

# Productivity, Markups, and Reallocation: Evidence from French Manufacturing Firms\*

Enrico De Monte<sup>†</sup>

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## Abstract

This paper investigates the evolution of aggregate productivity and markups among French manufacturing firms between 1994 and 2016, by focusing on the role of reallocation with respect to both aggregate measures. The reallocation of output to high-markup firms is often accompanied by the reallocation to high-productivity firms, which increases the aggregate of both markups and productivity. In this case, negative effects of markups, as a source of misallocation and welfare reduction, are mitigated by higher allocative efficiency. Instead, if aggregate markups rise without reallocation towards high-productivity firms, the economy takes larger damages. As a key finding the study shows that before 2000 both aggregate productivity and markups increase by the reallocation of sales shares towards high-productivity and high markup-firms. Post-2000, instead, the contribution of reallocation to aggregate productivity becomes negligible, inducing a slowdown in aggregate productivity growth, while I measure persistent reallocation of sales shares from lower to higher markup firms. This has important policy implications, which are discussed in the paper.

*Keywords:* productivity decomposition, production function estimation, business dynamism, market power, entry and exit.

JEL Classification: C13; D21; D24; L16; L60; O47

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<sup>†</sup>E-mail: enrico.demonte@zew.de. Affiliation: ZEW - Leibniz-Centre for European Economic Research. Address: L 7 1, 68161 Mannheim, Germany. ORCID: 0000-0001-7032-9475.

# 1 Introduction

Productivity and markups are tightly connected economic outcomes that affect welfare and by that our standard of living, which is why they are such relevant measures for industrial policy. An increasing level of productivity, i.e. an increase in the efficiency with which production inputs are transformed into output, is usually related to higher level of output and long-term growth both at the firm-level and for an entire economy (Mankiw et al., 1992; Prescott, 1998; Hall and Jones, 1999; Caselli, 2005). Instead, markups, i.e. firms' ability to open a gap between output prices and marginal costs, are considered to act as distortions to the economy, reducing investment in capital and innovation activity as well as the labor share (De Loecker et al., 2020; Autor et al., 2020). At the aggregate level, both productivity and markups not only change by individual firms' behaviour but also by the process of resource reallocation among firms, that is, when sales shares shift among producers.<sup>1</sup> For instance, the study shown by De Loecker et al. (2020) documented a massive increase in the aggregate markup between 1980-2016 due to reallocation of output towards high-markup firms.<sup>2</sup> Even though the evolution of aggregate markup is an important statistic to look at, considering its evolution by its own does not allow to draw relevant policy implications. The question is how do the dynamics driving aggregate markup evolution relate to the evolution of aggregate productivity. This paper aims to respond to this question by investigating jointly aggregate productivity and markups while looking particularly at the role played by output reallocation. Subsequently, policy implications are discussed.

To be more precise, in the case where output over time becomes increasingly allocated to both high-productivity and high-markup firms, i.e. if technologically advanced firms with higher markups grow faster than their competitors, policy interventions targeting high-markup firms' size could have negative effects, since, from a welfare perspective, high-markup firms should even produce more (Baqee and Farhi, 2020). In the case, instead, where output reallocation towards high-markup firms is not accompanied by reallocation to high-productivity firms - potentially occurring when dominant firms behave anti-competitively - competition and entry enhancing policies, aiming at reducing the size of high-markup firms by fostering reallocation towards smaller but efficient firms, would be beneficial.

To investigate these dynamics I use administrative data of French manufacturing firms

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<sup>1</sup>Aggregate productivity and markups are usually measured by a sales share weighted average of individual firms' productivity and markups allowing to decompose the aggregate measure into the contribution to aggregate growth related to individual firms' (average) change in aggregate productivity/markups and the one related to reallocation of sales shares (Van Biesebroeck, 2008a).

<sup>2</sup>The amplitude of the rise in the aggregate markup is controversially discussed in the literature, which is related to the estimation method of the production function (Demirer, 2020), the representativeness of public firms in US data (Traina, 2018), and measurement of marginal costs (Hall, 2018). Basu (2019) provides an overview on the literature analysing trends of the markup by comparing methods and results.

between 1994 and 2016. The estimation of a gross output translog production function, following [Akerberg et al. \(2015\)](#), allows to derive firm-level productivity. Further, I estimate markups by applying the production-approach pioneered by [Hall \(1986, 1988\)](#) and [De Loecker and Warzynski \(2012\)](#). Reallocation effects to both aggregate productivity and markups are investigated by the use of an appropriate decomposition method by taking into account firm entry and exit. Analysing the link between productivity and markups growth with a particular look at the role of reallocation, based on a joint measurement approach, and over such long time period, to the best of my knowledge, has not yet been done in the literature.

While staying descriptive, my results for French manufacturing firms show that there is an initial period between 1994 and around 2000 where both measures are positively impacted by reallocation effects, i.e. aggregate productivity and markups rise through the reallocation of sales shares towards high-productivity and high-markup firms. Post-2000, however, the contribution of reallocation to aggregate productivity growth slows down and, importantly, becomes disconnected from the contribution of reallocation to aggregate markups, which remains considerable. There is, hence, evidence that markups over time relate differently to aggregate productivity, leading to different conclusions in terms of policy intervention.

In the literature there is growing attention to the relation between markups and productivity, both at the firm-level and at the aggregate level. Higher production efficiency reduces marginal costs allowing a firm to increase its markups at a given output price level. In this situation, profit maximizing firms face little incentives to increase their production as this would decrease output price and consequently reduce the markup. Hence, markups create a wedge that leads to misallocation of output ([Hopenhayn, 2014](#); [Peters, 2020](#)). Mostly, high-markup firms are important drivers for higher productivity levels at the aggregate. However, without the markup wedge, allocative efficiency and so aggregate productivity would be higher.<sup>3</sup> In an general equilibrium approach, [Baqaee and Farhi \(2020\)](#) show for the US economy that output reallocation from low-markup to high-markup firms accounted for 50% of the productivity growth between 1997 and 2015 as these firms were also very efficient. However, the authors further demonstrate that if markups were removed, aggregate productivity could have grown by 15% higher than actually measured. [Edmond et al. \(2023\)](#) measure the effect of misallocation induced by markups on aggregate productivity using both a monopolistic and a oligopolistic model. Calibrating the model based on US data of manufacturing firms for the period 1972-2012, they show that markups account for a reduction in aggregate productivity between 2% - 6%. [De Monte and Koebel \(2024\)](#) present a Cournot model with heterogeneous firms

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<sup>3</sup>Allocative efficiency can be distinguished in two types: first, static allocative efficiency, i.e. when more productive firms produce more; and second, dynamic allocative efficiency, i.e. when output over time shifts to more productive firms ([Foster et al., 2001](#); [Haltiwanger, 2011](#)). In this study, I relate to the second type.

in fixed and variable costs, empirically estimated based on data of French manufacturing firms and find for the specific year 2015 only small effects of implied misallocation through markups. Here, closing down inefficient firms and reallocating output to more efficient firms yields the largest effects on aggregate productivity and welfare.

While these studies use structural competition models and simulation methods to quantify the reduction of aggregate productivity and welfare by markups, my approach involves estimates deduced from a production function, focusing on the process of reallocation of output and its effect on aggregate markups and productivity growth. My study contributes to the literature by showing for French manufacturing firms that there is quite an instability in how reallocation affects aggregate markups and productivity over time. [Syverson \(2019\)](#) and [Berry et al. \(2019\)](#) provide broader overviews on the literature w.r.t. markups and macroeconomic implications. The latter also shed light on shifts in fixed/sunk costs and changes in input market (monopsony) power, as determinants of the level of firms' markup, which, however, I do not take into account in this paper.<sup>4</sup>

The estimation of both firm-level productivity and markups lies at the heart of my study. In this regard, especially the use of revenue data to estimate productivity and markups, as I do, has been discussed controversially in the literature. [Klette and Griliches \(1996\)](#) showed that when estimating production functions, the use of revenue data leads to downwards biased output elasticities, which consequently also affects the estimation of productivity and markups. Further, [Bond et al. \(2021\)](#) demonstrate that using revenue data without controlling for individual firms' output prices not only produces biased estimates but is not informative as it turns out that the obtained markup estimator is identically equal to one under such a setting. Hence, [Hashemi et al. \(2022\)](#) pose the question how to interpret the estimate of the markup based on revenue data, when it empirically differs from one. The authors show that instead of output distortions, the obtained markup estimate rather represents input distortions, given inputs are measured in quantities. In contrast, [Foster et al. \(2008\)](#) show that there is a high correlation between quantity- and revenue-based productivity estimates, hence revenue-based productivity carries some useful information depending on the purpose of the study. Similarly, [De Ridder et al. \(2022\)](#) argue that using revenue data the production approach provides useful information in terms of the distribution of estimated firm-level markups, while it does not yield informative estimates of specific moments of the distribution, such as the mean. Evidence is provided using French firm-level data comprising output measures of both revenues and quantities, whereby the authors show that revenue- and quantity-based markups highly correlate. Followed by the presentation of the results, I will carefully discuss these issues to put my results into perspective.

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<sup>4</sup>More details on the interplay between fixed costs, variable costs, efficiency and markups are described in [De Monte and Koebel \(2024\)](#). The relation between monopsony power, output market power, and productivity are investigated by [Hahn \(2024\)](#) and [Rubens \(2023\)](#), and [Morlacco \(2020\)](#).

The reminder of the paper is organized as follows. Section 2 introduces the empirical framework. Section 3 describes the data and descriptive statistics. Section 4 presents the results of the aggregate productivity and markup decomposition and discusses policy implications. Section 5 provides robustness checks and considers the impact of potential biases. Section 6 finally concludes.

## 2 Empirical framework

The empirical framework consists in two components: First, the estimation approach of the production function from which firm-level productivity and markups are derived. Second, the aggregation and decomposition approach of productivity and markups, which enables to study the joint evolution of both aggregate measures as well as the role of output reallocation - the ultimate objective of the paper.

### 2.1 Production function estimation

Consider a given industry with  $N$  firms, indexed by  $n$  at a specific point in time  $t$ . Firms transform inputs into output, described by the following Hicks neutral *gross output translog* (TL) production function, given by

$$y_{nt} = \alpha_0 + \sum_i \alpha_i x_{nt}^i + \frac{1}{2} \sum_{ij} \alpha_{ij} x_{nt}^i x_{nt}^j + \omega_{nt} + \epsilon_{nt}, \quad (1)$$

lower case letters denote logs, where gross output production is supposed to be given by  $y_{nt} = \log(Y_{nt}) + \epsilon_{nt}$ , and  $x_{nt}^i$  with  $i = (k, l, m)$  denotes the input factors capital, labor, and intermediary products (materials),  $\omega_{nt}$  represents the log-level of TFP, and  $\epsilon_{nt}$  an *iid* shock.<sup>5</sup> TFP is unobserved by the econometrician and as such a residual of the production function. However, its decomposition from  $\epsilon_{nt}$  is made since TFP is assumed to be known or anticipated by the firm prior to  $t$  and, hence, potentially contributes to the firm's decisions about input quantities. Instead,  $\epsilon_{nt}$  is only observed by the firm ex-post, i.e. after  $t$ , and supposed to be uncorrelated with the input decisions. As common in the production function literature, I suppose that firms' capital stock evolves according to  $K_{nt} = \kappa(K_{n,t-1}, I_{nt})$ , where  $K_{nt} = \exp(x_{nt}^k)$  and  $I_{nt}$  denotes a firm's amount of investments. Moreover, since the French labor market is relatively regulated, I consider labor input as fixed. This timing assumption implies that capital and labor is chosen by the firms prior to observing their productivity  $\omega_{nt}$ . Instead, materials are supposed to be flexible, and hence adjustable w.r.t.  $\omega_{nt}$ . Input markets are supposed to be exogenous,

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<sup>5</sup>That is, gross output production is allowed to contain measurement errors that are, along with unanticipated shocks to production, comprised in  $\epsilon_{nt}$  (De Loecker and Warzynski, 2012).

i.e. firms do not detain any market power in the respective markets.<sup>6</sup> As extensively discussed in many studies such as [Olley and Pakes \(1996\)](#) (OP, henceforth), [Levinsohn and Petrin \(2003\)](#) (LP), [Akerberg et al. \(2015\)](#) (ACF) and [Wooldridge \(2009\)](#) a crucial difficulty to deal with when estimating production functions consists in the endogeneity of the explanatory variables, arising when a firm chooses its flexible inputs (here  $x_{nt}^m$ ) as a function of the productivity shocks  $\omega_{nt}$ . This is also known as the simultaneity bias, which OP propose to circumvent by a two-stage estimator, using firm investments as proxy variable to control for unobserved productivity. The LP approach suggests to use materials as a proxy since firm investments take frequently zero values. I will estimate the production function presented in equation (1) in the LP spirit and proceed very similar to ACF.<sup>7</sup> The identification strategy of the production function parameters is briefly presented in the following. In the first stage a scalar observable is used to control for the unobserved productivity. As auxiliary variable the flexible input factor intermediate products is used, which is supposed to be generated as a function of capital and labor input as well as the unobserved productivity, expressed by  $x_{nt}^m = h(x_{nt}^k, x_{nt}^l, \omega_{nt}, c_{nt})$ , where  $c_{nt}$  contains control variable such as a dummy variable for firm exit, 4-digits sector and time dummies. The key assumption in the first step is the assumption of strict monotonicity of  $x_{nt}^m$  in  $\omega_{nt}$ . This assumption implies invertibility of  $h$  in  $\omega_{nt}$ , yielding  $\omega_{nt} = h^{-1}(x_{nt}^k, x_{nt}^l, x_{nt}^m, c_{nt})$ , which is then substituted into equation (1) to obtain

$$\begin{aligned} y_{nt} &= \alpha_0 + \sum_i \alpha_i x_{nt}^i + \frac{1}{2} \sum_{ij} \alpha_{ij} x_{nt}^i x_{nt}^j + h^{-1}(x_{nt}^k, x_{nt}^l, x_{nt}^m, c_{nt}) + \epsilon_{nt} \\ &= f(x_{nt}^k, x_{nt}^l, x_{nt}^m, c_{nt}) + \epsilon_{nt}. \end{aligned} \quad (2)$$

I approximate  $f(\cdot)$  by a fourth order polynomial in inputs and add other control variables contained in  $c_{nt}$ . That is, the first stage yields the estimate  $\hat{f}(x_{nt}^k, x_{nt}^l, x_{nt}^m, c_{nt})$ , which is used in the second stage to accomplish the identification of the parameters of interest. For the second stage, the second key assumption lies on the law of motion of  $\omega_{nt}$ , which is assumed to be a first order Markov process, where firm entry and exit is allowed to impact the productivity i.e.,

$$\omega_{nt} = g(\omega_{n,t-1}, e_{nt}^-) + \xi_{nt}, \quad (3)$$

where  $g(\cdot)$  defines the productivity process,  $e_{nt}^- = 1$  if a firm exits in the subsequent period and zero else, which is included to control for self-selected exit ([Olley and Pakes, 1996](#)), and  $\xi_{nt}$  is an *iid* error term with  $E(\xi_{nt} | \omega_{n,t-1}, e_{nt}^-) = 0$ .<sup>8</sup> From equation (2) it

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<sup>6</sup>The assumption of exogenous input markets implies homogeneity in firms' input prices. By that, I assume that there is no input price bias when estimating the production function based on expenditure data ([De Loecker et al., 2016](#)).

<sup>7</sup>Also see [De Loecker and Warzynski \(2012\)](#) for a further application.

