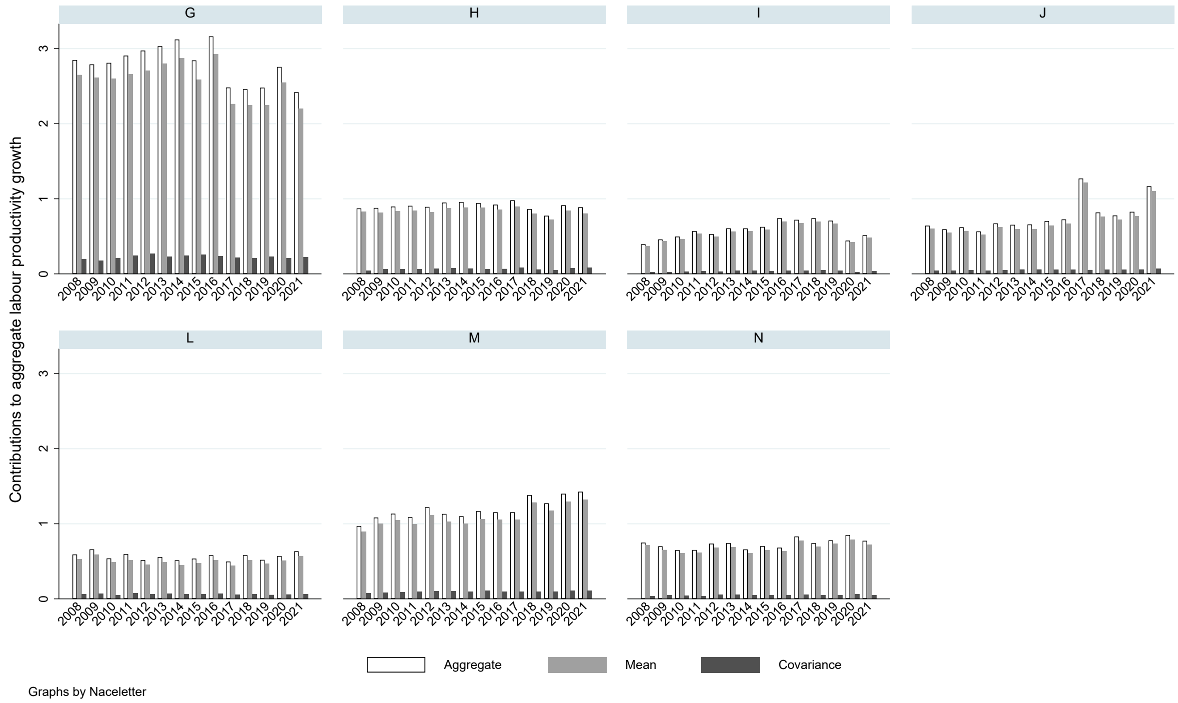


Figure 17: Sectoral contributions to labour productivity in services of exiting firms (mean values over countries)

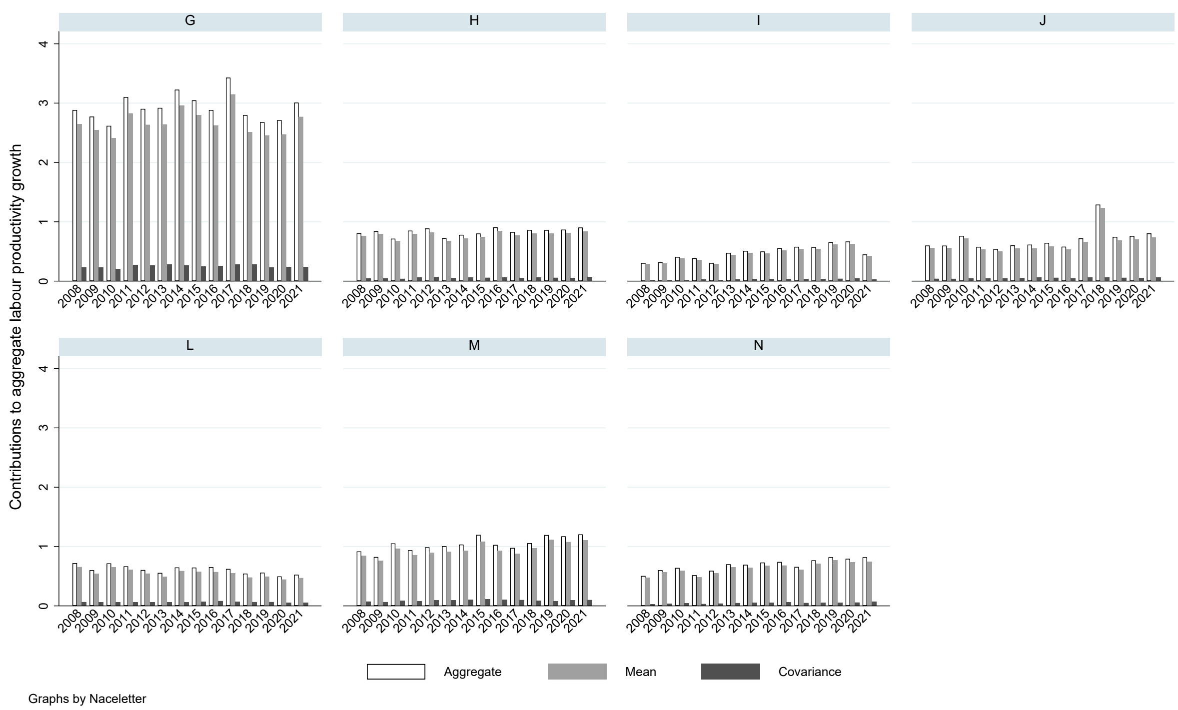
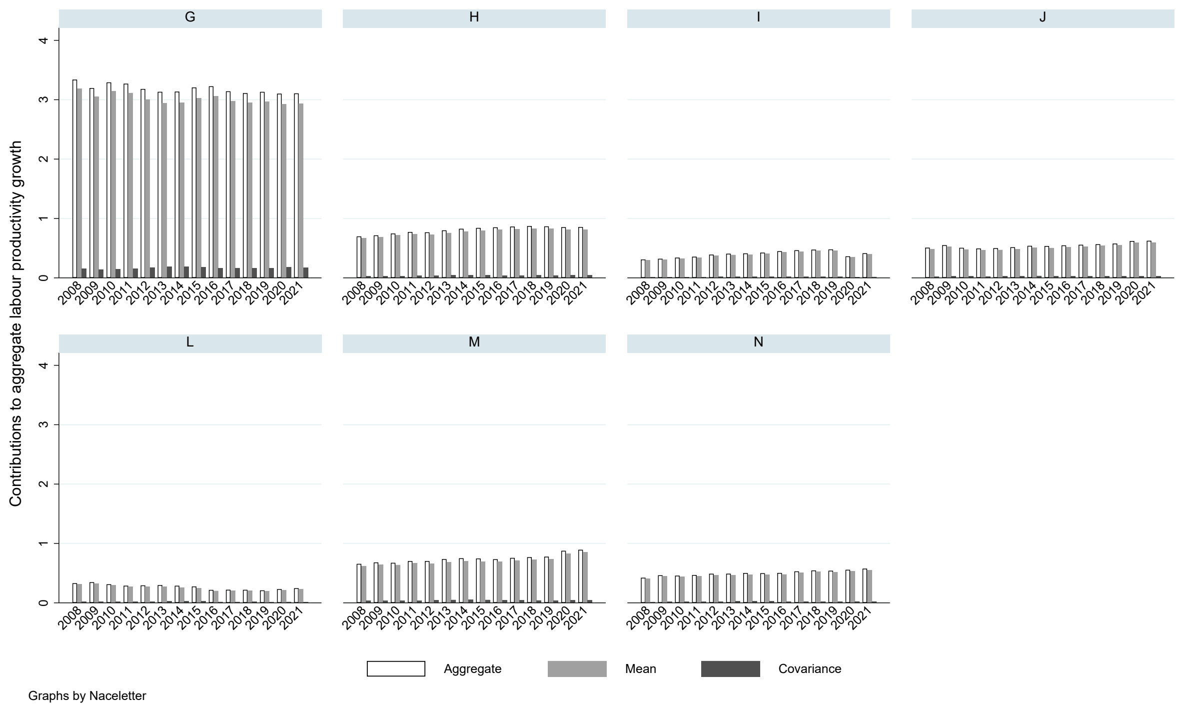


Figure 18: Sectoral contributions to labour productivity in services of incumbent firms (mean values over countries)



5 Estimated productivity indicators vs. value added per employee

5.1 Summary statistics of inputs and estimations

In this section, we will examine whether value added per employee or labour productivity, as investigated in the previous section, aligns with estimated measures of firm productivity. As estimated TFP requires information on all the inputs used in the production function. As such Table 9 and Table 10 in Appendix A.5 and Appendix A.6 show the number of observations per country and year respectively where values for operating revenue (OR), labour (L), material costs (M), tangible fixed assets (TF) and intangible fixed assets (ITF) are reported. The last column gives the number of observations for which we have data for every input factor available. For Denmark, the United Kingdom, Greece, Ireland and Lithuania there are no values for material costs reported. As already described in Section **??** we will not consider these countries for our analysis.

