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 across manufacturing, services, and other industries, using a large panel of firm-level data. Services account for approximately two-thirds of aggregate value added in Europe, a pattern we confirm by benchmarking our firm-level data against macroeconomic aggregates. We show that the observed macroeconomic slowdown in labor productivity is also evident in our micro-economic data. Focusing on productivity within service sectors, we highlight the central role of services in shaping overall productivity trends. We further investigate whether semi-parametric productivity estimators —-commonly used in the productivity literature–align with labor productivity. Given the different methodologies and assumptions, we find differences in alignment in these estimators, highlighting the need for methodological adaptations, especially for estimating TFP in services industries. Further, we decompose labor productivity growth into the contributions of entrants, incumbents, and exiting firms, and find that these dynamics differ between manufacturing and services. Entry and reallocation dynamics in services differ from those in manufacturing, with distinct implications for how productivity evolves at the aggregate level. Finally, we explore how regulation affects productivity growth and its components, using the OECD ETCR-indicator as a proxy for regulatory intensity in network sectors. Our results show that regulation has a stronger effect on manufacturing than on services, with implications for the allocation and reallocation of resources across firms. These findings contribute to a more nuanced understanding of productivity measurement and dynamics in the service-based economies of Europe.

Keywords: Productivity slowdown, firm-level data, services industries.

JEL Codes: E24, J24, L25, L80, O47

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1 Introduction

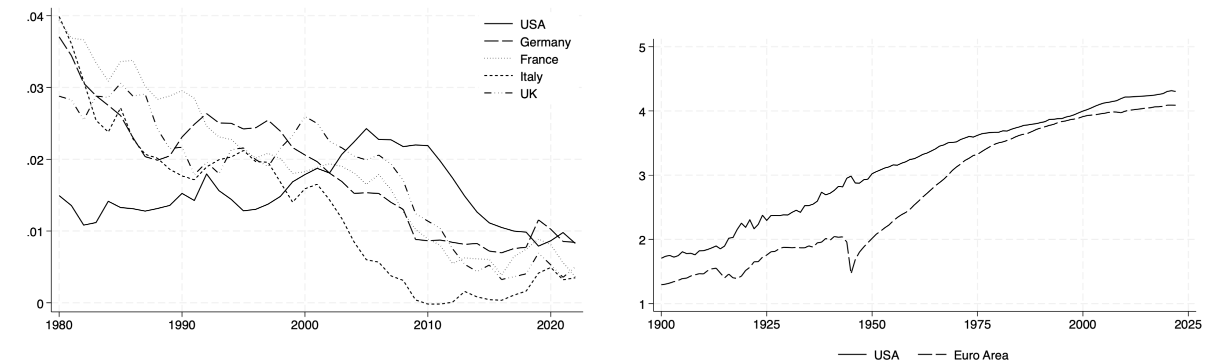
Productivity growth is a key driver of long-term welfare and prosperity. Yet in recent decades, Western economies have seen a slowdown in productivity gains (Goldin et al., 2024; Bergeaud et al., 2017). Figure 1a shows this downward trend for four large European economies and the US. As can be seen from Figure 1b, the more benign trend in the US has resulted in increasing gap in aggregate labor productivity 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 2a 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 2b 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 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. We further discuss our data cleaning steps and the coverage and representativeness of the resulting dataset in section 2 In section 3 we perform a micro-to-macro aggregation of labor productivity based on our firm-level data and benchmark our aggregates with macro-economic data. We also show the importance of sectoral heterogeneity within services, affecting productivity measurement. Section 4 decomposes aggregate labor productivity growth into to the contribution of entrants, exiters, and incumbent firms. In section 5 we compare labor productivity with total factor productivity estimates obtained from existing semi-parametric production function estimators. Section 6.1 shows how the regulatory environment affects labor productivity (growth) and its components (entry, exit and incumbent firms), using the OECD ETCR indicator as a proxy for regulatory intensity in network sectors. Finally, Section 7 concludes.

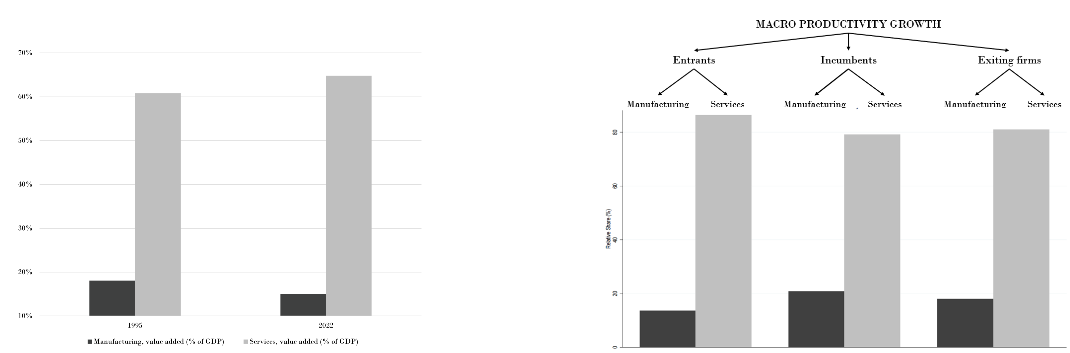
Figure 1: Evolution of labor productivity in Europe and the US



(a) 10 year growth rates of aggregate labor productivity in selected countries. Source: Bergeaud et al. (2016)

(b) Aggregate labor productivity evolution in the USA and the Euro area. Source: Bergeaud et al. (2016)

Figure 2: Share of manufacturing vs. services in Europe



(a) Share of manufacturing vs. services in Europe. Source: World bank

(b) Productivity decomposition manufacturing vs. services. Source Orbis.

2 Data

Firm data We construct the dataset for our analysis from raw data retrieved from annual versions of the Orbis Europe database (previously Amadeus) provided by Moody's (previously Bureau van Dijk). To create our dataset we follow the procedure indicated in Merlevede et al. (2015) and Kalemli-Ozcan et al. (2024) such that we observe entry and exit. We create a long panel for the period 1990-2022[1] of firms that are active in the business economy, but exclude firms active in the financial and insurance industry. We use the NACE revision 2 classification[2], Table C in Appendix provides a list of codes and industry descriptions. We exclude financial services and insurance activities (NACE code 'K') from the analysis.

The raw database provides us with the balance sheet and the profit and loss account of firms.[3] We focus on firms that file unconsolidated accounts (less than one percent of firms files consolidated accounts). Further we have information on the firm's main activity, its location, its date of incorporation, its ownership structure, and its affiliate structure (if the firm has any). Firms also have a unique firm ID that allows to link firms across different versions. For our purposes we specifically retain information on operating revenues, material input costs, tangible and intangible fixed assets, and the number of employees. Financial variables are expressed in euro and deflated by country-industry specific output deflators. Output deflators are taken from Eurostat and for earlier years we use information from the EU KLEMS database to complete the time frame. We define our capital deflator as the average of the following five NACE 2-digit industries: computer, electronic and optical products (26); electrical equipment (27); machinery and equipment (28); motor vehicles, trailers, and semi-trailers (29); and other transport equipment (30) (see Smarzynska Javorcik, 2004). We calculate an intermediate input deflator as a weighted average of output deflators where country-time-industry-specific weights are based on intermediate input uses retrieved from input-output tables (retrieved from the OECD).

We define the following variables. Output is measured as *'operating revenue turnover'*, real output y is obtained by deflating by the industry level producer price index. Value added VA is defined as output minus intermediates, i.e. *'operating revenue turnover'* minus *'material costs'*. Value added is double deflated, i.e. real value added is calculated as output deflated with an output deflator minus intermediate use deflated with the intermediate input deflator defined above. Labour is the *'number of employees'* (end-of-period). Capital is measured by *'tangible fixed assets'*, real capital is obtained by deflating by the capital deflator defined above. For the analysis presented in the paper we consider the following countries for which we have all necessary information to study productivity: Austria (AT), Belgium (BE), Bulgaria (BG), Czech Republic (CZ), Germany (DE), Estonia (EE), Spain (ES), Finland (FI), France (FR),

[1]Information prior to 1995 is very limited however.

[2]Nomenclature statistique des Activites economiques dans la Communaute Européenne.

[3]Financial information is available for items up to a level that is comparable across European countries.

Croatia (HR), Hungary (HU), Italy (IT), Latvia (LV), the Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Romania (RO), Sweden (SE), Slovenia (SI), and Slovakia (SK). Table 14 lists the number of observations per country. Reporting requirements imply that for some countries material costs are simply not available (e.g. Denkmark, Ireland), in many countries smaller firms face lighter reporting requirements typically reducing the number of available observations for material costs. Our dataset is essentially an extended version of the dataset created in Merlevede et al. (2015) and we refer to that paper for further detail.

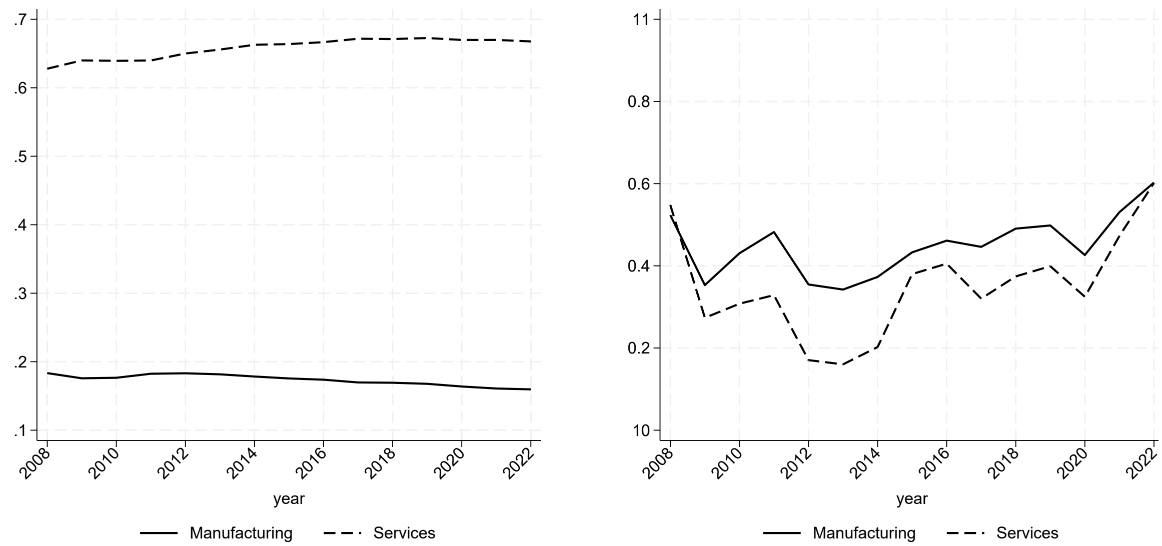
Coverage & representativeness To assess coverage and representativeness we compare our resulting firm-level dataset with Structural Business Statistics (SBS) retrieved from Eurostat that provides us with country-industry-time aggregate information on the population of firms in the business economy for the period 2008-2020.

For the period 2008-2020 our firm-level data cover between 35% and 45% annually of the number firms reported in SBS-data. Across country-industry-year level , our dataset covers on average 43.6% of the total number of firms, 52.9% of total employment, and 62.7% of total output annually. These numbers indicate that our sample effectively does reflect the bulk of economic activity in Europe and that we are capturing larger firms better than smaller firms. This is particularly relevant for our analysis as firm size determines how much firms contribute to aggregate productivity and its evolution. As the majority of value added and employment is driven by medium and large firms in the economy and those are better covered, our dataset allows for a meaningful analysis of firm-level mechanisms behind aggregate trends across countries and industries.

We also calculate correlations at the industry-country-year level between our data and data retrieved from Eurostat for an indication of overall representativeness of our data. We observe high correlations between the output and employment variables across the datasets. Specifically, the correlation for output and employment are high at 0.88 and 0.87 respectively. The correlation in terms of the number of firms is somewhat lower at 0.63, reflecting that small firms are more frequent in some industries and not as well captured as large firms in our data. Overall, these numbers show strong representativeness of our data. Although micro firms (1–9 employees) still make up the largest share of observations, firms with more than 250 employees are better covered. Full size-class distributions by sector can also be found in Appendix A. Detailed figures on geographical distributions, firm size distribution, and time trends on sectoral distributions are also available in Appendix A.

Aggregate characteristics Figure 3a shows the share of manufacturing and services in the total value added of our data. We notice that the share of manufacturing in value added in our data goes down, while the share of services sectors in value added goes up. The increasing importance of services relative to manufacturing is in mine with Eurostat data. Figure 3b shows unweighted mean real labor productivity for both manufacturing and services. The mean values for labor productivity in manufacturing and services lie close to each other, manufacturing being slightly more productive. Figure 4a shows the weighted contributions of manufacturing, services, and other industries to aggregate labor productivity. Services make up for the largest contribution to aggregate labor productivity and are gaining importance: their weighted contribution to aggregate labor productivity is rising over time. Figure 4b presents aggregate labor productivity levels retrieved from Eurostat, demonstrating that our dataset closely aligns with macroeconomic trends observed in official statistics.