<sup>8</sup>See Appendix A.2 for the definition of firm exit.

follows that

$$\widehat{\alpha_0 + \omega_{nt}}(\alpha) = \hat{f}(x_{nt}^k, x_{nt}^l, x_{nt}^m, c_{nt}) - \sum_i \alpha_i x_{nt}^i + \frac{1}{2} \sum_{ij} \alpha_{ij} x_{nt}^i x_{nt}^j, \quad (4)$$

where  $\alpha = (\alpha_i, \alpha_{ij})$  with  $i = \{k, l, m\}$ . The innovations in  $\omega_{nt}$ , namely  $\hat{\xi}_{nt}$ , are obtained by regressing  $\widehat{\alpha_0 + \omega_{nt}}(\alpha)$  on a higher order polynomial of  $\widehat{\alpha_0 + \omega_{n,t-1}}(\alpha)$  along with the exit dummy. Then, for some initial values for the parameters,  $\alpha$  can be estimated by a search over the space of the parameters in  $\alpha$ , imposing the moment conditions<sup>9,10</sup>

$$E \left[ \hat{\xi}_{nt}(\alpha) \mathbf{x}_{nt} \right] = 0, \quad (5)$$

with  $\mathbf{x}_{nt} \equiv (x_{nt}^k, x_{nt}^l, x_{n,t-1}^m, (x_{nt}^k)^2, (x_{nt}^l)^2, (x_{n,t-1}^m)^2, x_{nt}^l, x_{nt}^k, x_{n,t-1}^m, x_{nt}^k, x_{n,t-1}^m, x_{nt}^l)'$ . Note that the moment conditions are derived from the first order Markov assumption (given in equation (3)), implying orthogonality between the production input factors and the innovation to productivity,  $\xi_{nt}$ .

I rewrite these conditions as

$$E [d(\alpha, x_{nt})] = 0, \quad (6)$$

where  $d(\cdot)$  represents a  $L \times 1$  vector of moment conditions with  $L \geq J$ , where  $J$  is the total number of parameters to be estimated, and  $x_{nt}$  the data (all endogenous and exogenous variables). Using two-step GMM (Hansen, 1982), the parameters of interest can be estimated by

$$\hat{\alpha} = \arg \min_{\alpha} \bar{d}(\alpha)' W \bar{d}(\alpha), \quad (7)$$

where  $W$  is a  $L \times L$  optimal weighting matrix, given by the inverse of the covariance matrix of  $d(\alpha, x_{nt})$ ,<sup>11</sup> and

$$\bar{d}(\alpha) = \frac{1}{N} \sum_{n=1}^N \frac{1}{T_n} \sum_{t=1}^{T_n} d(\alpha, x_{nt}), \quad (8)$$

with  $T_n$  an individual firm's total number of observations.

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<sup>9</sup> The choice of the instruments in the moment equation (5) is related to the timing assumption mentioned above. Since I suppose that firms chose both capital and labor input at  $t - 1$ , whereas the flexible input materials is supposed to be chosen at  $t$ , I use the instruments  $x_{nt}^k$ ,  $x_{nt}^l$ , and  $x_{n,t-1}^m$  (as well as higher orders and combinations of them), that should be orthogonal to the shocks in innovation, given by  $\xi_{nt}$ .

<sup>10</sup>As initial values I use the estimated coefficients of an OLS regression of  $y_{nt}$  on all explanatory variables of the gross output translog production function.

<sup>11</sup>Here, the covariance matrix of  $d(\alpha, x_{nt})$  is estimated in a first step, using (7) while setting  $W$  to the  $L \times L$  identity matrix.



### 2.1.1 Firm-level productivity

After obtaining the estimates of the production function parameters, firms' productivity is recovered by

$$\hat{\omega}_{nt} = y_{nt} - \sum_i \hat{\alpha}_i x_{nt}^i + \frac{1}{2} \sum_{ij} \hat{\alpha}_{ij} x_{nt}^i x_{nt}^j - \hat{\epsilon}_{nt}, \quad (9)$$

where  $\hat{\epsilon}_{nt} = y_{nt} - \hat{f}(x_{nt}^k, x_{nt}^l, x_{nt}^m, c_{nt})$ .

### 2.1.2 Firm-level markups

According to the production approach introduced by Hall (1986, 1988) and De Loecker and Warzynski (2012) I estimate markups by the ratio of the output elasticity w.r.t. the variable input materials and its input share, given by

$$\hat{\mu}_{nt} = \frac{\hat{\theta}_{nt}^M}{\hat{a}_{nt}^M}, \quad (10)$$

where the output elasticity w.r.t materials,  $\hat{\theta}_{nt}^M$ , is obtained by<sup>12</sup>

$$\hat{\theta}_{nt}^M = \frac{\partial y_{nt}}{\partial x_{nt}^i} = \hat{\alpha}_m + \hat{\alpha}_{mm} x_{nt}^m + \hat{\alpha}_{km} x_{nt}^k + \hat{\alpha}_{lm} x_{nt}^l. \quad (11)$$

The input share of materials, generally expressed by  $a_{nt}^M = (P_{nt}^M M_{nt}) / (P_{nt} Y_{nt})$ , can be directly obtained from the data. However, since we do not observe  $Y_{nt}$  but  $\tilde{Y}_{nt} = Y_{nt} \exp(\epsilon_{nt})$ , where  $\epsilon_{nt}$  is the error from the regression equation (2), De Loecker and Warzynski (2012) propose to correct and estimate the input share by

$$\hat{a}_{nt}^M = \frac{P_{nt}^M M_{nt}}{P_{nt} \frac{\tilde{Y}_{nt}}{\exp(\hat{\epsilon}_{nt})}}. \quad (12)$$

## 2.2 Decomposition approach of aggregate productivity and markups

Olley and Pakes (1996) showed that the aggregate measure  $\Phi_t = \sum_{n=1}^{N_t} \phi_{nt} s_{nt}$ , with  $\phi_{nt}$  denoting an individual firm's productivity/markup, weighted by its sales share  $s_{nt}$ , can be decomposed into a *within change* (if firms' unweighted average changes) and a *between change* (if the covariance between productivity/markups and sales share changes, also referred to the process of *reallocation* w.r.t. firms' productivity/markups). Melitz and Polanec (2015) extent this approach by also taking into account the contribution of en-

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<sup>12</sup>The output elasticity w.r.t. the other inputs capital and labor can be obtained analogously. Firms' returns to scale is then obtained by taking the sum of all output elasticities, i.e.  $\widehat{RS}_{nt} = \hat{\theta}_{nt}^K + \hat{\theta}_{nt}^L + \hat{\theta}_{nt}^M$ .



tering and exiting firms to the aggregate measure, yielding

$$\begin{aligned}
\Delta\Phi &= \underbrace{(\Phi_{S,t} - \Phi_{S,t-k})}_{\text{Survivors}} + \underbrace{S_{E,t}(\Phi_{E,t} - \Phi_{S,t})}_{\text{Entrants}} + \underbrace{S_{X,t-k}(\Phi_{S,t-k} - \Phi_{X,t-k})}_{\text{Exiters}} \\
&= \underbrace{\Delta\bar{\phi}_S}_{\text{Within change}} + \underbrace{\Delta N_{SCOV_S}}_{\text{Between change}} + S_{E,t}(\Phi_{E,t} - \Phi_{S,t}) + S_{X,t-k}(\Phi_{S,t-k} - \Phi_{X,t-k}) \quad (13)
\end{aligned}$$

where  $\Delta$  denotes the first-difference operator and  $S_{Gt} = \sum_{n \in G} s_{nt}$  denotes the aggregate sales share of a group  $G$  with  $G = (E, S, X)$  the indexes referred to the group of entrants, survivors, and exiters.<sup>13</sup> In the the second equality, the first and the second term represents the within and between change component. That is, the sum of both terms describes the contribution of surviving firms to aggregate productivity growth, whereas the last two terms describe the contribution of the group of entrants and exiters, respectively, to aggregate productivity growth. The DOPD method implies that the aggregate measure of the group of surviving firms, given by either  $\Phi_{S,t}$  or  $\Phi_{S,t-k}$ , states for all groups the reference level. That is, the group of surviving firms contribute positively to aggregate productivity growth if their aggregate productivity at  $t$  is higher compared to that group's aggregate measure at  $t-k$ , i.e.  $\Phi_{S,t} - \Phi_{S,t-k} > 0$ . The group of entering (exiting) firms contributes positively to the aggregate's growth if their aggregate measure is higher (lower) compared to one of the group of surviving firms at  $t$  ( $t-1$ ), i.e.  $\Phi_{E,t} - \Phi_{S,t} > 0$  ( $\Phi_{S,t-k} - \Phi_{X,t-k} > 0$ ).<sup>14</sup>

In the productivity decomposition literature there exist other similar methods measuring aggregate productivity with firm entry and exit, notably the ones presented by [Griliches and Regev \(1995\)](#) (GR, henceforth) and [Foster et al. \(2001\)](#) (FHK, henceforth). The difference between the DOPD and the GR and FHK approach essentially lies in the above mentioned reference level, with which the aggregate measure of the different groups is compared to assess the respective growth contribution. For instance, GR use for all groups as reference level the average of the overall aggregate between two periods (i.e.  $\bar{\Phi} = (\Phi_t - \Phi_{t-k})/2$ ), while FHK use the measured overall aggregate level at the first period (i.e.  $\Phi_{t-k}$ ). [Melitz and Polanec \(2015\)](#) discuss and compare these methods in detail and show that their decomposition, using as reference level the aggregate measure of the group of surviving firms, more accurately reflects the contribution of each firm group. More precisely, let us consider positive productivity (and markup) growth among incumbents, which would be reflected by  $\Phi_{S,t} > \Phi_{S,t-k}$ . In that case, the reference levels  $\bar{\Phi}$  (GR) and  $\Phi_{t-k}$  (FHK) are smaller compared to  $\Phi_{S,t}$  (DOPD). Hence, using either the GR or FHK reference level leads to an overmeasurement of the contribution of entrants and an undermeasurement of the contribution of the groups of surviving and exiting firms.

A further aspect discussed in the literature concerns the used individual weight when

<sup>13</sup>See Section 3.1.2 for the definition of firm survival, entry, and exit.

<sup>14</sup>See Online Appendix C.1 for more details on the derivation of the DOPD approach.

measuring aggregate markups. For instance, [De Loecker et al. \(2020\)](#) point to the fact that the choice of the weight in use matters, comparing sales shares and total cost shares but focus on the first one for three reasons: First, sales dynamics are mainly affected by reallocation of revenues to high-markup firms, which could not be captured using input weights. Second, markups are linked to profit-rates, which are also weighted by revenue shares, which, therefore, establishes consistency in their framework. On the other hand, [Edmond et al. \(2023\)](#) argue that cost share weighting better reflects distortions to employment and investment decisions. I perform robustness checks of aggregate markup measures based on sales share and cost share weighting, which is discussed further below.

### 3 Data, variables, and descriptive statistics

#### 3.1 Data

I analyse French firm-level data where I combine the (fiscal) datasets FICUS and FARE covering the periods 1994-2007 and 2008-2016, respectively.<sup>15</sup> The datasets contain detailed information about firms' reports in balance sheets and income statements. In 2008 the French institute for statistics (INSEE) made significant changes w.r.t. the industrial sector nomenclature firms belong to. In both datasets, the principal sector identifier is at the 4-digit level, where in FICUS sectors were differently labelled compared to FARE.<sup>16</sup> In order to establish consistency in the sector nomenclature I manage to use throughout the whole period, 1994-2016, the same sector nomenclature. This is especially important since I aim to estimate the production function at the 2-digit level requiring consistency in the sector nomenclature. See Online Appendix A for a more detailed description of the construction of the dataset.

I only keep those firms with at least five employees to prevent estimates to be distorted by a large fraction of very small firms, likely to contain measurement errors. Furthermore, motivated by the fact that I estimate a TL production function, I only keep those firms that report positive values for sales, capital, and materials. The final dataset includes 19 2-digit manufacturing sectors, containing for the period 1994-2016 96,013 firms, summing up to 851,261 observations. Table 1 provides a description of the considered 2-digit sectors and the corresponding number of firms/observations. Note that some manufacturing sectors are excluded: 10 (manufacture of food products), 12 (manufacture of tobacco products), and 19 (manufacture of coke and refined petroleum products). Sector 10 is excluded for its untypical structure, i.e. a very large amount of very small firms, strongly

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<sup>15</sup>FICUS and FARE refer to "fichier de comptabilité unifié dans SUSE" and "fichier approché des résultats d'Esane", respectively. That is, FICUS was part of the French firm-level database SUSE. In 2008, FICUS was replaced by FARE, which, in turn, belongs to the database ESANE.

<sup>16</sup>In particular, in FICUS and FARE industrial sectors are classified according to NAF révision 1 and NAF révision 2, respectively, where NAF refers to the French industry classification ("nomenclature d'activités françaises").

influencing the aggregate measure. The sectors 12 and 19, instead, are excluded by reason of a low number of observations.

Table 1: Description of 2-digit manufacturing sectors<sup>a</sup>

Sector <sup>b</sup>	Description	# Firms	# Obs.
11	Manufacture of beverages	1,593	15,023
13	Manufacture of textiles	4,128	37,000
14	Manufacture of wearing apparel	7,295	42,244
15	Manufacture of leather and related products	1,611	12,571
16	Manufacture of wood and of products of wood and cork	6,609	59,224
17	Manufacture of paper and paper products	2,155	22,533
18	Printing and reproduction of recorded media	9,353	78,577
20	Manufacture of chemicals and chemical products	3,491	33,180
21	Manufacture of basic pharmaceutical products/preparations	745	6,820
22	Manufacture of rubber and plastic products	6,233	63,375
23	Manufacture of other non-metallic mineral products	5,763	49,739
24	Manufacture of basic metals	1,557	14,848
25	Manufacture of fabricated metal products	22,165	219,412
26	Manufacture of computer, electronic and optical products	4,144	32,243
27	Manufacture of electrical equipment	3,077	27,345
28	Manufacture of machinery and equipment n.e.c.	7,612	66,925
29	Manufacture of motor vehicles, trailers and semi-trailers	2,528	23,684
30	Manufacture of other transport equipment	975	7,883
31	Manufacture of furniture	4,979	38,635
	Total	96,013	851,261

<sup>a</sup> Source: FICUS/FARE database.

<sup>b</sup> Statistical classification of economic activities in the European Community, Rev. 2 (2008).

### 3.1.1 Production function variables

For the estimation of the production function I use as gross output measure firms' sales, the capital stock is proxied by tangible assets reported in firms' balance sheets, labor is measured by the number of full-time employees, and material input by the reported expenditures for raw materials. All monetary variables are deflated by the corresponding 2-digit sector price index.

### 3.1.2 Definition of firm survival, entry, and exit

As the DOPD framework aims to quantify the contribution of the groups of surviving, entering, and exiting firms to aggregate productivity (and markup) growth over time, measures of firms' activity status is required. Generally, as I use fiscal data, firms' report on their balance and income statement is mandatory, hence firms' appearance and disappearance in the data is quite informative about their actual date of birth and death in the legal sense. However, I also observe some non-report, especially for small firms, therefore, re-entry occurs to some extent. Based on that data characteristics, I first define each  $n$  firm's status at an arbitrary point in time  $t$  of being either a current survivor, entrant, or exitor, denoted by  $s_{nt}$ ,  $e_{nt}^+$ , and  $e_{nt}^-$ . See a detailed description of these variables in the Appendix A.2. I call this the definition of firm survival, entry, and exit at a yearly

basis.<sup>17</sup> For the definition of firm entry and exit over periods longer than one year, as it is needed for the application of the DOPD approach, I then apply the following approach: Let  $t - k$  and  $t$  be two periods in time. A firm is defined as a survivor from  $t - k$  to  $t$  if the firm is active both at  $t - k$  and at  $t$ , where firms are said to be active if they report positive values either in total production, turnover, or net profits. Furthermore, a firm is defined as an exitor if the firm has exited the market until  $t$ , i.e.  $e_{nr}^- = 1$ , for some year  $r$  satisfying  $t - k \leq r < t$ , and if the firm was active at  $t - k$  but inactive at  $t$ . Moreover, a firm is defined as an entrant if the firm has entered the market between both points in time, i.e.  $e_{nr}^+ = 1$ , for some year  $r$  satisfying  $t - k < r \leq t$  and if the firm was inactive at  $t - k$  but active at  $t$ .

