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Compositional changes in aggregate productivity in an era of globalisation and financial crisis

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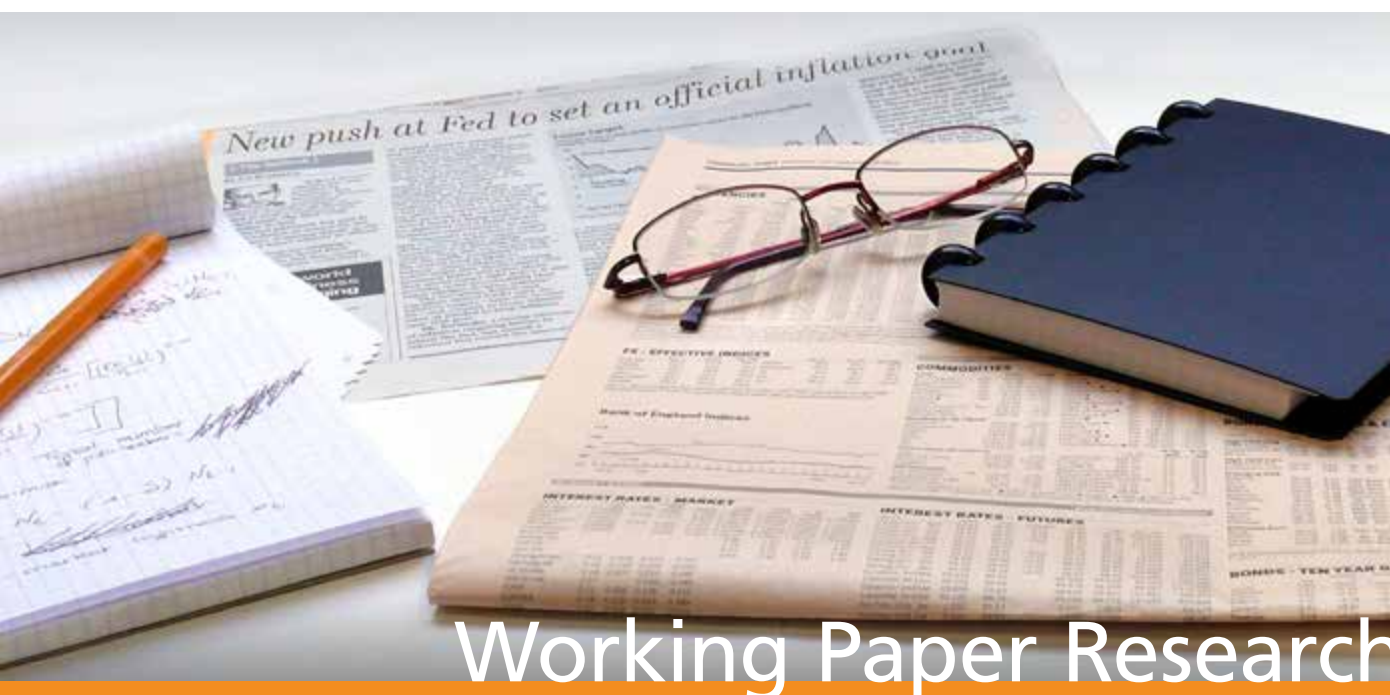
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Compositional changes in aggregate productivity in an era of globalisation and financial crisis



Working Paper Research

by Catherine Fuss and Angelos Theodorakopoulos

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Abstract

We demonstrate that common modeling assumptions underlying micro-unit productivity indices induce biases in the evolution and decomposition of standard aggregate productivity measures. After controlling for such biases, we decompose aggregate productivity based on groups of economically significant firm types. We show that large incumbent firms that both export and import determine the evolution of aggregate productivity for the Belgian manufacturing sector. Over time, the increase in average productivity outweighs the decline in the covariance between market shares and productivity of this group. The former result stems from stronger learning-by-doing effects for granular firms. The latter suggests an increase in resource misallocation due to market distortions. This pattern intensifies after the 2008 financial crisis. All other firm types, if anything, contribute negatively to aggregate productivity and productivity growth.

JEL classification: D24, F14, F60, L25, O47.

Key words: Aggregate Productivity, Decomposition, Globalisation, Trade, Granularity, Learning.

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1 Introduction

Policymakers consider productivity a key element of economic growth. However, trends in aggregate productivity are uninformative about their micro-level determinants which shed light on productivity itself. As such, various alternative methods to decompose aggregate productivity have been proposed. The decomposition literature spans from the seminal contributions of Baily et al. (1992) and Olley and Pakes (1996) to the most recent contribution of Melitz and Polanec (2015). The ultimate goal is to capture essential microeconomic sources and assess their relevance to aggregate productivity.

Decomposition analyses typically include two basic steps. First, since productivity of the aggregate is not directly observed, researchers rely on measures of aggregate productivity. These measures are computed as weighted averages of firm-level based productivity indices, i.e. labour productivity or total factor productivity.¹ Second, the analysis proceeds with using one of the available methods to decompose aggregate productivity. However, there is no consensus in the literature on which approach to follow; the choice depends directly on the research question and micro-level data at hand.

The majority of the decomposition methodologies focus on shifts in the distribution of firm-level productivities (within-firm) and the reallocation of market shares (between-firm) for various groups of firms. These groups mainly include entering, exiting and incumbent firms. However, firms operate in a globalised environment where competitive forces lead to productivity-enhancing restructuring. It has been shown, both empirically and theoretically, that the most productive firms select into internationalisation, i.e. trade and FDI (Bernard and Jensen 1999; Melitz 2003; Helpman et al. 2004), and learn once they engage in such activities (Kasahara and Rodrigue 2008; De Loecker 2013). Such firms have higher sales, pay higher wages, and are more capital and skill intensive. Most importantly, only a few of these firms account for the bulk of internationalised activity (Mayer and Ottaviano 2008).

To better understand the microeconomic determinants of aggregate productivity, research on this topic should include decompositions that are based on firm attributes of economic significance, e.g. trade, size, skill intensity, geography, etc. To our knowledge, only a few studies on the decomposition of aggregate productivity take these factors into account. Böckerman and Maliranta (2007) test for regional differences in the aggregate productivity growth of the Finnish manufacturing sector.² Bartelsman et al. (2013) find that variation in distortions (i.e. overhead labour and quasi-fixed capital) can explain cross-country differences in the resource reallocation component. Collard-Wexler and De Loecker (2015) examine the reallocation of resources within and between different types of production technology in the US steel industry.

¹This approach is also known as ‘bottom-up’ (Balk 2016).

²Also for Finland, using a similar dataset, Hyytinen et al. (2016) exploit cross-regional differences to illustrate their proposed procedure for statistical inference using the Olley and Pakes (1996) decomposition.

For the case of Belgium, Van Beveren and Vanormelingen (2014) find that human capital intensive and/or internationalised firms exert higher aggregate productivity growth which is driven by the within-firm component. However, they use a revenue-based productivity measure. Both theoretical (Melitz and Ottaviano 2008; Edmond et al. 2015) and empirical (De Loecker et al. 2016; Garcia-Marin and Voigtländer 2013) studies confirm that variable markups are an important margin of adjustment for firms during various trade and regional integration policies.³ As such, revenue-based productivity measures are also driven by the variation of firm-specific prices (Foster et al. 2008; De Loecker 2011). This is bound to bias both the contribution and evolution of the decomposed components, as noted by Petrin and Levinsohn (2012) and confirmed by Eslava et al. (2013) who find larger trade-induced effects on allocative efficiency for price-adjusted productivity measures. Therefore, markups consist of an important margin of adjustment for firms.

Overall, two important observations emerge. On the one hand, the literature delivers a plethora of results that vary quantitatively and qualitatively, even within decomposition methods. Such discrepancies are potentially driven by biases in the estimates of micro-unit productivity indices, which are mechanically transmitted to aggregate productivity measures. On the other hand, the decomposed components mask potential heterogeneity induced by various attributes of the firm. In both cases, we can end up with a distorted image about the micro-foundations of aggregate productivity, how they evolve over time, and how they react to changes in the operating environment of firms.

In this paper, we examine both of the above cases. First, we assess the effect of biases on various productivity indices for a given decomposition method of aggregate productivity. Such biases are frequently ignored in the empirical literature when computing firm-level productivity and include: using single factor instead of total factor productivity; the estimation of revenue instead of physical productivity;⁴ the estimation of physical productivity under alternative assumptions for the timing of the demand shocks; the presence of differences in production technology across industries; and the selection of samples with larger firms.

Second, we proceed using the most competitive productivity estimates available, i.e. the case of imperfect competition in the output market where demand shocks are observed by the firms post production and the production technology varies across industries for a representative sample of firms. Note that the chosen estimator is not a panacea; it is also based on assumptions that could potentially prove restrictive. Nevertheless, given the data in hand, it is the best

³In line with this argument, Epifani and Gancia (2011) show how the distribution of markups distorts the allocation of resources. Thus, trade can affect welfare through distributional changes in markups. Similarly, Peters (2013) considers the case where misallocation stems from output market imperfections.

⁴Foster et al. (2008) examine the effect on the components of aggregate productivity growth from using revenue based productivities. They use a dataset with information on output prices and quantities and thus directly observe measures of physical productivity. However, such datasets are rare and researchers mostly rely on monetary values and aggregate price deflators. As such, further structure and assumptions on the demand side are required to estimate physical productivity.

available alternative in terms of both the potential biases for which it corrects and its empirical robustness. With these estimates in hand, we decompose aggregate productivity based on economically significant firm attributes, i.e. trade, size, and combinations.

For the analysis, we use a detailed firm-level dataset representative of the Belgian manufacturing sector, for the period 1998-2012. The following findings emerge. Despite the empirical convenience in validating theoretical predictions about productivity, single factor productivity (e.g. labour productivity) leads to biased empirical conclusions about ‘true’ productivity (e.g. total factor productivity). Moreover, we confirm significant biases in the evolution of aggregate productivity in the absence of controls for output-price differences across firms (Foster et al. 2008).

Similar biases emerge when we estimate physical productivity (i.e. à la De Loecker 2011), under seemingly similar modelling assumptions. For example, if demand shocks are observed by the firm when deciding its inputs, physical productivity cannot be separated from markups and demand shocks without additional information, i.e. physical output or firm level prices. On the contrary, by assuming that demand shocks hit the firm ex-post production we can back out a measure closer to true physical productivity that we also consider the most competitive one for our decomposition analyses. Equally important is the bias from estimating production functions at the manufacturing instead of the industry level. In this case, we erroneously attribute variation from cross-industry differences in production technologies to aggregate productivity. Finally, sample selection, i.e. sample with larger firms, induces non-negligible biases in decomposition results.

After controlling for the aforementioned biases, we find that the reallocation of resources across firms has been decreasing steadily since 1998, with a drop during the 2008 financial crisis. Van Beveren and Vanormelingen (2014), using the same database for the period 1997-2009, find the opposite effect, i.e. a positive contribution of the reallocation mechanism on aggregate productivity growth. However, we see that this discrepancy in results is driven by price differences in their revenue-based productivity estimates,⁵ supporting our expectations about the significance of distributional changes in markups.

On the contrary, a decreasing trend in average firm productivity was reverted during the 2008 financial crisis. Note that the decreasing trend is mainly induced by small-sized firms which account for more than half of the sample size. Also, entering and exiting firms are minor contributors to aggregate productivity growth. This can be reconciled with the findings of Garcia-Macia et al. (2016) where incumbent firms that rely on own-product improvements instead of creative destruction appear to be the drivers of aggregate productivity growth. Overall, the within-firm component of incumbent firms drives the evolution of aggregate productivity, especially after the 2008 financial crisis.

⁵Their result matches ours when considering the case of perfect competition in the output market.

Finally, we further exploit the richness of the data and find that two-way traders, i.e. both exporters and importers, are the main contributors to aggregate productivity (growth). Interestingly, firm-size in itself is not a determining factor of aggregate productivity compared to the internationalisation status of firms. However, firm-size becomes a meaningful margin only when we consider it along with the internationalisation status of the firm.

Results suggest that the reallocation of resources across Belgian manufacturing firms decreased over time. There is a growing literature which attempts to understand the drivers of resource missallocation across firms and how this translates to aggregate productivity growth. Hopenhayn (2014) provides a detailed literature review on this topic. The main idea is that various policies and institutions prevent firms from equating their marginal revenue products of inputs with their marginal costs. This, in turn, has implications for aggregate growth. For example, we observe a large increase in misallocation during the 2008 financial crisis. This suggests that, on top of other distortions prevalent in the market, financial constraints can be considered as a potential source of misallocation during that period.⁶ However, our analysis can only provide suggestive evidence of potential distortions and is thus silent about their exact nature and taxonomy.