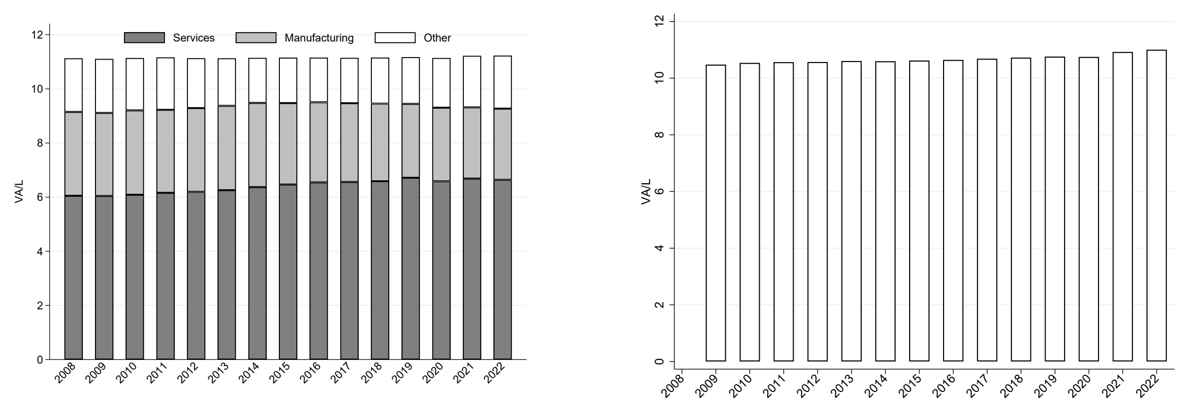
Figure 3: Share of manufacturing and services and mean productivity values



(a) Share of manufacturing vs. services. Source: Own data

(b) Mean labor productivity for manufacturing vs. services

Figure 4: Evolution of weighted labor productivity based on Orbis and Eurostat data



(a) Orbis

(b) Eurostat

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

3.1 Aggregate labor productivity growth

In the following section, we aim to perform a macro-aggregation of our micro data on firm-level productivity. We use real value added per employee or labor productivity as our productivity indicator. We calculate the growth rate of real value added per employee (labor productivity) as the year-on-year difference between the sum of real value-added per employee weighted by nominal value added shares. Real value added per employee is weighted by the nominal value-added shares. The change in aggregate labor productivity, $\Delta\Phi_t$, over time is calculated in Equation (1).

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

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

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

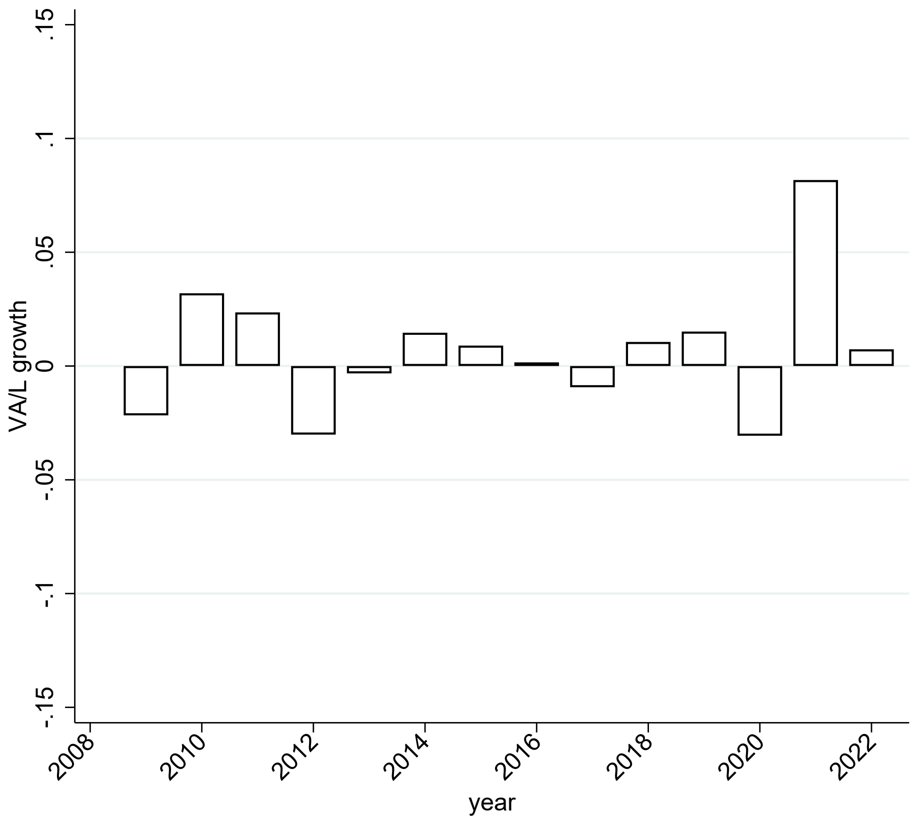
Where Φ_t is the level of aggregate labor productivity at time t, defined as the weighted average of firm-level productivity in Equation (2). With s_{it} being the weight defined as the firm's share of nominal value added in total nominal value added of all firms at time t, see Equation (3), and ϕ_{it} being the logarithm of labor productivity (real value-added per employee) of firm i at time t. Figure 5 shows the growth rate of value added per employee from 2008 until 2022. We notice that labor productivity growth rates show both positive and negative values over the considered period. The labor productivity growth calculated from our micro-level data shows a negative growth rates in 2009 and 2012 and fluctuations in the period 2020-2022. On average labor productivity growth rates are small, and a non-negligible part of all years in our sample show negative growth rates, indicating a slowdown of aggregate productivity growth.

3.2 Contributions of underlying sectors

Aggregate labor productivity Φ_t, can be decomposed into contributions from underlying sectors. In the following section, we decompose aggregate labor productivity into the contributions of manufacturing and services, and other sectors making up the business economy. The level of aggregate labor productivity equals the sum of the weighted contributions of labor productivity from manufacturing (M), Services (S) and other industries (O).[4] We rewrite this and identify $\tilde{\Phi}_{t_X} = \sum_{i \in X} s_{it}\phi_{it}$, which represents the weighted contribution of a specific sector X to aggregate

[4] Manufacturing includes industries CA to CM as listed in Table ??; services comprise industries G to N. All remaining industries are classified as 'other'.

Figure 5: Labor productivity growth in Orbis data



productivity. The decomposition of labor productivity into the three components is formalized in Equation (4) and Equation (5).

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

$$\Phi_t = \tilde{\Phi}_{t_M} + \tilde{\Phi}_{t_S} + \tilde{\Phi}_{t_O} \tag{5}$$

Following a similar logic, we can further decompose aggregate labor productivity into the contributions of the underlying sectors on the NACE 1-digit level. The aggregate values for the levels of labor productivity for sectors: manufacturing, services and other, and 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 labor productivity. Other service sectors each provide smaller contributions to the aggregate.

Similarly, the *growth rate* of aggregate labor productivity can also be decomposed into the sum of the contributions from the underlying sectors. We decompose the growth rate of labor productivity again into the contribution from the manufacturing (M), services (S) and other industries (O) as is shown in Equation (6).

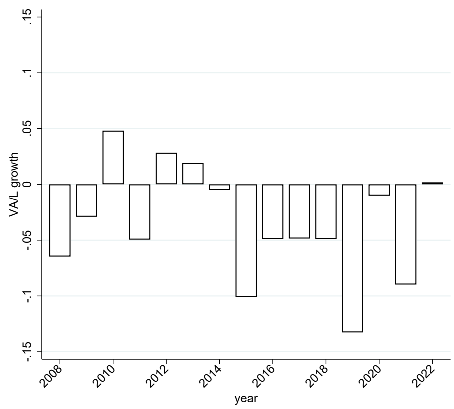
$$\Delta\Phi_t = \Delta\tilde{\Phi}_M + \Delta\tilde{\Phi}_S + \Delta\tilde{\Phi}_O \tag{6}$$

Figure 6 shows the weighted contributions of these three sectors to the aggregate *growth rate* of labor productivity in percentages. We notice that the weighted contributions of the three underlying sectors are larger and more volatile than fluctuations in the aggregate growth rate, but negative and positive growth patterns cancel each other out. Weighted labor productivity in the manufacturing sector is showing negative growth rates for most of the years, while in services, most growth rates are positive in the last 15 years. However, for service sectors, we notice strong fluctuations of positive and negative growth rates over the last four years, indicating strong effects of the COVID-19 crisis. More detailed growth patterns for the contributions of underlying sectors on the NACE-1-digit level to aggregate growth patterns can be found in Appendix B.

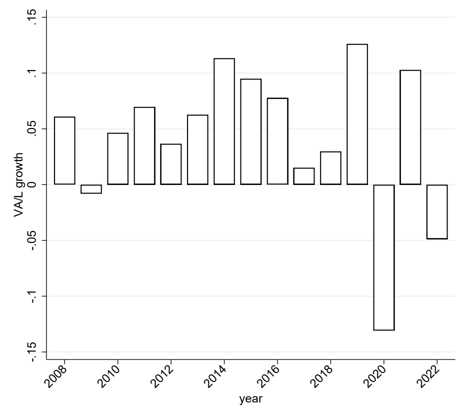
3.3 Olley-Pakes Decomposition

We apply the Olley and Pakes (1996) decomposition to the labor productivity growth of firms grouped by industry, to analyze the sectoral contributions and underlying dynamics to aggregate labor productivity growth. This decomposition allows us to separate aggregate productivity growth of a specific industry into an unweighted mean productivity term or a within-firm effect and a covariance term. The unweighted mean provides a baseline measure of firm productivity and the covariance term or between-firm effect captures the allocation of market shares across firms, see Equation (8). Where $\Delta\Phi_t$ is aggregate productivity growth at time t, see Equation

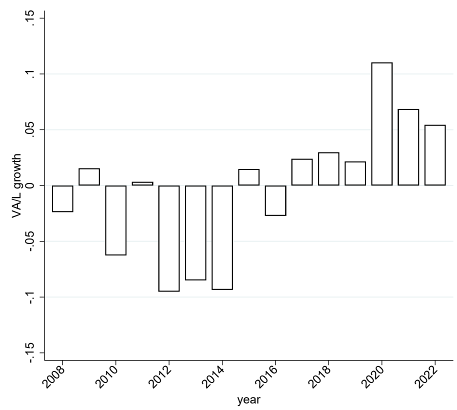
Figure 6: Sectoral contributions to aggregate productivity growth



(a) Manufacturing



(b) Services



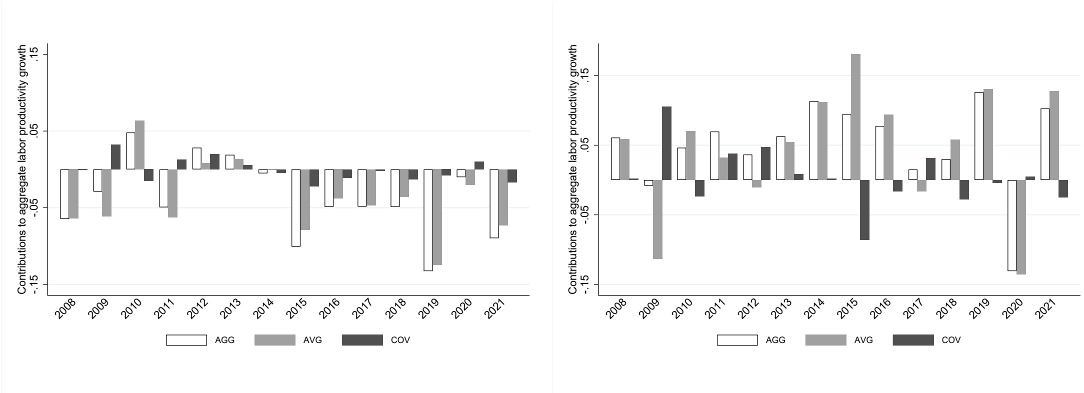
(c) Other

(7) $\Delta\Phi_{j,t}$ is the productivity growth of industry $j \in (M, S, O)$, 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. We aggregate firm-level productivity within each industry by computing the weighted sum of firm productivity using the firm's 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.

$$\Delta\Phi_t = \Sigma w_{j,t} \Delta\Phi_{j,t} \tag{7}$$

$$\Delta\Phi_{j,t} = \Delta\overline{\phi}_{j,t} + \Delta cov_{j,t} \tag{8}$$

Figure 7: OP decomposition of contributions of different industries to aggregate productivity growth



(a) Manufacturing

(b) Services

Figure 7 shows the results of the OP decomposition of aggregate labor productivity growth over three main industries: manufacturing (M), services (S), and other industries (O) making up the business economy. For all groups of industries considered, the unweighted mean is contributing most to the weighted aggregate growth rate, suggesting that larger firms (which receive higher weights) are contributing more to the aggregate growth rate. The covariance term fluctuates significantly, indicating varying degrees of reallocation of productivity. In manufacturing, most years have negative growth rates. The unweighted mean and the reallocation term are both negative in most of the years. Both existing firms are becoming less productive and resources are shifting towards less productive firms in manufacturing. In services, growth rates are often positive, the unweighted mean provides the largest contribution to the aggregate growth of service sectors. The covariance term is smaller and has more fluctuations over time. In 2009, the covariance term is strongly positive, pointing at a reallocation of productive factors towards more productive firms, while in recent years it is smaller and often negative: resources are shifted towards less productive firms, contributing negatively to aggregate growth. Notably, the post-pandemic period (2021) exhibits a significant rebound in productivity in services through the unweighted mean, showing that the existing firms experienced a growth in their productivity values.