It should be noted that the sample I treat contains only firms reporting at least five full-time employees. I control for the case if firms cross the threshold of five employees, to prevent from counting excess entry and exit. Applying the definition of firms' yearly activity status, I observe that a small share of firms enters and exits more than once. However, for longer time spans the identification of firms' survival/entry/exit reflect well a firms' actual activity status as consecutive years inactivity of more than one year is rather rare. A potential bias from an incorrect measure of firms' status should therefore reduce for time spans covering several years.<sup>18</sup>

### 3.2 Descriptive statistics

To provide an insight into the data, Table 2 shows the distribution of some variables w.r.t. firm size. All figures represent averages over the whole period 1994-2016. The first column contains different firm size groups, measured by the number of employees. The table shows that the share of firms in the sample is decreasing in firm size. More precisely, the largest share of firms is represented by the group of firms detaining between five and nine employees, given by 33.53%. The smallest share is represented by firms reporting 500 employees and more, given by only 1.61%. Instead, considering the shares of employees and sales, represented by the different firm size groups, we observe the pattern that both variables are increasing in firm size group. Here, firms with five to nine employees detain only 3.75% of total labor force (2.15% of total sales), whereas the biggest firm size group detains 42.75% of total labor (54.56% of total sales). Also, as expected, entry and exit rates are decreasing in firm size, where the smallest firm size group reveals the highest

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<sup>17</sup>In the data there also exists a variable indicating firms' official status of either activity or exit (cessation of activity). However, this variable is only available in the FARE/ESANE database, i.e. from 2009 on. To ensure consistency of the definition of firms' activity status I rely throughout the whole period on my own definition described in the Appendix A.2. For the period 2009 – 2016 I perform robustness checks comparing my exit measure with the official one provided in the data. As shown in the Appendix, Table A4 and A5, there is a high correlation between my own and the official measure for firm exit. As in my approach reactivation of firm activity in some cases is counted as re-entry, I count, however, somewhat more exits compared to the official measure (see Appendix, Table A3).

<sup>18</sup>See Appendix A.2, Figure A1 showing the frequencies of observed consecutive years of firm inactivity.

entry/exit rates.<sup>19</sup> Figure 1 shows the evolution of aggregate production and inputs.

Table 2: Summary statistics w.r.t. firm size : averages from 1994-2016<sup>a</sup>

Size group <sup>b</sup>	# of firms	Share of firms	Share of empl.	Share of sales	Entry rate	Exit rate	Age
5–9	12410	33.53	3.75	2.15	5.51	5.27	17.03
10–19	9228	24.94	5.63	3.41	4.49	4.89	19.89
20–49	8908	24.07	12.50	9.00	3.36	3.75	23.09
50–99	2927	7.91	9.04	6.91	3.04	3.63	25.90
100–199	1793	4.85	11.04	9.35	2.84	3.33	27.20
200–499	1146	3.10	15.29	14.61	2.57	2.99	27.63
500+	595	1.61	42.75	54.56	3.24	2.97	29.19
Total	37007	100.00	100.00	100.00	4.29	4.48	20.92

<sup>a</sup> Source: FICUS/FARE database, own calculations. All figures represent averages over the whole period 1994-2016. Shares and rates are given in %.

<sup>b</sup> Size group is given in terms of number of employees.

Here, aggregates are measured by the sum of the respective variable over all firms, where the initial year 1994 represents 100. The figure shows that the aggregate use of capital has increased steadily, reaching at 2016 186.5 w.r.t. the level of 1994. Aggregate gross output, closely followed by aggregate material input, represented by the solid and dotted line, respectively, increases until 2007 whereupon a quite dramatic drop is observed. Only from 2009 on the aggregate of both variables increases, reaching a level of 150.8 and 138.7 w.r.t. 1994. The aggregate use of labor, instead, has decreased relatively continuously form 2002 on, accounting at 2016 only 76.9.

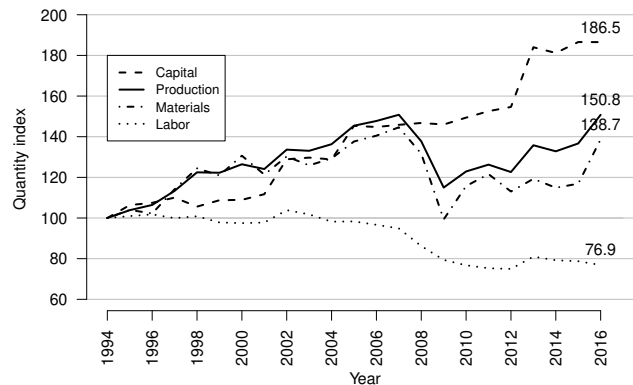


Figure 1: Aggregate production and inputs over time. Source: FICUS/FARE database, own calculations.

Finally, Figure 2 presents firm dynamics, i.e. the evolution of the number of firms along with the entry and exit rate. The upper line represents the number of firms, with the corresponding  $y$ -axis on the left. The figure shows that from 2002 on the number of firms is substantially decreasing reaching in 2016 a level of only about 77% compared to 1994, which translates into a yearly average growth rate of -1.12%. The evolution of the

<sup>19</sup>See Appendix A.1 for a similar table w.r.t. the 2-digit sectors instead of firm size.

number of active firms is also reflected in the entry and exit rate, with the corresponding  $y$ -axis on the right: While at the beginning of the sample period entry and exit rates are higher and oscillating at a similar level, from around 2002 on, the exit rate lies above the entry rate.<sup>20</sup>

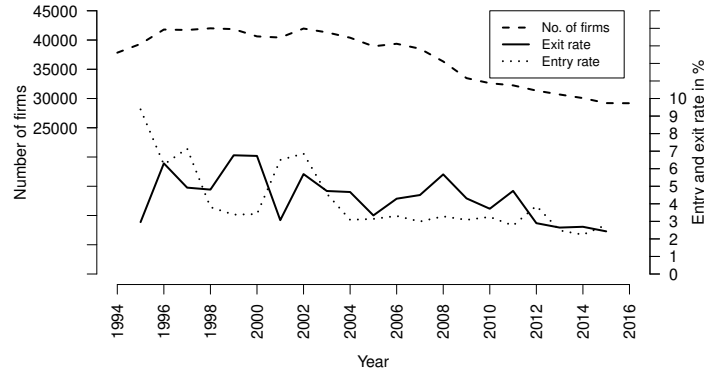


Figure 2: The evolution of the number of firms and the entry and exit rate. Source: FICUS/FARE database, own calculations.

## 4 Results of the decomposition and policy implications

In this section I present results of the decomposition exercise of both aggregate productivity and markups with a particular look at the role of resource reallocation.<sup>21</sup> Related policy implications are discussed subsequently.

### 4.1 Empirical decomposition of aggregate productivity

To measure and decompose aggregate productivity growth, the DOPD presented in equation (13) is applied on all firms in the sample, where I pursue the analysis in two ways: i) by applying the DOPD for identical time spans, i.e. between  $t - k$  and  $t$ , with  $k = 4$  and  $t \in \{1998, 2002, 2006, 2010, 2014, 2016\}$ ; and ii) by fixing the initial year of the sample period, i.e.  $t - k = 1994$ , and letting  $t > 1994$  vary such that the DOPD is cumulatively applied for each year. Results related to i) are presented in table form, whereas results related to ii) are presented graphically.

Consider first Table 3 the second column, providing the measures of the total growth in aggregate productivity over the different periods. It can be seen that over all periods a positive growth in aggregate productivity is measured, with the highest growth rates

<sup>20</sup>See Appendix A.2 for a detailed description of the measurement of firm entry and exit on a yearly basis.

<sup>21</sup>Aggregates are based on firm-level productivity and markups, obtained from the estimation of the TL production function presented above. See Online Appendix B for the results of the parameter estimates, output elasticities, and returns to scales.

for the periods 1994 – 1998 and 2006 – 2010, given by 12.73% and 8.48%. During the last two reported periods, however, I only measure an aggregate growth in productivity of 2.19%. Thus, the overall pattern suggests a slowdown aggregate productivity growth over time.

Further, the aggregate growth is decomposed into the contribution of the groups of survivors, entrants, and exitors. The figures show that the contribution of survivors represent for each period the most important driver for aggregate productivity growth. More specifically, this group’s contribution is separated into the within contribution, i.e. surviving firms’ contribution to productivity growth through their technological progress, and the between contribution, i.e. the contribution to productivity growth through the reallocation of sales shares among surviving firms. The figures show that the between contribution is measured to be an important driver of aggregate productivity growth for the periods 1994 – 1998 and 2002 – 2006, given by 7.08% and 2.67%, respectively. Here, the positive sign indicates reallocation of sales shares from less productive to more productive firms. The overall picture, though, suggests that after 1998 the reallocation process slowed significantly down. Moreover, the contribution to aggregate productivity growth of the groups of entering and exiting firms is comparatively small, where the sign of the groups’ contribution varies: Considering the contribution of entering firms, a positive sign indicates that for those periods entrants’ aggregate productivity was higher compared to that of the groups of surviving firms, thus increasing the overall aggregate productivity; Instead, a positive sign for the contribution of the group of exiting firms indicates a lower aggregate productivity of that group compared the group of surviving firms. In that cases, the manufacturing industry loses relatively unproductive firms, which is the case for most of the periods and in line with economic theory where less efficient firms are most likely to close their activity (Fariñas and Ruano, 2005).<sup>22</sup> Next, the DOPD approach is

Table 3: Aggregate productivity growth (DOPD) over all firms<sup>a</sup>

Period	Total Growth <sup>b</sup>	Contribution Within	Contribution Between	Contribution Entrants	Contribution Exitors
1994 – 1998	12.73	5.27	7.08	–0.30	0.66
1998 – 2002	6.64	4.93	–0.02	0.60	1.12
2002 – 2006	6.28	4.32	2.67	0.14	–0.45
2006 – 2010	8.48	8.56	–0.63	0.50	0.03
2010 – 2014	2.19	2.38	0.38	–2.32	1.74
2012 – 2016	2.19	2.13	0.05	0.14	–0.12

<sup>a</sup> Source: FICUS/FARE database, own calculations. All figures represent growth rates in % relative to the initial year of the given period. Average annual growth rates are given in parenthesis.

<sup>b</sup> The total growth in aggregate productivity is the sum of the contributions of survivors, entrants and exitors.

applied by keeping 1994 as initial year of reference. That is, the contributions to the

<sup>22</sup>See Online Appendix C.2, Table C1 for the measures of aggregate market share and productivity of the different groups and periods.



change in aggregate productivity of each component, i.e. from the groups of surviving firms and net entry, are added cumulatively throughout the years until 2016. Figure 3 provides the results of this exercise. Consider first the total aggregate (log) productivity growth, represented by the solid line. From 1994 to 2016 the aggregate productivity is continuously increasing. For the overall period I measure an aggregate productivity growth of about 34%, representing annual average growth rate (AAGR) of about 1.56%.<sup>23</sup> However, the AAGR is decreasing over time: While I measure from 1994 until 2000 an AAGR of 3.65%, for the period from 2001 to 2016 I measure an AAGR of only about 1.16%. Ben Hassine (2019) finds for the French economy between 2000-2012 a total growth of aggregate productivity of somewhat less than 10%, which is similar to my results for the same period given by about 11.2%. Further, the author finds for the period 2000 - 2007 (2008-2012) an AAGR of 0.66% (0.32%), while I find a lower AAGR given by 0.33% (-0.09%).<sup>24</sup> The finding of a decreasing AAGR confirm the results shown in Table 3 and also go in line with empirical evidence provided in the literature: For instance, Cette et al. (2017) and Ben Hassine (2019) document a slowdown in aggregate productivity growth for the French economy from 2000 on and Bellone et al. (2016) finds a similar pattern of the evolution of aggregate productivity for the period 1998 – 2007 in France. A slowdown in productivity growth is a well-known observation for many advanced countries, most prominently for the US (Byrne et al., 2016; Syverson, 2017; Decker et al., 2017), but also for countries within the euro zone, UK, and Japan (Bergeaud et al., 2016).

Further, the contribution of the group of survivors and net entry are represented by the dashed and dotted line, respectively. It can be seen that surviving firms contribute the overwhelming share to the total aggregate productivity evolution as the dashed line very closely follows the dotted line. Instead, the contribution of net entry is very low, where the positive entry effect is almost compensated by the negative exit effect. Also, from Table 3 and Figure 3 we cannot conclude a significantly stronger effect of firm entry during the phases of high growth, 1994-2000, which was shown by Asturias et al. (2023) for the economies of Korea and Chile. Additionally, Figure 3 also allows insights into learning and reallocation effects among surviving firms. As already suggested by the figures in Table 3, the contribution of surviving firms to aggregate productivity is further decomposed into

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<sup>23</sup>The total growth rate of about 34% is calculated by the difference in the log aggregate productivity measures, i.e.  $\Delta\Phi_{tot} = \Phi_{2016} - \Phi_{1994}$ , with  $\Phi_{2016} = 0.900$  and  $\Phi_{1994} = 0.556$ . The AAGR is computed by the log-difference of aggregate productivity divided by the number of growth years, i.e.  $\Phi_{2016} - \Phi_{1994}/(2016 - 1994)$ . In the literature, this is the most common way to measure total growth, since productivity from a production function is mostly obtained based on log values. See Online Appendix C.2, Table C2 for the exact figures. Further, Figure C1 provides the evolution of the AAGR of total aggregate productivity throughout the whole sample period.

<sup>24</sup>See Online Appendix C.2.1, Figure C2. Beside the fact that Ben Hassine (2019) considers growth patterns in TFP only, the study differs in several aspects to mine: first, the author considers firms with more than 9 employees; second while the study only includes five manufacturing sectors it also comprises the construction sector and selected service sectors; third a value-added Cobb-Douglas production function is considered. This, of course, also leads to differences in the estimated growth of aggregate productivity.

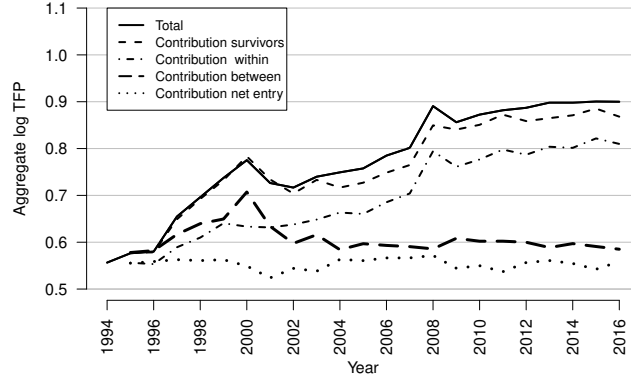


Figure 3: Aggregate log productivity decomposition. Source: FICUS/FARE database, own calculations.

the contribution through the unweighted productivity, i.e. the within-change (technical progress) and the between-change (reallocation effects). The figure shows that surviving firms' within-change (dotted-dashed line) exhibits the same tendency as that group's and the total aggregate productivity evolution (short-dashed and solid line). This again indicates that the within-change contribution of surviving firms accounts for a very large part of the overall evolution. The between-change contribution, indicated by the bottom line (long-dashed line), shows a strong impact until the year 2000, where productivity growth was mainly contributed by positive reallocation effects, that is, sales shares shifted from lower to higher productive firms. Post-2000 I measure a drop in these dynamics whereupon no considerable effect of reallocation of sales shares on aggregate productivity growth takes place. This indicates that the slowdown in productivity from 2000 is mainly due to a slowed reallocation process and less due to a slowed technical progress. On average over the whole period, within- and between-change accounts for about 69% and 31% of surviving firms productivity improvement. The finding that the within contribution of surviving firms is an important driver for aggregate productivity evolution and that net entry contribution plays a relatively smaller role compared to surviving firms' contribution goes in line with other studies in the literature ([Melitz and Polanec, 2015](#); [Baily et al., 1992](#); [Foster et al., 2001](#); [Ben Hassine, 2019](#)).

## 4.2 Empirical decomposition of aggregate markups

The purpose of considering aggregate markup dynamics is to compare its trends with that found for aggregate productivity with a particular look at the joint evolution of reallocation effects. I will first describe in detail the results of aggregate markup evolution and discuss subsequently relevant policy implications w.r.t aggregate productivity and resource allocation.