In addition, we find that resource reallocation is not a sufficient mechanism to explain the evolution of aggregate productivity. For this reason we need to look at changes in the distribution of firm-level productivities. On average, firms increase their productivity over time, and those that are most successful are both more deeply engaged in internationalisation and larger in size. All other firms lag behind and prevent aggregate productivity from reaching its full potential. As indicated from our production function estimates, learning mechanisms are important in explaining differences in the evolution of the within firm component and thus aggregate productivity growth. The idea is that firms learn from their actions, i.e. trade. This suggests that theoretical modelling should move to more complex structures where static reallocation is combined with dynamic learning mechanisms. Overall, we expect our results to be insightful both for Belgium's and other European economies' efforts to deregulate and reduce frictions in response to increased global competition and stagnated economic activity.

With the above in mind, the remainder of this paper is organised as follows. Section 2 describes the empirical methodology and Section 3 describes the data. Section 4 presents an analysis of potential biases and the main results from the decompositions for different groups of firms. Finally, Section 5 offers concluding remarks.

⁶See Hopenhayn (2014) for a nice literature review on the relevance of financial constraints in explaining misallocation and selection.

2 Empirical Methodology

We discuss three important components of our methodology. First, we document the computation of aggregate productivity. This includes the choice of a productivity measure and estimator, and market share weights. Second, we motivate our choice for the decomposition method of aggregate productivity that is best suited for our analysis, and generalise it to account for the number of additional groups we consider. Third, we describe how to obtain standard errors for the decomposed components.

2.1 Productivity and Weights

The literature offers a number of alternative choices for productivity estimators and measures (ω_{it}), and for market share weights (s_{it}). Since aggregate productivity does not always represent productivity of the aggregate when certain assumptions fail to hold, there is no consensus on superior alternatives. Balk (2016) provides a detailed discussion of how specific choices can affect the decomposition of aggregate productivity. Overall, the choice ultimately depends on the research question and available data.

Following Bartelsman and Dhrymes (1998), Foster et al. (2001) and Collard-Wexler and De Loecker (2015), we base our analysis on measures of gross-output productivity and deflated nominal gross-output shares as weights.⁷ We consider alternative productivity measures such as: labour productivity; total factor productivity under different assumptions in the output market; total factor productivity under different assumptions regarding the extent of common production technology across industries; and total factor productivity when facing sample restrictions. Using a given decomposition method and weights, we are then able to infer the implications of choosing specific productivity measures on aggregate productivity and its evolution.

We start with labour productivity (LP), defined as the share of output over labour.⁸ We then switch to an estimate of total factor productivity assuming perfect competition in the output market (PC). This competing productivity index provides the closest approximation to disembodied technological change.⁹ For the estimation, we consider a flexible gross-output production function $Y_{it} = F_K(K_{it}, L_{it}, M_{it})e^{\omega_{it} + \varepsilon_{it}}$, with Hicks-neutral total factor productivity ω_{it} (herein TFP). In logs, the production function to be estimated is of the following form:

$$y_{it} = f_K(k_{it}, l_{it}, m_{it}) + \omega_{it} + \varepsilon_{it} \quad (1)$$

where y_{it} , k_{it} and m_{it} are log values of deflated (at the industry level) sales, beginning of the

⁷Using weights based on nominal gross-output or labour shares results are qualitatively robust.

⁸See Balk (2016) for a review of the potential biases induced when aggregating labour productivity.

⁹Most, if not all, estimates of total factor productivity are different from disembodied technological change, known as the ‘Solow Residual’ (Solow 1957). They also include the impact of inputs that are not measured or available in the data (e.g. management practices and human capital skills). Results should be interpreted bearing this in mind.

period capital stock, and material costs, respectively, and l_{it} is the log of the total number of full-time equivalent (FTE) employees of firm i in period t . κ represents the level of common production technology across firms $f_{\kappa}(\cdot)$, i.e. sector or industry. TFP is unobserved to the econometrician but known to the firm. Ex-post shocks, i.e. after the firm's decision on input use, are picked up by ε_{it} .

Capital is assumed to be predetermined and therefore chosen one period prior to the realisation of TFP. Labour is assumed to be a dynamic input, meaning that it is variable in period t but has dynamic implications due to the presence of adjustment costs. Therefore, it is chosen during the realisation of TFP, i.e. between $t - 1$ and t . The only flexible input is material that freely adjusts in each period and has no dynamic implications.¹⁰

Estimation of the production function is based on the two-step estimator proposed by Gandhi, Navarro, and Rivers (2017b) (herein GNR). On top of the transmission bias, i.e. firms observing their productivity when choosing their inputs, this estimator controls for the value-added bias that arises from estimating a value-added rather than a gross-output production function. A detailed description of the assumptions, steps followed, and its dominance over competing estimators can be found in GNR.¹¹

Similar to most proxy variable methods, this procedure identifies both production function parameters and the effects on current TFP (in expectation) of lagged observable actions of firm i in period t . In principle, we should control for any action or change in the firm's operating environment. However, due to data limitations we can control only for variables observed in the data. We expect trade to be the most important control especially when considering Belgium, a small open European economy during the latest financial and Eurozone crisis. Such controls are also internally consistent with the choice of firm attributes (e.g. trade and size) used for the decomposition analysis in the following section. For example, two-way traders represent firms most engaged in trade and largest in size (Mayer and Ottaviano 2008).

For our specification we consider a controlled Markov process where, in addition to lagged TFP, we allow past experience from export (Van Biesebroeck 2005), import (Kasahara and Rodrigue 2008), and two-way trade to affect current TFP.¹² Following Aw et al. (2011) and De Loecker (2013) we use the following flexible parametric specification for the TFP process:

$$\begin{aligned} \omega_{it} = & \sum_{j=1}^4 \rho_j \omega_{it-1}^j + \rho_x x_{it-1} + \rho_m m_{it-1} + \rho_{xm} x m_{it-1} + \rho_{x\omega} x_{it-1} \omega_{it-1} \\ & + \rho_{m\omega} m_{it-1} \omega_{it-1} + \rho_{xm\omega} x m_{it-1} \omega_{it-1} + \rho_t + \rho_s + \xi_{it} \end{aligned} \quad (2)$$

¹⁰Results are robust to the alternative assumption that labour is predetermined.

¹¹See Gandhi et al. (2017a) for an exposition of the sizeable effects of value-added bias on productivity heterogeneity. Merlevede and Theodorakopoulos (2017) show the impact of such a misspecification when estimating learning by doing effects.

¹²With lagged values, we inherently assume that it takes one period for actions to affect TFP. Such an assumption can be relaxed and tested for robustness against alternative specifications with deeper lags.

where x_{it-1} , m_{it-1} and xm_{it-1} are dummies reflecting whether a firm is an exporter, importer or two-way trader, respectively. These groups are mutually exclusive and the reference group of purely domestic firms is subsumed in the constant. Also, ρ_t and ρ_s are fixed-effects that account for relevant unobserved macroeconomic shocks and aggregate structural differences across industries, respectively.¹³ ξ_{it} captures, unanticipated at $t - 1$, exogenous shocks that affect firm's TFP in time t .

Based on estimates of the production function coefficients ($\hat{f}_K(\cdot)$) and ex-post shocks to production ($\hat{\varepsilon}_{it}$), we can compute TFP ($\hat{\omega}_{it}$) and other relevant variables, i.e. output elasticities of inputs and returns to scale, for firm i in period t , using equation (1). In addition, using equation (2), we can also directly identify the effects on future TFP when engaging in international trade that can be causally interpreted as: learning by exporting ($\frac{\partial \omega_{it}}{\partial x_{it-1}}$); learning by importing ($\frac{\partial \omega_{it}}{\partial m_{it-1}}$); and learning by two-way trading ($\frac{\partial \omega_{it}}{\partial xm_{it-1}}$).

With the available firm-level data, we do not observe physical output at the firm level, but only monetary values which we deflate at the industry level. Under the assumption of perfect competition in the output market of each industry, both *LP* and *PC* produce indices of physical productivity. However, under any type of imperfectly competitive output market structure, price differences across firms emerge. In this case, the productivity measures should be interpreted as revenue-based (Klette and Griliches 1996).

To avoid potential price biases in aggregate productivity as shown in Foster et al. (2008), we estimate TFP controlling for unobserved variation in firm-specific prices. To do so, we circumvent the data limitations by introducing more structure and assumptions in the empirical model. This includes an iso-elastic demand system coupled with monopolistic competition, similar to De Loecker (2011).¹⁴ However, the approach we follow is more flexible since it is able to identify time-varying instead of constant markups by assuming a CES demand system with time-varying elasticity of demand. This is expected to be insightful to the extent to which, on average, firms adjust their markups over time.

Under these assumptions the production function to be estimated is of the following form:

$$r_{it} = \left(\frac{\sigma_t + 1}{\sigma_t} \right) f_K(k_{it}, l_{it}, m_{it}) - \frac{1}{\sigma_t} y_t + \left(\frac{\sigma_t + 1}{\sigma_t} \right) \omega_{it} + \chi_{it} + \left(\frac{\sigma_t + 1}{\sigma_t} \right) \varepsilon_{it} \quad (3)$$

where r_{it} is the (observed in the data) log value of deflated sales at the industry level, given by $r_{it} = (p_{it} - p_t) + y_{it}$. p_{it} and p_t are the log values of the output price of firm i and the aggregate output deflator (aggregate price index), respectively. y_t is the log value of a quantity index serving as an aggregate demand shifter. This is computed using the log value of a simple

¹³Fixed effects enter additively in order to restrict the parameter space and improve the efficiency of the estimation. This should be considered with caution since non-linearities in the fixed-effects would saturate the model, resulting in incidental parameters bias.

¹⁴Note that we do not have data on multi-product firms and thus need to assume that each firm produces one unique variety.

average of deflated sales. χ_{it} captures firm specific demand shocks, σ_t is the time varying elasticity of demand derived from a generalised version of a CES demand system and $\frac{\sigma_t+1}{\sigma_t}$ is by construction the inverse of the markup. It is now straightforward to see that not accounting for price differences in the output market (i.e. *PC*) leads to estimates of both the production function parameters and productivity that are decreasing functions of any potential unobserved (heterogeneity in) markups.

To control for the price bias, we follow the estimation procedure proposed by GNR (see Appendix C4 of their paper) and provide estimates based on two different assumptions. Firms are either assumed to observe demand shocks post production (*IC*), or, alternatively, demand shocks are observed once firms make their input decisions (*ICalt*). The former is preferable, because it permits TFP to be identified separately from demand shocks and markups.

Note that this estimator is not a panacea; it is also based on assumptions that could potentially prove restrictive. For example, if the assumption for *IC* fails to hold then we end up with a productivity estimate where we cannot net out demand shocks, i.e. $\omega_{it} + \left(\frac{\sigma_t}{\sigma_t+1}\right)\chi_{it}$, similar to *ICalt*, i.e. $\left(\frac{\sigma_t+1}{\sigma_t}\right)\omega_{it} + \chi_{it}$. Nevertheless, given the data at hand, it is the best available alternative in terms of both the potential biases for which it corrects and its empirical robustness for identifying true TFP. We expect these two cases to be informative about the extent to which two seemingly similar assumptions, within the same estimation method, lead to different conclusions about aggregate productivity.

We also estimate TFP based on *IC* when excluding micro firms¹⁵ (*ICsize*), in order to explore whether decompositions are sensitive to sample selection. A sample that drops small firms could potentially bias the impact of entry and exit on aggregate productivity (Foster et al. 2002). Finally, for each of the above cases, we consider two alternative levels (κ) of common production technology across firms $f_\kappa(\cdot)$. First, we estimate TFP by pooling all firms in the manufacturing sector (*Manuf*). Second, we estimate TFP by pooling firms in each industry (*Nace*) separately.¹⁶ This allows us to examine the importance of properly accounting for differences in production technologies across industries on aggregate productivity.

TFP is a unitless measure. To guarantee that our measure is insensitive to measurement units and allows for transitive comparisons, we compare it to a reference firm at the start of the period (see Aw et al. 2001; Pavcnik 2002; Van Biesebroeck 2008). Therefore, all productivity measures used in the decompositions are expressed as the difference between each firm's estimated TFP and that of a reference firm with mean TFP in the same industry in the base period.

¹⁵Less than 10 employees and up to €2 million operating revenue (European Commission 2017).

¹⁶We use the A*38 industry classification that represents intermediate SNA/ISIC aggregation. See Table 3 in Appendix A for correspondence with the NACE Rev.2 2-digit classification.

2.2 Decomposition of Aggregate Productivity

We define aggregate productivity (Ω_t), as the share weighted average of the log of firm productivity:¹⁷

$$\Omega_t = \sum_{i \in \Pi_t} s_{it} \omega_{it} \quad \text{s.t.} \quad \sum_{i \in \Pi_t} s_{it} = 1 \quad (4)$$

where $s_{it} = \sum_{i \in \Pi_t} \left(\frac{Y_{it}}{\sum_{i \in \Pi_t} Y_{it}} \right)$ is the share weight, Y is real output, and Π_t is the set of all active firms in each period.