4 The role of entry and exit

4.1 Contributions of entry, exit and incumbent firms

In the following paragraph, we make a decomposition of labor productivity growth into the contributions of entrants, incumbent firms and firms leaving the market, adding the role of entry and exit to our analysis. Following the theoretical framework proposed 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).

$$\Phi_1 = s_{S1}\Phi_{S1} + s_{X1}\Phi_{X1} = \Phi_{S1} + s_{X1}(\Phi_{X1} - \Phi_{S1}) \tag{9}$$

$$\Phi_2 = s_{S2}\Phi_{S2} + s_{E2}\Phi_{E2} = \Phi_{S2} + s_{E2}(\Phi_{E2} - \Phi_{S2}) \tag{10}$$

Equation (9) shows Φ_1: the aggregate productivity difference between surviving firms and exiting firms. Equation (10) shows Φ_2: the aggregate productivity difference between entrants and surviving firms. Equation (11) subtracts productivity in period 2 from productivity in period 1: $\Delta\Phi = \Phi_1 - \Phi_2$. The productivity difference between period 1 and 2 can then be decomposed into the contribution of entry, exit and survivors. 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 components 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 difference across all firms and a reallocation effect, see Equation (11). 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, reflecting technological advancements, managerial improvements, and process optimizations. 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. The between-firm effect represents the reallocation of market shares from less productive to more productive firms, indicating whether resources are efficiently allocated within the economy. The productivity variable we will use in our decomposition is real value added per employee or labor productivity. The weight variable is the share of the nominal value added of a specific firm in total nominal value added in a certain year.

$$\begin{aligned}\Delta\Phi &= (\Phi_{S2} - \Phi_{S1}) + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}) \\ &= \Delta\bar{\varphi}_S + \Delta\text{cov}_S + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1}) \\ \Delta\Phi &= WH + BW + EN + EX\end{aligned} \tag{11}$$

We decompose aggregate labor productivity growth into four components: the contribution of entrants: 'EN', 'exiting firms: 'EX', a between effect of surviving firms: 'BW' which captures a reallocation of resources between firms and a within effect of surviving firms 'WH': which captures whether existing firms are becoming more productive. Figure 8 shows aggregate weighted labor productivity growth in our sample. We show the annual contributions of the four components to year-on-year labor productivity growth combined with the aggregate value of labor productivity growth. 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 to productivity growth or decline and shows in most years the opposite sign as the between-firm component. When existing firms become more productive, resources get redistributed from less productive firms towards more productive firms or vice versa.

4.2 Manufacturing, services and other industries

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 labor productivity into the contributions of entry, exit, between and within firm effects for three main groups of industries: Manufacturing, services and other industries. Figure 9 shows the decomposition for the three broad industries into the four contributions. Aggregate growth rates vary by industry. Similar to our aggregate decomposition across all industries, the within-firm productivity growth (WH) is the dominant driver of aggregate productivity fluctuations, providing the largest contribution in most of the years, while the between-firm reallocation (BW) component often shows the opposite sign, suggesting that market shares are shifting from the less productive firms towards the incumbent more productive firms. Entry (EN) and exit (EX) effects display heterogeneity for different industries. Manufacturing shows only small contributions for entry and exit in most of the years, while for services, entry and exit have larger contributions but in opposite directions. Other industries have the largest and most volatile contributions of entry and exit to aggregate growth patterns and again entry and exit have the opposite sign.

Contributions of industries to productivity of entrants, exiters and surviving firms In this paragraph, we analyze how different industries contribute to aggregate labor productivity (Φ) across three distinct groups of firms: entrants see Equation (12), incumbents (survivors), see

Figure 8: Contributions from entry, exit, between and within firm components to aggregate labor productivity growth

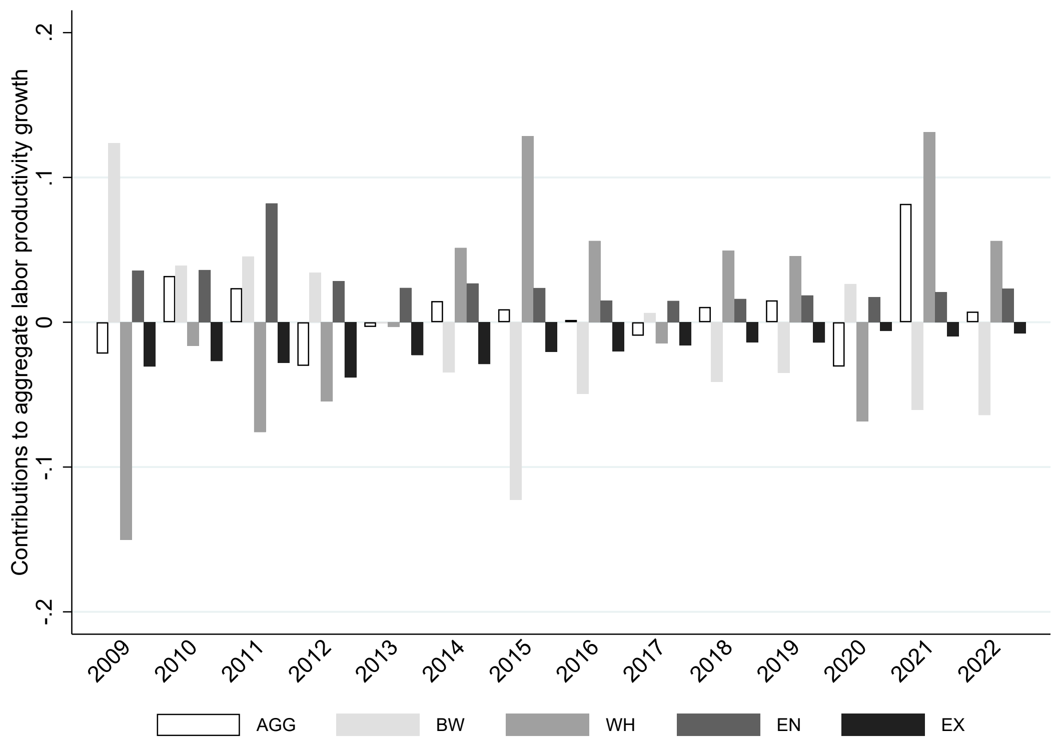
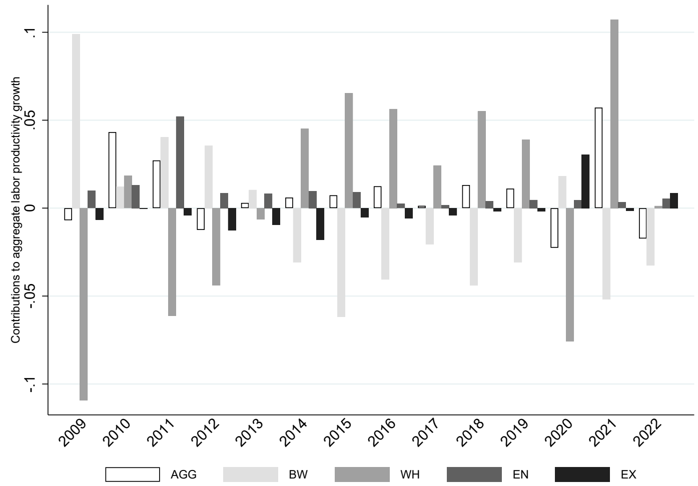
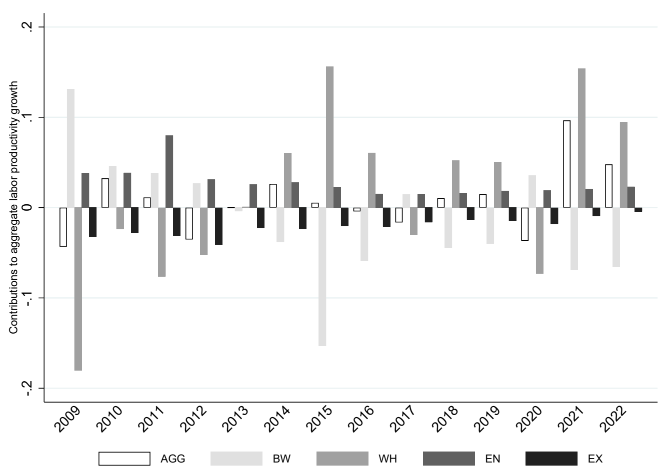


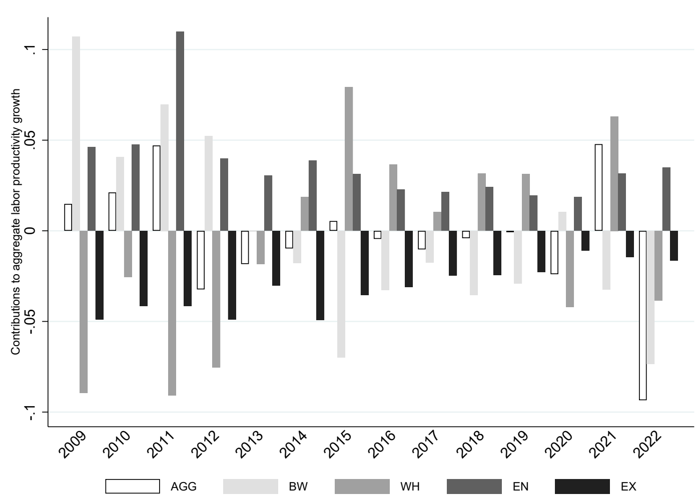
Figure 9: Industry by industry decomposition of contributions to aggregate productivity growth



(a) Manufacturing



(b) Services



(c) Other

Equation (13), and exiters, see Equation (14). For each of these groups, we decompose aggregate labor productivity into contributions from three main industries: manufacturing (M), services (S), and other industries (O). Aggregate productivity for each group is computed as a weighted sum of sectoral productivity contributions, where the weights (s_{G_M}, s_{G_S}, and s_{G_O}) represent the sectoral shares in nominal value added for group G (entrants (E), survivors (S), or exiters (X)).

$$\Phi_E = s_{E_M}\Phi_{E_{Manufacturing}} + s_{E_S}\Phi_{E_{Services}} + s_{E_O}\Phi_{E_{Other}} \tag{12}$$

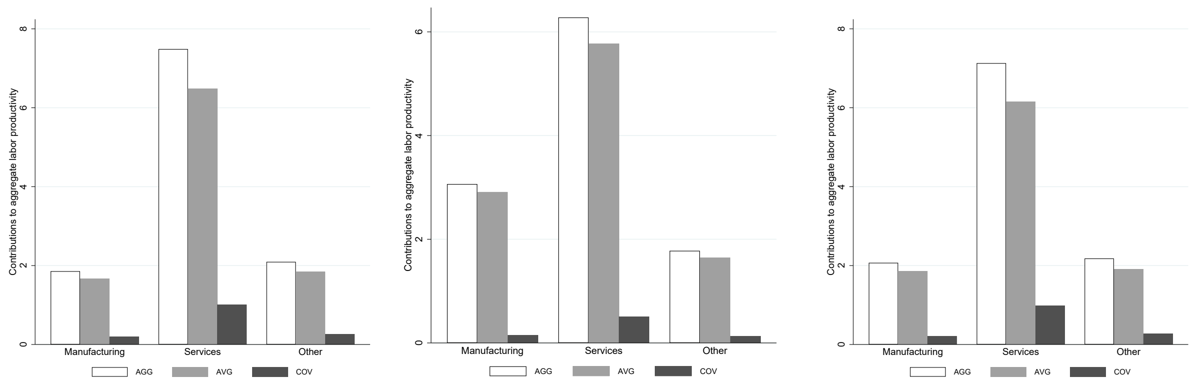
$$\Phi_S = s_{S_M}\Phi_{S_{Manufacturing}} + s_{S_S}\Phi_{S_{Services}} + s_{S_O}\Phi_{S_{Other}} \tag{13}$$

$$\Phi_X = s_{X_C}\Phi_{X_{Manufacturing}} + s_{X_M}\Phi_{X_{Services}} + s_{X_S}\Phi_{X_{Other}} \tag{14}$$

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: manufacturing, services and other industries 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 manufacturing, services, and other industries among newly established firms, while the aggregate productivity of exiters captures the productivity of firms leaving the market. Survivors contribute to aggregate productivity by representing ongoing operations in the economy. Figure 10 shows the sectoral contributions of manufacturing, services, and other industries to aggregate productivity of entrants, exiters and incumbent firms, respectively. Across all firm types, services consistently account for the largest share of aggregate productivity, followed by manufacturing and other industries. The decomposition reveals that within-firm improvements are the dominant source of productivity growth across sectors, while the covariance term, which captures reallocation effects, remains relatively small. This suggests that productivity dynamics are primarily driven by improvements within firms rather than by a reallocation of market shares toward more productive firms.

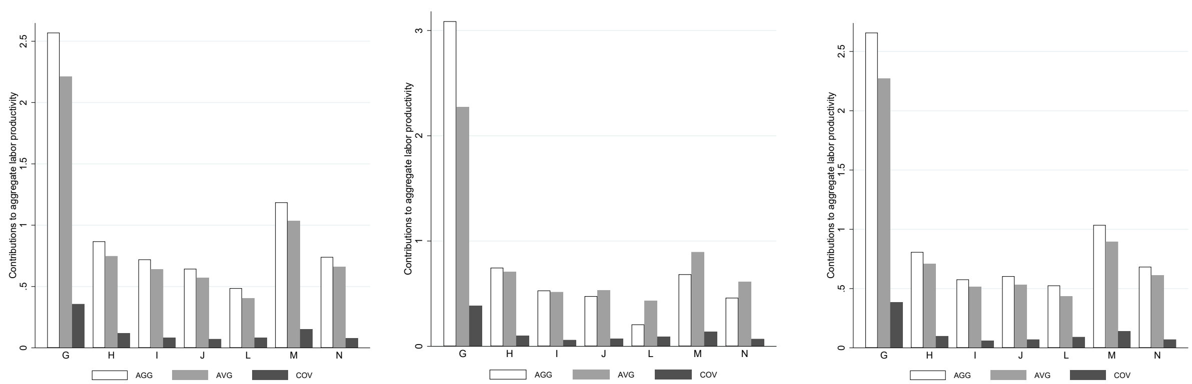
Further sectoral heterogeneity: contributions of underlying sectors to aggregate labor productivity in services As shown in the previous section, services contribute most to the aggregate labor productivity levels of entrants, exiters and incumbent firms. We now further divide into the contributions of the underlying service sectors on the NACE 1-digit level to the aggregate productivity of entrants, exiters and incumbent firms. Figure 11 shows the contributions of NACE-1-digit sectors to aggregate labor productivity of services. Firms classified as G: Wholesale, retail and repair of motor vehicles are providing the largest contribution to labor productivity in services for entrants, incumbents. For all categories, the within-firm

Figure 10: Sectoral contributions to aggregate productivity of entrants, incumbents and exiting firms



(a) Entry (b) Surviving (c) Exit

Figure 11: Sectoral contributions of services to aggregate productivity of entrants, incumbents and exit mean values over countries and years



(a) Entry (b) Surviving (c) Exit

component contributes most to aggregate productivity, while the between-firm component or the covariance is much smaller, pointing to the existing firms becoming more productive and only limited reallocation of resources from low-productive to high-productive firms.