The decomposition of aggregate markups growth is conducted analogously to the one of aggregate productivity. Table 4 reports the results considering equal time spans of four

years. Consider first the overall growth during the different periods, shown in the second column. Aggregate markups experienced changing growth patterns, where I measure especially during the period 1994-1998 a relatively strong increase, given by 8.37%. In the two subsequent periods, instead, aggregate markups show a negative growth, whereupon a positive growth trend is measured.

Consider now the contribution to the total growth in markups by the groups of surviving, entering, and exiting firms. The table shows that the sharp increase in the first period was mainly contributed by the group of surviving firms and, more specifically, by that group's between contribution, which is given by 7.5%. That is, during that period, aggregate markups grew predominantly by sales shares shifting from low-markup to high-markup firms. In the subsequent period, 1998 – 2002, there is no total growth measured, where a positive within contribution, i.e. average growth in markups of the group of surviving firms, given by 4.05%, is almost entirely compensated by the negative between contribution, given by  $-3.35\%$ . Further, the relatively strong negative growth in total markups during the period 2006 – 2010, given by  $-5.46\%$ , is mainly induced by a negative within contribution of surviving firms, given by  $-2.46\%$ , and a comparatively strong negative contribution of the group of entering firms, given by  $-6.94\%$ . For that period, this implies that surviving firms lowered on average their markups and new establishments negatively contributed to total aggregate markup growth by lower markups compared to the group of surviving firms. The period 2006 – 2010 is then characterized by increasing total markups, predominantly induced by an increase in the group of surviving firms average markup, shown by a positive within contribution of 6.15%. After a very slow growth during the period 2010 – 2014, my results reveal more dynamics for 2012 – 2016, where aggregate markup growth is driven by increases in surviving firms' average markups, given by 3.91%, and by a more dynamic reallocation process, where, like in the first period, sales shares shift from lower-markup to high-markup firms, measured by a between contribution of 4.05%.<sup>25</sup>

Further, Figure 4 graphically illustrates the evolution of aggregate markup along with the contribution of the group of surviving firms and the contribution of net entry, beginning at 1994 and letting  $t$  vary until 2016. The total aggregate markup, shown by the solid line, experiences between 1994 and 1998 an increase whereupon I measure a relative continuing decrease until 2005. After a sharp increase between 2007 and 2009, I measure again a decline, with a relatively stable aggregate markup from 2011 until 2015 and a drop for the very last year of the sample period. More precisely, in 1994 I measure a total aggregate markup of 1.16, i.e. prices are on average about 16% higher compared to marginal costs. The highest measured aggregate markup in 2009 is given by about 1.30,

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<sup>25</sup>See Online Appendix C.3, Table C3 for the measures of aggregate market share and markups of the different groups and periods.

Table 4: Aggregate markup growth (DOPD) over all firms<sup>a</sup>

Period	Total Growth <sup>b</sup>	Contribution Within	Survivors Between	Contribution Entrants	Contribution Exiters
1994 – 1998	8.37	1.68	7.50	0.11	–0.91
1998 – 2002	–0.01	4.05	–3.35	–0.34	–0.38
2002 – 2006	–5.46	–2.46	0.66	–6.94	3.28
2006 – 2010	5.83	6.15	1.62	–0.26	–1.68
2010 – 2014	1.74	1.12	0.99	–3.61	3.24
2012 – 2016	5.90	3.91	4.05	–1.78	–0.28

<sup>a</sup> Source: FICUS/FARE database, own calculations. All figures represent growth rates in % relative to the initial year of the given period. Average annual growth rates are given in parenthesis.

<sup>b</sup> The total growth in aggregate markup is the sum of the contributions of survivors, entrants and exiters.

declining in 2015 (2016) to about 1.22 (1.19).<sup>26</sup> The controversial discussion on the rise in markups, which mainly takes place based on US data, has shown that measurement and the way the markup is estimated leads to very different conclusions, ranging from a sharp increase (De Loecker et al., 2020) to only modest increases, if at all (Traina, 2018; Demirer, 2020; Hall, 2018; Jaumandreu, 2022). The here presented results join this discussion, showing relatively stable aggregate markups for the French manufacturing industry over the past decades - a pattern that is also shown for other European countries (Deutsche Bundesbank, 2017; De Loecker and Eeckhout, 2018; Ganglmair et al., 2020; Weche and Wambach, 2021).

For almost all periods, the group of surviving firms (short-dashed line) contributes positively to the aggregate evolution. In addition, Figure 4 shows the decomposition of the contribution of the group of surviving firms into the within and between components. The within contribution (dotted-dashed line), i.e. surviving firms contribution to the aggregate markup through average markup variation, is minor at the beginning of the period but becomes dominant over time as it follows always closer the overall aggregate contribution of surviving firms (dashed line). The between contribution (long-dashed line) through reallocation of sales shares plays an important role at the beginning of the period. This leads to relatively high volatility in surviving firms' markup and an increase in the aggregate markup until 2001, whereupon reallocation effects sharply drop. From 2002 until 2016, however, the contribution of reallocation of sales shares towards higher markup firms steadily increases, and, hence, remains an important driver for aggregate markup evolution.

The sign of the contribution of net entry (dotted line), instead, changes: While exiting firms mostly contribute positively to aggregate markups, implying that firms that shut down between 1994 and the respective year reveal a smaller aggregate markup compared to the aggregate markup of the group of surviving firms, the group of entering firms

<sup>26</sup> Also see Bellone et al. (2016) who find for the French manufacturing a similar pattern of decreasing markups for the period 1998-2007.

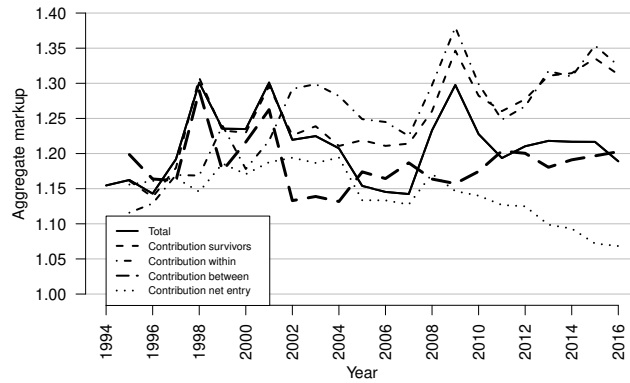


Figure 4: Aggregate markup decomposition. Source: FICUS/FARE database, own calculations.

contributes mostly negative to the aggregate markup (especially towards the end of the sample period). That is, in the latter case, new entering firms have at the aggregate a smaller markup compared to the group of surviving firms. Therefore, the net entry effect becomes negative, which can be seen as the total aggregate markup lies between the one of surviving firms and net entry. On average, surviving firms lead to an increase in the markup of 6.7 percentage points, compared to 1994. Instead, the group of entering and exiting firms contribute to the total aggregate markup on average with  $-4.5$  and  $4.1$  percentage points, respectively.<sup>2728</sup>

### 4.3 Relation between productivity and markups and policy implications

De Loecker et al. (2020) argue that the striking increase in the aggregate markup in the US was mainly supported by reallocation of sales shares overtime to high-markup firms but they do not address the question whether those firms were just more productive, helping to increase welfare, or whether they exploited inelastic demand via their dominant market position. My results show that this might also change over time, which is important as it has quite different implications for policy recommendations. That is, in the case of the French manufacturing industry, high growth of aggregate productivity between 1994 and 2000 was substantially driven by reallocation of sales shares towards more productive firm, just as the level of aggregate of markups, which likewise increased substantially through the allocation of sales shares to high-markup firms. Moreover, while post-2000 the contribution of reallocation to productivity growth becomes negligible, the contribution of reallocation to growth in aggregate markups always remains positive (see Table 4 and Figure 4, the long-dashed line). By that, reallocation of sales shares towards high-markup

<sup>27</sup>See Online Appendix C.3, Table C4 for exact figures.

<sup>28</sup>See Section 5 where the robustness of the provided results will be discussed in more detail.

firms contributed to maintain a certain level of the aggregate markup, especially towards the end of the sample period. In other words, there is evidence of a decoupling between the contribution of resource allocation of sales shares comparing aggregate productivity and markups, which is an important finding for policy considerations. This is because if increases in the aggregate markup are characterized by reallocation of sales shares towards both higher markup and more efficient firms, such as between 1994-2000, the economy as a whole becomes more efficient, producing less total costs, which increases welfare (Baqae and Farhi, 2020; De Monte and Koebel, 2024). In this case, policy interventions targeting to reduce high-markup firms' size to decrease their market power and, by that, the aggregate markup, would also lead to reduced aggregate productivity. In these times it would hence be recommendable to keep applying the current antitrust framework, i.e. it should not be necessary to strengthen rules, for instance, in terms of mergers and acquisitions (M&A). Moreover, for specific cases it might be appropriate to incentivize firms to increase their production, for instance by subsidizing new production plants, which could, for a given market, lead to decreasing output prices and so to a reduction of markups. If, instead, high-markup firms become allocated larger market (or sales) shares, which do not mirror their relative efficiency, suggested by my results for the period post-2000, the economy takes damages as firms with increasing market shares might exploit their growing dominant position by increasing their markup through higher prices, leading to a direct welfare reduction. In this case, it would be appropriate to design policies aiming to reinforce antitrust rules in order to prevent from excessive M&A activity. Also, firm entry enhancing policy interventions, such as the financial promotion of innovative startups, to reduce the size of dominant high-markup firms by a higher degree of competition, would be beneficial.

## 5 Impact of potential biases and robustness

In this section I discuss the impact of biases potentially occurring by using revenue data. Further, I discuss the statistical validity of the aggregate measures, and present some robustness checks w.r.t. the aggregation method and the production function specification.

### 5.1 Impact of potential biases using revenue data

A limitation of my approach to estimate productivity and markups is that I am not able to control for heterogeneity in firms' output prices, leading to the well-known output price bias (Klette and Griliches, 1996). In the best case, quantities as output measures (instead of revenues) should be used, which does allow to avoid such bias. Using US establishment-level data, Foster et al. (2008) investigate differences between revenue-based productivity (TFPR) and quantity-based productivity (TFPQ), both at the establishment- and at the



aggregate-level. They find that TFPR and TFPQ measures highly correlate (given by a correlation coefficient of 0.75), while TFPQ is shown to be more dispersed compared to TFPR. Further, they show that aggregate productivity growth measures based on TFPQ and TFPR yield the same result in terms of total growth, however, differences occur w.r.t. the different decomposition components (within/between growth, entry and exit). In particular, the authors argue that, according to their findings, older firms charge higher prices where firm age also correlates with their market share. Hence, using revenue-based productivity yields higher between growth measures and a lower contribution of firm entry to aggregate productivity growth. In other words, using TFPR underestimates the contribution of firm entry and overstates the contribution of the between growth contribution. Concerning the results presented in this paper, this implies on the one hand that the relatively high aggregate productivity growth rates between 1994 and 2000 are likely be overestimated to some extent, as they were mainly driven by a high between contribution, i.e. high aggregate productivity improvements through reallocation. Post-2000, the contribution of between growth is nearly zero and could therefore even be negative. On the other hand, the measured small effect of firm entry to aggregate productivity growth is likely to be underestimated. However, the results presented by [Foster et al. \(2008\)](#) do not suggest that we should expect a fundamental change in the general patterns if the output price bias was fully controlled for.

Concerning the measurement of markups, [Bond et al. \(2021\)](#) demonstrate that using the production approach with revenue data does not provide informative measures of the markup. [Hashemi et al. \(2022\)](#) further argues that rather than output distortion, the obtained markup from the production approach provides input distortions. While [De Ridder et al. \(2022\)](#) agree that revenue-based markup estimation by the production approach does not yield consistent estimates of the level of markups, they also demonstrate that the approach carries useful information about the distribution of markups, which is important for my purpose. This study serves particularly well as a robustness check to my case as the authors likewise use French data of manufacturing firms, a sub-sample of firms that also appear in my sample, but for which both output quantity and price data is available.<sup>29</sup> Further, very similar to my approach, their study relies on the estimation of a gross output translog production function, where the markup is recovered based on the output elasticity w.r.t. materials. As an important result, the study shows that the output measurement error, which is taken into account through the first step of the estimation of the production function, plays a far more important role compared to occurring output price bias.<sup>30</sup> Similar to the case of productivity, the authors find a high correlation between

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<sup>29</sup>In particular, the authors merge the FARE data, which is also used in this study, containing typical data on firm-level revenues and expenditures, with the EAP (Enquete Annual de Production) survey data, which additionally contains information on product quantities and prices (measured for ten 2-digit industries). The final data set contains firms with at least 20 employees, covering the period 2009-2019.

<sup>30</sup>See Section 2.1.2 which describes how the measurement error in the output variable is taken into



revenue-based and quantity-based markups (ranging between 0.41 and 0.82, depending on the estimation approach of the production function). Also, they show that revenue-quantity-based markups measures correlate very similarly with market shares. Hence, I expect that general patterns of reallocation dynamics, measured by the change in the correlation between firms' markups and sales shares, will be uncovered. Further, while the authors argue that revenue-based markups should not be used to compute levels of the markup, such as the mean, they empirically illustrate that the aggregate level of revenue- and quantity-based (sales-weighted) measures behave relatively similar for most 2-digit industries, arguing that revenue-based markups are quite useful to study markups trend over time, which is one of the main objectives of this study.

## 5.2 Statistical validity

To test for statistical validity of the aggregate measures I provide the estimates along with the 95% confidence interval (CI). The results show that the aggregate productivity always lies within the 95% CI, where the upper and lower bounds exhibit the same tendency as the weighted average, indicating statistically viable measures. Only for the high-growth period between 1994 and 2000 the upper bound of the 95 % CI is relatively large compared to the subsequent period where the 95% CI is closely located around the weighted average (see Appendix B.2, Figure B1) Likewise, the aggregate markup measure always lies within the very narrow 95% CI, implying statistically viable measures. For some years, such as for 2005 to 2007, the lower bound of the 95% CI is not different from one, which means that here, on average over all firms and industries, absence of market power (as it would be the case in perfect competition) cannot be rejected (see Appendix B.3, Figure B3).

## 5.3 Sales-share vs. cost-share aggregation

For markups only, I compare aggregate markups based on sales-weighted and total cost-weighted average (both derived from the translog production function). [Edmond et al. \(2023\)](#) show that the sales-weighted average equals the cost-weighted average additional to a term reflecting the variance of markups. As a consequence, the authors argue that aggregate markups based on sales shares overstate the actual level of aggregate markups. My results show that both weighting methods yield very similar levels throughout the whole period, suggesting that here the weight in use does not substantially matter in term of the presented results. (see Appendix B.3, Figure B5).

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account when estimating markups.

## 5.4 Production function specification

I estimate firms' individual productivity and markup based on a Cobb-Douglas (CD) production function and compare the evolution of both aggregate measures with the one obtained based on the TL production function specification.<sup>31</sup> The results show that estimates of aggregate productivity based on the TL production function lie at a higher level compared to the estimates based on the CD production function (see Appendix B.2.2, Figure B2). Comparing Figure B1 and B2 we see that the CI of the aggregate productivity based on the TL production function does not comprise the estimated aggregate productivity based on the CD production function, suggesting that both measures are statistically significantly different from each other. The qualitative patterns, however, are very similar, that is a sharper increase in the aggregate productivity for the period from 1994 to 2000 and a slowdown afterwards. Van Biesebroeck (2008b) discusses the estimation of production functions comparing different estimation approaches. He finds that while results for output elasticities, based on different methods, vary considerably, differences in the productivity residuals and productivity growth estimates remain less affected. This is also reflected in my results, where the estimation of the CD and TL production function imply considerable differences in firms' output elasticities, whereas the aggregate productivity growth patterns only yields minor difference over time. However, the parameter estimates belonging to higher order polynomials contained in the TL production function are, for many sectors, statistically significantly different from zero, indicating that the CD specification, that ignores higher order polynomials, suffers from misspecification (see Online Appendix B, Table B1). Hence, the aggregate productivity resulting from productivity estimates based on the TL production function is the preferable measure.