5.2 Estimating total factor productivity

Next to value added per employee which is a widely available metric, productivity can be estimated in various ways (Van Beveren, 2012). Estimating total factor productivity (TFP) requires addressing potential biases arising from unobserved productivity shocks and firms' input choices. We employ three alternative estimation methods to obtain firm-level TFP estimates: (i) Ordinary Least Squares (OLS) with industry-specific regressions and country-fixed effects, (ii) the Olley-Pakes (OP) methodology, and (iii) the Wooldridge-Levinsohn-Petrin (WLP) approach. For each approach, we estimate separately for each industry using broad NACE categories while accounting for country-level heterogeneity through the inclusion of country dummies. A table with the different industry groups based on their NACE codes can be found in Appendix C

5.2.1 OLS with country fixed effects

The simplest approach to estimating TFP is via an OLS regression of firm output on input factors. Specifically, we start from the following gross output Cobb-Douglas production function of a firm i in sector j at time t:

$$y_{ijt} = \beta_j + \beta_{kj} k_{ijt} + \beta_{lj} k_{ijt} + \beta_{mj} m_{ijt} + \gamma_c + \epsilon_{ijt} \tag{16}$$

where y_{ijt} is firm output (operating revenue) in industry j, country c, and year t, k_{ijt} and l_{ijt} represent capital and labor inputs, β_j is an industry fixed effect, and γ_c is a country fixed effect. The residual ϵ_{ijt} is interpreted as firm-level TFP. Advanced parametric and semi-parametric estimation methods have been developed as an addition to simple estimations based on the linearized production function. OLS on a linearized production function requires exogenous inputs to estimate consistently, which is not the case. Firms choose their inputs knowing their productivity level, creating an endogeneity of inputs, leading to inconsistent estimates of the coefficients in the production function. Nevertheless we report these estimates for comparison. Semi-parametric estimation methods try to correct for this bias and are discussed in the following sections.

5.2.2 Olley-Pakes estimation

The semi-parametric estimator first developed by Olley and Pakes (1996) takes care of the endogeneity problem by using the firm's investment decision as a proxy for unobserved productivity shocks. The model addresses selection bias by incorporating an entry and exit rule. Here we start from the following gross output Cobb-Douglas production function of a firm i in sector j at time t:

$$y_{ijt} = \beta_j + \beta_{kj} k_{ijt} + \beta_{lj} k_{ijt} + \beta_{mj} m_{ijt} + \gamma_c + \omega_{ijt} + \epsilon_{ijt} \tag{17}$$

Where ω_{ijt} is the unobserved productivity parameter. In order to recover this productivity term, the production function is estimated in two stages. First, we control for simultaneity by using investment as a proxy for unobserved productivity shocks. Investment I_{ijt} is assumed to be a monotonically increasing function of productivity, allowing us to invert this relationship and express productivity as a function of investment and capital. Additionally, the Olley-Pakes model corrects for selection bias: The survival probability of a firm is estimated in the second stage, ensuring that productivity estimates account for firms' exit decisions. For the Olley-Pakes method, we first regress the output on labour and materials (variable inputs) and a polynomial of investment and capital (state variables). This allows to recover the elasticities of the variable inputs. Subsequently, we invert our production function conditional on investment, which allows us to estimate the capital coefficient consistently. In our analysis we allow for the labour, capital and material elasticities to vary across industries but they remain the same across all countries. The OP estimator has the advantage of explicitly controlling for selection and simultaneity, making it preferable to OLS. However, it requires firms to report investment consistently, which may be problematic in service industries where investment in tangible assets is less frequent.

5.2.3 Wooldridge-Levihnson-Petrin methodology

An alternative approach, developed by Levinsohn and Petrin (2003) and extended by Wooldridge (2009), replaces investment from the Olley-Pakes methodology with intermediate inputs (e.g., materials) as a proxy for productivity shocks. The advantage of this method is that intermediate inputs are typically observed more frequently than investment, reducing potential data limitations. We estimate the production function using the Wooldridge (2009) two-equation approach, which improves efficiency by jointly estimating both the first- and second-stage equations within a single system Generalized Method of Moments (GMM) framework. This improves robustness compared to the traditional two-step OP and LP methodology. We start again from the gross output production function. and use lagged labour and lagged material input as instruments in the Generalized Methods of Moments equation to recover the labour, capital and material elasticity. Again, we estimate separately for each industry and impose identical labour and capital elasticities across countries. We include again a country dummy for the productivity term to take into account differences in productivity levels between countries.

5.3 Correlation between productivity measures

Since productivity can be measured by various methodologies, it is worth considering whether these different estimation methods align with each other and as such measure the same thing. We compare the correlation of value-added per employee (VA/L) with estimated productivity measures: We use estimated with Ordinary Least Squares (OLS) including country fixed effects, the Olley-Pakes methodology and the Wooldridge-Levinsohn-Petrin (WLP) methodology. Table 3 shows that OLS exhibits the highest correlation with VA/L while WLP has the lowest correlation. Olley-Pakes falls between the two other estimations. All correlation measures are below 0.5 pointing at estimated productivity being another metric than labour productivity because now other input factors: capital and material are considered in the production function. Differences between OLS and the other semi-parametric estimators arise because semi-parametric estimators rely on different assumptions: Olley-Pakes inverts on investments as a proxy for unobserved productivity while Wooldridge-Levihnson-Petrin inverts on the lagged values of labour and material inputs. Although the estimated TFP measures rely on different assumptions their mutual correlations are noticeably higher than the correlation with value added per employee.

Table 3: Cross-correlation of different productivity indicators (full sample)

Variables	VA/L	TFP (OLS)	TFP (OP)
TFP (OLS)	0.473		
TFP (OP)	0.407	0.975	
TFP (WLP)	0.220	0.805	0.870

5.4 Differences in correlation between services and manufacturing

Table 4 and Table 5 present the correlation coefficients for different productivity measures for the manufacturing sector and the services sector. Since manufacturing and services are inherently different sectors, productivity estimations for these sectors and correlations between the productivity estimations can differ significantly. In manufacturing, the estimated TFP indicators show stronger alignment with value-added per employee, as when compared to correlation in the full sample, suggesting a more consistent measurement of productivity across different estimation techniques and the current estimation methodology being better tailored towards manufacturing activities. In contrast, correlations between value added per employee and estimated TFP measures in services are noticeably weaker. The weaker correlations in services likely reflect the sector's inherent heterogeneity and measurement challenges. Unlike manufacturing, where production processes are more standardized and capital intensity is higher, services exhibit greater variation in firm structures, labor dependence, and intangible inputs, making productivity estimation more sensitive to methodological choices, which could lead to discrepancies between estimation techniques. For both manufacturing and services, the correlation between the different estimated productivity measures remains high. These findings highlight the need for methodological refinements in TFP estimation for services, as existing approaches may not fully capture sector-specific productivity dynamics and could introduce biases that distort comparisons across firms and industries.

Table 4: Cross-correlation of different productivity indicators for manufacturing

Variables	VA/L	TFP (OLS)	TFP (OP)
TFP (OLS)	0.521		
TFP (OP)	0.473	0.975	
TFP (WLP)	0.354	0.814	0.802

Table 5: Cross-correlation of different productivity indicators for services

Variables	VA/L	TFP (OLS)	TFP (OP)
TFP (OLS)	0.458		
TFP (OP)	0.386	0.975	
TFP (WLP)	0.174	0.835	0.908

5.5 Differences in correlation and sectoral heterogeneity

In the following section, we take a look at differences in correlation between different types of services. Since the correlation between value added per employee and different estimated productivity measures is lower for services than for manufacturing, we take a look at further sectoral heterogeneity for value-added per employee and estimated TFP. When looking at service sectors separately on the NACE-1-digit level, we see that the correlation between productivity measures is higher than when considering all service sectors in one sample. The correlation tables for services on the NACE-1-digit level can be found in Appendix D. The lower correlation in the full services sector compared to the underlying sectors likely results from heterogeneity across service industries, as different service sectors (e.g., communication, retail, transportation) are different, they exhibit varying relationships between value-added and TFP measures. Correlations in the full sample of services might reduce strong within-group correlations. Correlation measures the strength of linear association, which is affected by variance. As such, increased variance in the full sample weakens correlation strength. If the overall services sector has a higher dispersion in VA/L or in the other TFP measures, this will result in lower correlation coefficients even when within-sector relationships are strong.