5 Estimated productivity and value added per employee

In this section, we will examine whether value added per employee or labor productivity, as investigated in the previous section, aligns with estimated measures of firm productivity. Estimated TFP requires information on all the inputs used in the production function. As such Table 14 and Table 15 in Appendix A.4 and Appendix A.5 show the number of observations per country and year respectively where values for operating revenue (OR), labor (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 such, will not consider these countries in our analysis.

5.1 Estimating total factor productivity

Value added per employee is a widely available metric for measuring the productivity of firms and often serves as a benchmark measure. However, value added per employee does not account for differences in capital intensity across firms or sectors. To address this limitation, we estimate productivity using a value-added production function that incorporates both labor and capital inputs. Estimating total factor productivity (TFP) from such a function requires correcting for potential biases arising from unobserved productivity shocks and firms' endogenous input choices. We employ four alternative estimation methods to obtain firm-level TFP estimates: (i) Ordinary Least Squares (OLS), (ii) the Olley-Pakes (OP) methodology, (iii) the Wooldridge-Levinsohn-Petrin (WLP) approach, and (iv) the methodology developed by Ackerberg Caves and Frazer (ACF). Although OLS suffers from simultaneity bias and selection bias (Van Beveren, 2012), we include it as a benchmark to compare our productivity values. For each approach, we estimate separately for each industry using broad NACE categories. A table with the different industry groups for the estimation and their corresponding NACE codes can be found in Appendix D.

5.1.1 OLS on the value-added production function

Although suffering from simultaneity and selection biases, the simplest approach to estimating TFP is using an OLS regression of the firm's value added on the input factors: labor and capital We use Equation (15): a value-added Cobb-Douglas production function of a firm i in sector j at time t.

$$y_{ijt} = \beta_j + \beta_{kj} k_{ijt} + \beta_{lj} k_{ijt} + \epsilon_{ijt} \tag{15}$$

Where y_{ijt} is firm value added (operating revenue net of material costs) in industry j, and year t, k_{ijt} and l_{ijt} represent capital and labor inputs. The residual ϵ_{ijt} is interpreted as firm-level TFP. In addition to OLS estimation based on a linearized production function, more advanced parametric and semi-parametric methods have been developed to address its limitations. The OLS approach assumes that input choices are exogenous, but this assumption is typically violated in practice. Firms adjust their input decisions based on their productivity, creating endogeneity and leading to biased and inconsistent coefficient estimates. Despite these limitations, we report OLS estimates as a benchmark to facilitate comparison across different estimation approaches.

5.1.2 Olley - Pakes methodology

The semi-parametric estimation methodology was first developed by Olley and Pakes (1996) and takes care of the endogeneity problem by using the firm's investment decision as a proxy for unobserved productivity shocks, which are potentially correlated with input choices. In our analysis, we allow for the labor and capital elasticities to vary across different industries, but they remain the same across all countries. We take Equation (16): a value-added Cobb-Douglas production function of a firm i in sector j at time t to our data:

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

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 of firm i in industry j at time t: i_{ijt} is assumed to be a monotonically increasing function of productivity conditional on capital, see Equation (17). Therefore allowing us to invert this relationship and express productivity as a function of investment and capital, see Equation (18).

$$i_{ijt} = h(\omega_{ijt}, k_{ijt}) \tag{17}$$

$$\omega_{ijt} = h^{-1}(i_{ijt}, k_{ijt}) \tag{18}$$

In order to implement this approach, we first regress the output on labor and materials (variable inputs) and a polynomial of investment and capital (state variables). See Equation (19), where $\phi(i_{ijt}, \omega_{ijt})$ is a third-order polynomial series in investment and capital.

$$y_{ijt} = \beta_{lj} l_{ijt} + \phi(i_{ijt}, k_{ijt}) + \epsilon_{ijt} \tag{19}$$

This regression allows to recover the elasticity of the variable input: labor. Subsequently, we invert our production function conditional on investment, which allows us to estimate the capital coefficient β_{kj} consistently. The second stage provides estimates for all production function coefficients by relying on the law of motion for productivity, see Equation (20). We use nonlinear leas squares to estimate Equation (21) where the function g(.) is approximated by a second order polynomial.

$$\omega_{ijt} = g(\omega_{ijt-1}) + \xi_{ijt} \tag{20}$$

$$y_{ijt} - \beta_{lj} l_j = \beta_j + \beta_{kj} k_{ijt} + g(\phi_{t-1} - \beta_j - \beta_{kj} k_{ijt-1}) + \epsilon_{ijt} \tag{21}$$

The OP estimator has the advantage of explicitly controlling for selection and simultaneity biases, making it preferable to OLS estimation. However, it requires firms to report investment consistently, which may be problematic when investment is lumpy or less frequently reported, which might be the case in service sectors.

5.1.3 Wooldrigde - Levihnson - Petrin methodology

An alternative approach to estimating firm-level productivity, originally developed by Levinsohn and Petrin (2003) and extended by Wooldridge (2009), replaces investment (as used in the Olley-Pakes framework) with intermediate inputs—such as materials—as a proxy for unobserved productivity shocks. This substitution is advantageous because intermediate inputs tend to be observed more frequently and reliably in firm-level data than investment, reducing the impact of data gaps or lumpy investment behavior. We consider a value-added Cobb-Douglas production, see Equation (16). Following Wooldridge (2009), we assume that intermediate input demand is a function of productivity and capital, allowing us to invert for unobserved productivity, see Equation (22) and Equation (23).

$$m_{ijt} = h(\omega_{ijt}, k_{ijt}) \tag{22}$$

$$\omega_{ijt} = h^{-1}(m_{ijt}, k_{ijt}) \tag{23}$$

This functional relationship allows us to approximate productivity as a flexible control function ϕ_{ijt}, typically modeled as a second-order polynomial in materials and capital. The innovation of the Wooldridge approach is to estimate the system in a single step using GMM. The moment conditions rely on assuming that ω_{ijt} evolves as a first-order Markov process, see Equation (20) and that lagged inputs are valid instruments. The estimation equations become Equation (24).

$$\begin{aligned} y_{ijt} &= \beta_{lj}\, l_{ijt} + \beta_{kj}\, k_{ijt} + \phi(m_{ijt}, k_{ijt}) + \epsilon_{ijt} \\ y_{ijt} &= \beta_{lj}\, l_{ijt} + \beta_{kj}\, k_{ijt} + f\big(\phi(m_{ijt-1}, k_{ijt-1})\big) + \xi_{ijt} + \epsilon_{ijt} \end{aligned} \tag{24}$$

Where $f(\cdot)$ is given by the law of motion of productivity, see Equation (25.)

$$\mathbb{E}(\omega_{ijt} \mid \omega_{ijt-1}) = f\big(\phi(m_{ijt-1}, k_{ijt-1})\big) \tag{25}$$

Finally, the moment conditions are given in Equation (26).

$$\mathbb{E}\left(\epsilon_{ijt} + \xi_{ijt} \begin{bmatrix} l_{ijt-1} \\ l_{ijt-2} \end{bmatrix}\right) = 0 \tag{26}$$

Where lagged labor and lagged materials serve as instruments for the potentially endogenous inputs labor and capital. We implement the estimation separately for each broad industry category j (based on broad NACE codes), assuming homogeneous output elasticities for labor and capital across countries.

5.1.4 Ackerberg - Caves - Frazer methodology

The semi-parametric estimation method developed by Ackerberg et al. (2015) (henceforth: ACF) refines earlier approaches to production function estimation by addressing identification challenges related to simultaneity bias. Generalising the control function framework introduced by Olley and Pakes (1996) and Levinsohn and Petrin (2003), the ACF method improves the estimation of production function parameters by carefully modeling the timing of input choices. Specifically, ACF accounts for the fact that labor input may be chosen contemporaneously with material inputs and unobserved productivity shocks, while capital is typically determined in advance. By exploiting the functional dependence of intermediate inputs on productivity and other state variables, the ACF procedure uses a two-stage approach: the first stage non-parametrically controls for unobserved productivity, while the second stage estimates the parameters of the production function using moment conditions based on input choices that are orthogonal to future productivity shocks. This method reduces potential biases and allows for more credible estimation of total factor productivity (TFP), especially in settings where firms exhibit flexible input adjustment behavior and where simultaneity poses a serious problem for standard OLS estimation. The ACF method starts from a value-added production function, see Equation (16). In the first stage, ACF use a non-parametric function $\phi_t(\cdot)$ to control for unobserved productivity, assuming that intermediate input demand is strictly increasing in productivity conditional on capital and labor, see Equation (27)

$$y_{ijt} = \phi_t(l_{ijt}, k_{ijt}, m_{ijt}) + \varepsilon_{ijt} \tag{27}$$

where $\phi_t(\cdot)$ is a flexible proxy for the composite term $\beta_l l_{ijt} + \beta_k k_{ijt} + \omega_{ijt}$. In the second stage, ACF estimate the production function parameters using moment conditions that exploit the assumption that future productivity innovations are uncorrelated with current input choices and productivity follows a first-order Markov process, see Equation (28), where $g(\cdot)$ is approximated by a second-order polynomial.

$$\omega_{ijt} = g(\omega_{ijt-1}) + \xi_{ijt} \tag{28}$$

For second stage of the estimation, ACF uses the moment conditions in Equation (29).

$$\mathbb{E}\left(\xi_{it}\begin{bmatrix}k_{ijt}\\ l_{ijt-1}\end{bmatrix}\right)=0 \tag{29}$$

where ξ_{ijt} is the residual from the law of motion of productivity. We estimate again separately for each broad industry category j (based on broad NACE codes), assuming homogeneous output elasticities for labor and capital across countries.

5.2 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. We calcualte TFP based on the estimation methodologies in the previous paragaraph and we compare the correlation of value added per employee (VA/L). We use TFP estimated with Ordinary Least Squares (OLS) on the value-added production function, the Wooldridge-Levinsohn-Petrin (WLP) methodology, and the Ackerberg-Caves-Frazer methodology. Table 1 shows that OLS exhibits the highest correlation with VA/L while ACF shows the lowest correlation. The correlation of productivity estimated with the WLP and OP methodology falls between the two other estimations. All correlation measures are above 0.5, indicating that estimated productivity measures align with labor productivity, although not perfectly, as another input factor: capital is considered in the production function. Differences between OLS and the other semi-parametric estimators arise because semi-parametric estimators rely on different assumptions: OP inverts on investments as a proxy for unobserved productivity, while WLP inverts on the lagged values of labor and material inputs. The ACF methodology inverts material input demand as a proxy for unobserved productivity. Although the estimated TFP measures rely on different assumptions, their mutual correlations are in most cases higher than the correlation with value added per employee.

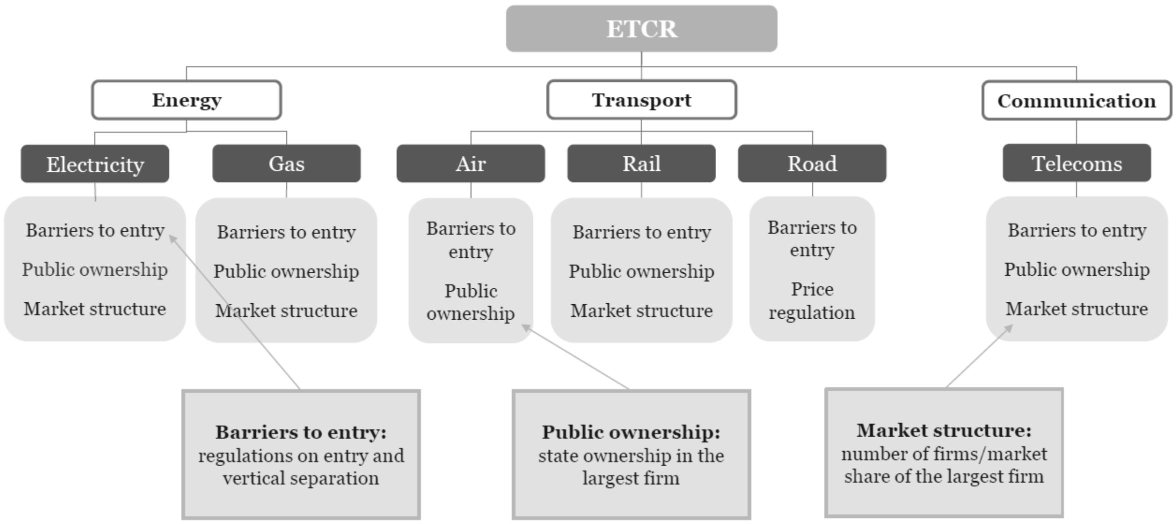
Table 1: Cross-correlation of different productivity indicators (full sample)