Similar to the case of aggregate productivity, I compare the evolution of aggregate markups with the ones estimated based on a Cobb-Douglas production function (implying constant output elasticities). The results demonstrate that markups based on the TL production function are comparatively more stable over time and lie at a lower level (see Appendix B.3, Figure B4). Demirer (2020) in fact shows that a CD specification leads to underestimation of the output elasticity w.r.t. the fixed input and overestimation of the output elasticity of the flexible input, which consequently leads to an overestimation of markups. He argues that even when using a CES labor-augmented production function, this bias is only partially corrected, suggesting the need for a more flexible production function specification. Using a TL production, as in my case, already allows more flexibility in the estimation of the output elasticity and the markup, and should, therefore, be preferably used.

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<sup>31</sup>The estimation procedure of the CD production function is presented in Appendix B.1.

## 6 Conclusion

This paper investigates the evolution of aggregate productivity and markups of French manufacturing firms with a special focus on the role of resource reallocation w.r.t. both aggregate measures. For this purpose, I use firm-level data covering the period from 1994 to 2016. Firm-level productivity is estimated based on a gross output translog production function relying on [Akerberg et al. \(2015\)](#), while markups are obtained by using the production-approach presented by [Hall \(1986, 1988\)](#) and [De Loecker and Warzynski \(2012\)](#). The decomposition method presented by [Melitz and Polanec \(2015\)](#) is then applied to study the contribution of reallocation effects to both aggregate productivity and markups.

I find that aggregate productivity in the French manufacturing industry increases considerably by about 34% between 1994 and 2016, characterized by a high-growth period until 2000, where the process of reallocation of sales shares towards more productive firms contributed significantly to the higher growth rates. Post-2000, reallocation slowed down and productivity growth was almost only carried by individual firms increases in productivity. Firm entry and exit turned out to contribute less aggregate productivity growth. Aggregate markups are found to remain relatively stable over the whole period, which contrasts the influential study of [De Loecker et al. \(2020\)](#) based on US firm-level data, documenting a drastic increase in aggregate markups.

As a key finding the results show that while the contribution of reallocation of sales shares to aggregate productivity slows significantly down, the contribution of reallocation to aggregate markups remains positive and substantial particularly towards the end of the sample period. This indicates a decoupling of reallocation effects w.r.t. aggregate productivity and markups, which has important policy implications. More precisely, in times where reallocation of sales shares towards high-markup firms coincides with the reallocation towards more efficient firms, such as between 1994 and 2000, potential negative effects of a higher level of aggregate markups w.r.t. welfare are mitigated by a higher level of allocative efficiency. Policy intervention targeting high-markup firms' size to reduce aggregate markups would be costly in terms of aggregate productivity and welfare, as these most efficient firms should even be larger ([Baqee and Farhi, 2020](#); [De Monte and Koebel, 2024](#)). Here, it seems appropriate to keep applying the present framework of antitrust regulation. If instead, reallocation only occurs towards high-markup but not towards high-productivity firms, such as post-2000, dominant firms are more likely to exploit their position by increasing both market shares and prices at the cost of the total economy. In this case, policy intervention targeting explicitly high-markup firms' size, for instance, by reinforcing antitrust rules and fostering firm entry by startup subsidize programs would be appropriate.

The analysis of the determinants affecting the process of reallocation of sales shares

in terms of firms' productivity and markups is left for future research.

The study has several limitations. First, I rely on a revenue-based production function that does not take into account price heterogeneity in output and input markets, leading to biased estimates if output/input prices are correlated with firms' optimal quantity choices (Hashemi et al., 2022; Bond et al., 2021). Even though Foster et al. (2008) for productivity and De Ridder et al. (2022) for markups showed that estimates based on a revenue production functions yielding useful information, the development and use of firm-level price indicators could prevent from such biases (see, for instance, Hahn (2024), Mertens (2022, 2020), Morlacco (2020), and Asker et al. (2019)). Second, using a Hicks neutral gross output translog production function implies a homothetic shift of the technology over time, letting the relative marginal productivities unaffected by productivity. This means that heterogeneity in output elasticities, for instance, only occurs due to variation in firms input mix but not due to time-varying parameters and/or further unobserved sources of heterogeneity. Novel nonparametric production function estimation methods, such as developed by Gandhi et al. (2020), Demirer (2020), and Malikov et al. (2020), are promising to prevent from misspecification issues. Lastly, fixed costs are not considered in this study which leaves the question to which extent firms incur higher markups to cover fixed costs and how investments in fixed costs translate into lower variable costs affecting the estimate of the output elasticity w.r.t. the flexible input used to compute the markup (Jaumandreu, 2022). Technological differences among firms, taking into account the relation between firm-level fixed and variable costs while enabling endogenous markups, are studied in more detail in a Cournot competition framework by De Monte and Koebel (2024) using a similar data set.

## Appendix

### A Data and variables

#### A.1 Descriptive statistics

Table A1 illustrates averages over the period 1994-2016 w.r.t. each manufacturing sector in the sample. The table shows that sector 25 (manufacturing for fabricated metal products) states the largest sector in terms of the number of firms, including on average 25.7% of all firms and 13.3% of total employment. Instead, in terms of sales, sector 29 (manufacturing for motor vehicles/(semi-) trailers), states the largest sector, with an average share of total sales of about 14.5%. Entry and exit rates are relatively stable across sectors. Here, the sector with the highest degree of firm dynamics is given by sector 14 (wearing apparel) with an average entry and exit rate of 6.1% and 8.7%, respectively.

Table A1: Summary statistics w.r.t. the included sectors: averages from 1994-2016<sup>a</sup>

2-digit sector <sup>b</sup>	# of firms	Share of firms	Share of empl.	Share of sales	Entry rate	Exit rate	Age
11	653	1.76	1.75	3.52	4.26	2.81	43.47
13	1608	4.35	2.89	1.88	3.65	4.88	22.73
14	1836	4.96	3.19	1.71	6.18	8.73	17.50
15	546	1.48	1.38	0.70	4.24	5.90	21.50
16	2574	6.96	2.77	1.84	4.05	3.99	19.98
17	979	2.65	3.40	3.45	3.13	3.76	23.20
18	3416	9.23	3.46	2.02	3.78	4.91	20.23
20	1442	3.90	7.67	12.46	3.77	4.50	23.20
21	296	0.80	3.65	5.43	3.89	4.94	25.07
22	2755	7.45	8.55	6.22	3.48	3.63	20.11
23	2162	5.84	5.47	4.66	4.40	4.83	21.54
24	645	1.74	3.96	5.13	4.32	3.76	22.45
25	9539	25.78	13.30	8.67	4.27	3.45	20.42
26	1401	3.79	6.59	6.65	5.66	6.08	18.51
27	1188	3.21	6.06	5.13	4.55	4.70	21.25
28	2909	7.86	7.89	6.92	4.99	4.86	20.88
29	1029	2.78	10.43	14.50	4.00	3.95	20.64
30	342	0.92	5.16	7.82	5.05	4.76	20.63
31	1679	4.54	2.45	1.31	4.28	5.05	18.08
Total	36999	100.00	100.00	100.00	4.29	4.48	20.94

<sup>a</sup> Source: FICUS/FARE database, own calculations. All figures represent averages over the whole period 1994-2016. Shares and rates are given in %.

<sup>b</sup> 11-beverages, 13-textiles, 14-wearing apparel, 15-leather/related products, 16-wood/products of wood and cork, 17-paper/paper products, 18-printing/reproduction of recorded media, 20-chemicals/chemical products, 21-pharmaceutical products/preparations, 22-rubber/plastic products, 23-other non-metallic mineral products, 24-basic metals, 25-fabricated metal products, 26-computer, electronic, and optical products, 27-electrical equipment, 28-machinery and equipment, 29-motor vehicles/(semi-) trailers, 30-other transport equipment, 31-furniture.

## A.2 Measuring firm entry and exit on a yearly basis

I here define firms' status of being either survivor, entrant, or exitor, which might change from year to year. Let  $a_{nt} \in \{0, 1\}$  be a firm state variable, taking the value zero in case of inactivity and one if the firm is active. A firm is said to be active at  $t$ , if it reports nonzero data for one of the following variables: total production, turnover and/or net profits. In all other cases the firm is supposed to be inactive. Further, survival is denoted by  $s_{nt} \in \{0, 1\}$  with  $s_{nt} = 1$  if  $a_{n,t-1} = a_{nt} = a_{n,t+1} = 1$ . Entry is denoted by  $e_{nt}^+ \in \{0, 1\}$  with  $e_{nt}^+ = 1$  if  $a_{n,t-1} = 0$  and  $a_{nt} = a_{n,t+1} = 1$ . Exit is denoted by  $e_{nt}^- \in \{0, 1\}$  with  $e_{nt}^- = 1$  if  $a_{n,t-1} = a_{nt} = 1$  and  $a_{n,t+1} = 0$ . In the literature firm entry and exit is often measured by looking one period ahead (see for instance [Blanchard et al. \(2014\)](#)). It is then specified that  $e_{nt}^+ = 1$  if  $a_{n,t-1} = 0$  and  $a_{n,t} = 1$ , and similarly with firm exit. However, measuring entry and exit in this way introduces some ambiguity with respect to the identification of entrants and exitors. This can be seen in Table A2. In the very last row, where the firm is only active at  $t$ , it could be considered as an entrant and/or exitor at  $t$ . Instead, I prefer to use the alternative convention and consider firms exhibiting an activity sequence as described in the last row of Table A2 as unidentified.

Table A2: Firm status example

Variable activity (0/1)			Status at $t$	Binary firm status variables at $t$
$a_{n,t-1}$	$a_{nt}$	$a_{n,t+1}$		
1	1	1	Survivor	$s_{nt} = 1, e_{nt}^+ = 0, e_{nt}^- = 0$
0	1	1	Entrant	$s_{nt} = 0, e_{nt}^+ = 1, e_{nt}^- = 0$
1	1	0	Exitor	$s_{nt} = 0, e_{nt}^+ = 0, e_{nt}^- = 1$
0	1	0	Not identified	$s_{nt} = 0, e_{nt}^+ = 0, e_{nt}^- = 0;$

Notice that firms' status is defined before any basic data cleaning. That is, before cleaning the data I assign both firms' activity status and their status of being either survivor, entrant, or exitor. This uncleaned dataset contains 337,488 firms summing up to 2,477,786 observations, which is a considerably larger dataset compared to the cleaned one with 96,013 firms and 851,261 firms, shown in Table 1. However, as also described in the main text, it might be that firms disappear from the data through reporting error and/or temporal inactivity. According to the procedure described above, if a firm is not active for more than one period, I count re-entry. Hence, a firm might enter or exit more than once. To illustrate some implications of my approach, Figure A1 shows the frequencies (in thousands) of consecutive years of inactivity. It can be seen that a single year of inactivity is relatively frequently observed, almost 35,000 times (based on the uncleaned data containing 2,477,786 observations). However, consecutive years of inactivity of more than one year are rare and the observed frequencies are decaying with the length of consecutive years of inactivity. Hence, the way I measure entry and exit for time spans longer than one period, based on the above definitions, captures well firms actual status of being survivor/entrant/exitor as re-activation of a firm's business becomes very rare for a period of inactivity of say four years.

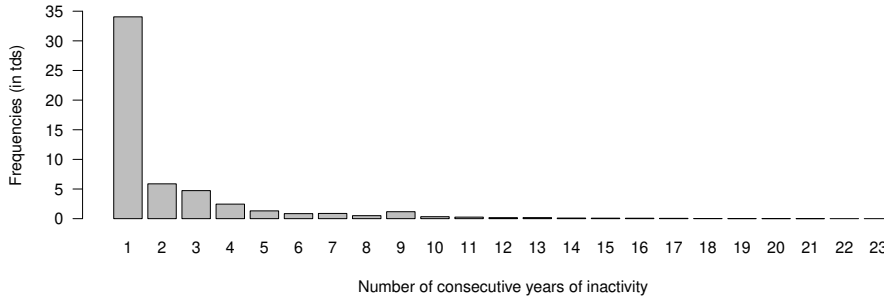


Figure A1: Frequencies of the observed number of consecutive years of inactivity. Source: FICUS/FARE database, own calculations.

It is noteworthy to mention that the database FARE (ESANE) also contains an official firm status variable. More precisely, from 2009 on there exists a variable indicating whether a firm is either active or whether it stopped its activity (exit). I use this variable to perform robustness checks on my own definition for firm exit. For that purpose, let  $e_{nt}^{-,ESANE} = 1$  if the firm is officially indicated to has stopped its activity and zero if the

firm is officially active. An arising problem with this variable is that a firm might officially close its activity at some point in time  $s$ , i.e.  $e_{ns}^{-,ESAN} = 1$ , while it does not report any positive value of sales (and other production input variables). That is, for that firm and at this year of official exit, any value for productivity can be measured, which is, however, necessary to perform statistical analysis of the effect of firm exit on productivity. A further problem is that firms may be measured to exit the market for several consecutive years as the bankruptcy process takes some time, i.e, for instance,  $e_{nt}^{-,ESANE} = e_{n,t+1}^{-,ESANE} = 1$ . To overcome the mentioned issues, I adapt the official variable slightly: Let  $e_{nt}^{-,ESANE\ bis} = 1$  if the firm is active according to my own definition of firm activity, i.e. if  $a_{nt} = 1$  (see above), and if the firm in the subsequent period is for the first time officially indicated to exit the market, i.e.  $e_{n,t+1}^{-,ESANE} = 1$ , and zero else. Table A3 compares the annual counts (over all sectors) of active firms according to my own definition (column 2) with the ESANE definition (column 3), and also compares the number of exits according to my own definition (column 4) with the ESANE definition (column 5) and with the adapted ESANE (bis) definition (column 6). Comparing first my own and the ESANE definition in terms of firm activity, it can be seen that I count somewhat more active firms compared to the ESANE definition. For instance, according to my own definition, for the year 2009 I count 108,335 active firms whereas according to the ESANE definition there are 94,591 active firms. This difference is due to the fact that according my definition a firm might be active and exit the following period, while according to the ESANE definition a firm is either active or exits the market, which excludes some firms from being active even if they report positive production/input values. Comparing the annual number of exits we can see that according to my definition I also count more exits compared to the official variable: For 2009 I measure 9,984 exitors while the official ESANE variable yields the number of 7,268. Instead, the adapted ESANE variable, where both activity and exit (in the subsequent period) is allowed, I measure for 2009 5,616 exits. So there is quite a difference between the annual number of exits based on my own and the official measure, which is mostly explained by the fact that, according to my measurement, firms might exit more than once. Considering longer time spans, i.e. the number of firms exited not on a yearly basis but during longer time spans, this should however, become less problematic as suggested by Figure A1.



Table A3: Firms' status: activity and exit

Year ( $t$ )	Number of active firms		Number of exitors		
	Own def. $\sum_n^{N_t} a_{nt}$	ESANE def. $\sum_n^{N_t} 1_{[e_{nt}^{-,ESANE}=0]}$	Own def. $\sum_n^{N_t} e_{nt}^{-}$	ESANE def $\sum_n^{N_t} = e_{nt}^{-,ESANE}$	ESANE def. bis $\sum_n^{N_t} = e_{nt}^{-,ESANE\ bis}$
1994	97726	-	-	-	-
1995	100233	-	5488	-	-
1996	107516	-	11848	-	-
1997	106669	-	8844	-	-
1998	106049	-	9041	-	-
1999	104878	-	11797	-	-
2000	101975	-	12208	-	-
2001	98056	-	5069	-	-
2002	105133	-	8343	-	-
2003	104112	-	8628	-	-
2004	103109	-	11001	-	-
2005	97163	-	5326	-	-
2006	101026	-	7319	-	-
2007	99195	-	9271	-	-
2008	113787	-	8260	-	-
2009	108335	94591	9984	7268	5616
2010	112839	102144	9012	5774	4363
2011	112224	101629	10722	5536	3499
2012	116022	107518	8442	4094	4011
2013	120384	112712	9851	2583	2524
2014	129049	118744	16448	4800	4717
2015	114698	106094	10668	3080	2986
2016	117608	109049	-	2997	2997

Source: FICUS/FARE database, own calculations. ESANE refers to "Élaboration des Statistiques Annuelles d'Entreprise", representing a data device in place from 2008 on, and which contains the firm-level database FARE.