6 Concluding Remarks

We investigate the contribution of different sectors to aggregate labor productivity growth using firm-level data from a large sample of 21 European countries. Our dataset provides a comprehensive representation of the European economy, ensuring that our findings are broadly applicable. At the aggregate level, services emerge as the dominant contribution to both labor productivity and its growth over time. This finding underscores the increasing importance of the service sector in shaping overall economic performance, particularly in advanced economies where structural shifts from manufacturing to services have been ongoing.

When comparing value added per employee with common productivity estimation methodologies, we observe significant differences in correlation between manufacturing and service sectors. While semi-parametric estimation methods are widely used in the literature, our analysis suggests that their application to services may introduce biases. Specifically, correlations between different productivity estimators are lower in services than in manufacturing, indicating potential inconsistencies in measurement. This raises concerns about the suitability of existing approaches when applied to service industries, which may exhibit distinct production functions, input-output relationships, and competitive dynamics compared to manufacturing. Our findings highlight the need for refining productivity estimation techniques to better capture the unique characteristics of service sector firms. Future research should explore alternative methodologies that account for intangibles, heterogeneity in production processes, and potential measurement issues that may arise from sectoral differences. Addressing these challenges is crucial for accurately assessing productivity trends and informing policy decisions aimed at fostering growth in both manufacturing and services.

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A Data representativeness

A.1 Representativeness over aggregate sectors

Figure 19: Number of firms Eurostat

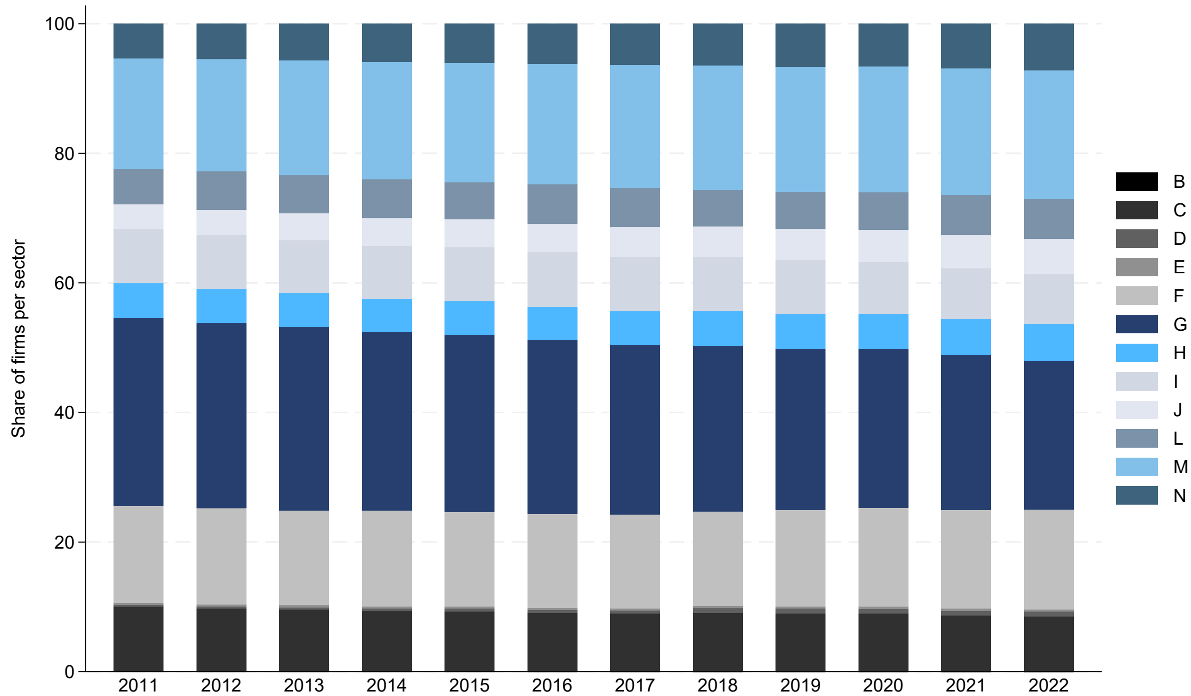
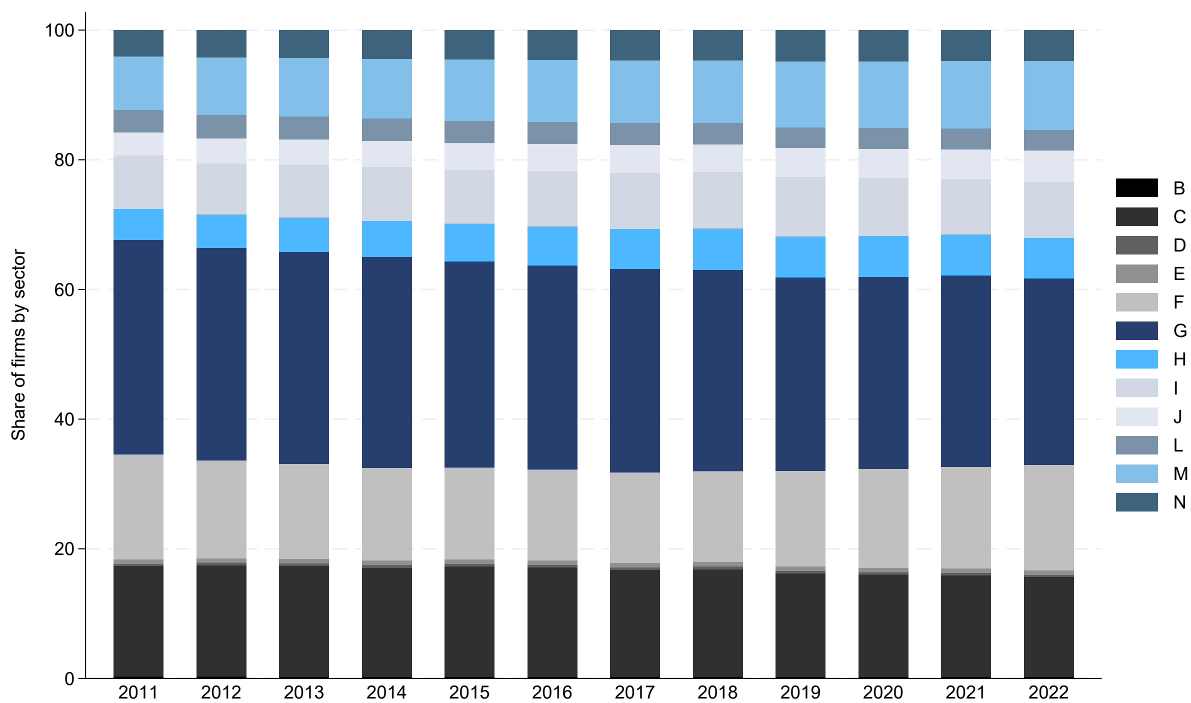