Various methods to decompose aggregate productivity have been proposed. On the one hand, several decompositions examine the margins of aggregate productivity levels (static). On the other hand, a variety of decompositions focus on the sources of aggregate productivity growth (dynamic).¹⁸

We follow the widely used method of Olley and Pakes (1996) (OP), where productivity is decomposed into two components in each period:

$$\Omega_t = \frac{1}{N_t} \sum_{i \in \Pi_t} \omega_{it} + \sum_{i \in \Pi_t} (s_{it} - \bar{s}_t)(\omega_{it} - \bar{\omega}_t) = \bar{\omega}_t + cov(s_{it}, \omega_{it}) \quad (5)$$

where N_t is the number of elements in Π_t , $\bar{\omega}_t$ is the unweighted average of productivity (within-firm), and $cov(s_{it}, \omega_{it})$ is the covariance between market share and productivity (between-firm). The latter is of particular policy interest since it is considered as an indicator of underlying mechanisms of aggregate productivity (growth). For example, for the case of a deregulation of the US telecommunications equipment industry, OP interpret higher values of the covariance term as a reallocation of resources to the most productive firms. Similarly, Bartelsman et al. (2013) provide evidence that lower values indicate the presence of market distortions induced by policies, which can explain productivity differences across countries.

On the one hand, Balk (2016) describes the covariance term as a ‘statistical artefact’ that does not necessarily represent key microeconomic mechanisms. On the other hand, Maliranta and Määttänen (2015) provide both empirical and theoretical evidence that the covariance term performs well when capturing important distortions, i.e. output tax and subsidy scheme, compared to others, i.e. entry and exit costs. Therefore, we need to use theoretical models that capture the extent to which certain types of distortions explain differences in the marginal value of inputs across firms. Hopenhayn (2014) provides a detailed review of such models and summarises their relevance in explaining productivity gaps. Overall, we interpret the covariance term as a measure of resource (mis)allocation, bearing in mind that it most likely does not

¹⁷The arithmetic mean of the logs is equivalent to the geometric mean of the levels. See Balk (2016) for a brief discussion on the implications of alternative aggregation methodologies. Melitz and Polanec (2015) derive and decompose the arithmetic mean of both the logs and levels of productivity. Results remain similar.

¹⁸See Melitz and Polanec (2015) for an empirical comparison between their approach and various dynamic decomposition methods.

capture all potential market distortions and even if it does we will not be able to identify their exact nature and taxonomy.

It is straightforward to extend the decomposition for a number of disjunct groups:

$$\Omega_t = \sum_{j=\Psi_t} s_{jt} \left(\sum_{i \in \Pi_{jt}} \frac{s_{it}}{s_{jt}} \omega_{it} \right) = \sum_{j=\Psi_t} s_{jt} \Omega_{jt} \quad \text{s.t.} \quad \sum_{j=\Psi_t} s_{jt} = 1 \quad (6)$$

where the set Ψ_t defines the abbreviations of the names of the mutually exclusive groups considered (i.e. $\bigcup_{j \in \Psi_t} \Pi_{jt} = \Pi_t$ and $\bigcap_{j \in \Psi_t} \Pi_{jt} = \emptyset$), s_{jt} is the aggregate market share of group j , and Ω_{jt} is group j 's aggregate productivity.

To measure the contribution of each group on aggregate productivity, we use a reference group $\mathcal{A}_t \subset \Psi_t$. This way, in each period, we can express the aggregate productivity contribution of the complement group(s) \mathcal{A}_t^c as:

$$\Omega_t = \Omega_{\mathcal{A}_t} + \sum_{j=\mathcal{A}_t^c} s_{jt} (\Omega_{jt} - \Omega_{\mathcal{A}_t}) \quad (7)$$

where $\mathcal{A}_t \cap \mathcal{A}_t^c = \Psi_t$.¹⁹

To understand whether the aggregate productivity of different groups is driven by changes in the average productivity or reallocation of resources within each group relative to the reference group, we insert (5) into (7):

$$\begin{aligned} \Omega_t = & \bar{\omega}_{\mathcal{A}_t} + cov_{\mathcal{A}_t}(s_{it}, \omega_{it}) \\ & + \sum_{j=\mathcal{A}_t^c} \left[s_{jt} (\bar{\omega}_{jt} - \bar{\omega}_{\mathcal{A}_t}) + s_{jt} (cov_j(s_{it}, \omega_{it}) - cov_{\mathcal{A}_t}(s_{it}, \omega_{it})) \right] \end{aligned} \quad (8)$$

where, for each group j , $\bar{\omega}_{jt} = \frac{1}{N_{jt}} \sum_{i \in \Pi_{jt}} \omega_{it}$ is its unweighted average productivity and $cov_j(s_{it}, \omega_{it}) =$

$\sum_{i \in \Pi_{jt}} \left(\frac{s_{it}}{s_{jt}} - \frac{\sum_{i \in \Pi_{jt}} \frac{s_{it}}{s_{jt}}}{N_{jt}} \right) \left(\omega_{it} - \bar{\omega}_{jt} \right)$ is the covariance between its market share and productivity.²⁰

On the one hand, our main focus is on the cross-sectional importance of the productivity distribution of different groups of firms, i.e. entry and exit, trade, size, and combinations of those, on the aggregate.²¹ Therefore, we compute equation (7) and (8) for each period in the

¹⁹To motivate their analysis, Maliranta and Määttänen (2015) use this specification to identify the contribution of non-staying firms on aggregate productivity.

²⁰Maliranta and Määttänen (2015) use a transformation of this equation, defined as ‘Augmented Static OP Productivity Decomposition’, to study how entering and exiting firms contribute to the covariance term. Collard-Wexler and De Loecker (2015) define this equation as ‘within technology’ decomposition and combine it with a ‘between technology’ transformation of the OP decomposition. Their goal is to explain changes in aggregate productivity through changes within and across two vintage technologies in the steel industry.

²¹See Maliranta and Määttänen (2015) for a discussion on the importance of static measures on understanding the components of aggregate productivity growth.

dataset.

On the other hand, we are also interested in the contribution of certain groups of firms to aggregate productivity growth. In this case, due to compositional changes between firms over time, the literature suggests a variety of dynamic decomposition methods, spanning from the seminal contribution of Baily et al. (1992) to the most recent one of Melitz and Polanec (2015). However, if we look carefully, our analysis so far is sufficient to directly identify the contribution of certain groups. For example, for the case of surviving, entering and exiting firms, the terms in brackets in equation (8) are analogous to the terms considered in the ‘Dynamic OP Decomposition’ developed by Melitz and Polanec (2015). Therefore, when considering entering firms, they can be directly interpreted as the contribution of entering firms on aggregate productivity growth.²² Finally, for all other groups, the yearly differences of each component in equation (8) can be interpreted as approximate percentage contributions to productivity growth.²³

2.3 Statistical Inference

The empirical literature on the micro-level determinants of aggregate productivity has typically assessed the relevance of the components of aggregate productivity on the basis of visual inspections. However, this approach casts doubts on the validity of the results since it is not based on formal statistical inference. Even though the decomposition is an exact procedure, i.e. analysis of variance, there is inherent uncertainty induced. As in any empirical work, the analysis is based on micro-level data. Even in the case of accessing census datasets covering the full population, the analysis will still be subject to sampling error.²⁴

To take this uncertainty into account, formal statistical inference is needed. However, with few exceptions, most of the empirical literature is silent about these issues. Foster et al. (2006) create a regression analogue to both decompose productivity growth in components for continuing, exiting and entering firms, and provide estimates for their standards errors, respectively. Collard-Wexler and De Loecker (2015) retrieve standard errors after bootstrapping the decomposed components of aggregate productivity growth along the TFP estimation procedure.

To address this issue we follow the procedure introduced by Hyytinen, Ilmakunnas, and Maliranta (2016) (henceforth HIM). This regression-based method allows us to retrieve point

²²Since in a dynamic context exit is forward looking, we can interpret the minus of exitor’s (\mathcal{A}^c) $t - 1$ counterpart from equation (8) as the contribution of exiting firms to aggregate productivity growth. For the contribution of surviving firms, we can use the yearly differences in the reference group (\mathcal{A}) plus their counterpart in brackets for exiting firms (\mathcal{A}^c), as shown in equation (8).

²³We under(over)-estimate when exiting firms in the group of interest have lower(higher) aggregate productivity compared to surviving firms. The magnitude of the bias depends on the relative importance of each group in terms of market shares.

²⁴Note that any of the productivity measures used in the decompositions are either computed or estimated and therefore susceptible to measurement error. See Hausman (2001) for a short review on the potential biases induced from mismeasured left hand side variables in econometric analysis. However, as is typical in the decomposition literature, this is something we do not account for in our methodology.

estimates with autocovariance and heteroscedasticity-robust standard errors for each component in the OP decomposition. The idea is based on the dissection of a simple regression:

$$E[\omega_{it}|s_{it}] = E[\omega_{it}] + \text{cov}(s_{it}, \omega_{it})\text{var}(s_{it})^{-1}(s_{it} - E[s_{it}]) \quad (9)$$

that reveals the potential for estimating the components of an OP decomposition using an ordinary least squares (OLS) regression. A pooled OLS regression of firm productivity on a full set of time dummies and scaled²⁵ share weights gives estimates for both the within and between component in each period. The point estimates are numerically equivalent to the right hand side components in equation (5) and the standard errors are autocovariance and heteroscedasticity-robust.

Following HIM, with the relevant scaling of the regressors, we extend this approach to account for the mutually exclusive groups considered in equation (8). Overall, we retrieve a time-series of point estimates, with their respective confidence intervals, that we illustrate in time-line charts for an easier interpretation.

3 Data

We use the Annual Accounts, VAT declarations and Transactions Trade dataset from the National Bank of Belgium (NBB). The combined dataset is representative of the Belgian manufacturing sector with detailed information on the balance sheet and trade activities of individual firms.

We focus on the sample of Belgian active manufacturing²⁶ firms that file unconsolidated accounts²⁷ over the period 1998-2012. We retain firms reporting sales, capital stock at the start of the period, number of employees in FTE, material costs, and exporting and importing status. We remove outliers using the BACON method proposed by Billor et al. (2000).²⁸ The manufacture of coke and refined petroleum products (19) is removed, due to the insufficient number of observations for estimating TFP at the industry level. Overall, we end up with an unbalanced panel of 21643 firms and 178695 observations for the period 1998-2012 (see Table 1 for summary statistics for the firm-level variables in the sample).

We need to deflate monetary variables using the appropriate NACE Rev.2 2-digit output deflator from the EU KLEMS database to estimate TFP. Real output (Y) is sales deflated with producer price indices. Capital (K) is tangible fixed assets deflated by the average of the deflators

²⁵Demeaned shares weights over the cross sectional variance times the number of firms in each period.

²⁶Table 3 in Appendix A provides an overview of the NACE Rev.2 2-digit industries and their correspondence to the more aggregate A*38 code that represents intermediate SNA/ISIC aggregation.

²⁷This refers to accounts not integrating the statements of possible controlled subsidiaries or branches of the concerned company.

²⁸BACON stands for Block Adaptive Computationally efficient Outlier Nominators. It is a multiple outlier detection method. The variables considered in the method are log of output, labour, capital and material.

of various NACE Rev.2 2-digit industries (Javorcik 2004).²⁹ Real material inputs (M) is material inputs deflated by an intermediate input deflator constructed as a weighted average of output deflators, where country-time-industry specific weights are based on intermediate input uses retrieved from input-output tables. Labour (L), is the number of employees in FTE.

Table 1: Summary Statistics

	Obs.	Mean	St.Dev.	p25	p50	p75
<i>Sales^a</i>	178695	10855	87434	382	1048	3754
<i>Capital stock^a</i>	178695	1699	12843	62	218	696
<i>Material costs^a</i>	178695	8542	74713	218	665	2630
<i>Employment in FTE</i>	178695	35	159	2.4	6.8	21
<i>Surviving</i>	178695	.94	.24	1	1	1
<i>Entering^b</i>	178695	.034	.18	0	0	0
<i>Exiting</i>	178695	.026	.16	0	0	0
<i>Experimenting</i>	178695	.0015	.038	0	0	0
<i>Domestic</i>	178695	.56	.5	0	1	1
<i>Exporting</i>	178695	.064	.25	0	0	0
<i>Importing</i>	178695	.1	.3	0	0	0
<i>Two-way-trading</i>	178695	.27	.44	0	0	1

Notes: ^a monetary variables in thousand Euro, ^b includes Experimenting firms. NBB database for 21643 manufacturing firms from 1998 to 2012.