To further compare the different exit measures, Table A4 presents a confusion matrix confronting my own and the official ESANE exit measure (left matrix) as well as my own and the adapted (bis) ESANE exit measure (right matrix). Here, the rows represent the values the ESANE variables for firm exit can take (zero for no-exit and one for exit), and the columns represent the values my own variable for exit can take (zero for no-exit and one for exit). Consider first the left matrix, which shows that in 90.2% of all cases no-exit according to the official ESANE measure corresponds to no-exit according to my measure. Further, in 5.92% no-exit according to the ESANE measure corresponds to an exits according to my approach. Instead, in 1.73% of all cases, the official ESANE measure of a firm exit corresponds to no-exit measured based on my own variable. Finally, in 2.15% of all cases, the official ESANE measure and my own measure of exit coincide. The confusion matrix on the right, confronting the adapted ESANE (bis) measure with my own one, shows a similar pattern, however, as expected, with an improved performance. Here, in 94.94% of all cases of non-exit according to the adapted ESANE variable corresponds to no-exit according to my own measure. In 2.52% of all cases the adapted ESANE (bis) variable for exit corresponds to an exit based on my own measure. This improvement is also reflected when simply correlating the different variables for firm exit with each other, shown in Table A5. More precisely, the correlation coefficient between my own measure for exit and the one based on the official ESANE variable is estimated by 0.62, while the correlation coefficient between the adapted ESANE bis variable of exit with my own one is slightly higher, given by 0.67.

The presented results show that the way I measure exit is relatively close to the

officially available information on firm exit and a reliable measure, especially when it comes to measuring firm exit over longer time periods. To establish consistency throughout the whole sample horizon, however, the use of my own variable for firm exit (as well as firm survival and entry) is preferable.

Table A4: Confusion matrix confronting different firm exit measures

a) With ESANE exit      b) With ESANE bis exit

	0	1
0	90.20	5.92
1	1.73	2.15

	0	1
0	94.94	1.17
1	1.38	2.52

Source: FICUS/FARE database, own calculations.

Table A5: Correlation matrix of firm exit measures

	Own exit	ESANE exit	ESANE bis exit
Own exit	1.00	0.62	0.67
ESANE exit		1.00	0.92
ESANE bis exit			1.00

Source: FICUS/FARE database, own calculations.

## B Robustness checks

### B.1 Production function specification

As both firm-level productivity and markups are derived from the production function, empirical results presented in this study strongly depend on the outcome of the estimation of the TL production function coefficients. The most natural way to check the results on robustness is to compare patterns of aggregate productivity and markups based on different production function specifications. For this purpose, I estimate a Cobb-Douglas (CD) gross output production function, given by

$$y_{nt} = \alpha_K x_{nt}^k + \alpha_L x_{nt}^l + \alpha_M x_{nt}^m + \omega_{nt} + \epsilon_{nt},$$

where  $\alpha_K$ ,  $\alpha_L$ , and  $\alpha_M$  denote technology parameters related to the output elasticities w.r.t. capital, labor, and materials. The estimation routine is analogue to the one presented for the TL production function (Section 2). In particular, the first stage of the estimation of the CD production function is the same as for the TL production function. Only the second stage changes.

The first stage yields  $\hat{f}(\cdot)$ , here likewise approximated by a forth order polynomial in the inputs, based on which, in the case of a CD production function, we obtain

$$\hat{\omega}_{nt}(\alpha) = \hat{f}(x_{nt}^k, x_{nt}^l, x_{nt}^m, c_{nt}) - \alpha_K x_{nt}^k - \alpha_L x_{nt}^l - \alpha_M x_{nt}^m,$$

with  $\alpha = \{\alpha_K, \alpha_L, \alpha_M\}$ . The innovations in  $\omega_{nt}$ , i.e.,  $\hat{\xi}_{nt}$ , can then be estimated by regressing  $\widehat{\omega}_{nt}(\alpha)$  on a higher order polynomial of  $\widehat{\omega}_{n,t-1}(\alpha)$  along with the exit dummy for some initial values for the parameters in  $\alpha$ . For the second stage estimation I here use the following moment conditions to finally estimate the parameters of the CD specification:

$$E \left[ \hat{\xi}_{nt}(\alpha) \mathbf{x}_{nt} \right] = 0,$$

with  $\mathbf{x}_{nt} \equiv (x_{nt}^k, x_{nt}^l, x_{n,t-1}^m)$ . See Online Appendix D, Table D1 reporting for each 2-digit industry separately the estimated coefficients as well as the resulting returns to scale.

## B.2 Aggregate productivity

### B.2.1 Aggregate productivity and the confidence interval

To assess statistical viability to the aggregate productivity measure, Figure B1 shows the weighted average along with the 95 % confidence interval (CI). The CI is bootstrapped, using 400 replications.

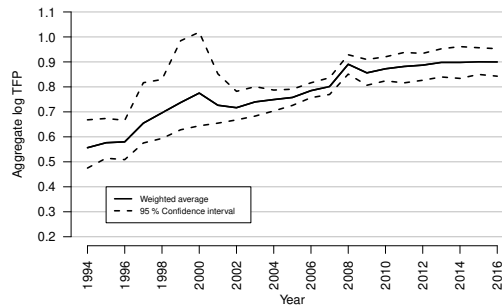


Figure B1: Aggregate productivity with the 95 % confidence interval. The confidence intervals are bootstrapped using 400 replications. Source: FICUS/FARE database, own calculations.

### B.2.2 Aggregate productivity derived from the Cobb-Douglas production function

Further, Figure B2 shows aggregate (log) TFP derived from the TL production function (solid line) vs. aggregate (log) TFP derived from the CD specification (dashed line). My estimates yield that aggregate productivity based on the CD specification yields a consistently lower aggregate log productivity level but follows qualitatively a similar pattern compared to the outcome based on the TL specification.

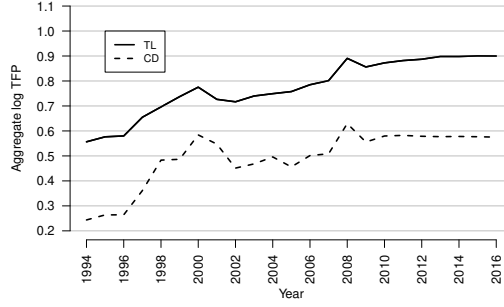


Figure B2: Aggregate log productivity: Translog (TL) vs. Cobb-Douglas (CD) production function. Source: FICUS/FARE database, own calculations.

## B.3 Aggregate markups

### B.3.1 Aggregate markups and the confidence interval

Similar to the case of aggregate productivity, statistical viability for the measure of aggregate markups is assessed by providing the bootstrapped 95% confidence interval.

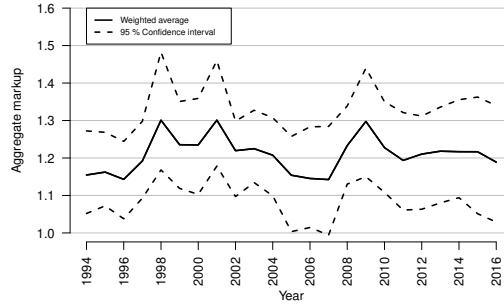


Figure B3: Aggregate markups with the 95 % confidence interval. The confidence intervals are bootstrapped using 400 replications. Source: FICUS/FARE database, own calculations.

### B.3.2 Aggregate markups: sources of variation

Remember first that aggregate markups are calculated as a weighted average of firm-level markup, given by

$$\hat{\mu}_t = \sum_n \hat{\mu}_{nt} s_{nt} \quad \text{with} \quad \hat{\mu}_{nt} = \frac{\hat{\theta}_{nt}^M}{\hat{\alpha}_{nt}^M},$$

where the first equality describes the weighted average of firms' markup weighted by their sales share. The markup is obtained by the ratio of the output elasticity and the input share w.r.t. materials, denoted by  $\hat{\theta}_{nt}^M$  and  $\hat{\alpha}_{nt}^M$ . The aggregate markup changes for three reasons: (i) changing sales shares, (ii) changing output elasticities, and (iii) changing input shares.

## Aggregate markups and changing output elasticity w.r.t. materials

To check for robustness of the aggregate markup measure I first compare the aggregate markups using the output elasticity w.r.t. materials  $\hat{\theta}_{nt}^M$ , obtained from the TL production function, with aggregate markup when using the output elasticity from the CD production function. That is, in the latter case,  $\hat{\theta}_{nt}^M = \hat{\alpha}_M$  implying constant elasticity across firms and years for a given 2-digit sector. Figure B4 shows the results. While the aggregate markup seems to remain relatively constant over time when using the flexible firm-level output elasticity from the estimation of the TL production function, represented by the solid line, using a constant elasticity from the CD production function yields a considerable higher and increasing level of aggregate markup over time.

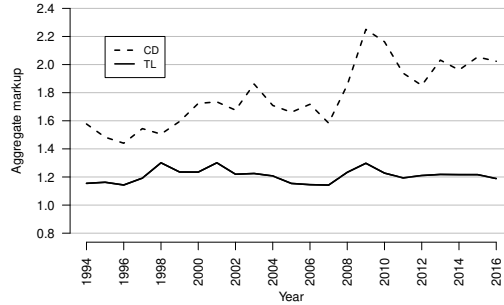


Figure B4: Aggregate markups: Using output elasticity based on translog (TL) vs. Cobb-Douglas (CD) production function. Source: FICUS/FARE database, own calculations.

## Aggregate markups and changing shares

The second robustness check w.r.t. the markup measure is done by replacing sales shares by total cost shares. A firm's total cost is defined by

$$C_{nt}^{tot} = P_t^k K_{nt} + P_t^l L_{nt} + P_t^m M_{nt},$$

where  $P_t$  denotes the user cost of capital, and  $P_t^l$  and  $P_t^m$  denote the labor and material price. In order to calculate the user cost of capital, I follow Hall and Jorgenson (1967), i.e.,  $P_t^k = P_t^I(1 + r_t) - P_{t+1}^I(1 - \delta_t)$ , with  $P_t^I$  denoting the price index for investment, available at the 2-digit level,  $r_t$  is the long-run rate of interest, and  $\delta_t$  the annual rate of capital depreciation, available at the 2-digit level.<sup>32</sup> Labor prices are firm specific and obtained by dividing firms' labor expenditures by the number of employees. Material prices are only available at the 2-digit level.<sup>33</sup> A firm's total cost share is then given by

<sup>32</sup>The interest rate is provided by the Banque de France at: <https://www.banque-france.fr/statistiques/taux-et-cours/taux-indicatifs-des-bons-du-tresor-et-oat>.  $\delta_t$  is calculated by considering the ratio between the consumption of fixed capital and fixed capital, see [www.insee.fr/fr/statistiques/2383652?sommaire=2383694](http://www.insee.fr/fr/statistiques/2383652?sommaire=2383694).

<sup>33</sup>The sectoral price data are available at <https://www.insee.fr/fr/statistiques/2832666?sommaire=2832834>

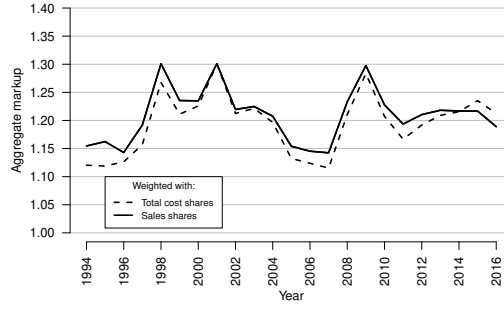


Figure B5: Aggregate markups: Using sales shares vs. total cost shares. Source: FICUS/FARE database, own calculations.

$$s_{nt}^C = C_{nt}^{tot} / \sum_n C_{nt}^{tot}.$$

Figure B5 illustrates the comparison. It can be seen that aggregate productivity based on firms' cost shares, given by the dashed line, yields an only slightly higher aggregate markup compared to the use of sales shares. The overall patterns of both curves, however, are very similar.

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# Online Appendix

## Productivity, Markups, and Reallocation: Evidence from French Manufacturing Firms

Enrico De Monte\*

October 7, 2024

### A Data

#### Merging of the data sets FICUS and FARE

For my analysis I merge the two fiscal firm-level datasets FICUS and FARE, covering the periods from 1994 to 2007, and 2008 to 2016, respectively. Both in FICUS and FARE firms are classified by a 4-digit sector nomenclature "NAF" (nomenclature d'activit française). However, from FICUS to FARE this sector nomenclature has significantly changed. In FICUS, the nomenclature was organized according to "NAF 1", while in FARE the nomenclature is organized according to "NAF 2". In this study I treat one single data set, 1994 - 2016, by establishing consistency in the sector nomenclature NAF 2 throughout the whole period. That is, I assign the current 4-digit sector nomenclature NAF 2 retrospectively for all firm observations from FICUS. For firms that are observed either in FICUS and FARE or only in FARE the 4-digit sector according to NAF 2 they belong to is known. However, for firms that have exited the market before 2008 I do not know to which NAF 2 4-digit sector they would have belonged to if they had continued

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\*E-mail: [enrico.demonte@zew.de](mailto:enrico.demonte@zew.de); Address: ZEW - Leibnitz Centre for European Economic Research, L 7,1, 68161 Mannheim;

their activity. To also classify these firms by the NAF 2 4-digit nomenclature I use the following methodology. I first only look at firms that are observed in both data sets FICUS and FARE. From these observations I build a transition matrix where each row represents a 4-digit sector according to NAF 1 and each column represents a 4-digit sector according to NAF 2. Each cell of the transition matrix contains the number of firms transiting from a specific 4-digit sector in FICUS (NAF 1) to the new 4-digit sector in FARE (NAF 2). Table A1 shows an exemplifying transition matrix, where I chose the NAF 1 4-digit sectors 201A - 205C, belonging to the manufacturing sector of wood and products of wood. For instance it can be seen that there are 2060 firms observed that were classified in FICUS in 201A (first row) and in FARE in the sector 1610 (third columns), while there are only 46 observations that were classified in 201A (FICUS) and in 0220 (FARE, first column). From these observed transition frequencies I then calculate the transition probabilities by simply dividing each element of the matrix by the sum of its corresponding row. That is, the NAF 1 - NAF 2 transition probabilities are calculated by

$$p_{ij} = \frac{\sum_{n \in \mathcal{I}, \mathcal{J}}^{N_i} \mathbf{1}_{[n \in \mathcal{I} \text{ and } n \in \mathcal{J}]}}{\sum_{n \in \mathcal{I}}^{N_i} \mathbf{1}_{[n \in \mathcal{I}]}} \quad (1)$$

where  $n$  is a firm observed in both FICUS and FARE,  $\mathcal{I}$  and  $\mathcal{J}$  are specific 4-digit sectors according to NAF 1 and NAF 2, respectively.  $\mathbf{1}$  is an index variable equal to 1 if the condition in parenthesis is fulfilled. Table A2 contains the transition probabilities according to the observed transitions Table A1. It can be seen that those 4-digit transitions between FICUS and FARE that were more frequently observed obtain accordingly higher probabilities. In a second step, firms only observed in FICUS belonging to a specific NAF 1 4-digit sector, are assigned to a NAF 2 4-digit sector, by drawing from a discrete probability distribution, which corresponds to the row in the probability transition matrix, i.e. the NAF 1 4-digit sector a firm belongs to and its potential transition possibilities.

Table A1: FICUS - FARE: Observed transition frequencies

NAF 1	0220	1392	1610	1621	1622	1623	1624	1629	NAF 2										Total
									2223	2512	3101	3109	3319	4329	4332	4391	4399	5610	
201A	46	0	2060	5	6	22	35	12	0	0	0	7	0	0	25	24	9	5	2256
201B	0	0	498	0	0	0	0	0	0	0	0	0	0	17	4	36	24	0	579
202Z	0	0	0	108	0	0	0	0	0	0	0	0	0	0	4	0	0	0	112
203Z	0	7	33	0	15	1880	8	8	41	26	0	41	0	6	1005	386	34	0	3490
204Z	0	0	17	0	0	4	857	6	0	0	0	0	35	0	6	0	0	0	925
205A	4	16	10	4	0	21	5	1215	0	0	12	317	0	0	87	0	4	10	1861
205C	0	0	0	0	0	0	0	86	0	0	0	0	0	0	0	0	0	0	86

Source: FICUS/FARE database, own calculations.