Figure 20: Number of firms Orbis



A.2 Evolution of key variables over time

Figure 21: Number of firms Eurostat

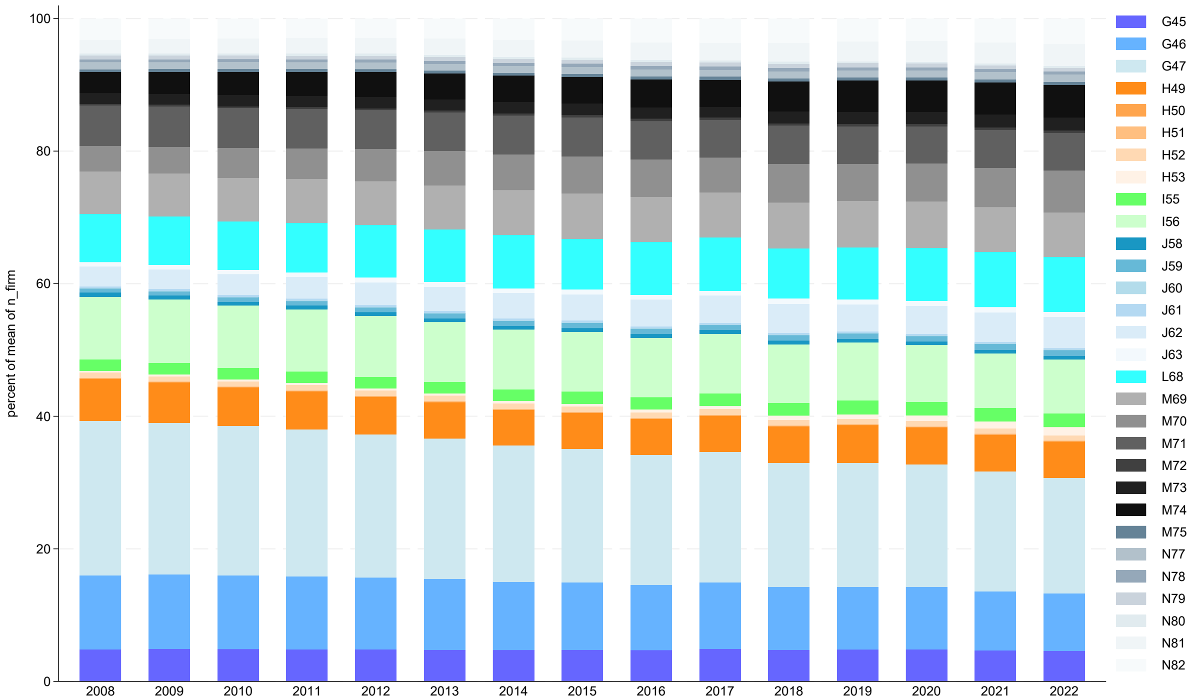


Figure 22: Number of firms Orbis

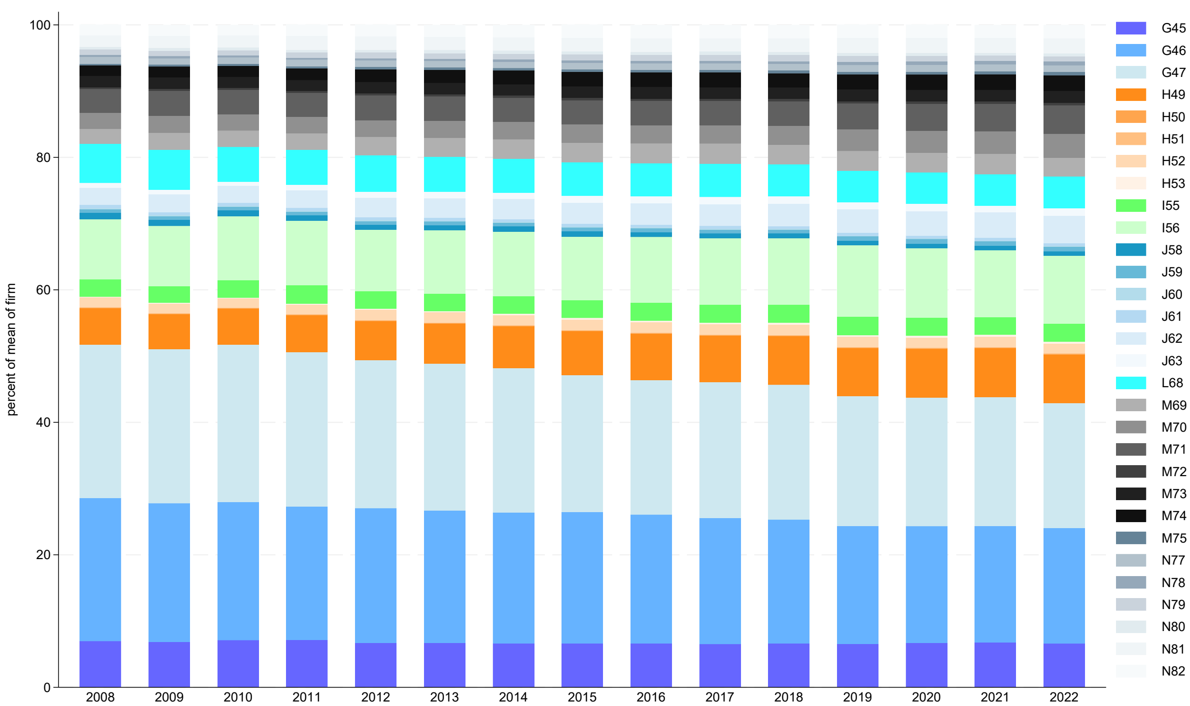


Figure 23: Employment Eurostat

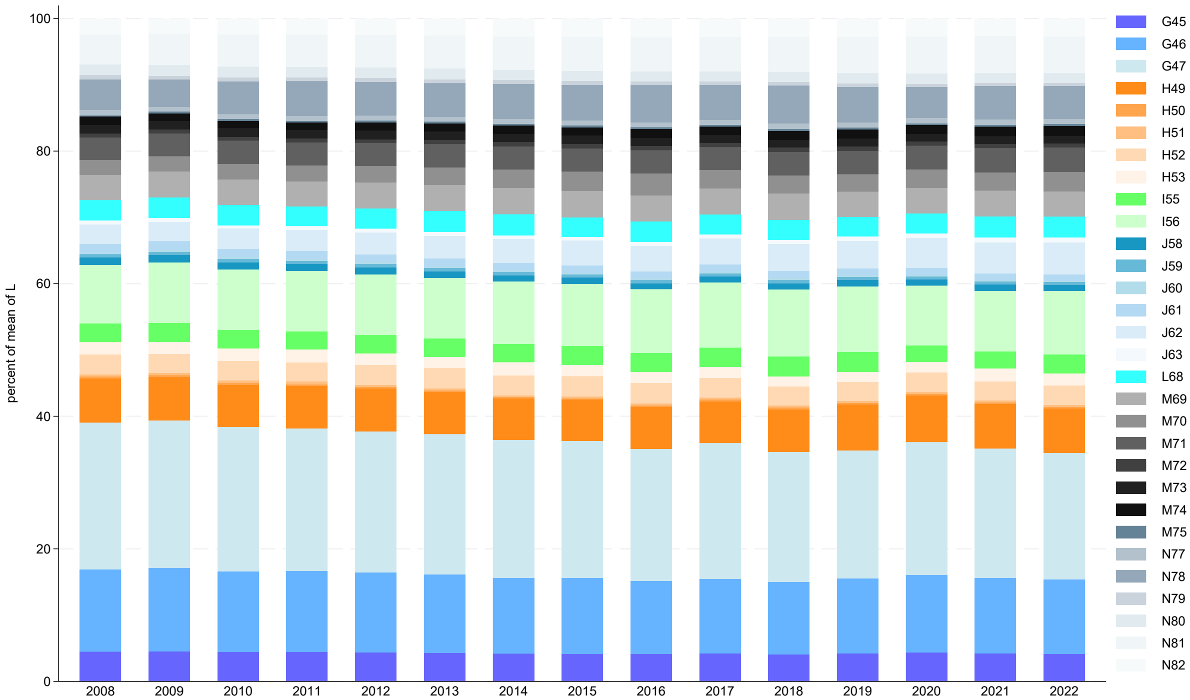


Figure 24: Employment Orbis

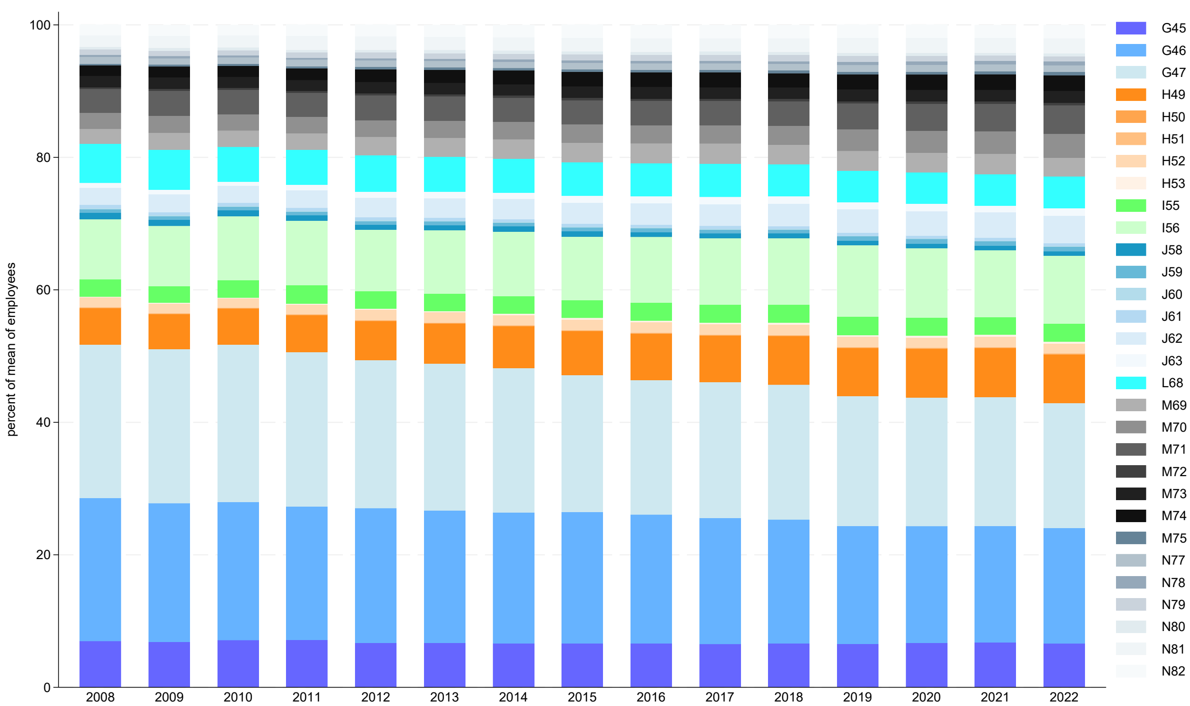


Figure 25: Output Eurostat

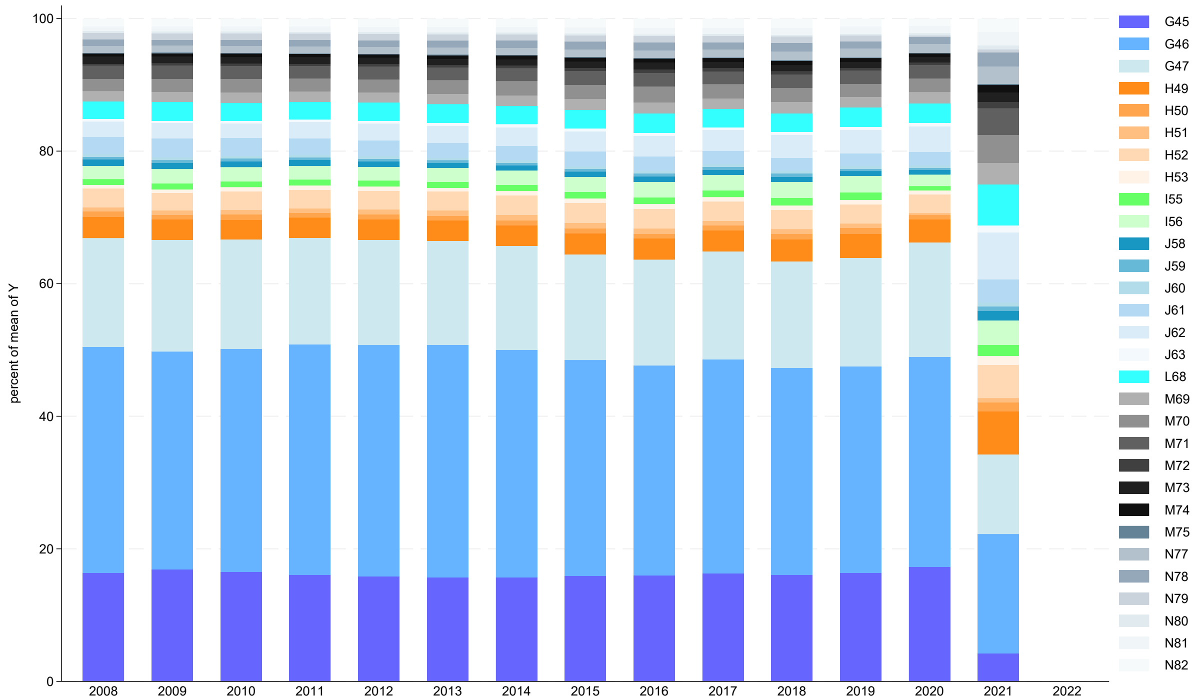


Figure 26: Output Orbis

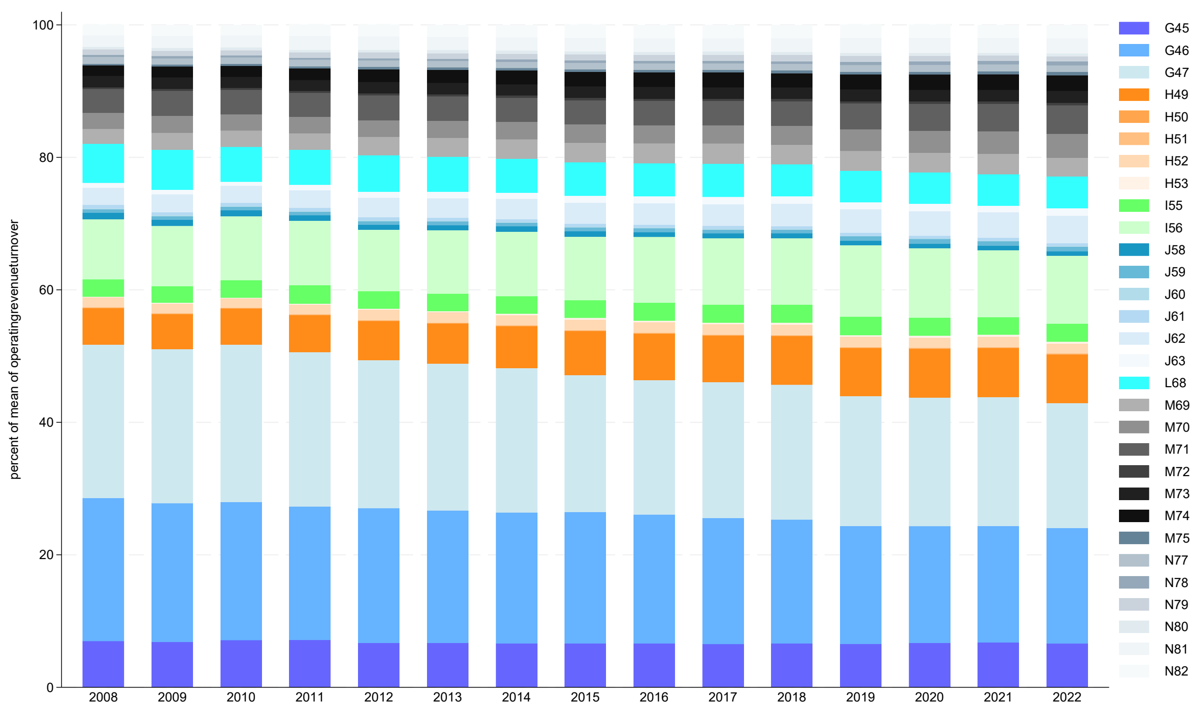


Figure 27: Value added Eurostat

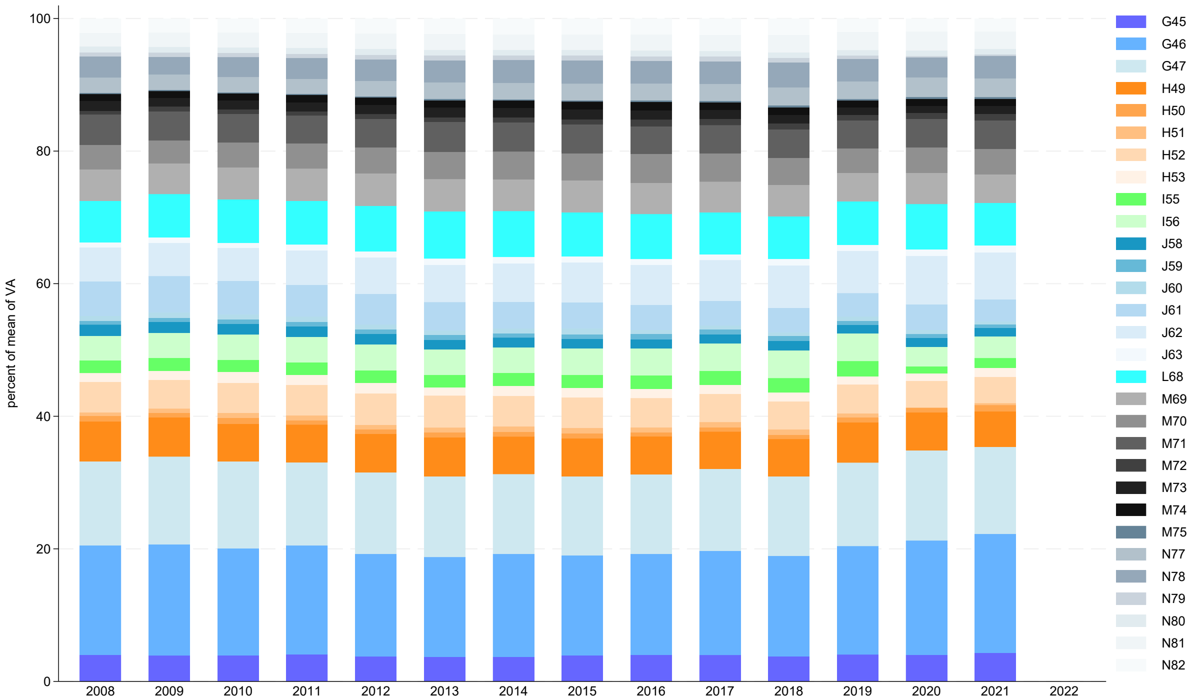
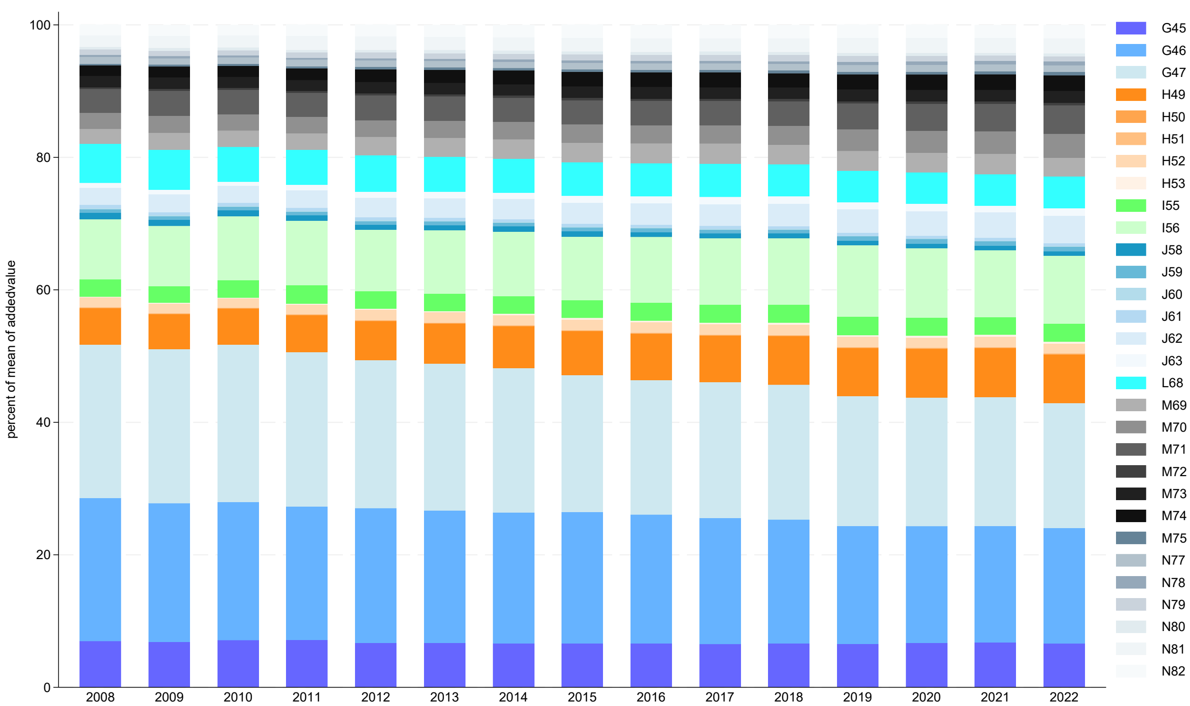


Figure 28: Value added Orbis



A.3 Geographical and sectoral representativeness

Table 6: Sectoral and geographical representativeness (2019)

	NACE code											
	B	C	D	E	F	G	H	I	J	L	M	N
AT												
Orbis	0.16%	31.58%	1.71%	1.05%	11.88%	30.63%	6.21%	2.72%	4.85%	1.01%	4.24%	3.96%