For the decomposition analysis we construct dummy variables which classify the firms in mutually exclusive groups to be considered in each period. On the one hand, *Surviving*, includes the firms that exist both in $t - 1$ and $t + 1$. *Entering* is a backward looking variable and considers the firms that do not exist in $t - 1$ but exist in t . Inversely, *Exiting* is a forward looking variable and takes the value of 1 when firms are present in t , but not in $t + 1$. *Experimenting* consists of firms that appear only in t . Since the latter group represents only 0.15% of the total sample, i.e. approximately 5% of entrants, we incorporate it in the *Entering* group.³⁰ Therefore, we end up with three mutually exclusive groups of firms: *Surviving*; *Entering*; and *Exiting*.³¹

On the other hand, when considering trade, *Domestic*, *Exporting*, *Importing* and *Two-way-trading*, are mutually exclusive dummy variables indicating whether, at each point in time, a firm is purely domestic, exporting, importing, or both exporting and importing, respectively. We see that 44% of the sample engages in some type of trade activity, which is consistent with Belgium's economic history as a small and heavily trade oriented economy.

²⁹Electrical equipment (27); machinery and equipment n.e.c. (28); motor vehicles, trailers and semi-trailers (29); and other transport equipment (30).

³⁰This choice is made in order to reduce the complexity of the analysis. It does not distort the contribution of entering firms in the decompositions.

³¹Note that the variables are constructed based on information from the initial sample.

4 Results

In this section we first assess the importance of various productivity indices for a given decomposition method and share weights. Then, based on the most competitive case, we analyse the components of aggregate productivity in detail.

4.1 Productivity Indices

Production Function Estimates. Table 2 presents the production function estimates for the cases discussed in Section 2.1, i.e. *PC*, *IC*, *ICalt* and *ICsize*. In the first column, under perfect competition in the output market, firms face decreasing returns to scale (*RTS*). In the presence of price differences across firms, output elasticities of inputs and thus *RTS* will be biased downward since we only observe sales deflated at the industry level (Klette and Griliches 1996). The size of the bias is an increasing function of the inverse of the markup. Columns 2 and 3 confirm the existence of such a bias. Compared to column 1, all estimated output elasticities have higher values that result in increasing *RTS*. This is the outcome when firms charge higher prices that exceed their marginal costs.³²

Note that, even though the estimator in column 3 does not separate TFP from markups and demand shocks, results are similar to those in column 2. Since markups only vary over time, time variation is captured by the aggregate yearly demand shifter in the production function (2) and the time fixed effects in the Markov process (3). Therefore, coefficients for the estimated production function and Markov process are fairly similar. Nevertheless, this does not imply that TFP estimates from *IC* and *ICalt* are similar, since the latter entails variation in markup and demand shocks, i.e. $(\frac{\sigma_t+1}{\sigma_t})\omega_{it} + \chi_{it}$. Results hold when estimating any of the previous cases for each industry separately (see Tables 5-8 in Appendix A).

In the lower panel of Table 2, we find that firms learn from international trade, i.e. *Exporting* (De Loecker 2013), *Importing* (Kasahara and Rodrigue 2008) and *Two-way-trading*. To our knowledge, the latter effect has not been reported in the literature. However, it is an intuitive result, since firms that engage in exporting and importing are more likely to benefit from both activities. In addition, there appears to be a ranking in terms of the learning effects. Be it at the fourth decimal, the long-run³³ learning effects range from 4.60% for *Two-way-trading* firms to 3.65% for *Exporting* firms (see Table 4 in Appendix A). This suggests that, in the long run, firms that both export and import benefit the most from internationalisation.

Performing the analysis per industry reveals that this pattern is only significant in a few industries (see Tables 5-8 in Appendix A). This is in line with Lileeva and Trefler (2010), where

³²Multiplying any of the estimated output elasticities and *RTS* in columns 2-3 with the inverse of their respective markup leads approximately to the estimates of column 1.

³³The long-run effects are calculated using estimates from equation (2). Each effect is computed as the product of the average short-run effects on future TFP from exporting, importing and two-way trading times $1/(1-\rho) * 100$, where ρ is the average persistence of TFP.

the heterogeneous productivity impact from exporting is explained by a firm's initial productivity level as well as differential effects from investing. This result can also be reconciled by the fact that a large share of Belgian manufacturing firms export products that they do not produce, i.e. Carry-Along Trade (Bernard et al. 2018). Therefore, the potentials of learning by exporting are expected to vary across firms depending on the nature of trade. Overall, heterogeneity in the result emphasises the importance of controlling for technological differences across industries, i.e. estimating production functions at a more disaggregated level where firms are technologically more uniform.

Table 2: Production Function Estimates

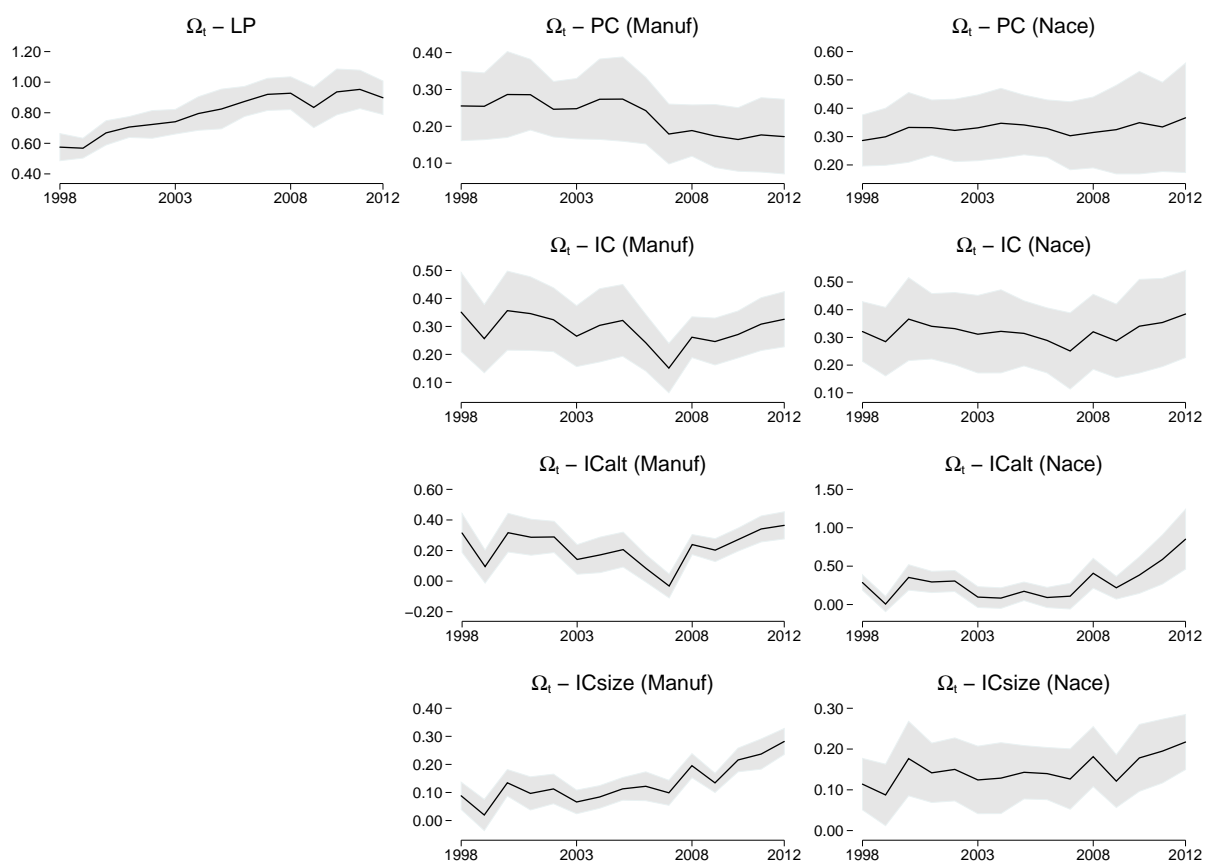
	(1) <i>PC</i>	(2) <i>IC</i>	(3) <i>ICalt</i>	(4) <i>ICsize</i>
$\bar{\theta}_{it}^k$	0.062*** (0.002)	0.070*** (0.003)	0.070*** (0.003)	0.063*** (0.007)
$\bar{\theta}_{it}^l$	0.267*** (0.002)	0.297*** (0.003)	0.296*** (0.003)	0.268*** (0.009)
$\bar{\theta}_{it}^m$	0.633*** (0.002)	0.710*** (0.005)	0.710*** (0.005)	0.756*** (0.020)
$R\bar{T}S_{it}$	0.963*** (0.002)	1.077*** (0.006)	1.076*** (0.006)	1.086*** (0.029)
$R\bar{T}S_{it} - 1$	-0.037*** (0.002)	0.077*** (0.006)	0.076*** (0.006)	0.086*** (0.029)
\bar{Markup}_t		1.121*** (0.006)	1.121*** (0.006)	1.104*** (0.028)
Learning by ...				
$Exporting_{it-1}$	0.002*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.001 (0.001)
$Importing_{it-1}$	0.004*** (0.000)	0.004*** (0.001)	0.004*** (0.001)	0.003*** (0.001)
$Two-way-Trading_{it-1}$	0.003*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.003*** (0.001)
Observations	154637	154088	154088	69565

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all manufacturing firms. $\bar{\theta}_{it}^k$, $\bar{\theta}_{it}^l$ and $\bar{\theta}_{it}^m$ are averages of the estimated output elasticities of capital, labour and material respectively. $R\bar{T}S_{it}$ is the average of the estimated RTS . \bar{Markup}_t is the average of the estimated annual markups. The lower panel gives the average, of the estimated in equation (2), effects on future TFP from exporting, importing and two-way trading. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Note that the learning effects reported above point to the potential determinants of future productivity. At first glance this could be considered sufficient to describe the drivers of aggregate productivity growth. However, aggregate productivity is a share weighted average of firm-level productivity indices. Even if the determinants of firm-level productivity are known, this is not the case for the share weights used to compute aggregate productivity. Overall, these results can be informative only for the determinants of the within component of aggregate productivity. As such, we need to explore each of the components of aggregate productivity further.

Aggregate Productivity. In Figure 1, we compare the evolution of aggregate productivity under various assumptions, estimators, and samples. The top left panel uses simple labour productivity. We find that aggregate productivity has been increasing for the Belgian manufacturing sector since 1998, with a temporary downturn during the financial crisis in 2008 and the Euro-zone crisis in 2011. However, this trend is inconsistent with the other alternatives we consider.

Figure 1: Annual aggregate productivity.



Notes: Authors' calculations. Ω_t is the share weighted average of the logarithm of productivity with deflated nominal sales as weights. The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval following the procedure of HIM.

When comparing the second and third columns, we see that even a seemingly 'trivial assumption,' i.e. the aggregation of firms in groups, can bias the measure of aggregate productivity.

Intuitively, as pointed out earlier, there is heterogeneity in the production technology across industries. If not properly accounted for, i.e. in the second column, TFP estimates mismeasure the contribution of certain industries on the aggregate. This reiterates the importance of estimating production functions at a more disaggregated level. Therefore, even within the same TFP estimator, different assumptions about the environment in which firms operate can lead to significantly different predictions.

Further, in the third column, trends in aggregate productivity are found to be distorted when price differences in the output market are not accounted for, i.e. *PC* differs from *IC*.³⁴ This suggests that firms adjust their prices/markups when hit by shocks, which is an important element both at the micro and aggregate levels. Notice that the two middle panels in column 3 reveal patterns that are reasonably similar. However, the micro-mechanisms behind these aggregate fluctuations may differ. For example, TFP estimates under *ICalt* also include demand shocks and markups that potentially drive the components of aggregate productivity in a different way than under *IC*.

4.2 Decomposition

OP Decomposition. In Figure 2 we decompose aggregate productivity and only consider TFP measures that are based on production functions estimated at the industry level, i.e. *Nace*. Each row contains panels for aggregate productivity (first column) and an OP decomposition with a within-firm (second column) and a between-firm (third column) component. Shaded areas represent autocovariance and heteroscedasticity robust 95% confidence intervals (by year). The last column plots estimated markups for the cases of imperfect competition considered.

We see a sharp decline in markups during the financial crisis in 2008 which lasts until 2012 when economic and political uncertainty in the Eurozone prevailed. This provides suggestive evidence that markups are an important margin of adjustment for firms in the presence of shocks.³⁵ Such an adjustment is expected to be prevalent in the decomposition analysis of aggregated micro-units. This becomes clear when we compare the first two rows (in which we do not control for price differences) with the other rows. The trends are sufficiently different to illustrate that it is imperative to control for such price differences in the estimation procedure (Foster et al. 2008).