Table A2: FICUS - FARE: Transitions probabilities

NAF 1	0220	1392	1610	1621	1622	1623	1624	1629	NAF 2										Total
									2223	2512	3101	3109	3319	4329	4332	4391	4399	5610	
201A	0.02	0.00	0.91	0.00	0.00	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	1.00
201B	0.00	0.00	0.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.06	0.04	0.00	1.00
202Z	0.00	0.00	0.00	0.96	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
203Z	0.00	0.00	0.00	0.00	0.00	0.54	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.29	0.11	0.01	0.00	1.00
204Z	0.00	0.00	0.02	0.00	0.00	0.00	0.93	0.01	0.00	0.00	0.00	0.00	0.04	0.00	0.01	0.00	0.00	0.00	1.00
205A	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.65	0.00	0.00	0.01	0.17	0.00	0.00	0.05	0.00	0.00	0.01	1.00
205C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Source: FICUS/FARE database, own calculations.



## B Translog production function estimation

I here present the results from the translog (TL) production function estimation conducted for each 2-digit sector separately. In particular, Table B1 provides the coefficient estimates, which, however, are not easily interpretable. Table B2 shows, the more informative corresponding median output elasticity w.r.t. the inputs capital, labor, and materials, as well as the median returns to scale. Further, the corresponding median average distance (MAD) as well as the share of negative estimates are reported. Figure B1 illustrates the kernel density estimates of output elasticities and returns to scale over all firms and years. It can be seen that the output elasticity w.r.t. capital input is strongly concentrated around 0.1. Instead, the density of the elasticity w.r.t. labor is highest around 0.4. The density of the elasticity w.r.t. materials shows a bi-modal pattern, with a higher concentration between 0.3 and 0.4, as well as between 0.5 and 0.6. Returns to scale are highly concentrated around 1.0 and 1.05. Additionally, Figure B2 illustrates the median output elasticities and returns to scale over time. It can be seen that even though the coefficients of the TL production function are supposed to be fixed over time, the production technology, in terms of the output elasticity for a given input, might change through changes in firms' input mix. The figure shows that the median output elasticity of labor is higher at the beginning of the period and decreases over time, while the median output elasticity w.r.t. materials slightly increases.

The first stage of the production function estimation allows to recover the production function residual  $\hat{\epsilon}_{nt}$  (equation (7) in the paper). It is then further used to recover firm-level productivity (equation (14) in the paper) as well as to estimate the input share of materials to derive firm-level markups (equation (17) and (15) in the paper). Figure B3 shows the kernel density estimate of the residual, with a strong concentration around zero, close to normality.

Table B1: Coefficients estimates of the TL production function (ACF)

Sector	$\alpha_K$	$\alpha_L$	$\alpha_M$	$\alpha_{KK}$	$\alpha_{LL}$	$\alpha_{MM}$	$\alpha_{KL}$	$\alpha_{KM}$	$\alpha_{ML}$	# Obs.	# Firms
Beverages	0.060 (0.0026)	0.368 (0.0192)	0.661 (0.0328)	0.080 (0.0044)	-0.019 (9e-04)	0.100 (0.0048)	0.030 (0.0010)	-0.087 (0.0041)	-0.021 (0.0010)	12743	1330
Textiles	0.138 (0.0070)	0.157 (0.0076)	0.681 (0.0338)	0.047 (0.0024)	0.168 (0.0081)	0.123 (0.0062)	-0.023 (0.0013)	-0.037 (0.0014)	-0.110 (0.0055)	31761	3599
Wearing apparel	0.137 (0.0079)	0.318 (0.0142)	0.721 (0.0364)	0.028 (0.0013)	0.101 (0.0061)	0.155 (0.0078)	-0.013 (0.0012)	-0.022 (0.0010)	-0.124 (0.0063)	33225	5384
Leather/ related products	0.123 (0.0065)	0.100 (0.0025)	0.759 (0.0395)	0.028 (7e-04)	0.189 (0.0109)	0.120 (0.0058)	-0.026 (0.0016)	-0.011 (5e-04)	-0.132 (0.0077)	10553	1337
Wood/products of wood and cork	0.134 (0.0102)	0.196 (0.0107)	0.581 (0.0286)	0.015 (0.0028)	0.103 (0.0090)	-0.034 (0.0024)	-0.083 (0.0053)	0.052 (0.0017)	0.005 (0.0034)	50589	5538
Paper/ paper products	0.078 (0.0030)	0.238 (0.0095)	0.659 (0.0349)	0.059 (0.0031)	0.126 (0.0068)	0.097 (0.0050)	-0.013 (7e-04)	-0.040 (0.0016)	-0.082 (0.0048)	19862	1937
Printing/reprod. of recorded media	0.163 (0.0078)	0.006 (0.0015)	0.735 (0.0362)	0.001 (6e-04)	0.257 (0.0126)	0.074 (0.0049)	-0.039 (0.0024)	0.015 (9e-04)	-0.143 (0.0074)	66497	7911
Chemicals/ chemical products	0.177 (0.0093)	0.130 (0.0056)	0.746 (0.0371)	0.095 (0.0046)	0.168 (0.0082)	0.101 (0.0049)	-0.035 (0.0016)	-0.070 (0.0035)	-0.076 (0.0035)	28717	3043
Pharma. products/ preparations	0.177 (0.0097)	0.024 (0.0012)	0.790 (0.0407)	0.064 (0.0034)	0.123 (0.0075)	0.102 (0.0051)	-0.017 (0.0014)	-0.060 (0.0030)	-0.065 (0.0035)	5902	640
Rubber/ plastic products	0.144 (0.0078)	0.128 (0.0075)	0.637 (0.0314)	-0.010 (0.0012)	0.141 (0.0071)	0.048 (0.0039)	-0.016 (0.0013)	0.009 (3e-04)	-0.069 (0.0041)	55614	5494
Other non-metallic mineral products	-0.011 (1e-04)	0.561 (0.0275)	0.594 (0.0294)	0.048 (0.0014)	0.008 (9e-04)	0.085 (0.0042)	0.017 (7e-04)	-0.038 (0.0013)	-0.063 (0.0031)	42255	4792
Basic metals	0.126 (0.0065)	0.251 (0.0104)	0.622 (0.0318)	0.064 (0.0029)	0.180 (0.0093)	0.107 (0.0052)	-0.037 (0.0021)	-0.028 (9e-04)	-0.109 (0.0056)	12978	1354
Fabricated metal products	0.201 (0.0100)	0.257 (0.0126)	0.496 (0.0246)	0.044 (0.0022)	0.149 (0.0076)	0.067 (0.0043)	-0.034 (0.0023)	-0.030 (6e-04)	-0.065 (0.0039)	191460	19405
Computer/electronic/ optical products	0.100 (0.0056)	-0.024 (6e-04)	0.790 (0.0390)	-0.011 (0.0013)	0.245 (0.0103)	0.096 (0.0057)	-0.003 (8e-04)	0.013 (1e-04)	-0.158 (0.0073)	26831	3423
Electrical equipment	0.193 (0.0098)	0.005 (0.0020)	0.719 (0.0345)	0.043 (0.0022)	0.220 (0.0100)	0.123 (0.0061)	-0.032 (0.0015)	-0.031 (0.0017)	-0.124 (0.0056)	23439	2602
Machinery and equipment	0.182 (0.0102)	-0.093 (0.0050)	0.778 (0.0403)	-0.009 (0.0026)	0.309 (0.0172)	0.083 (0.0054)	-0.058 (0.0036)	0.031 (1e-04)	-0.147 (0.0087)	57187	6446
Motor vehicles/ (semi-) trailers	0.246 (0.0105)	0.083 (0.0054)	0.654 (0.0336)	0.070 (0.0034)	0.214 (0.0101)	0.117 (0.0064)	-0.063 (0.0023)	-0.033 (0.0017)	-0.103 (0.0058)	20532	2191
Other transport equipment	0.166 (0.0090)	-0.094 (0.0054)	0.832 (0.0399)	0.080 (0.0026)	0.323 (0.0164)	0.110 (0.0063)	-0.054 (0.0021)	-0.031 (0.0015)	-0.160 (0.0083)	6656	806
Furniture	0.120 (0.0060)	-0.021 (0.0015)	0.800 (0.0416)	0.014 (0.0012)	0.192 (0.0108)	0.101 (0.0047)	-0.030 (0.0016)	-0.008 (3e-04)	-0.105 (0.0068)	32234	4007

Source: FICUS/FARE database, own calculations. Standard errors are bootstrapped using 400 replications and reported in parenthesis.

Table B2: Translog production function: Median output elasticities w.r.t. inputs and return to scales

Sector	Statistic	Input			
		Capital	Labor	Materials	Return to Scales
All	Elasticity	0.122	0.461	0.474	1.045
	MAD	0.039	0.097	0.113	0.031
	Share $\leq 0$	3.160	0.190	1.160	0.000
Beverages	Elasticity	0.159	0.361	0.606	1.124
	MAD	0.059	0.020	0.065	0.013
	Share $\leq 0$	5.010	0.000	0.330	0.000
Textiles	Elasticity	0.124	0.435	0.455	1.011
	MAD	0.038	0.109	0.092	0.053
	Share $\leq 0$	2.490	0.620	1.000	0.000
Wearing apparel	Elasticity	0.104	0.471	0.528	1.104
	MAD	0.046	0.202	0.253	0.024
	Share $\leq 0$	0.910	0.140	14.230	0.000
Leather/ related products	Elasticity	0.083	0.441	0.521	1.039
	MAD	0.013	0.097	0.070	0.031
	Share $\leq 0$	0.330	0.410	1.180	0.000
Wood/products of wood and cork	Elasticity	0.101	0.390	0.555	1.044
	MAD	0.031	0.068	0.036	0.015
	Share $\leq 0$	5.810	0.030	0.000	0.000
Paper/ paper products	Elasticity	0.097	0.404	0.532	1.032
	MAD	0.037	0.048	0.050	0.016
	Share $\leq 0$	5.760	0.000	0.230	0.000
Printing/reprod. of recorded media	Elasticity	0.130	0.480	0.431	1.042
	MAD	0.008	0.084	0.049	0.038
	Share $\leq 0$	0.000	0.130	0.150	0.000
Chemicals/ chemical products	Elasticity	0.130	0.371	0.594	1.087
	MAD	0.063	0.074	0.081	0.033
	Share $\leq 0$	8.790	0.620	0.590	0.000
Pharma. products/ preparations	Elasticity	0.148	0.265	0.626	1.034
	MAD	0.052	0.058	0.082	0.019
	Share $\leq 0$	7.110	1.190	0.260	0.000
Rubber/ plastic products	Elasticity	0.111	0.395	0.551	1.050
	MAD	0.012	0.064	0.043	0.022
	Share $\leq 0$	0.000	0.020	0.020	0.000
Other non-metallic mineral products	Elasticity	0.100	0.464	0.496	1.070
	MAD	0.034	0.059	0.054	0.026
	Share $\leq 0$	0.630	0.000	0.090	0.000
Basic metals	Elasticity	0.113	0.484	0.448	1.039
	MAD	0.037	0.089	0.068	0.022
	Share $\leq 0$	4.970	0.330	0.340	0.000
Fabricated metal products	Elasticity	0.178	0.545	0.312	1.035
	MAD	0.029	0.054	0.046	0.027
	Share $\leq 0$	0.070	0.000	0.200	0.000
Computer/electronic/ optical products	Elasticity	0.119	0.446	0.481	1.048
	MAD	0.026	0.131	0.079	0.045
	Share $\leq 0$	2.510	0.880	2.350	0.000
Electrical equipment	Elasticity	0.095	0.389	0.541	1.023
	MAD	0.031	0.089	0.078	0.026
	Share $\leq 0$	2.480	0.370	1.600	0.000
Machinery and equipment	Elasticity	0.048	0.454	0.554	1.046
	MAD	0.029	0.121	0.065	0.049
	Share $\leq 0$	17.660	0.400	0.610	0.000
Motor vehicles/ (semi-) trailers	Elasticity	0.101	0.392	0.558	1.045
	MAD	0.046	0.077	0.064	0.020
	Share $\leq 0$	6.820	0.340	1.420	0.000
Other transport equipment	Elasticity	0.107	0.580	0.429	1.103
	MAD	0.041	0.168	0.126	0.069
	Share $\leq 0$	5.850	0.950	5.330	0.000
Furniture	Elasticity	0.085	0.339	0.611	1.029
	MAD	0.012	0.067	0.049	0.020
	Share $\leq 0$	0.240	0.100	0.060	0.000

Source: FICUS/FARE database, own calculations. MAD denotes the Median Average Deviation.

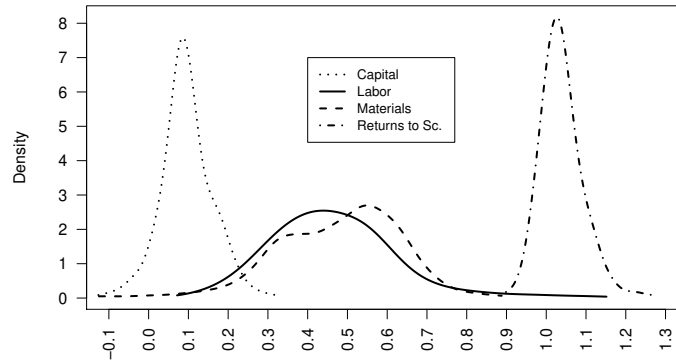


Figure B1: Kernel density estimates of output elasticities and returns to scale. Source: FICUS/FARE database, own calculations.

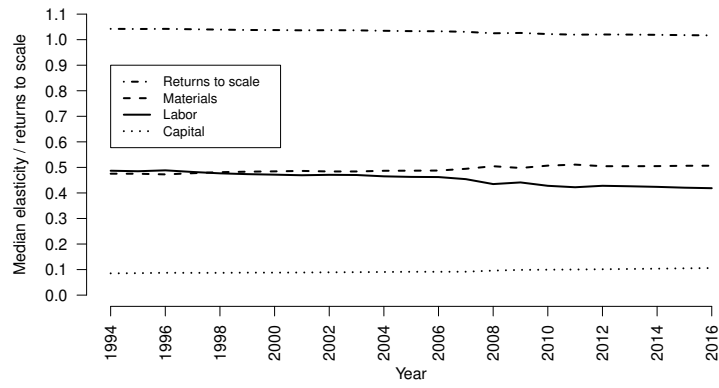


Figure B2: Median output elasticities and returns to scale over time. Source: FICUS/FARE database, own calculations.

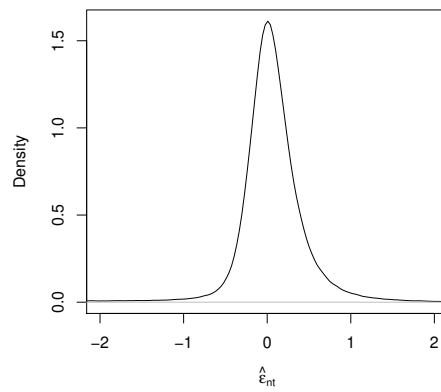


Figure B3: Distribution of residual: production function first stage regression. Source: FICUS/FARE database, own calculations.