Eurostat	0.09%	7.78%	0.71%	0.65%	11.13%	23.58%	4.37%	14.24%	6.41%	4.58%	20.58%	5.87%
BE												
Orbis	0.35%	22.69%	0.52%	1.57%	9.58%	40.22%	6.64%	1.61%	4.87%	1.73%	6.01%	4.21%
Eurostat	0.03%	5.79%	0.11%	0.22%	17.98%	19.14%	3.16%	7.63%	6.11%	7.54%	24.68%	7.60%
BG												
Orbis	0.13%	13.43%	0.53%	0.34%	8.09%	33.99%	9.53%	8.96%	4.12%	4.70%	12.72%	3.45%
Eurostat	0.09%	9.00%	0.47%	0.23%	6.08%	41.22%	6.70%	7.88%	4.37%	6.88%	13.62%	3.46%
CZ												
Orbis	0.23%	22.11%	1.05%	1.44%	11.88%	25.90%	5.14%	5.35%	4.31%	6.81%	12.13%	3.65%
Eurostat	0.04%	17.18%	1.13%	0.66%	17.48%	21.46%	3.96%	5.70%	4.99%	4.97%	19.08%	3.35%
DE												
Orbis	0.40%	32.12%	8.29%	2.52%	5.66%	27.22%	4.93%	2.35%	4.40%	1.52%	6.45%	4.14%
Eurostat	0.06%	8.24%	2.82%	0.40%	14.61%	22.28%	4.10%	9.15%	4.93%	6.19%	18.85%	8.37%
EE												
Orbis	0.22%	11.40%	0.22%	0.45%	19.09%	22.81%	8.42%	5.01%	6.41%	5.26%	14.83%	5.91%