Variables	VA/L	TFP (OLS)	TFP (WLP)	TFP (OP)
TFP (OLS)	0.818			
TFP (WLP)	0.714	0.840		
TFP (OP)	0.647	0.934	0.778	
TFP (ACF)	0.846	0.958	0.806	0.852

6 Product market liberalization and productivity outcomes

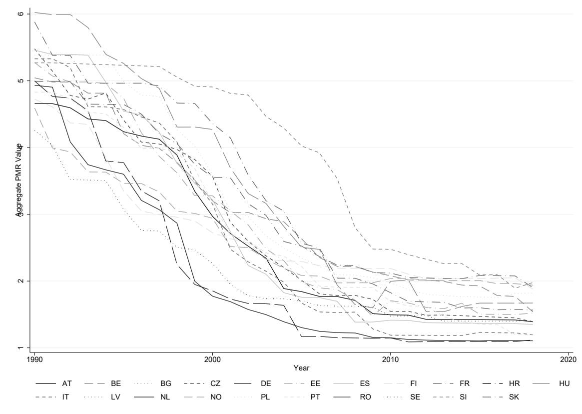
6.1 The OECD ETCR indicator

Figure 12: Structure of the OECD ETCR-PMR indicator

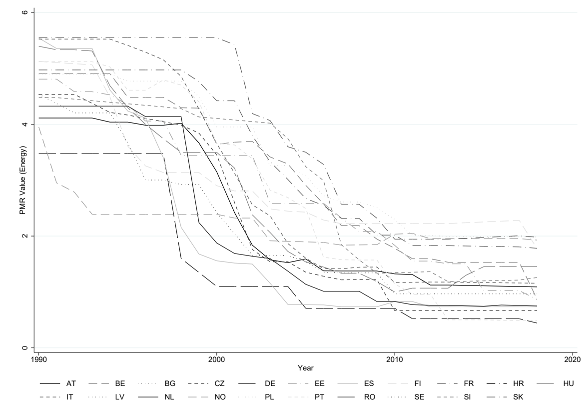


We investigate the relationship between product market liberalisation, as captured by the OECD ETCR indicator, and the productivity outcomes derived from the decomposition presented in Section 4. The OECD ETCR (Energy, Transport and Communications Regulation) indicator measures the extent of regulatory restrictions in network sectors—specifically electricity, gas, transport (e.g. rail, road, air), and communications (e.g. telecoms and post). The structure of the ETCR indicator is shown in Figure 12. The aggregate indicator is the weighted average of the sub-indicators on Energy, Transport and Communication, these are then further subdivided into electricity and gas for the component energy, air, rail and road for transport and telecommunication. Each sub-indicator measures barriers to entry, public ownership and market structure. The ETCR indicator is designed to capture how market-oriented or restrictive these sectors are, based on factors such as the degree of state control, barriers to entry, and the presence of vertical integration. The indicator ranges from 0 (least restrictive, more market-driven) to 6 (most restrictive, highly regulated), and is updated every year allowing for consistent cross-country and time-series comparisons. The ETCR is particularly relevant for studying how regulatory environments influence productivity, investment, and competitive dynamics in both upstream and downstream sectors of the economy. The evolution of the aggregate ETCR indicator and the subindicators for Electricity, Transport and Communication is shown in Figure 13. Regulation in all countries in our sample is decreasing over time, however, at different paces. The correlation between the three sub-indicators is shown in Table 2. Correlations between the underlying components of the regulatory indicator are relatively high.

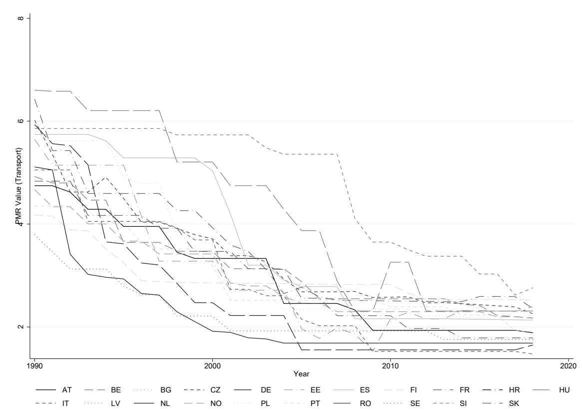
Figure 13: Evolution of the aggregate ETCR indicator and subindicators over countries and over time



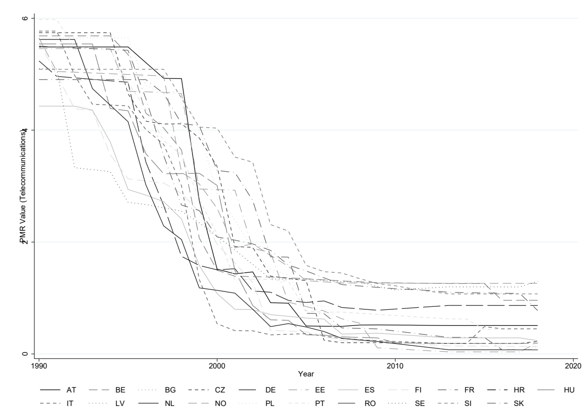
(a) Aggregate ETCR-indicator



(b) ETCR-indicator for energy



(c) ETCR-indicator for transport



(d) ETCR-indicator for communication

Table 2: Correlation between the sub-indicators of the ETCR-indicator

Variables	AGG	ENERGY	TRANSPORT
ENERGY	0.896		
TRANSPORT	0.941	0.716	
ECOMM	0.925	0.830	0.799

6.2 The influence of regulation on labor productivity

We analyse the relationship between regulation and labor productivity by regressing aggregate labor productivity values and aggregate labor productivity, labor productivity of entrants, incumbents and exiting firms and labor productivity of the manufacturing and services sector on the OECD ETCR indicator. Aggregate labor productivity and the aggregate labor productivity of entrants, incumbents and exiting firms are aggregated using the same methodology as described in Section 3 but we aggregate at the industry-country-year-level. We weigh the ETCR (Energy, Transport, and Communications Regulation) indicator by the intermediate input-use shares of different sectors, calculated from harmonized input-output tables provided by the OECD also on the industry-country-year level. This procedure, following closely the methodology of Bourlès et al. (2013), allows us to construct a sector-level measure of regulatory exposure that reflects the extent to which each downstream industry relies on regulated upstream sectors, as shown in Equation (30), where $ETCR_{ct}$ is the ETCR-indicator in country c at time t and w_{cjt} is a weight for the input use of industry j in country c at time t derived from the OECD input-output tables.

$$ETCR_{Wjct} = w_{cjt} \cdot ETCR_{ct} \tag{30}$$

For example, if the transport sector accounts for 10% of the intermediate input consumption in the manufacturing sector, then 10% of the ETCR value from the transport sector is attributed to manufacturing's regulatory burden. By aggregating these shares across the relevant ETCR sectors (energy, transport, and communications), we obtain a comprehensive, time-varying regulatory exposure index for each country-industry-year combination. Importantly, we distinguish between inputs sourced from domestic and foreign suppliers. This results in one aggregate ETCR-indicator and two additional separate measures of regulatory exposure: one based on domestic upstream input use and the other based on foreign input use. As such, we compute three versions of this exposure measure: (i) using total intermediate input use (i.e., combining both domestic and foreign suppliers), (ii) using only domestic input use, and (iii) using only foreign input use. This decomposition allows us to assess whether domestic or foreign regulatory environments drive productivity dynamics in downstream sectors.

The regression equation is presented in Equation (31), where Φ_X denotes a component of labor productivity. This includes the aggregate (weighted) labor productivity ('AGG'), the unweighted average ('AVG'), and the covariance term ('COV'). We estimate this regression for three different breakdowns: (i) all firms combined, (ii) by firm type: entrants, survivors, and exiters, and (iii) separately for the manufacturing and services sectors. The weighted decomposition of the terms was done on the sector level and follows the methodology described in Section 4. A list with sectors on which level the decomposition is done and the ETCR-indicators are calculated can be found in Appendix E.

$$\Phi_X = \gamma \cdot ETCR_{Wjct} \tag{31}$$

6.3 Regression results

Table 3 shows that across all sectors, higher levels of regulation—as captured by the ETCR index—are associated with higher levels of productivity driven by a positive and significant within-firm component of labor productivity but also with a significantly negative covariance term. In net terms, this indicates a trade-off: while regulation appears to foster productivity improvements within continuing firms, it simultaneously distorts the allocation of resources across firms. The positively significant within-firm component shows that more stringent regulation is linked to higher levels of overall labor productivity, primarily caused by existing firms that are more productive. At the same time more regulation is linked to a reallocation of activity toward less productive firms, thereby hindering efficient resource reallocation and lowering aggregate labor productivity. These effects are primarily driven by domestic suppliers, as indicated by significantly positive and negative coefficients for domestic ETCR exposure, while the corresponding coefficients for foreign suppliers show not to be statistically significant.

Tables 4, 5, 6 further present results disaggregated by firm groups—entrants, survivors, and exiting firms. In all three groups, aggregate labor productivity values are positively correlated with more stringent regulation, the within-firm component is positive and significant while the covariance term remains negatively correlated with the aggregate ETCR indicator, confirming the pattern observed at the aggregate level. Again, the effect is largely driven by domestic regulatory exposure: the unweighted mean and covariance term for domestic suppliers are both significant across all groups.

Table 7 and Table 8 present regression results separately for manufacturing and services. Although aggregate productivity is no longer significantly affected, the within-firm component remains positively and significantly associated with regulation, while the covariance term continues to be negative and significant. The effects are more pronounced in manufacturing, where both within- and between-firm effects exhibit larger magnitudes. This suggests that more stringent regulation in manufacturing is associated with stronger productivity gains within firms but also a sharper decline in productivity-enhancing reallocation. As before, domestic supply chain exposure is the primary channel through which regulation affects productivity dynamics, showing significant between and within components in all the cases.

Table 3: Influence of the aggregate ETCR indicator on growth components for all sectors in the economy (standard errors clustered on country-level)

VARIABLES	(1) AGG	(2) AGG	(3) AGG	(4) AVG	(5) AVG	(6) AVG	(7) COV	(8) COV	(9) COV
ETCR suppliers	0.706**			1.003**			-0.298**		
	(0.306)			(0.409)			(0.128)		
ETCR suppliers (domestic)		0.748**			1.040**			-0.291**	
		(0.329)			(0.433)			(0.131)	
ETCR suppliers (foreign)			1.314			3.737			-2.422**
			(2.252)			(3.129)			(1.000)
Constant	11.08***	11.09***	11.17***	10.59***	10.61***	10.67***	0.487***	0.480***	0.491***
	(0.138)	(0.135)	(0.133)	(0.193)	(0.189)	(0.187)	(0.0628)	(0.0618)	(0.0595)
Observations	14,805	14,805	14,805	14,805	14,805	14,805	14,805	14,805	14,805
R-squared	0.038	0.039	0.002	0.054	0.054	0.009	0.024	0.021	0.019

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports regression results of the weighted ETCR (Energy, Transport, and Communications Regulation) indicator on different components of aggregate labor productivity, based on the Olley-Pakes decomposition. AGG denotes aggregate labor productivity; AVG refers to the unweighted average of firm-level labor productivity; and COV represents the covariance term, capturing reallocation effects between productivity and firm size. The explanatory variables are sector-level ETCR indicators, weighted by input use from regulated upstream sectors using OECD Input-Output tables. ETCR suppliers reflects overall exposure to regulation in all supplying sectors. ETCR suppliers (domestic) includes only inputs from domestic regulated suppliers, while ETCR suppliers (foreign) includes only inputs from foreign regulated suppliers. Standard errors are clustered at the country level.

Table 4: Influence of the aggregate ETCR indicator on growth components for entering firms (standard errors clustered on country-level)

VARIABLES	(1) AGG_{EN}	(2) AGG_{EN}	(3) AGG_{EN}	(4) AVG_{EN}	(5) AVG_{EN}	(6) AVG_{EN}	(7) COV_{EN}	(8) COV_{EN}	(9) COV_{EN}
ETCR suppliers	0.827**			1.166**			-0.339**		
	(0.305)			(0.416)			(0.150)		
ETCR suppliers (domestic)		0.880**			1.204**			-0.324**	
		(0.329)			(0.438)			(0.152)	
ETCR suppliers (foreign)			1.459			4.899			-3.441**
			(2.540)			(3.557)			(1.262)
Constant	10.94***	10.95***	11.04***	10.31***	10.33***	10.40***	0.621***	0.611***	0.640***
	(0.142)	(0.140)	(0.133)	(0.202)	(0.199)	(0.195)	(0.0760)	(0.0747)	(0.0736)
Observations	13,856	13,856	13,856	13,856	13,856	13,856	13,856	13,856	13,856
R-squared	0.039	0.040	0.001	0.062	0.061	0.013	0.017	0.014	0.020

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table presents regression results of the aggregate ETCR (Energy, Transport, and Communications Regulation) indicator on components of aggregate labor productivity for surviving firms, based on the Olley-Pakes decomposition. AGG_{EN} denotes aggregate labor productivity of entering firms, AVG_{EN} is the unweighted average labor productivity among entering firms, and COV_{EN} captures the covariance between firm size and productivity, reflecting reallocation effects of entering firms. The ETCR suppliers variable is constructed by weighting the ETCR index using sectoral intermediate input shares from OECD Input-Output tables. ETCR suppliers (domestic) reflects exposure to regulation from domestic upstream suppliers, while ETCR suppliers (foreign) captures exposure from foreign upstream suppliers. Standard errors are clustered at the country level.