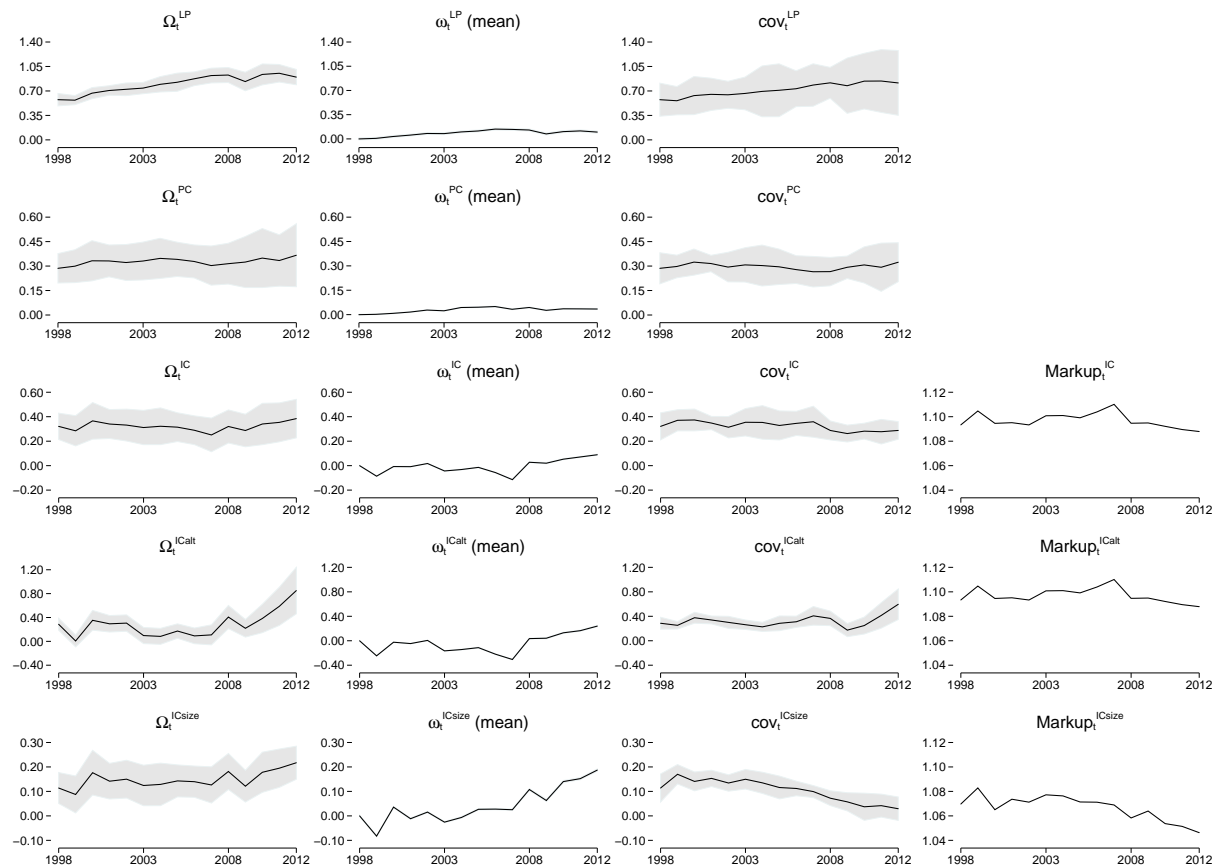
In the third and fourth rows we see that seemingly ‘minor’ differences in a certain set of assumptions may have a considerable impact even within the same estimation procedure. In the fourth row, from 2009 onwards there is a vast increase in the covariance term. This is interpreted

³⁴Foster et al. (2008) are the first to report this result. They mainly focus on how price differences across plants affect the contribution of entering and exiting firms on aggregate productivity growth.

³⁵Our analysis can accommodate only time-varying markups that vary across industries but not across firms within industries. Therefore, we are unable to elaborate on incomplete pass-through (Melitz and Ottaviano 2008; De Loecker et al. 2016). However, the analysis is sufficient to highlight the distortive capacity of markups on the decomposition of aggregate productivity.

as an ‘improvement’ in the reallocation mechanism, which is in line with the within-firm component contributing positively to the evolution of aggregate productivity during that period. However, the row above suggests a relatively constant reallocation process. This discrepancy is generated by the fact that the TFP measure used in the fourth row, $\tilde{\omega}_{it} = \left(\frac{\sigma_t+1}{\sigma_t}\right)\omega_{it} + \chi_{it}$, is an increasing function of ω_{it} (true TFP as identified in the third row), $\frac{\sigma_t+1}{\sigma_t}$ (inverse of markup) and χ_{it} (demand shocks). When the markup decreases, $\tilde{\omega}_{it}$ increases and hence, from the properties of the covariance, the between-firm component increases mechanically.

Figure 2: Aggregate productivity, OP decomposition and markups.

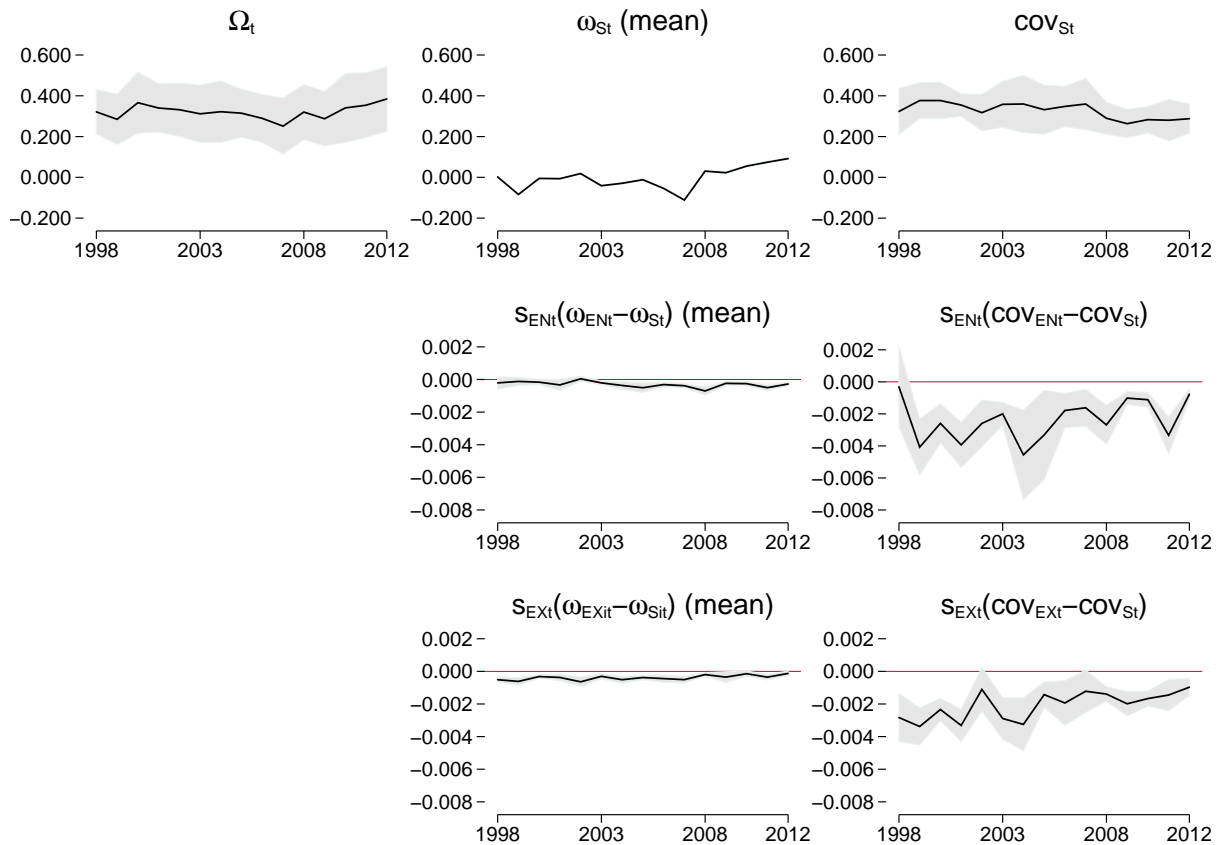


Notes: Authors’ calculations. Ω_t is the share weighted average of the logarithm of productivity with deflated nominal sales as weights and is the sum of the components in the second and third columns. All TFP measures are based on production functions estimated at the industry level (*Nace*). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM. Markup is the average across industries of estimated markups in each year.

Finally, the last row of Figure 2—which uses a similar estimation procedure as the third row but excludes micro firms which account for more than half of the sample—shows that using a restricted sample might skew results and lead to incorrect conclusions. To correct for the biases described above, we proceed with the decomposition analysis for TFP estimated using the *IC* procedure on an industry-by-industry basis for all firms in the sample.

Entry and exit. In Figure 3 we consider a decomposition for the following groups of firms: *Surviving (S)*; *Entering (EN)*; and *Exiting (EX)*. The group of surviving firms is taken as the basis, whereas entering and exiting firms are shown relative to this group in the second and third rows, respectively. Summing both components of the OP decomposition, i.e. mean (second column) and covariance (third column), gives the aggregate productivity for each group (first column).

Figure 3: OP decomposition with entry and exit.



Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all of the components in the second and third columns. TFP is computed from a production function estimated under *IC* at the industry level (*Nace*). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

The last two rows show negative contributions of groups *EN* and *EX* on aggregate productivity relative to *S*. If *EN* had not entered and *EX* had exited earlier, aggregate productivity at time t would have been on average 0.52% higher. On the one hand, if firms are to exit in $t + 1$, they depress aggregate productivity in the present period. Once they exit, aggregate productivity increases by roughly 0.25%. This is because their current aggregate productivity is, on average, lower compared to the group of surviving firms. On the other hand, entering firms (*EN*) reduce aggregate productivity (growth) by 0.27% due to their lower aggregate productivity compared to incumbent (*S*) firms. The gaps in the aggregate productivity of groups *EX* and *EN* relative to

S are mainly driven by the differences in the covariance term. In the last row, the gaps in both components of the OP decomposition have been narrowing over time for the group of exiting firms. These gaps have remained fairly stable over time for entering firms.³⁶ This suggests that the group of exiting firms, unlike the entering ones, were relatively more productive near the end of the sample period and thus contributed less to overall productivity growth.

In absolute terms, the contribution of both EN and EX on aggregate productivity (growth)³⁷ has been small because of their small market shares. This confirms earlier findings by Foster et al. (2008), Maliranta and Määttänen (2015) and Melitz and Polanec (2015) for US manufacturing, the Finish business sector, and Slovenian manufacturing, respectively. Overall, *Surviving* firms in the Belgian manufacturing sector are responsible for the bulk of aggregate productivity (growth).³⁸ This result is not surprising given Belgium's level of economic development.

Both the mean and covariance components of the group of surviving firms (S) are important determinants of the evolution of aggregate productivity.³⁹ Interestingly, they started moving in opposite directions from the start of the financial crisis in 2008. The average productivity of group S in 2007 shifts from a slowly decreasing trend to an increasing one. There is a clear upward trend when we exclude micro firms (see Figure 8 in Appendix A). This suggests that a big part of the variation is driven by micro firms which seem more responsive to changes in their operating environment. These firms are on average less productive and represent more than half of the sample.

The relationship between market shares and productivity has weakened over time, with a considerable drop from 2007 onwards. This suggests that an increase in the presence of resource misallocation prevented the Belgian manufacturing sector from reaching its full potential. Van Beveren and Vanormelingen (2014) use the same dataset for the period 1997-2009 and find that resource reallocation is a positive and stable contributor to aggregate productivity growth. However, their estimates do not control for price bias and results are driven by changes in markups. This can be seen from the fact that our results in column PC in Figure 2 qualitatively verify their reported estimates for the respective period. Overall, after the outbreak of the financial crisis, the increase in average productivity of incumbent firms dominated the increase in the misallocation of resources, and determined aggregate productivity (growth).

Trade. In Figure 4 we further decompose surviving firms in four mutually exclusive groups based on their engagement in international trade: *Domestic* ($S, 1$); *Exporting* ($S, 2$); *Importing*

³⁶Melitz and Polanec (2015) report similar results when decomposing aggregate productivity growth in Slovenia with their preferred decomposition method. The results can also be reconciled with the concept of dynamic selection introduced by Sampson (2016).