Eurostat	0.18%	9.52%	0.30%	0.33%	15.21%	21.34%	7.29%	4.15%	8.36%	8.54%	18.31%	6.47%
ES												
Orbis	0.27%	15.61%	0.35%	0.46%	16.07%	32.28%	5.23%	10.21%	3.38%	3.29%	8.50%	4.35%
Eurostat	0.07%	6.43%	0.56%	0.24%	14.34%	27.77%	7.67%	10.90%	2.61%	6.95%	15.88%	6.58%
FI												
Orbis	0.42%	12.94%	0.50%	0.72%	22.10%	23.76%	7.65%	6.12%	4.95%	2.61%	12.64%	5.59%
Eurostat	0.39%	8.63%	0.41%	0.65%	17.90%	17.26%	8.55%	5.30%	4.86%	13.52%	16.23%	6.30%
FR												
Orbis	0.36%	13.86%	0.20%	0.95%	15.04%	28.12%	5.52%	10.39%	5.02%	2.90%	10.85%	6.79%
Eurostat	0.04%	7.14%	0.99%	0.37%	16.59%	23.00%	4.96%	9.03%	5.03%	7.47%	17.97%	7.42%
HR												
Orbis	0.17%	14.12%	0.35%	0.81%	13.71%	23.89%	6.06%	10.66%	5.55%	2.12%	17.52%	5.03%
Eurostat	0.11%	12.40%	0.33%	0.47%	12.74%	20.49%	7.57%	12.15%	6.15%	2.98%	18.11%	6.50%
HU												

Table 6: Sectoral and geographical representativeness (2019)