Table 5: Influence of the aggregate ETCR indicator on growth components for incumbent firms (standard errors clustered on country-level)

VARIABLES	(1) AGG_{SU}	(2) AGG_{SU}	(3) AGG_{SU}	(4) AVG_{SU}	(5) AVG_{SU}	(6) AVG_{SU}	(7) COV_{SU}	(8) COV_{SU}	(9) COV_{SU}
ETCR suppliers	0.825**			1.113**			-0.288**		
	(0.328)			(0.438)			(0.132)		
ETCR suppliers (domestic)		0.873**			1.155**			-0.282*	
		(0.353)			(0.463)			(0.136)	
ETCR suppliers foreign			1.690			3.914			-2.224**
			(2.263)			(3.069)			(0.917)
Constant	11.07***	11.08***	11.17***	10.65***	10.67***	10.75***	0.421***	0.414***	0.423***
	(0.141)	(0.138)	(0.136)	(0.195)	(0.191)	(0.188)	(0.0606)	(0.0594)	(0.0571)
Observations	14,147	14,147	14,147	14,147	14,147	14,147	14,147	14,147	14,147
R-squared	0.047	0.049	0.003	0.061	0.061	0.010	0.024	0.021	0.018

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table presents regression results of the aggregate ETCR (Energy, Transport, and Communications Regulation) indicator on components of aggregate labor productivity for surviving firms, based on the Olley-Pakes decomposition. AGG_{su} denotes aggregate labor productivity of surviving firms, AVG_{su} is the unweighted average labor productivity among surviving firms, and COV_{su} captures the covariance between firm size and productivity, reflecting reallocation effects of surviving firms. The ETCR suppliers variable is constructed by weighting the ETCR index using sectoral intermediate input shares from OECD Input-Output tables. ETCR suppliers (domestic) reflects exposure to regulation from domestic upstream suppliers, while ETCR suppliers (foreign) captures exposure from foreign upstream suppliers. Standard errors are clustered at the country level.

Table 6: Influence of the aggregate ETCR indicator on growth components for exiting firms (standard errors clustered on country-level)

VARIABLES	(1) AGG_{EX}	(2) AGG_{EX}	(3) AGG_{EX}	(4) AVG_{EX}	(5) AVG_{EX}	(6) AVG_{EX}	(7) COV_{EX}	(8) COV_{EX}	(9) COV_{EX}
ETCR suppliers	0.942**			1.293**			-0.351*		
	(0.386)			(0.527)			(0.176)		
ETCR suppliers (domestic)		1.023**			1.349**			-0.326*	
		(0.417)			(0.555)			(0.178)	
ETCR suppliers (foreign)			1.000			4.837			-3.837**
			(2.919)			(4.021)			(1.418)
Constant	10.89***	10.90***	11.01***	10.24***	10.26***	10.34***	0.646***	0.635***	0.672***
	(0.158)	(0.155)	(0.147)	(0.223)	(0.219)	(0.212)	(0.0781)	(0.0770)	(0.0749)
Observations	12,324	12,324	12,324	12,324	12,324	12,324	12,324	12,324	12,324
R-squared	0.034	0.036	0.001	0.054	0.053	0.011	0.012	0.010	0.021

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table presents regression results of the aggregate ETCR (Energy, Transport, and Communications Regulation) indicator on components of aggregate labor productivity for surviving firms, based on the Olley-Pakes decomposition. AGG_{EX} denotes aggregate labor productivity of exiting firms, AVG_{EX} is the unweighted average labor productivity among exiting firms, and COV_{EX} captures the covariance between firm size and productivity, reflecting reallocation effects of exiting firms. The ETCR suppliers variable is constructed by weighting the ETCR index using sectoral intermediate input shares from OECD Input-Output tables. ETCR suppliers (domestic) reflects exposure to regulation from domestic upstream suppliers, while ETCR suppliers (foreign) captures exposure from foreign upstream suppliers. Standard errors are clustered at the country level.

Table 7: Influence of the aggregate ETCR indicator on labor productivity growth for manufacturing sectors (standard errors clustered on country-level)

VARIABLES	(1) AGG	(2) AGG	(3) AGG	(4) AVG	(5) AVG	(6) AVG	(7) COV	(8) COV	(9) COV
ETCR suppliers	1.513			2.202*			-0.689**		
	(0.910)			(1.103)			(0.256)		
ETCR suppliers (domestic)		1.625			2.305*			-0.680**	
		(0.961)			(1.150)			(0.259)	
ETCR suppliers (foreign)			-0.298			3.875			-4.173*
			(7.753)			(9.796)			(2.287)
Constant	10.83***	10.84***	11.03***	10.39***	10.42***	10.59***	0.441***	0.426***	0.435***
	(0.184)	(0.175)	(0.204)	(0.236)	(0.225)	(0.265)	(0.0617)	(0.0587)	(0.0679)
Observations	7,659	7,659	7,659	7,659	7,659	7,659	7,659	7,659	7,659
R-squared	0.047	0.051	0.000	0.073	0.074	0.003	0.054	0.049	0.026

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table presents regression results of the aggregate ETCR (Energy, Transport, and Communications Regulation) indicator on different components of aggregate labor productivity for manufacturing firms, based on the Olley-Pakes decomposition. 'AGG' denotes aggregate labor productivity, 'AVG' is the unweighted mean of firm-level labor productivity, and 'COV' represents the covariance term, capturing reallocation effects. 'ETCR suppliers' is the ETCR indicator weighted by sectoral intermediate input shares from the OECD Input-Output tables. 'ETCR suppliers (domestic)' reflects exposure to regulation from domestic upstream suppliers, while 'ETCR suppliers (foreign)' captures exposure from foreign upstream suppliers. Standard errors are clustered at the country level.

Table 8: Influence of the aggregate ETCR indicator on labor productivity growth for services sectors (standard errors clustered on country-level)

VARIABLES	(1) AGG	(2) AGG	(3) AGG	(4) AVG	(5) AVG	(6) AVG	(7) COV	(8) COV	(9) COV
ETCR suppliers	0.315			0.680**			-0.365***		
	(0.208)			(0.305)			(0.128)		
ETCR suppliers (domestic)		0.341			0.703**			-0.362**	
		(0.231)			(0.332)			(0.135)	
ETCR suppliers (foreign)			0.718			3.272*			-2.553***
			(1.128)			(1.698)			(0.753)
Constant	11.30***	11.31***	11.35***	10.68***	10.70***	10.73***	0.617***	0.608***	0.611***
	(0.116)	(0.114)	(0.0990)	(0.179)	(0.177)	(0.163)	(0.0771)	(0.0764)	(0.0718)
Observations	5,785	5,785	5,785	5,785	5,785	5,785	5,785	5,785	5,785
R-squared	0.014	0.015	0.001	0.039	0.038	0.015	0.039	0.034	0.032

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table presents regression results of the aggregate ETCR (Energy, Transport, and Communications Regulation) indicator on different components of aggregate labor productivity for service firms, based on the Olley-Pakes decomposition. 'AGG' denotes aggregate labor productivity, 'AVG' is the unweighted mean of firm-level labor productivity, and 'COV' represents the covariance term, capturing reallocation effects. 'ETCR suppliers' is the ETCR indicator weighted by sectoral intermediate input shares from the OECD Input-Output tables. 'ETCR suppliers (domestic)' reflects exposure to regulation from domestic upstream suppliers, while 'ETCR suppliers (foreign)' captures exposure from foreign upstream suppliers. Standard errors are clustered at the country level.

7 Concluding Remarks

We investigate the contribution of different sectors to aggregate labor productivity (growth) using firm-level data from a large panel of 21 European countries. We show that our dataset provides a comprehensive representation of the European economy and aligns with macro-economic data. At the aggregate level, services account for broadly two-thirds of value added in the economy. As such services sectors emerge as the dominant contribution to labor productivity. 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. Labor productivity growth is slowing down as shown in our data and in aggregate macro-economic figures. When decomposing aggregate labor productivity into the contributions of entrants, exits and incumbent firms, the within-effect or the contribution to labor productivity of existing firms is the highest, pointing at productivity gains for existing firms, while the reallocation component goes in the opposite direction, showing resources are shifting away from less productive firms.

When comparing value added per employee to standard productivity estimation methods that account for capital inputs, we observe substantial differences in correlation. These discrepancies arise because semi-parametric estimation approaches rely on different identifying assumptions, which not only affect their correlation with value added per employee but also lead to variation among the different semi-parametric estimation methodologies themselves.

An analysis of labor productivity components and product market liberalization as measured by the OECD ETCR indicator shows that higher levels of regulation are correlated with positive aggregate levels of labor productivity, a positive within-firm component and a negative between-firm component or a reallocation of productivity towards less productive firms. The results of these regressions are confirmed when performing on different groups of firms: entrants, survivors, exiting firms. When comparing the response of the manufacturing sectors vers rus services, both sectors have a significantly positive within-firm components and a negative reallocation term, but the magnitude of the effect is higher for manufacturing than for services. Future research on the productivity of services 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.

References

Ackerberg, D. A., K. Caves, and G. Frazer (2015): "Identification Properties of Recent Production Function Estimators," *Econometrica*, 83, 2411–2451.

Andrews, D., C. Criscuolo, and P. N. Gal (2016): "The Best versus the Rest," .

Ayerst, S., D. M. Nguyen, and D. Restuccia (2024): "The Micro and Macro Productivity of Nations," Working Paper 32750, National Bureau of Economic Research.

Bergeaud, A., G. Cette, and R. Lecat (2016): "Productivity Trends in Advanced Countries between 1890 and 2012," *Review of Income and Wealth*, 62, 420–444.

——— (2017): "Total Factor Productivity in Advanced Countries: A Longterm Perspective," *International Productivity Monitor*, 32, 6–24.

Bernard, A. B., V. Smeets, and F. Warzynski (2017): "Rethinking deindustrialization," *Economic Policy*, 32, 5–38.

Bourlès, R., G. Cette, J. Lopez, J. Mairesse, and G. Nicoletti (2013): "Do Product Market Regulations in Upstream Sectors Curb Productivity Growth? Panel Data Evidence For OECD Countries," *The Review of Economics and Statistics*, 95, 1750–1768.

Cette, G., J. Lopez, J. Mairesse, and G. Nicoletti (2024): "Trust, Intangible Assets, and Productivity," Working Paper 32513, National Bureau of Economic Research.

Draghi, M. (2024): "The Future of European Competitiveness," .

Gandhi, A., S. Navarro, and D. A. Rivers (2020): "On the Identification of Gross Output Production Functions," *Journal of Political Economy*, 128, 2973–3016.

Goldin, I., P. Koutroumpis, F. Lafond, and J. Winkler (2024): "Why Is Productivity Slowing Down?" *Journal of Economic Literature*, 62, 196–268.

Gordon, R. J. and H. Sayed (2020): "Transatlantic Technologies: The Role of ICT in the Evolution of U.S. and European Productivity Growth," *International Productivity Monitor*, 38, 50–80.

Kalemli-Ozcan, S., B. Sorensen, C. Villegas-Sanchez, V. Volosovych, and S. Yesiltas (2024): "How to Construct Nationally Representative Firm Level Data from the Orbis Global Database: New Facts on SMEs and Aggregate Implications for Industry Concentration," *American Economic Journal: Macroeconomics*, 16, 353–74.

Levinsohn, J. and A. Petrin (2003): "Estimating Production Functions Using Inputs to Control for Unobservables," *The Review of Economic Studies*, 70, 317–341.

Melitz, M. J. and S. Polanec (2015): "Dynamic Olley-Pakes productivity decomposition with entry and exit," *RAND Journal of Economics*, 46, 362–375.

Merlevede, B., M. De Zwaan, K. Lenaerts, and V. Purice (2015): "Multinational Networks, Foreign, and Domestic Firms in Europe," Tech. rep., Working Paper Department of Economics, Ghent University.

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

Restuccia, D. (2019): "Misallocation and aggregate productivity across time and space," *Canadian Journal of Economics/Revue canadienne d'économique*, 52, 5–32.

Smarzynska Javorcik, B. (2004): "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages," *American Economic Review*, 94, 605–627.

Van Beveren, I. (2012): "Total factor productivity estimation: A practical review," *Journal of Economic Surveys*, 26, 98–128.

Wooldridge, J. M. (2009): "On estimating firm-level production functions using proxy variables to control for unobservables," *Economics Letters*, 104, 112–114.