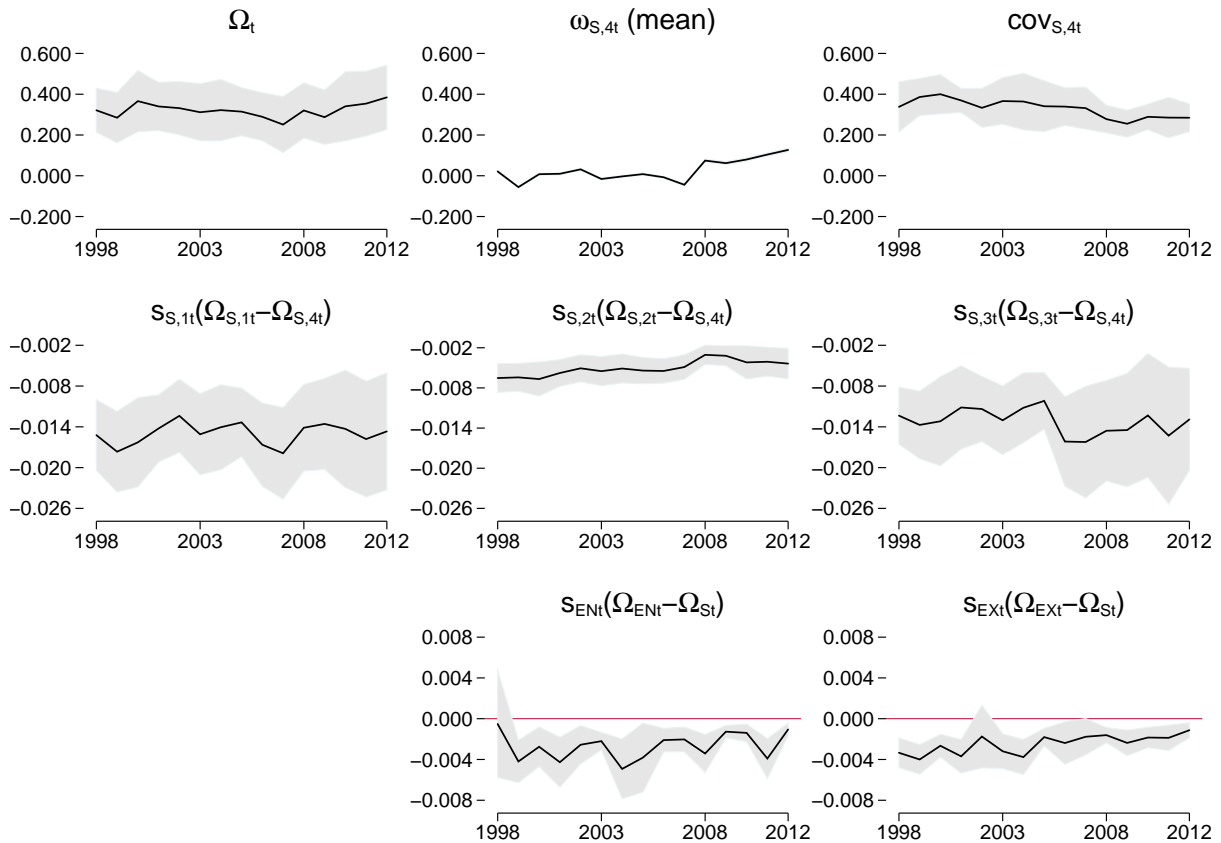
³⁷See aggregate productivity growth in Figure 7 in Appendix A.

³⁸Note that both entry and exit are defined on a yearly basis. Therefore, fast growing young firms of high potential are expected to be in the *Surviving* category of our sample. Dumont et al. (2016) find that across the EU, surviving entrants gradually become more efficient and contribute positively to aggregate productivity growth.

³⁹For further empirical support on the mean component see: Foster et al. (2008). For further empirical support on the covariance component see: Aw et al. (2001); Foster et al. (2001, 2006); and Melitz and Polanec (2015).

($S, 3$); and *Two-way-trading* ($S, 4$) firms. Figure 4 shows that predominantly incumbent two-way traders determine the evolution of aggregate productivity. The trends of the OP components for group $S, 4$ are in line with those for group S in the previous figure. The other groups lag behind, but for exporting survivor firms ($S, 2$) we observe some signs of convergence up to 2007 followed by a divergence thereafter.

Figure 4: OP decomposition with entry, exit and trade

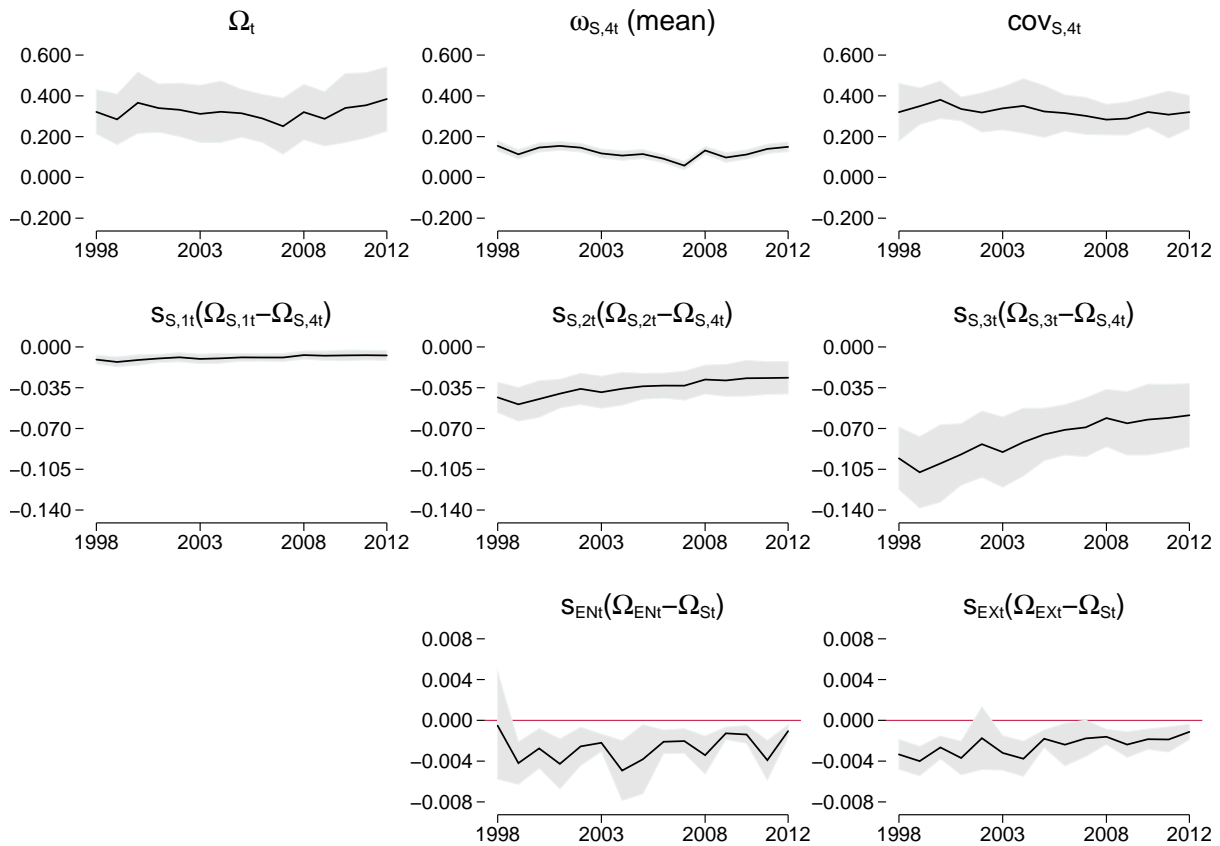


Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all other components in the panel. TFP is computed from a production function estimated under *IC* at the industry level (*Nace*). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

It appears that firms that exclusively export were more affected by the financial and Euro-zone crisis than *Two-way-trading*. These firms are likely not diversified in terms of exporting destinations and therefore suffer more from any negative macroeconomic shocks. In the Mayer et al. (2014) context, in response to trade/macro-economic events, these firms need to skew their sales towards their better performing products in order to increase their productivity. However, for *Exporting* firms this adjustment is expected to be smaller compared to *Two-way-trading* firms, since, in the case of Belgium, they are relatively small firms that sell less products to fewer countries (Bernard et al. 2014). Therefore, the scope for adjustment in the product margin is limited for these firms.

Size. In Figure 5 we decompose the set of surviving firms in size-based mutually exclusive groups. Four size categories are determined using the EU's definition that depends on staff headcount and turnover criteria (European Commission 2017): *Micro* ($S, 1$); *Small* ($S, 2$); *Medium* ($S, 3$); and *Large* ($S, 4$). We find that *Large* firms drive aggregate productivity, while other size groups remain relatively unproductive. This result is in line with findings of significant TFP differences between small and large firms in Van Biesebroeck (2005). Interestingly, the less productive *Micro*, *Small* and *Medium* groups follow a similar path of convergence over time.

Figure 5: OP decomposition with entry, exit and size



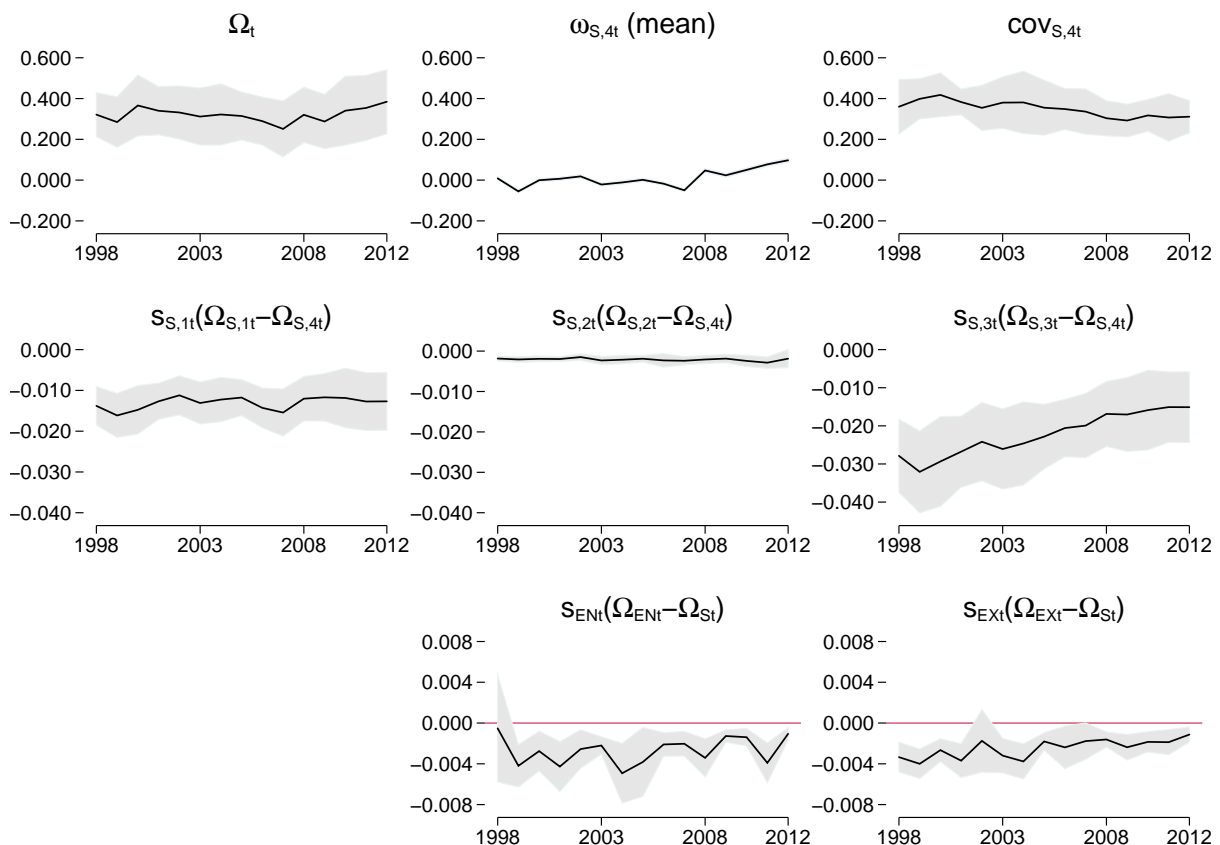
Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all other components in the panel. TFP is computed from a production function estimated under *IC* at the industry level (*Nace*). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

Trade and Size. Results presented in Figure 5 potentially mask heterogeneity induced by further firm-characteristics. Therefore, we unravel potential heterogeneity in size groups in Figure 6 by splitting the set of surviving firms in four mutually exclusive groups, based on size and trade activity: *Small & Domestic* ($S, 1$); *Large & Domestic* ($S, 2$); *Small & Trade* ($S, 3$); and *Large & Trade* ($S, 4$).⁴⁰ From Figure 6 it is clear that group $S, 4$ determines the evolution

⁴⁰*Small* refers to firms with less than 50 employees and at least €10 million turnover, and *Large* includes the rest of the firms in the sample. *Trade* includes any type of trade activity, i.e. firms that are not *Domestic*.

of aggregate productivity. This is in line with the majority of exports being accounted for by few exporting firms that have more employees and are on average more productive than smaller exporters (Bernard et al. 2014).