	NACE code											
	B	C	D	E	F	G	H	I	J	L	M	N
Orbis	0.39%	24.88%	1.46%	2.09%	7.83%	28.27%	5.64%	2.89%	5.12%	7.31%	9.51%	4.61%
Eurostat	0.06%	8.48%	0.18%	0.27%	14.56%	21.31%	5.16%	4.94%	7.81%	5.61%	23.50%	8.14%
IT												
Orbis	0.20%	21.65%	0.34%	0.87%	14.77%	26.37%	5.00%	11.05%	5.08%	2.82%	6.37%	5.48%
Eurostat	0.05%	10.18%	0.26%	0.25%	13.35%	29.44%	3.27%	9.22%	2.92%	6.07%	20.70%	4.29%
LV												
Orbis	0.44%	15.37%	0.78%	0.44%	14.12%	33.54%	7.82%	5.07%	4.39%	3.84%	8.98%	5.20%
Eurostat	0.26%	9.93%	0.47%	0.31%	10.54%	23.58%	6.95%	3.76%	6.84%	11.98%	18.40%	6.95%
NO												
Orbis	0.54%	9.06%	0.46%	0.57%	21.98%	27.95%	4.90%	12.18%	4.64%	2.75%	8.75%	6.23%
Eurostat	0.38%	5.68%	0.17%	0.43%	19.20%	16.16%	6.75%	4.16%	6.07%	17.25%	16.84%	6.91%
PL												
Orbis	0.43%	18.43%	0.82%	1.99%	10.73%	27.92%	6.15%	3.35%	6.48%	6.96%	11.71%	5.03%
Eurostat	0.13%	11.88%	0.18%	0.40%	17.76%	26.91%	8.72%	3.45%	6.63%	2.91%	16.50%	4.52%
PT												
Orbis	0.21%	16.75%	0.07%	0.32%	15.03%	40.21%	1.17%	15.12%	1.52%	3.00%	4.18%	2.43%
Eurostat	0.11%	7.44%	0.49%	0.14%	9.77%	23.60%	3.39%	12.75%	2.27%	5.38%	14.25%	20.41%
RO												
Orbis	0.22%	11.68%	0.19%	0.70%	12.10%	34.35%	11.73%	6.02%	4.15%	2.58%	11.82%	4.46%
Eurostat	0.19%	10.54%	0.20%	0.60%	11.71%	33.40%	10.66%	5.45%	5.24%	3.63%	13.66%	4.71%
SE												
Orbis	0.11%	10.59%	0.17%	0.30%	23.81%	23.67%	4.40%	7.93%	6.17%	1.86%	15.94%	5.05%
Eurostat	0.09%	7.34%	0.34%	0.21%	15.61%	17.43%	4.46%	4.71%	9.46%	6.77%	27.70%	5.87%
SI												
Orbis	0.11%	17.12%	0.35%	0.49%	15.80%	22.60%	8.32%	9.33%	4.47%	2.02%	15.82%	3.56%
Eurostat	0.07%	13.48%	0.93%	0.28%	13.26%	17.63%	5.96%	8.68%	6.89%	2.66%	24.54%	5.62%
SK												
Orbis	0.13%	14.52%	0.30%	0.71%	11.05%	25.33%	5.62%	4.90%	5.48%	4.68%	17.43%	9.85%
Eurostat	0.05%	15.94%	0.12%	0.32%	21.44%	20.70%	4.49%	3.77%	5.21%	3.15%	16.74%	8.06%

A.4 Representativeness over size classes for NACE 2 digit sectors

Table 7: Data representativeness: shares of firms by size class per NACE 2-digit sector

	0-9 employees		10-19 employees		20-49 employees		50-249 employees		250+ employees	
	Eurostat	Orbis	**Eurostat**	Orbis	**Eurostat**	Orbis	**Eurostat**	Orbis	**Eurostat**	Orbis
G45	**94.25%**	82.51%	**3.55%**	9.38%	**1.49%**	5.28%	**0.60%**	2.49%	**0.11%**	0.34%
G46	**92.30%**	76.14%	**4.91%**	12.30%	**1.29%**	7.62%	**1.29%**	3.44%	**0.20%**	0.50%
G47	**94.97%**	84.16%	**3.13%**	9.20%	**1.30%**	4.44%	**0.49%**	1.70%	**0.10%**	0.50%
H49	**92.21%**	77.24%	**4.09%**	11.04%	**2.56%**	7.42%	**0.99%**	3.63%	**0.15%**	0.67%
H50	**92.38%**	73.02%	**3.45%**	12.57%	**2.19%**	8.03%	**1.50%**	5.33%	**0.49%**	1.06%
H51	**88.52%**	59.02%	**4.16%**	8.46%	**3.30%**	14.70%	**2.60%**	12.47%	**1.43%**	5.35%
H52	**84.32%**	62.07%	**6.56%**	14.50%	**5.05%**	11.73%	**3.25%**	9.16%	**0.83%**	2.54%
H53	**97.14%**	77.67%	**1.55%**	10.70%	**0.87%**	7.56%	**0.32%**	2.96%	**0.12%**	1.11%
I55	**89.21%**	65.71%	**5.76%**	16.38%	**3.49%**	11.87%	**1.38%**	5.49%	**0.16%**	0.55%
I56	**89.12%**	75.30%	**7.55%**	16.30%	**2.71%**	6.68%	**0.55%**	1.51%	**0.06%**	0.23%
J58	**92.96%**	76.39%	**3.11%**	9.93%	**2.12%**	7.65%	**1.42%**	5.11%	**0.40%**	0.91%
J59	**97.47%**	88.10%	**1.28%**	6.00%	**0.79%**	3.56%	**0.38%**	1.98%	**0.07%**	0.35%
J60	**88.02%**	69.50%	**5.95%**	14.42%	**3.14%**	8.49%	**2.13%**	5.31%	**0.76%**	2.28%
J61	**89.50%**	73.10%	**5.11%**	12.19%	**3.14%**	7.99%	**1.56%**	4.68%	**0.69%**	2.04%
J62	**94.92%**	77.82%	**2.41%**	9.62%	**1.60%**	7.01%	**0.88%**	4.55%	**0.19%**	1.01%
J63	**95.47%**	84.97%	**2.31%**	8.01%	**1.29%**	3.90%	**0.76%**	2.57%	**0.16%**	0.55%
L68	**98.36%**	90.79%	**1.02%**	5.05%	**0.43%**	2.70%	**0.17%**	1.30%	**0.02%**	0.16%
M69	**96.77%**	89.88%	**2.17%**	6.10%	**0.79%**	2.55%	**0.22%**	1.19%	**0.04%**	0.28%
M70	**98.05%**	88.75%	**1.03%**	5.65%	**0.60%**	3.28%	**0.27%**	1.88%	**0.06%**	0.43%
M71	**96.37%**	84.56%	**2.08%**	8.02%	**1.05%**	4.73%	**0.42%**	2.24%	**0.07%**	0.46%
M72	**92.64%**	69.16%	**3.14%**	12.13%	**2.33%**	9.11%	**1.57%**	7.35%	**0.32%**	2.24%
M73	**96.56%**	85.93%	**1.95%**	7.43%	**1.00%**	4.31%	**0.42%**	2.01%	**0.07%**	0.33%
M74	**99.01%**	90.02%	**0.60%**	5.81%	**0.28%**	2.85%	**0.10%**	1.16%	**0.01%**	0.16%
M75	**95.78%**	88.33%	**2.95%**	7.66%	**1.07%**	3.29%	**0.17%**	0.62%	**0.03%**	0.10%
N77	**95.84%**	81.27%	**2.23%**	9.51%	**1.31%**	6.14%	**0.52%**	2.60%	**0.10%**	0.47%
N78	**76.82%**	65.58%	**6.14%**	9.13%	**7.31%**	9.94%	**7.38%**	11.22%	**2.36%**	4.13%
N79	**95.42%**	87.38%	**2.69%**	7.33%	**1.32%**	3.50%	**0.50%**	1.58%	**0.08%**	0.21%
N80	**79.72%**	50.55%	**6.57%**	12.28%	**7.04%**	14.52%	**5.25%**	16.15%	**1.42%**	6.51%
N81	**91.73%**	67.68%	**4.30%**	13.52%	**2.47%**	10.16%	**1.22%**	6.68%	**0.28%**	1.96%
N82	**97.14%**	78.46%	**1.37%**	10.11%	**0.89%**	6.43%	**0.48%**	3.85%	**0.11%**	1.15%

A.5 Number of observations per country

Table 9: Number of observations per country total (N), Operating revenue (OR), labour (L), materials (M) , tangible fixed assets (TF) intangible fixed assets (ITF) and all together.