A Data representativeness

A.1 Geographical representativeness

Table 9: 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 9: 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.2 Representativeness over sectors

A.2.1 Number of firms

Table 10: Representativeness of data based on the number of firms over NACE 1 aggregate sectors

	NACE Code											
	B	C	D	E	F	G	H	I	J	L	M	N
2011												
Orbis	0.26%	10.52%	0.84%	0.52%	14.19%	22.95%	4.05%	5.24%	6.30%	10.84%	17.03%	7.26%
Eurostat	0.09%	9.69%	0.29%	0.32%	15.03%	28.34%	5.25%	8.26%	4.18%	5.57%	17.29%	5.67%
2012												
Orbis	0.26%	10.42%	0.87%	0.52%	14.11%	23.12%	4.13%	5.45%	6.53%	10.71%	16.59%	7.31%
Eurostat	0.09%	9.44%	0.32%	0.34%	14.89%	27.95%	5.20%	8.16%	4.34%	5.96%	17.59%	5.72%
2013												
Orbis	0.26%	10.31%	0.87%	0.53%	13.91%	23.16%	4.20%	5.52%	6.71%	10.56%	16.59%	7.37%
Eurostat	0.09%	9.27%	0.35%	0.34%	14.70%	27.56%	5.15%	8.08%	4.56%	5.96%	18.02%	5.92%
2014												
Orbis	0.26%	10.20%	0.88%	0.53%	13.62%	22.91%	4.31%	5.50%	6.97%	10.49%	16.78%	7.53%
Eurostat	0.09%	9.04%	0.41%	0.33%	14.82%	26.82%	5.07%	8.08%	4.72%	6.03%	18.43%	6.16%
2015												
Orbis	0.26%	10.18%	0.89%	0.54%	13.50%	22.76%	4.41%	5.59%	7.17%	10.39%	16.58%	7.74%
Eurostat	0.08%	8.95%	0.43%	0.34%	14.70%	26.50%	5.13%	8.19%	4.84%	5.76%	18.77%	6.31%
2016												
Orbis	0.25%	10.00%	0.89%	0.53%	13.39%	22.46%	4.50%	5.72%	7.37%	10.35%	16.68%	7.86%
Eurostat	0.08%	8.71%	0.45%	0.33%	14.57%	25.96%	5.17%	8.19%	4.91%	6.07%	18.92%	6.62%
2017												
Orbis	0.25%	9.94%	0.88%	0.53%	13.41%	22.19%	4.55%	5.77%	7.43%	10.43%	16.65%	7.96%
Eurostat	0.08%	8.65%	0.43%	0.33%	14.65%	25.33%	5.26%	8.23%	5.12%	6.00%	19.20%	6.73%
2018												
Orbis	0.25%	9.85%	0.84%	0.53%	13.39%	21.76%	4.67%	5.78%	7.61%	10.44%	16.76%	8.13%
Eurostat	0.08%	8.45%	0.68%	0.34%	14.79%	24.96%	5.37%	8.15%	5.22%	5.72%	19.39%	6.84%
2019												
Orbis	0.23%	9.50%	0.88%	0.50%	13.60%	21.31%	4.71%	6.00%	7.55%	10.82%	17.11%	7.78%
Eurostat	0.07%	8.87%	0.75%	0.33%	14.92%	24.77%	5.46%	8.16%	4.87%	5.90%	19.23%	6.66%
2020												
Orbis	0.22%	9.40%	0.88%	0.50%	13.71%	21.24%	4.72%	6.08%	7.53%	10.93%	17.07%	7.71%
Eurostat	0.08%	8.84%	0.71%	0.33%	15.34%	24.45%	5.55%	7.91%	4.98%	5.98%	19.20%	6.63%
2021												
Orbis	0.18%	9.38%	0.92%	0.48%	12.37%	21.24%	4.51%	5.49%	5.50%	9.74%	15.32%	5.54%
Eurostat	0.07%	8.31%	0.68%	0.31%	14.78%	23.02%	5.45%	7.47%	5.07%	6.06%	18.91%	6.65%
2022												
Orbis	0.17%	9.07%	0.90%	0.46%	12.58%	20.52%	4.54%	5.46%	5.73%	10.01%	15.73%	5.49%
Eurostat	0.07%	8.16%	0.71%	0.31%	14.96%	22.19%	5.41%	7.41%	5.32%	6.09%	19.19%	6.98%

A.2.2 Output

Table 11: Representativeness of data based on output over NACE 1 aggregate sectors

	NACE Code B	C	D	E	F	G	H	I	J	L	M	N
2011												
Orbis	2.28%	26.15%	5.65%	0.90%	6.20%	35.22%	4.78%	1.35%	4.34%	2.19%	5.86%	5.08%
Eurostat	1.56%	26.92%	5.34%	0.90%	6.28%	37.44%	5.14%	1.95%	4.53%	1.76%	4.77%	3.41%
2012												
Orbis	2.40%	25.74%	5.92%	0.91%	5.80%	35.24%	4.99%	1.38%	4.48%	2.24%	5.81%	5.09%
Eurostat	1.61%	26.80%	5.95%	0.92%	6.01%	37.01%	5.23%	1.93%	4.52%	1.79%	4.79%	3.45%
2013												
Orbis	2.28%	26.06%	6.00%	0.91%	5.60%	35.37%	5.05%	1.41%	4.56%	2.07%	5.61%	5.07%
Eurostat	1.53%	26.52%	5.91%	0.93%	5.87%	37.28%	5.23%	1.96%	4.48%	1.84%	4.89%	3.57%
2014												
Orbis	2.08%	26.42%	5.79%	0.88%	5.50%	34.88%	5.16%	1.44%	4.92%	1.98%	5.87%	5.08%
Eurostat	1.32%	26.43%	5.57%	0.95%	6.05%	37.10%	5.44%	2.03%	4.61%	1.83%	5.06%	3.61%
2015												
Orbis	1.71%	27.10%	5.87%	0.90%	5.63%	34.32%	5.48%	1.50%	4.97%	1.96%	5.43%	5.13%
Eurostat	0.95%	26.09%	5.38%	0.96%	6.24%	36.77%	5.60%	2.16%	4.84%	1.87%	5.30%	3.84%
2016												
Orbis	1.46%	26.91%	5.43%	0.89%	5.42%	34.79%	5.31%	1.50%	5.06%	2.07%	6.08%	5.08%
Eurostat	0.57%	26.53%	4.94%	0.95%	6.19%	36.62%	5.60%	2.24%	4.89%	1.98%	5.55%	3.96%
2017												
Orbis	1.44%	26.96%	5.57%	0.91%	5.46%	34.70%	5.28%	1.54%	5.15%	2.01%	5.87%	5.11%
Eurostat	0.65%	26.88%	5.19%	0.97%	6.18%	36.21%	5.56%	2.24%	4.90%	1.88%	5.34%	3.98%
2018												
Orbis	1.60%	26.59%	5.58%	0.90%	5.49%	34.57%	5.35%	1.51%	5.29%	1.95%	5.99%	5.18%
Eurostat	0.74%	26.56%	5.41%	0.98%	6.60%	35.73%	5.55%	2.31%	4.92%	1.86%	5.22%	4.11%
2019												
Orbis	1.45%	26.49%	5.38%	0.89%	5.74%	34.55%	5.36%	1.61%	5.34%	1.87%	6.21%	5.11%
Eurostat	0.51%	28.64%	5.66%	0.99%	6.67%	34.76%	5.50%	2.28%	4.69%	1.84%	4.76%	3.70%
2020												
Orbis	1.11%	26.55%	5.02%	0.97%	5.98%	35.09%	5.45%	1.08%	6.15%	1.97%	5.90%	4.74%
Eurostat	0.45%	27.96%	5.40%	1.05%	7.21%	36.20%	5.05%	1.52%	5.02%	1.93%	4.90%	3.32%
2021												
Orbis	1.15%	25.10%	5.68%	0.92%	5.35%	32.21%	5.23%	1.03%	5.02%	1.79%	4.71%	3.42%
Eurostat	0.79%	33.71%	7.15%	1.34%	9.13%	13.74%	5.98%	2.15%	5.77%	2.46%	6.14%	3.98%
2022												
Orbis	1.60%	24.11%	8.58%	0.85%	5.10%	31.67%	5.53%	1.19%	3.99%	1.56%	4.31%	3.10%
Eurostat	1.35%	33.50%	9.90%	1.25%	8.78%	12.65%	6.21%	2.65%	5.43%	2.24%	5.81%	4.01%

A.2.3 Employment

Table 12: Representativeness of data based on employment over NACE 1 aggregate sectors

	NACE Code											
	B	C	D	E	F	G	H	I	J	L	M	N
2011												
Orbis	0.74%	26.66%	1.08%	1.28%	9.68%	22.43%	7.43%	5.08%	4.77%	2.30%	7.61%	10.93%
Eurostat	0.42%	22.54%	0.92%	1.00%	9.89%	24.90%	7.77%	7.71%	4.41%	1.94%	8.42%	10.06%
2012												
Orbis	0.69%	26.21%	1.09%	1.26%	9.00%	22.54%	7.49%	5.05%	4.71%	2.13%	8.79%	11.03%
Eurostat	0.43%	22.49%	0.93%	1.03%	9.65%	24.73%	7.67%	7.82%	4.49%	2.01%	8.66%	10.09%
2013												
Orbis	1.49%	26.16%	1.10%	1.28%	8.53%	21.93%	7.58%	5.18%	4.79%	2.04%	8.34%	11.57%
Eurostat	0.42%	22.36%	0.92%	1.10%	9.35%	24.57%	7.69%	7.85%	4.55%	2.08%	8.86%	10.25%
2014												
Orbis	0.61%	26.24%	1.12%	1.27%	8.73%	22.61%	7.78%	5.54%	4.93%	1.90%	7.48%	11.79%
Eurostat	0.33%	22.01%	0.92%	1.07%	9.36%	24.19%	7.74%	8.07%	4.63%	2.10%	9.04%	10.53%
2015												
Orbis	0.66%	26.10%	1.05%	1.28%	8.35%	22.78%	7.81%	5.71%	5.09%	1.87%	7.41%	11.90%
Eurostat	0.38%	21.77%	0.91%	1.07%	9.12%	24.22%	7.66%	8.15%	4.73%	1.97%	9.24%	10.77%
2016												
Orbis	0.51%	25.44%	1.00%	1.28%	8.69%	22.44%	7.67%	6.12%	5.08%	1.83%	7.83%	12.10%
Eurostat	0.29%	21.32%	0.87%	1.09%	9.06%	23.63%	7.84%	8.40%	4.80%	2.07%	9.59%	11.05%
2017												
Orbis	0.48%	25.54%	0.93%	1.29%	9.09%	21.85%	7.77%	6.23%	5.23%	1.86%	7.60%	12.14%
Eurostat	0.31%	21.39%	0.91%	1.11%	9.11%	23.41%	7.76%	8.63%	4.91%	2.04%	9.24%	11.19%
2018												
Orbis	0.49%	25.14%	0.96%	1.28%	8.72%	21.83%	7.95%	6.38%	5.37%	1.80%	7.75%	12.34%
Eurostat	0.27%	21.43%	0.98%	1.13%	9.30%	23.16%	7.62%	8.76%	5.00%	2.03%	9.15%	11.15%
2019												
Orbis	0.45%	24.11%	0.93%	1.26%	9.38%	20.89%	7.64%	6.49%	5.95%	2.48%	8.51%	11.89%
Eurostat	0.28%	22.57%	1.02%	1.19%	9.83%	22.69%	7.70%	8.42%	4.88%	1.93%	8.76%	10.71%
2020												
Orbis	0.46%	24.13%	0.94%	1.34%	9.32%	21.43%	7.95%	6.00%	6.01%	2.49%	8.17%	11.77%
Eurostat	0.30%	22.72%	1.04%	1.25%	10.31%	23.24%	7.79%	7.40%	5.08%	1.94%	8.75%	10.17%
2021												
Orbis	0.43%	25.47%	1.00%	1.44%	9.52%	21.04%	8.41%	5.11%	5.56%	1.71%	7.67%	10.35%
Eurostat	0.28%	21.87%	1.00%	1.15%	10.01%	21.90%	7.54%	7.30%	5.02%	2.00%	8.61%	10.01%
2022												
Orbis	0.44%	25.07%	1.09%	1.48%	9.53%	20.88%	8.25%	5.63%	5.89%	1.59%	7.59%	9.79%
Eurostat	0.27%	21.50%	1.00%	1.13%	10.07%	21.58%	7.39%	7.84%	5.20%	1.95%	8.71%	10.10%

A.3 Representativeness over size classes

Table 13: Sectoral representativeness over size classes in 2019

NACE code	Size class 0-9 empl.	10-19 empl.	20-49 empl.	50-249 empl.	250+ empl.
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%

A.4 Number of observations per country

Table 14: Number of observations per year total (N), Operating revenue (OR), labour (L), tangible fixed assets (TF), materials (M), and all together

Country	N	OR	L	TF	M	ORLMTF
AT	2516170	456011	1091446	2181320	69473	52412
BE	9172913	3854592	3329213	8448187	364810	329513
BG	3619610	3476706	3237316	3618381	2220298	2131156
CZ	3721662	3143792	1842509	2851923	2315242	1399926
DE	11300000	4320730	8087930	9766986	708663	588900
EE	2168617	1896657	1012690	1373446	1176994	643295
ES	17000000	15600000	11800000	16400000	12800000	10200000
FI	3417889	3165655	1620691	2885278	1848981	965386
FR	21000000	19600000	11600000	21000000	14500000	8724242
HR	2036465	2034792	1501492	2031530	1880866	1468162
HU	6527886	5540123	2913841	4827936	1474908	392929
IT	17800000	17800000	9409951	17800000	13600000	8869300
LV	1378439	1269996	1230280	1374228	43042	41297
NL	13500000	218649	6222022	11100000	39975	32459
NO	5701929	5524803	4674419	5657807	2524552	2269762
PL	3263471	2680339	1205865	2014342	2124346	811343
PT	6116181	5468110	4515150	5347769	3687476	2903976
RO	13800000	13200000	12400000	13800000	10600000	9584681
SE	7767870	7505391	6179444	5873221	3119860	2678505
SI	1737163	1610362	1065267	1458832	1429662	877862
SK	2690641	2605419	1300691	2485513	2072771	1165999

A.5 Number of observations per year

Table 15: Number of observations per year total (N), Operating revenue (OR), labour (L), tangible fixed assets (TF), materials (M), and all together