Figure 6: OP decomposition with entry, exit, trade and size



Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all other components in the panel. TFP is computed from a production function estimated under *IC* at the industry level (*Nace*). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

In the second row, we see that the convergence trend described above is existent only for the group of non-domestic firms. This confirms that the trends for smaller-sized firms above were driven by other firm characteristics. Over time, the increase in the within-firm component for this group of firms dominates the decrease in the contribution of the between-firm component. Overall, this translates to large firms that engage in international trade undergoing a substantial increase in their productivity, despite lower levels of resource reallocation. Our results indicate the importance of international trade in shaping aggregate productivity (growth) for a small open economy such as Belgium.

5 Conclusion

The evolution of aggregate productivity is an important determinant of economic growth. A large literature has tried to understand the micro-origins of aggregate productivity and various methods for its computation and decomposition have been put forth. However, there is substantial heterogeneity in reported results, mainly for two reasons. First, biased firm-level productivity measures skew aggregate productivity. Second, certain firm attributes that determine aggregate productivity growth remain uncovered.

In this paper we account for these cases and estimate TFP under various assumptions. As such, we assess the biases by contrasting different productivity measures for a given decomposition method and weights. After controlling for such biases, we introduce a new dimension in the decomposition based on firm attributes. This allows us to assess whether there is a handful of firms driving aggregate productivity.

For the analysis, we use a detailed firm-level dataset for the Belgian manufacturing sector, over the period 1998-2012. Our results can be summarised as follows. First, we demonstrate and confirm important biases arising from ignoring output-price differences across firms, estimating physical productivity under different assumptions (i.e. timing of demand shocks, estimating production functions at the manufacturing instead of the industry level, and selection of samples with larger firms). Failing to correct for these biases may thus result in false conclusions about the evolution of aggregate productivity and its decomposed components.

Second, after controlling for such biases, we find that the reallocation of resources across firms has been steadily decreasing since 1998, with a rapid drop during the 2008 financial crisis. Inversely, we find that the decreasing trend in average firm-productivity reversed during the 2008 financial crisis. Overall, the within-firm component of incumbent firms drives the evolution of aggregate productivity, especially after the 2008 financial crisis.

We exploit the richness of the data, and find that two-way traders are the main contributors of aggregate productivity (growth). It appears that learning is an important mechanism in explaining such productivity differences over time. Interestingly, firm-size in itself is not a determining factor of aggregate productivity compared to the internationalisation of firms.

Firms increase their productivity over time and those that are most successful are both larger in size and more deeply engaged in internationalisation. All other firms lag behind and prevent aggregate productivity from reaching its full potential. Knowing which type of firms have significantly been driving the economy or suffering during good and bad times is expected to provide policymakers and institutions with a strong reference point for shaping future policies.

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Appendices

A Additional Figures and Tables

Table 3: List of NACE Rev.2 2-digit industries in the manufacturing sector.

A*38	Division	Description
CA	10; 11; 12	Manufacture of food products; Manufacture of beverages; Manufacture of tobacco products
CB	13; 14; 15	Manufacture of textiles; Manufacture of wearing apparel; Manufacture of leather and related products
CC	16; 17; 18	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials; Manufacture of paper and paper products; Printing and reproduction of recorded media
CE	20	Manufacture of chemicals and chemical products
CF	21	Manufacture of basic pharmaceutical products and preparations
CG	22; 23	Manufacture of rubber and plastic products; Manufacture of other non-metallic mineral products
CH	24; 25	Manufacture of basic metals; Manufacture of fabricated metal products, except machinery & equip.
CI	26	Manufacture of computer, electronic and optical products
CJ	27	Manufacture of electrical equipment
CK	28	Manufacture of machinery and equipment n.e.c.
CL	29; 30	Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment
CM	31; 32; 33	Manufacture of furniture; Other manufacturing; Repair and installation of machinery and equipment

Note: A*38 code refers to the intermediate SNA/ISIC aggregation.

Table 4: Long-run Effects from Learning by Trading

Learning by ... in %	(1) <i>PC</i>	(2) <i>ICalt</i>	(3) <i>IC</i>	(4) <i>ICsize</i>
<i>Exporting_{it-1}</i>	1.78***	3.65***	3.09***	0.96
<i>Importing_{it-1}</i>	4.15***	4.51***	4.16***	3.60***
<i>Two-way-trading_{it-1}</i>	2.87***	4.60***	4.24***	4.09***

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The long-run effects are calculated using estimates from equation (2). Each column is computed as the product of the average short-run effects on future TFP from exporting, importing and two-way trading times $1/(1 - \rho) * 100$; where ρ is the average persistence of TFP. Each column is estimated using all firms in the manufacturing sector. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure.

Table 5: Production Function Estimates under PC

	NACE Rev.2, A *38 SNA/ISIC aggregation											
	CA	CB	CC	CE	CF	CG	CH	CI	CJ	CK	CL	CM
$\tilde{\theta}_{it}^k$	0.057*** (0.003)	0.067*** (0.004)	0.054*** (0.004)	0.046*** (0.011)	-0.005 (0.032)	0.051*** (0.005)	0.048*** (0.003)	0.037*** (0.010)	0.030*** (0.008)	0.031*** (0.005)	0.040*** (0.012)	0.049*** (0.004)
$\tilde{\theta}_{it}^l$	0.232*** (0.004)	0.251*** (0.006)	0.267*** (0.009)	0.231*** (0.015)	0.290*** (0.048)	0.242*** (0.006)	0.307*** (0.006)	0.304*** (0.011)	0.280*** (0.012)	0.284*** (0.007)	0.249*** (0.014)	0.265*** (0.005)
$\tilde{\theta}_{it}^m$	0.640*** (0.003)	0.647*** (0.005)	0.624*** (0.003)	0.716*** (0.007)	0.663*** (0.012)	0.668*** (0.004)	0.600*** (0.003)	0.579*** (0.007)	0.641*** (0.007)	0.652*** (0.004)	0.695*** (0.008)	0.618*** (0.004)
$\tilde{R}\tilde{T}S_{it}$	0.929*** (0.003)	0.966*** (0.005)	0.944*** (0.007)	0.994*** (0.010)	0.948*** (0.032)	0.961*** (0.005)	0.955*** (0.005)	0.919*** (0.009)	0.951*** (0.009)	0.966*** (0.005)	0.984*** (0.010)	0.932*** (0.004)
$\tilde{R}\tilde{T}S_{it} - 1$	-0.071*** (0.003)	-0.034*** (0.005)	-0.056*** (0.007)	-0.006 (0.010)	-0.052* (0.032)	-0.039*** (0.005)	-0.045*** (0.005)	-0.081*** (0.009)	-0.049*** (0.009)	-0.034*** (0.005)	-0.016 (0.010)	-0.068*** (0.004)
Learning by ...												
$\tilde{E}xporting_{it-1}$	0.006*** (0.001)	0.004 (0.003)	-0.001 (0.001)	0.014 (0.009)	0.024 (0.038)	0.002 (0.002)	0.002** (0.001)	0.007 (0.006)	-0.332*** (0.004)	-0.000 (0.002)	-0.002 (0.005)	0.000 (0.002)
$\tilde{I}mporting_{it-1}$	0.004*** (0.001)	0.008*** (0.002)	0.004*** (0.001)	0.012* (0.007)	0.005 (0.042)	0.003*** (0.001)	0.002** (0.001)	0.006 (0.004)	-0.210*** (0.003)	0.006*** (0.002)	0.001 (0.003)	0.004*** (0.001)
$\tilde{T}wo-way-trading_{it-1}$	0.005*** (0.001)	0.010*** (0.001)	0.006*** (0.001)	0.006 (0.009)	0.007 (0.032)	0.004*** (0.001)	0.002* (0.001)	0.008*** (0.003)	-0.907*** (0.002)	0.001 (0.001)	-0.002 (0.006)	0.006*** (0.001)
Observations	30187	11622	24119	4757	836	15617	32006	3938	3397	9710	2974	13730

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all firms in the respective industry. $\tilde{\theta}_{it}^k$, $\tilde{\theta}_{it}^l$ and $\tilde{\theta}_{it}^m$ are averages of the estimated output elasticities of capital, labour and material respectively. $\tilde{R}\tilde{T}S_{it}$ is the average of the estimated RTS . The lower panel gives the average, of the estimated in equation (2), effects on future TFP from exporting, importing and two-way trading. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Table 6: Production Function Estimates under IC

	NACE Rev.2, A *38 SNA/ISIC aggregation											
	CA	CB	CC	CE	CF	CG	CH	CI	CJ	CK	CL	CM
$\tilde{\theta}_{it}^k$	0.064*** (0.003)	0.077*** (0.006)	0.069*** (0.004)	0.054*** (0.011)	0.025 (0.050)	0.047*** (0.008)	0.050*** (0.004)	0.059*** (0.010)	0.037*** (0.011)	0.036*** (0.006)	0.039** (0.016)	0.063*** (0.004)
$\tilde{\theta}_{it}^l$	0.252*** (0.005)	0.283*** (0.009)	0.286*** (0.006)	0.232*** (0.017)	0.332*** (0.070)	0.264*** (0.008)	0.329*** (0.005)	0.323*** (0.013)	0.293*** (0.015)	0.304*** (0.008)	0.275*** (0.019)	0.306*** (0.007)
$\tilde{\theta}_{it}^m$	0.705*** (0.005)	0.725*** (0.012)	0.692*** (0.007)	0.763*** (0.010)	0.694*** (0.022)	0.723*** (0.008)	0.654*** (0.004)	0.628*** (0.010)	0.690*** (0.012)	0.699*** (0.007)	0.759*** (0.018)	0.693*** (0.008)
$\tilde{RT}S_{it}$	1.022*** (0.006)	1.085*** (0.015)	1.046*** (0.009)	1.049*** (0.014)	1.050*** (0.047)	1.034*** (0.013)	1.032*** (0.006)	1.010*** (0.013)	1.020*** (0.019)	1.038*** (0.009)	1.073*** (0.024)	1.062*** (0.013)
$\tilde{RT}S_{it} - 1$	0.022*** (0.006)	0.085*** (0.015)	0.046*** (0.009)	0.049*** (0.014)	0.050 (0.047)	0.034*** (0.013)	0.032*** (0.006)	0.010 (0.013)	0.020 (0.019)	0.038*** (0.009)	0.073*** (0.024)	0.062*** (0.013)
\tilde{Markup}_t	1.102*** (0.006)	1.120*** (0.015)	1.108*** (0.010)	1.063*** (0.009)	1.046*** (0.028)	1.082*** (0.011)	1.089*** (0.004)	1.088*** (0.010)	1.078*** (0.016)	1.073*** (0.009)	1.092*** (0.021)	1.123*** (0.013)
Learning by ...												
$Exporting_{it-1}$	0.009*** (0.001)	0.006* (0.003)	-0.001 (0.001)	0.017** (0.007)	0.072 (0.230)	0.002 (0.002)	0.002* (0.001)	0.015** (0.008)	0.002 (0.004)	-0.000 (0.003)	0.004 (0.006)	0.002 (0.002)
$Importing_{it-1}$	0.008*** (0.002)	0.011*** (0.002)	-0.001 (0.001)	0.008 (0.006)	0.083 (0.155)	0.002 (0.002)	0.002* (0.001)	0.018*** (0.006)	0.005 (0.004)	0.008*** (0.002)	0.007 (0.005)	0.006*** (0.002)
$Two\text{-}way\text{-}trading_{it-1}$	0.010*** (0.002)	0.011*** (0.003)	0.001 (0.001)	0.000 (0.008)	0.056 (0.067)	0.001 (0.002)	-0.000 (0.001)	0.023*** (0.004)	0.003 (0.004)	0.002 (0.002)	0.016** (0.006)	0.009*** (0.002)
Observations	30187	11636	24052	4764	836	15629	32032	3938	3397	9702	2954	13726

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all firms in the respective industry. $\bar{\theta}_{it}^k$, $\bar{\theta}_{it}^l$ and $\bar{\theta}_{it}^m$ are averages of the estimated output elasticities of capital, labour and material respectively. $\bar{RT}S_{it}$ is the average of the estimated RTS_{it} . \bar{Markup}_t is the average of the estimated annual markups. The lower panel gives the average, of the estimated in equation (2), effects on future TFP from exporting, importing and two-way trading. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Table 7: Production Function Estimates under *ICalt*