Country	N	OR	L	M	TF	ITF	All
AT	2331755	446179	1014124	66831	2032774	2032485	50364
BE	8712932	3825429	3201626	353298	8036553	8084050	319091
BG	3603409	3461578	3222559	2209873	3602342	3602202	2121071
CZ	3307598	2910880	1689708	2179516	2670936	2670608	1355491
DE	10900000	4214415	7719083	694764	9376129	9377896	574830
DK	4734311	778633	1971030	0	4020442	4014650	0
EE	1959760	1722005	938977	1078773	1285954	1238350	581449
ES	16300000	14900000	11300000	12300000	15700000	15700000	9729155
FI	3170911	2993212	1466052	1853784	2709772	2713315	967163
FR	20300000	19100000	11600000	14000000	20200000	20200000	8671667
GB	40100000	4646316	10800000	0	27000000	27000000	0
GR	708288	702118	596441	0	707910	707910	0
HR	1898485	1896815	1401139	1752781	1893584	1893584	1369688
HU	6142256	5217982	2705767	1459627	4559098	4662328	375266
IE	2397159	290368	638128	0	1671538	1668055	0
IT	16800000	16800000	8955614	12800000	16800000	16800000	8438041
LT	510007	449930	437384	0	446683	446763	0
LV	1272531	1187616	1154303	39557	1268334	1268343	38261
NL	12800000	215490	6075908	39923	10500000	10500000	32266
NO	5321493	5148139	4301588	2391811	5299534	5299534	2144505
PL	2882859	2395277	1102535	1898537	1851560	1768790	704941
PT	5712235	5117873	4200741	3476318	5037503	5030475	2729565
RO	13000000	12400000	11500000	10000000	13000000	13000000	8990436
SE	5996433	5775366	4849316	2266871	4224791	4142875	1911653
SI	1620083	1493426	957112	1331890	1345888	1320104	786163
SK	2380060	2301968	1206400	1857394	2165533	2165040	1078016

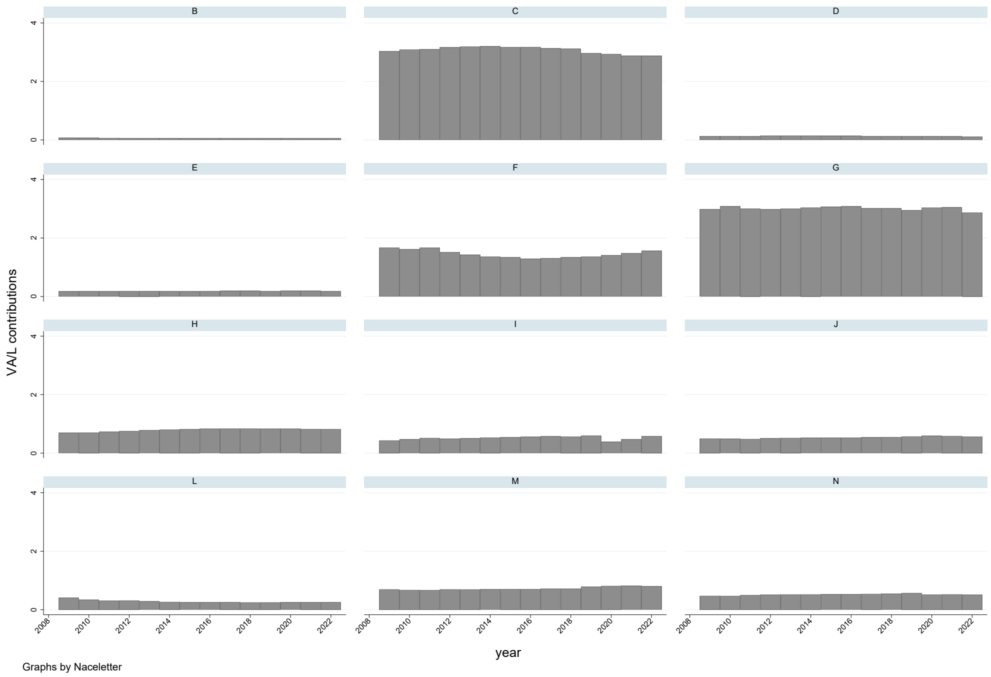
A.6 Number of observations per year

Table 10: Number of observations per year total (N), Operating revenue (OR), labour (L), materials (M) , tangible fixed assets (TF) intangible fixed assets (ITF) and all together.

Year	N	OR	L	M	TF	ITF	All
1990	155	153	59	65	149	64	57
1991	19161	18807	10175	11160	18164	11135	9471
1992	179190	176750	80844	155741	169972	155313	76829
1993	277394	273432	117205	267548	262288	264508	110136
1994	345070	339863	169002	341415	324510	336713	157790
1995	1249415	891145	627795	1177461	640336	1152816	331070
1996	1617722	1182708	828038	1546726	850621	1520639	496312
1997	2077326	1488973	967055	1938292	1086331	1925167	594746
1998	2540440	1862654	1123344	2410587	1381274	2392722	804496
1999	3043935	2121264	1353755	2837915	1557720	2826861	974176
2000	3402866	2338187	1688578	3144517	1712518	3132672	1204340
2001	3665169	2523438	2003423	3357143	1805764	3343202	1428121
2002	4128720	2924447	2280948	3742396	1981689	3745849	1603317
2003	4452825	3077112	2365578	4023504	2089636	4012099	1671102
2004	5214776	3673505	2649689	4736510	2535255	4735625	1790019
2005	6222176	4207901	3000667	5679657	2808147	5678022	1813797
2006	6845752	4487692	3751281	6235462	2782036	6238411	2155446
2007	7599853	5074169	4301929	6913123	2946902	6927091	2285529
2008	7926385	5205958	4522907	7104277	3049279	7120174	2379461
2009	8225801	5397832	4744466	7082294	3223876	7106390	2495145
2010	8535817	5623389	4510592	7308431	3107356	7337898	2277770
2011	9020462	5918543	4822394	7655162	3244355	7678141	2473692
2012	9044545	5729758	4571259	7605422	3297715	7596480	2275921
2013	9169173	5773230	4441305	7623643	3271887	7614551	2260584
2014	9193033	5630864	4576364	7650805	3170025	7640627	2296789
2015	9067223	5298927	4448204	7750380	3100325	7736144	2227183
2016	9306564	5246803	4843300	7843212	3036248	7832524	2210046
2017	9616975	5388152	5346124	8050327	3210871	8035737	2380194
2018	9552664	5156865	5328599	7925396	3068409	7912017	2250417
2019	10900000	6084604	6085679	9015395	3769093	9001181	2519932
2020	11100000	6031226	6694217	9103186	3762571	9091089	2637598
2021	11100000	5915557	6710104	9090210	3634320	9077759	2565789
2022	10200000	5350597	6033524	8080088	3199937	8067692	2211807

B Aggregate labour productivity across different sectors

Figure 29: Aggregate labour productivity: contributions from sectors on NACE-1-digit level



C NACE categories for productivity estimation

Table 11: Industries taken together for the estimation.

Industry Code	**NACE Codes**
B	05–09
CA	10–12
CB	13–15
CC	16–18
CE	19–21 (includes 21 due to low observations)
CG	22–23
CH	24–25
CI	26
CJ	27
CK	28
CL	29–30
CM	31–33
D	35
E	36–39
F	41–43
G	45–47
H	49–53
I	55–56
JA	58–60
JB	61
JC	62–63
L	68
MA	69–72 (includes 72 due to low observations)
MC	73–75
N	77–82

D Correlation of productivity estimates for NACE - 1 - digit sectors

Table 12: Cross-correlation of different productivity indicators for wholesale, retail and repair of motor vehicles

Variables	VA_L	TFP_OLS	TFP_OP
TFP_OLS	0.736		
TFP_OP	0.638	0.973	
TFP_WLP	0.436	0.901	0.946

Table 13: Cross-correlation of different productivity indicators for transport services

Variables	VA_L	TFP_OLS	TFP_OP
TFP_OLS	0.883		
TFP_OP	0.814	0.982	
TFP_WLP	0.809	0.941	0.949

Table 14: Cross-correlation of different productivity indicators for food an accommodation

Variables	VA_L	TFP_OLS	TFP_OP
TFP_OLS	0.816		
TFP_OP	0.847	0.997	
TFP_WLP	0.808	0.824	0.847

Table 15: Cross-correlation of different productivity indicators for communication services

Variables	VA_L	TFP_OLS	TFP_OP
TFP_OLS	0.770		
TFP_OP	0.601	0.948	
TFP_WLP	0.663	0.766	0.807

Table 16: Cross-correlation of different productivity indicators for real estate

Variables	VA_L	TFP_OLS	TFP_OP
TFP_OLS	0.846		
TFP_OP	0.763	0.982	1
TFP_WLP	0.744	0.963	0.9776

Table 17: Cross-correlation of different productivity indicators for professional services

Variables	VA_L	TFP_OLS	TFP_OP
TFP_OLS	0.889		
TFP_OP	0.853	0.981	
TFP_WLP	0.888	0.956	0.976

Table 18: Cross-correlation of different productivity indicators for education and support services

Variables	VA_L	TFP_OLS	TFP_OP
TFP_OLS	0.841		
TFP_OP	0.787	0.992	
TFP_WLP	0.779	0.942	0.949