Year	N	OR	L	TF	M	ORLMTF
1990	154	152	58	64	148	56
1991	19082	18728	10112	11093	18091	9413
1992	179089	176644	80761	155652	169888	76775
1993	277295	273328	117109	267451	262198	110905
1994	344916	339703	168879	341270	324376	159891
1995	1080550	819777	583395	1026021	640368	333062
1996	1401815	1095511	776702	1352327	850641	498906
1997	1851107	1399107	916109	1736531	1086438	600856
1998	2162355	1731339	1065004	2108822	1381543	815810
1999	2479816	1940970	1287445	2413488	1557947	983683
2000	2737141	2138502	1619141	2657990	1712827	1214767
2001	2892347	2304662	1930495	2810273	1805984	1438529
2002	3248726	2665425	2199869	3131947	1981954	1613671
2003	3464815	2833073	2294464	3351779	2090053	1680273
2004	4091099	3405250	2585126	3992040	2536095	1791828
2005	5021113	3949044	2939786	4889104	2809164	1815540
2006	5572767	4228093	3692179	5401800	2782477	2157234
2007	6260891	4838510	4245352	6033136	2947906	2288465
2008	6569823	5005160	4468154	6187841	3050531	2382000
2009	6849429	5208938	4690280	6149769	3225231	2504487
2010	7108815	5454895	4453993	6346081	3109859	2280025
2011	7507009	5775012	4767628	6648541	3247807	2476894
2012	7439458	5599275	4520029	6550912	3302903	2279666
2013	7468279	5655635	4389699	6508696	3278651	2265407
2014	7371558	5522427	4523824	6419918	3178098	2302460
2015	7377533	5426223	4481588	6631773	3241475	2330194
2016	7526078	5440912	4525364	6764856	3211144	2360053
2017	7839737	5648358	4756945	6996058	3405584	2547794
2018	7891944	5641397	4678645	7013949	3400055	2496698
2019	8455700	5981765	4676873	7400479	3779355	2534012
2020	8644505	6011971	5040396	7494068	3787583	2658486
2021	8769914	6043269	5116489	7586770	3783980	2663086
2022	8698830	5910970	4870846	7358257	3616786	2427995
2023	6872117	4961263	3879167	5907440	3021694	2017380

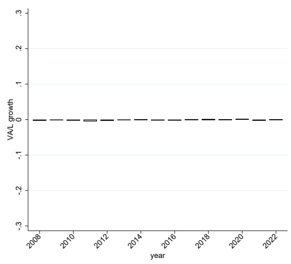
B Aggregate labor productivity (growth) across sectors

B.1 Aggregate labor productivity growth across sectors (NACE-1-digit-level)

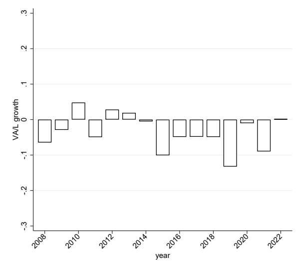
B.2 Aggregate labor productivity across manufacturing, services and other sectors

B.3 Aggregate labour productivity across service sectors

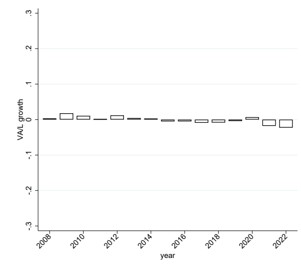
Figure 14: Contribution of service sectors to aggregate labor productivity growth



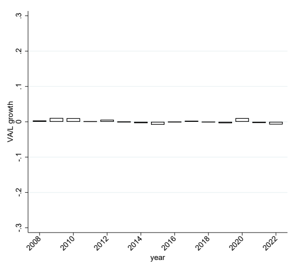
(a) Contribution of NACE sector B to aggregate labor productivity growth



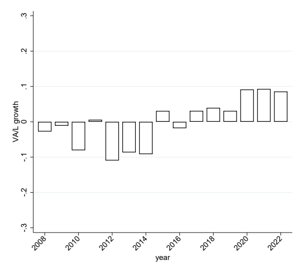
(b) Contribution of NACE sector C to aggregate labor productivity growth



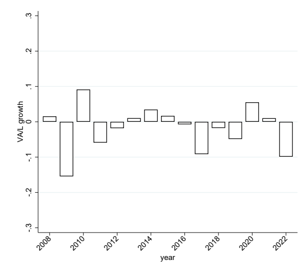
(c) Contribution of NACE sector D to aggregate labor productivity growth



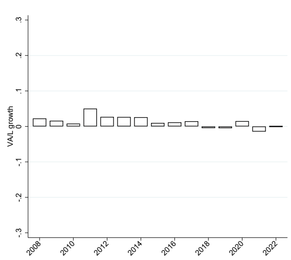
(d) Contribution of NACE sector E to aggregate labor productivity growth



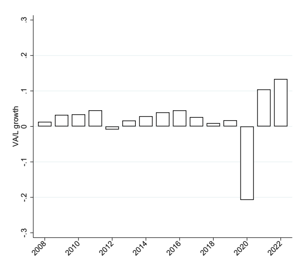
(e) Contribution of NACE sector F to aggregate labor productivity growth



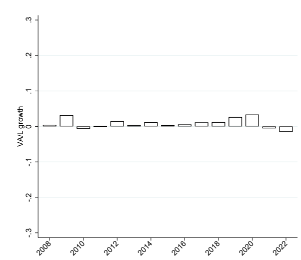
(f) Contribution of NACE sector G to aggregate labor productivity growth



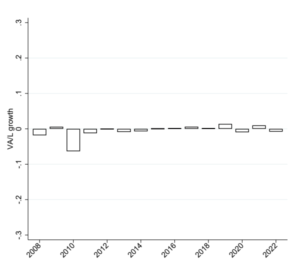
(g) Contribution of NACE sector H to aggregate labor productivity growth



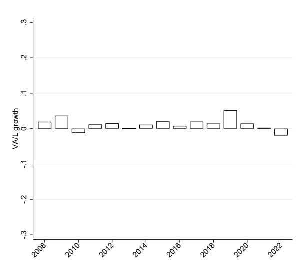
(h) Contribution of NACE sector I to aggregate labor productivity growth



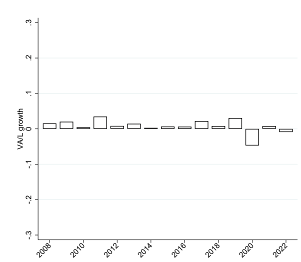
(i) Contribution of NACE sector J to aggregate labor productivity growth



(j) Contribution of NACE sector L to aggregate labor productivity growth

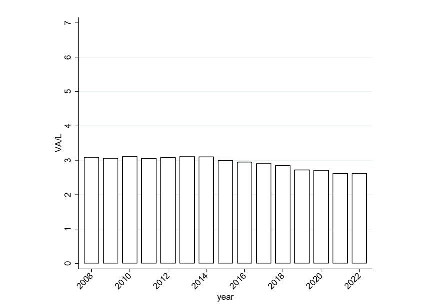


(k) Contribution of NACE sector M to aggregate labor productivity growth

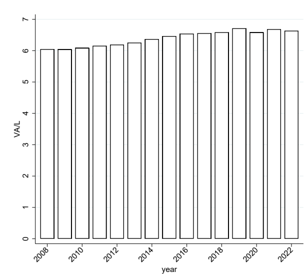


(l) Contribution of NACE sector N to aggregate labor productivity growth

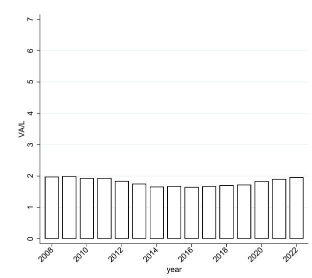
Figure 15: Sectoral contributions to aggregate labor productivity



(a) Manufacturing

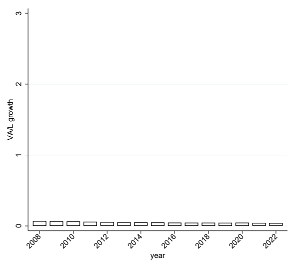


(b) Services

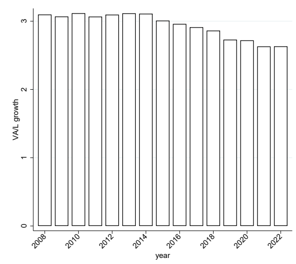


(c) Other

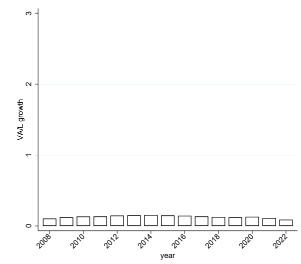
Figure 16: Contribution of service sectors to aggregate labor productivity



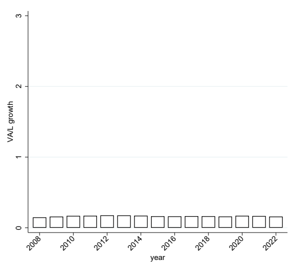
(a) Contribution of NACE sector B to aggregate labor productivity



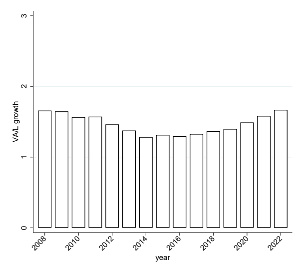
(b) Contribution of NACE sector C to aggregate labor productivity



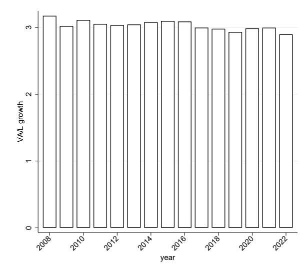
(c) Contribution of NACE sector D to aggregate labor productivity



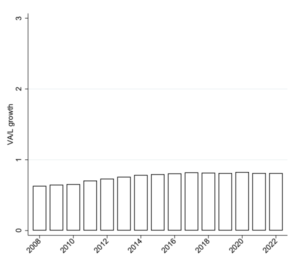
(d) Contribution of NACE sector E to aggregate labor productivity



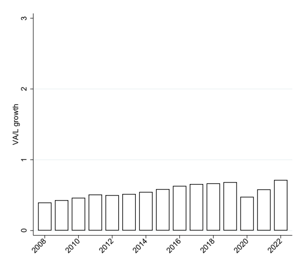
(e) Contribution of NACE sector F to aggregate labor productivity



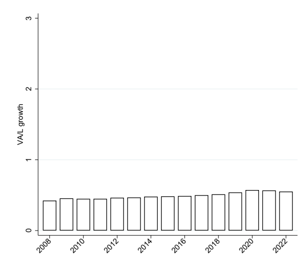
(f) Contribution of NACE sector G to aggregate labor productivity



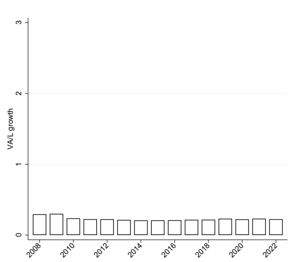
(g) Contribution of NACE sector H to aggregate labor productivity



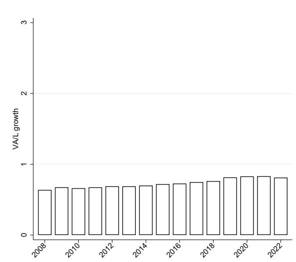
(h) Contribution of NACE sector I to aggregate labor productivity



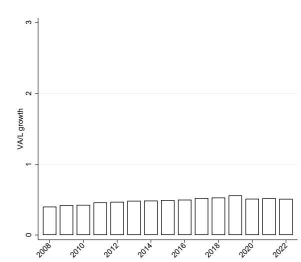
(i) Contribution of NACE sector J to aggregate labor productivity



(j) Contribution of NACE sector L to aggregate labor productivity



(k) Contribution of NACE sector M to aggregate labor productivity



(l) Contribution of NACE sector N to aggregate labor productivity

C NACE revision 2 classification

Code	Description	2-digit range
B	Mining and quarrying	05 to 09
Manufacturing (CA-CM)		
CA	Manufacture of food products, beverages and tobacco products	10 to 12
CB	Manufacture of textiles, apparel, leather and related products	13 to 15
CC	Manufacture of wood and paper products, and printing	16 to 18
CD	Manufacture of coke, and refined petroleum products	19
CE	Manufacture of chemicals and chemical products	20
CF	Manufacture of pharmaceuticals, medicinal chemical/botanical products	21
CG	Manufacture of rubber/plastics, other non-metallic mineral products	22 + 23
CH	Manufacture of basic metals and fabricated metal products	24 + 25
CI	Manufacture of computer, electronic and optical products	26
CJ	Manufacture of electrical equipment	27
CK	Manufacture of machinery and equipment n.e.c.	28
CL	Manufacture of transport equipment	29 + 30
CM	Other manufacturing, repair and installation of machinery/equipment	31 to 33
D	Electricity, gas, steam and air-conditioning supply	35
E	Water supply, sewerage, waste management and remediation	36 to 39
F	Construction	41 to 43
Services (G-N)		
G	Wholesale and retail trade, repair of motor vehicles and motorcycles	45 to 47
H	Transportation and storage	49 to 53
I	Accommodation and food service activities	55 + 56
JA	Publishing, audiovisual and broadcasting activities	58 to 60
JB	Telecommunications	61
JC	IT and other information services	62 + 63
L	Real estate activities	68
MA	Legal, accounting, management, architecture, engineering, technical testing and analysis activities	69 to 71
MB	Scientific research and development	72
MC	Other professional, scientific and technical activities	73 to 75
N	Administrative and support service activities	77 to 82

D NACE categories for productivity estimation

Table 17: Industries groups for the estimation of productivity.

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

E NACE categories for ETCR regressions

Table 18: Industries groups for the regressions on the ETCR indicator.

Industry Code	NACE Codes
B	05–09 (Includes the groups B05_06 B07_08 and B09)
C10T12	10–12
C13T15	13–15
C16	16
C17_18	17–18
C19	19
C20	20
C21	21
C22	22
C23	23
C24	24
C25	25
C26	26
C27	27
C28	28
C29	29
C30	30
C31T33	31–33
D	35
E	36–39
F	41–43
G	45–47
H49	49
H50	50
H51	51
H52	52
H53	53
I	55–56
J58T60	58–60
J61	61
J62_63	62–63
L	68
M	69–75
N	77–82