	NACE Rev.2, A *38 SNA/ISIC aggregation											
	CA	CB	CC	CE	CF	CG	CH	CI	CJ	CK	CL	CM
$\tilde{\theta}_{it}^k$	0.064*** (0.003)	0.077*** (0.006)	0.069*** (0.004)	0.054*** (0.011)	0.025 (0.056)	0.049*** (0.005)	0.062*** (0.003)	0.057*** (0.010)	0.045*** (0.011)	0.038*** (0.006)	0.039*** (0.014)	0.063*** (0.004)
$\tilde{\theta}_{it}^l$	0.255*** (0.005)	0.283*** (0.009)	0.286*** (0.006)	0.232*** (0.017)	0.332*** (0.070)	0.262*** (0.008)	0.329*** (0.005)	0.328*** (0.013)	0.300*** (0.015)	0.305*** (0.008)	0.275*** (0.019)	0.306*** (0.008)
$\tilde{\theta}_{it}^m$	0.705*** (0.005)	0.725*** (0.012)	0.692*** (0.007)	0.763*** (0.010)	0.694*** (0.022)	0.723*** (0.008)	0.654*** (0.004)	0.629*** (0.010)	0.691*** (0.012)	0.699*** (0.007)	0.759*** (0.018)	0.693*** (0.008)
$\tilde{RT}S_{it}$	1.024*** (0.006)	1.085*** (0.015)	1.046*** (0.009)	1.049*** (0.014)	1.050*** (0.052)	1.035*** (0.011)	1.045*** (0.005)	1.013*** (0.013)	1.036*** (0.018)	1.042*** (0.009)	1.073*** (0.023)	1.062*** (0.013)
$\tilde{RT}S_{it} - 1$	0.024*** (0.006)	0.085*** (0.015)	0.046*** (0.009)	0.049*** (0.014)	0.050 (0.052)	0.035*** (0.011)	0.045*** (0.005)	0.013 (0.013)	0.036* (0.018)	0.042*** (0.009)	0.073*** (0.023)	0.062*** (0.013)
\tilde{Markup}_t	1.102*** (0.006)	1.120*** (0.015)	1.108*** (0.010)	1.063*** (0.009)	1.046*** (0.028)	1.083*** (0.011)	1.089*** (0.004)	1.089*** (0.010)	1.078*** (0.016)	1.073*** (0.009)	1.092*** (0.021)	1.123*** (0.013)
Learning by ...												
$Exporting_{it-1}$	0.007*** (0.001)	0.005 (0.003)	-0.001 (0.001)	0.016** (0.008)	0.071 (0.051)	0.001 (0.002)	0.001 (0.001)	0.009 (0.007)	0.001 (0.004)	-0.001 (0.002)	0.002 (0.005)	0.002 (0.002)
$Importing_{it-1}$	0.006*** (0.001)	0.010*** (0.002)	-0.000 (0.001)	0.008 (0.006)	0.086* (0.050)	0.002 (0.002)	0.000 (0.001)	0.008 (0.006)	0.004 (0.004)	0.006*** (0.002)	0.004 (0.005)	0.005*** (0.002)
$Two\text{-}way\text{-}trading_{it-1}$	0.009*** (0.001)	0.009*** (0.002)	0.001 (0.001)	-0.002 (0.007)	0.062 (0.050)	0.002 (0.002)	-0.002 (0.001)	0.010* (0.005)	0.000 (0.003)	0.001 (0.002)	0.011* (0.006)	0.007*** (0.001)
Observations	30187	11636	24052	4764	836	15629	32032	3938	3397	9702	2954	13726

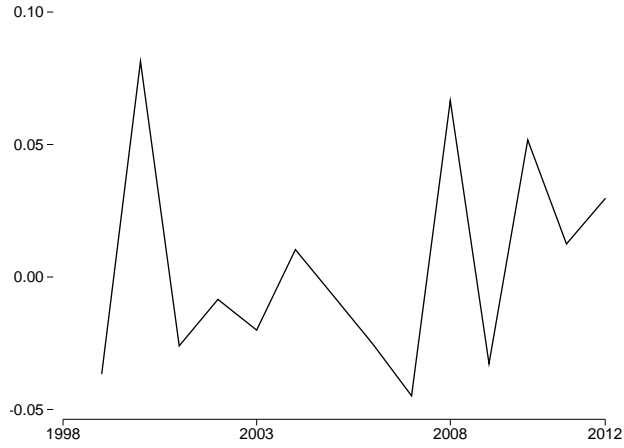
Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all firms in the respective industry. $\tilde{\theta}_{it}^k$, $\tilde{\theta}_{it}^l$ and $\tilde{\theta}_{it}^m$ are averages of the estimated output elasticities of capital, labour and material respectively. $\tilde{RT}S_{it}$ is the average of the estimated RTS_{it} . \tilde{Markup}_t is the average of the estimated annual markups. The lower panel gives the average, of the estimated in equation (2), effects on future TFP from exporting, importing and two-way trading. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Table 8: Production Function Estimates under $ICsize$

	NACE Rev.2, A *38 SNA/ISIC aggregation											
	CA	CB	CC	CE	CF	CG	CH	CI	CJ	CK	CL	CM
$\tilde{\theta}_{it}^k$	0.076*** (0.005)	0.052*** (0.010)	0.057*** (0.008)	0.063*** (0.016)	0.008 (0.091)	0.053*** (0.007)	0.058*** (0.007)	0.003 (0.029)	0.042*** (0.012)	0.024*** (0.006)	0.028 (0.018)	0.047*** (0.005)
$\tilde{\theta}_{it}^l$	0.197*** (0.008)	0.257*** (0.019)	0.282*** (0.018)	0.192*** (0.023)	0.299 (0.316)	0.227*** (0.009)	0.322*** (0.012)	0.326*** (0.046)	0.291*** (0.033)	0.313*** (0.012)	0.240*** (0.025)	0.257*** (0.012)
$\tilde{\theta}_{it}^m$	0.799*** (0.007)	0.742*** (0.033)	0.737*** (0.037)	0.762*** (0.011)	0.684*** (0.239)	0.729*** (0.012)	0.683*** (0.015)	0.694*** (0.027)	0.701*** (0.058)	0.690*** (0.011)	0.795*** (0.041)	0.707*** (0.018)
$\tilde{RT}S_{it}$	1.072*** (0.009)	1.051*** (0.048)	1.076*** (0.050)	1.017*** (0.019)	0.991** (0.419)	1.008*** (0.015)	1.064*** (0.022)	1.022*** (0.052)	1.034*** (0.087)	1.027*** (0.014)	1.062*** (0.056)	1.012*** (0.026)
$\tilde{RT}S_{it} - 1$	0.072*** (0.009)	0.051 (0.048)	0.076 (0.050)	0.017 (0.019)	-0.009 (0.419)	0.008 (0.015)	0.064*** (0.022)	0.022 (0.052)	0.034 (0.087)	0.027* (0.014)	0.062 (0.056)	0.012 (0.026)
\tilde{Markup}_t	1.078*** (0.007)	1.087*** (0.048)	1.092*** (0.054)	1.026*** (0.012)	1.025*** (0.357)	1.031*** (0.015)	1.077*** (0.023)	1.073*** (0.039)	1.065*** (0.086)	1.039*** (0.013)	1.104*** (0.053)	1.051*** (0.025)
Learning by ...												
$Exporting_{it-1}$	0.003* (0.002)	0.012 (0.224)	0.001 (0.115)	0.008 (0.014)	-0.010 (0.420)	-0.002 (0.002)	0.001 (0.001)	-0.014 (0.024)	-0.002 (0.052)	-0.003 (0.003)	0.002 (0.322)	-0.002 (0.002)
$Importing_{it-1}$	0.001 (0.001)	0.010 (0.084)	0.001 (0.149)	-0.006 (0.009)	0.027 (0.166)	0.000 (0.001)	0.001 (0.001)	0.012 (0.016)	0.005 (0.126)	0.002 (0.002)	0.007 (0.174)	0.007*** (0.002)
$Two\text{-}way\text{-}trading_{it-1}$	0.002 (0.002)	0.014 (0.062)	0.000 (0.105)	-0.010 (0.010)	0.015 (0.253)	-0.002 (0.001)	-0.000 (0.001)	0.024 (0.015)	0.004 (0.125)	0.002 (0.002)	0.009 (0.080)	0.007*** (0.002)
Observations	11551	6424	8753	3420	643	8714	13995	1574	1886	5144	1775	5128

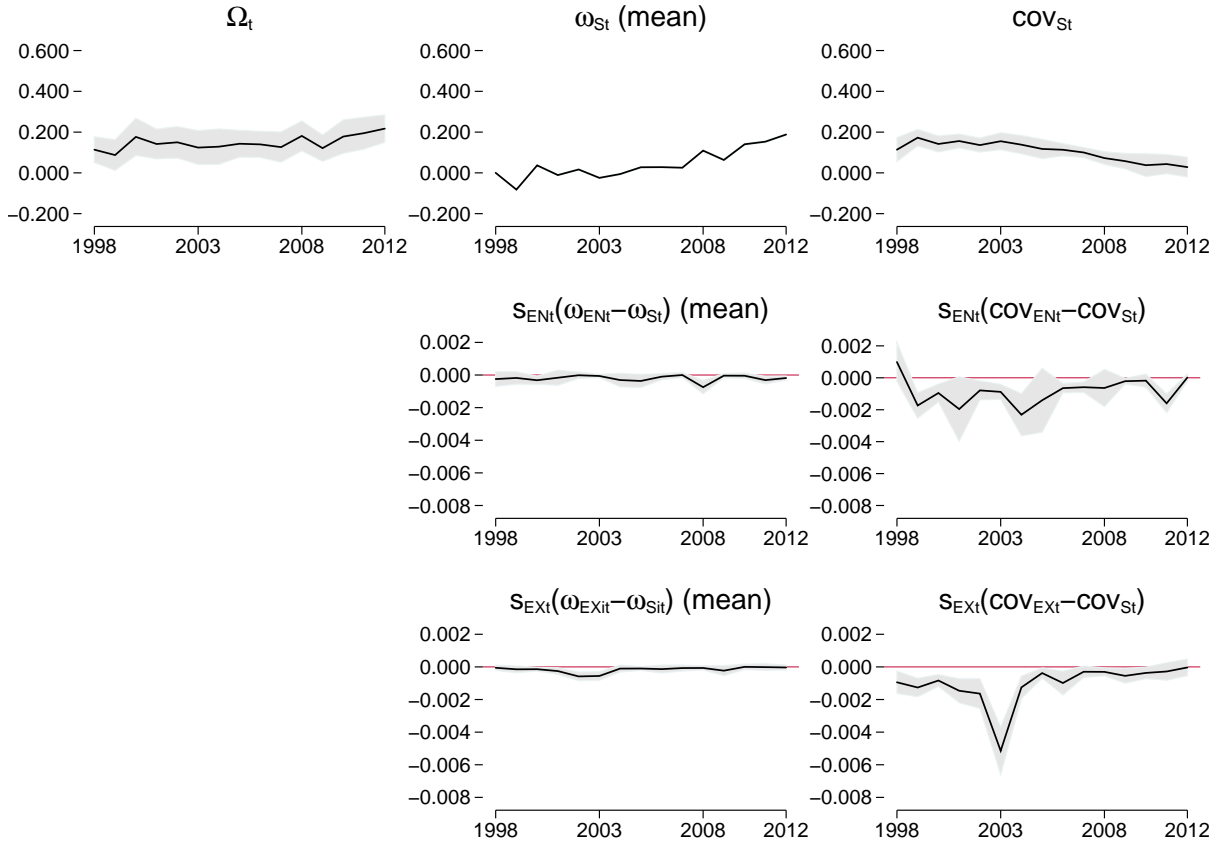
Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Each column is estimated using all firms in the respective industry. $\tilde{\theta}_{it}^k$, $\tilde{\theta}_{it}^l$ and $\tilde{\theta}_{it}^m$ are averages of the estimated output elasticities of capital, labour and material respectively. $\tilde{RT}S_{it}$ is the average of the estimated RTS_{it} . \tilde{Markup}_t is the average of the estimated annual markups. The lower panel gives the average, of the estimated in equation (2), effects on future TFP from exporting, importing and two-way trading. Standard errors are block-bootstrapped with 200 replications over the GNR two-step estimation procedure and reported in parentheses below point estimates.

Figure 7: Aggregate productivity growth.



Notes: Authors' calculations. This is the first year difference of Ω_t . Ω_t is the share weighted average of TFP with deflated nominal sales as weights. TFP is computed from a production function estimated under *IC* at the industry level (*Nace*).

Figure 8: OP decomposition with entry and exit.



Notes: Authors' calculations. Ω_t is the share weighted average of TFP with deflated nominal sales as weights and is the sum of all of the components in the second and third columns. TFP is computed from a production function estimated under *IC* at the industry level (*Nace*). The shaded area represents the autocovariance and heteroscedasticity robust 95% confidence interval, for each point estimate of the OP decomposition, following the procedure of HIM.

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Governor of the National Bank of Belgium

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