## C Decomposition analysis

### C.1 Derivation of the DOPD approach

In the framework of the DOPD approach, aggregate productivity/markup is decomposed in the following way: Let  $S_{Gt} = \sum_{n \in G} s_{nt}$  denote the aggregate sales share of a group  $G$ , where  $G = (E, S, X)$  indexes the group of entrants, survivors, and exitors. A group's aggregate productivity is then defined by  $\Phi_{Gt} = \sum_{n \in G} (s_{nt}/S_{Gt}) \phi_{nt}$ , where  $\phi_{nt}$  denotes the firm-level measure of either TFP or markup. Consider two periods,  $t - k$  and  $t$ , where firms from  $t - k$  to  $t$  either survive or exit the market. That is, the set of active firms at  $t - k$  is composed of those firms that will survive and those that will finally exit the market at some period  $s$  with  $t - k \leq s < t$ . At  $t$  the set of active firms is composed of those firms that have survived from  $t - k$  and new firms that have entered the market at some period  $s$  with  $t - k < s \leq t$ . According to the DOPD approach presented by [Melitz and Polanec \(2015\)](#), the aggregate measure at  $t - k$  and  $t$  is described by

$$\Phi_{t-k} = S_{S,t-k} \Phi_{S,t-k} + S_{X,t-k} \Phi_{X,t-k} = \Phi_{S,t-k} + S_{X,t-k} (\Phi_{X,t-k} - \Phi_{S,t-k}) \quad (2)$$

$$\Phi_t = S_{S,t} \Phi_{S,t} + S_{E,t} \Phi_{E,t} = \Phi_{S,t} + S_{E,t} (\Phi_{E,t} - \Phi_{S,t}). \quad (3)$$

Adding to the first equality of the first and second line  $S_{X,t-k} \Phi_{S,t-k} - S_{X,t-k} \Phi_{S,t-k}$  and  $S_{E,t} \Phi_{S,t} - S_{E,t} \Phi_{S,t}$ , respectively, and recognizing that  $S_{S,t-k} + S_{X,t-k} = 1$  and  $S_{S,t} + S_{E,t} = 1$  yields the second equality.

Hence, the aggregate's growth between  $t - k$  and  $t$  can be expressed by

$$\Phi_t - \Phi_{t-k} = \underbrace{\Phi_{S,t} - \Phi_{S,t-k}}_{\text{Contr. survivors}} + \underbrace{S_{E,t}(\Phi_{E,t} - \Phi_{S,t}) + S_{X,t-k}(\Phi_{S,t-k} - \Phi_{X,t-k})}_{\text{Contr. Net-entry}}. \quad (4)$$

As shown in the main text, the contribution of survivors can be further decomposed into its within and between contribution.

### C.2 Decomposition tables for aggregate productivity

Table [C1](#) shows aggregate measures for the group of survivors, entrants, and exitors, both those of sales shares and productivity. Panel A shows the respective measures at the respective first year ( $t - k$ ), corresponding to equation (2) and Panel B shows the respective measures at the second year ( $t$ ), corresponding to equation (3) (see Online Appendix Section [C](#)).

Table C1: Aggregate productivity and sales shares

Panel A: Measures at $t - k$							
$t - k$	$t$	$\Phi_{S,t-k}$	$S_{S,t-k}$	$\Phi_{X,t-k}$	$S_{X,t-k}$	No. Surv.	No. Exitors
1994	1998	0.57	90.76	0.49	9.24	27871	4145
1998	2002	0.67	87.95	0.57	12.05	30842	6575
2002	2006	0.72	79.76	0.73	20.24	30362	6347
2006	2010	0.79	88.42	0.78	11.58	26196	5988
2010	2014	0.89	81.73	0.79	18.27	24276	3860
2012	2016	0.88	93.04	0.90	6.96	23771	2804
Panel B: Measures at $t$							
$t - k$	$t$	$\Phi_{S,t}$	$S_{S,t}$	$\Phi_{E,t}$	$S_{E,t}$	No. Surv.	No. Entrants
1994	1998	0.70	88.54	0.67	11.46	27871	8359
1998	2002	0.72	82.84	0.74	17.16	30842	6212
2002	2006	0.79	76.39	0.79	23.61	30362	4556
2006	2010	0.87	92.30	0.93	7.70	26196	3352
2010	2014	0.92	79.12	0.81	20.88	24276	2905
2012	2016	0.90	84.93	0.90	15.07	23771	1791

Source: FICUS/FARE database, own calculations. The columns  $\Phi_{G,j}$  and  $S_{G,j}$  with  $G = \{S, X, E\}$  and  $j = \{1, 2\}$ , denote the aggregate productivity and the aggregate sales share of the firm groups survivors, exitors, and entrants - measured for the initial year (Year 1) and the last year of the period (Year 2). All sales shares  $S_{G,j}$  are given in %.

Table C2 presents the aggregate measures, graphically shown in the main text. That is, the tables contain of aggregate productivity/markup (and aggregate sales shares) of the group of survivors, entrants, and exitors as well as these groups' contribution to the aggregate. Note that the index  $t$  corresponds to the respective year (column 1), whereas the index  $t - k$  always corresponds to the measure at the initial year 1994. This means that contributions to the aggregate measure are always cumulatively w.r.t. 1994.

Table C2: DOPD: Aggregate productivity 1994-2016

Year ( $t$ )	$\Phi_t$	$\Phi_{S,t}$	$S_{S,t}$	$\Phi_{S,t-k}$	$S_{S,t-k}$	Contr. Surv.	Contr. Within	Contr. Between	$\Phi_{E,t}$	$S_{E,t}$	Contr. Entry.	$\Phi_{X,t-k}$	$S_{X,t-k}$	Contr. Exit.	Contr. Net-E
1994	0.556	-	-	-	-	-	-	-	-	-	-	-	-	-	-
1995	0.576	0.578	96.32	0.556	100.00	0.021	-0.000	0.021	0.543	0.04	-0.001	0.000	0.00	0.000	-0.001
1996	0.580	0.578	93.52	0.557	97.48	0.021	-0.004	0.025	0.600	0.06	0.001	0.546	0.03	0.000	0.002
1997	0.655	0.649	90.16	0.562	92.99	0.092	0.032	0.060	0.661	0.10	0.001	0.489	0.07	0.005	0.006
1998	0.696	0.692	88.54	0.564	90.76	0.135	0.053	0.083	0.673	0.11	-0.003	0.492	0.09	0.007	0.004
1999	0.737	0.732	85.05	0.567	87.58	0.174	0.083	0.092	0.711	0.15	-0.005	0.490	0.12	0.010	0.005
2000	0.775	0.783	81.81	0.559	79.55	0.226	0.076	0.150	0.732	0.18	-0.010	0.551	0.20	0.002	-0.008
2001	0.726	0.734	79.50	0.522	75.33	0.203	0.100	0.103	0.733	0.20	0.002	0.560	0.25	-0.009	-0.008
2002	0.717	0.704	73.04	0.537	78.99	0.172	0.106	0.066	0.737	0.27	0.007	0.511	0.21	0.005	0.013
2003	0.740	0.733	70.04	0.534	74.53	0.202	0.117	0.085	0.750	0.30	0.004	0.524	0.25	0.003	0.007
2004	0.749	0.717	68.33	0.554	70.42	0.186	0.133	0.053	0.769	0.32	0.009	0.475	0.30	0.023	0.032
2005	0.758	0.727	54.58	0.539	61.57	0.197	0.130	0.067	0.783	0.45	0.021	0.515	0.38	0.009	0.030
2006	0.785	0.749	53.90	0.548	59.16	0.218	0.155	0.063	0.806	0.46	0.018	0.503	0.41	0.018	0.036
2007	0.802	0.765	53.20	0.547	57.35	0.235	0.174	0.061	0.824	0.47	0.020	0.507	0.43	0.017	0.037
2008	0.891	0.850	56.34	0.550	55.40	0.319	0.264	0.055	0.919	0.44	0.022	0.507	0.45	0.019	0.041
2009	0.856	0.841	55.27	0.540	51.37	0.312	0.232	0.080	0.861	0.45	0.004	0.516	0.49	0.012	0.016
2010	0.872	0.851	53.27	0.533	49.58	0.323	0.249	0.074	0.892	0.47	0.017	0.523	0.50	0.005	0.022
2011	0.882	0.872	51.64	0.533	46.69	0.345	0.270	0.075	0.886	0.48	0.004	0.523	0.53	0.006	0.009
2012	0.887	0.859	53.86	0.535	47.60	0.330	0.259	0.072	0.912	0.46	0.022	0.522	0.52	0.007	0.028
2013	0.898	0.865	47.89	0.538	46.05	0.337	0.276	0.061	0.919	0.52	0.023	0.519	0.54	0.010	0.033
2014	0.898	0.871	47.02	0.540	45.07	0.344	0.274	0.070	0.911	0.53	0.015	0.517	0.55	0.013	0.027
2015	0.900	0.885	45.35	0.537	44.10	0.358	0.294	0.064	0.905	0.55	0.005	0.520	0.56	0.010	0.015
2016	0.900	0.868	45.15	0.538	42.79	0.341	0.283	0.058	0.916	0.55	0.020	0.518	0.57	0.012	0.032

Source: FICUS/FARE database, own calculations.  $t$  refers to the respective year, while  $t - k$  always refers to the initial year 1994. Contributions of survivors and net entry are, hence, always w.r.t. 1994.  $\Phi_G$  and  $S_G$  with  $G = \{S, E, X\}$  denotes aggregate productivity and sales share of the group of survivors, entrants, and exitors.  $S_G$  are given in percent.



### C.2.1 Annual average growth rates of aggregate productivity

Based on Table C2 (i.e. the second column,  $\Phi_t$ ), Figure C1 shows the average annual growth rate (AAGR) of aggregate productivity. Here, the AAGR for each year is calculated by  $AAGR_{t_0,t} = (\Phi_t - \Phi_{t_0})/(t - t_0)$ , with  $t > 1994$  and  $t_0 = 1994$ . As also described in the paper, the AAGR exhibits a strong increase until 2000, up to about 3.5%, whereupon the AAGR is decreasing over time with some exceptions between 2005 and 2008. Figure C2 confronts the evolution of aggregate productivity (shown on left  $y$ -axis) with the AAGR for different time periods (shown on the right  $y$ -axis). Here, the AAGR for different periods, i.e. from  $t - k$  to  $t$ , is computed by  $AAGR_{t-k,t} = (\Phi_t - \Phi_{t-k})/(t - k)$ , given by 1.56% (1994-2016), 3.65% (1994-2000), 0.33% (2000-2007),  $-0.09\%$  (2008-2012), and 0.032% (2012-2016). The purpose of the figure is to compare my results with those of Ben Hassine (2019), who likewise estimates aggregate productivity using French firm-level data. The author finds (for the whole French economy) for 2000-2007 (2008-2012) an AAGR of 0.66% (0.32%), which is, hence, somewhat higher compared to my results for the respective periods.



Figure C1: The average annual growth rate (AAGR) of aggregate productivity. Source: FICUS/FARE database, own calculations.

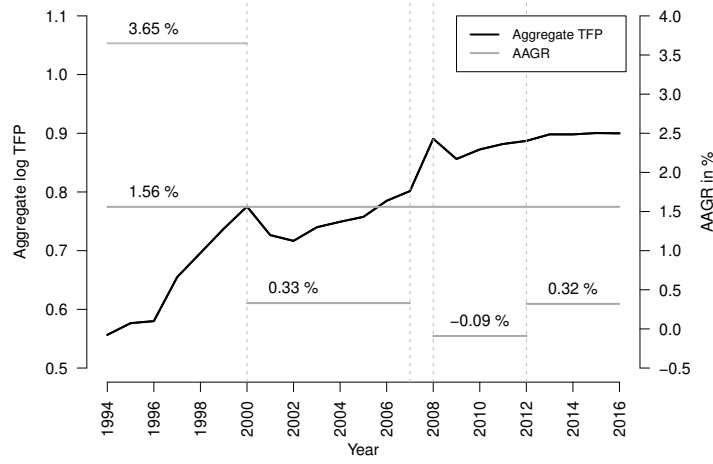


Figure C2: Aggregate productivity and the average annual growth rate (AAGR). Source: FICUS/FARE database, own calculations.

### C.3 Decomposition tables for aggregate markups

Analogously to the case of aggregate productivity, Table C3 shows aggregate measures for the group of survivors, entrants, and exitors, both those of sales shares and markups. Panel A shows the respective measures at the first year ( $t - k$ ), corresponding to equation (2) and Panel B shows the respective measures at the second year ( $t$ ), corresponding to equation (3) (see Appendix C).

Table C3: Aggregate markups and sales shares

Panel A: Measures at $t - k$							
$t - k$	$t$	$\Phi_{S,t-k}$	$S_{S,t-k}$	$\Phi_{X,t-k}$	$S_{X,t-k}$	No. Surv.	No. Exitors
1994	1998	0.14	90.76	0.17	9.24	27871	4145
1998	2002	0.25	87.95	0.19	12.05	30842	6575
2002	2006	0.30	79.76	0.02	20.24	30362	6347
2006	2010	0.16	88.42	0.22	11.58	26196	5988
2010	2014	0.29	81.73	0.02	18.27	24276	3860
2012	2016	0.23	93.04	0.20	6.96	23771	2804
Panel B: Measures at $t$							
$t - k$	$t$	$\Phi_{S,t}$	$S_{S,t}$	$\Phi_{E,t}$	$S_{E,t}$	No. Surv.	No. Entrants
1994	1998	0.23	88.54	0.18	11.46	27871	8359
1998	2002	0.26	82.84	0.14	17.16	30842	6212
2002	2006	0.28	76.39	-0.13	23.61	30362	4556
2006	2010	0.23	92.30	0.14	7.70	26196	3352
2010	2014	0.32	79.12	0.04	20.88	24276	2905
2012	2016	0.30	84.93	0.07	15.07	23771	1791

Source: FICUS/FARE database, own calculations. The columns  $\Phi_{G,j}$  and  $S_{G,j}$  with  $G = \{S, X, E\}$  and  $j = \{1, 2\}$ , denote the aggregate productivity and the aggregate sales share of the firm groups survivors, exitors, and entrants - measured for the initial year (Year 1) and the last year of the period (Year 2). All sales shares  $S_{G,j}$  are given in %.

Table C4 presents the aggregate measures, graphically shown in the main text. That is, the tables contain of aggregate productivity/markup (and aggregate sales shares) of the group of survivors, entrants, and exitors as well as these groups' contribution to the aggregate. Note that the index  $t$  corresponds to the respective year (column 1), whereas the index  $t - k$  always corresponds to the measure at the initial year 1994. This means that contributions to the aggregate measure are always cumulatively w.r.t. 1994.

Table C4: DOPD: Aggregate markup 1994-2016

Year (t)	$\Phi_t$	$\Phi_{S,t}$	$S_{S,t}$	$\Phi_{S,t-k}$	$S_{S,t-k}$	Contr. Surv.	Contr. Within	Contr. Between	$\Phi_{E,t}$	$S_{E,t}$	Contr. Entry.	$\Phi_{X,t-k}$	$S_{X,t-k}$	Contr. Exit.	Contr. Net-E
1994	1.155	-	-	-	-	-	-	-	-	-	-	-	-	-	-
1995	1.162	1.161	96.32	1.155	100.00	0.006	-0.039	0.044	1.195	3.68	0.001	0.000	0.00	0.000	0.001
1996	1.143	1.138	93.52	1.154	97.48	-0.018	-0.027	0.008	1.242	6.48	0.007	1.232	2.52	-0.002	0.005
1997	1.192	1.180	90.16	1.152	92.99	0.027	0.017	0.009	1.310	9.84	0.013	1.159	7.01	-0.001	0.012
1998	1.301	1.308	88.54	1.147	90.76	0.155	0.016	0.137	1.294	11.46	-0.001	1.210	9.24	-0.006	-0.007
1999	1.235	1.233	85.05	1.180	87.58	0.050	0.057	-0.008	1.268	14.95	0.006	1.205	12.42	-0.003	0.003
2000	1.235	1.230	81.81	1.182	79.55	0.064	0.013	0.051	1.186	18.19	-0.011	1.103	20.45	0.016	0.005
2001	1.301	1.296	79.50	1.210	75.33	0.113	0.036	0.080	1.214	20.50	-0.023	1.098	24.67	0.028	0.005
2002	1.220	1.226	73.04	1.200	78.99	0.026	0.092	-0.067	1.204	26.96	-0.006	1.202	21.01	-0.001	-0.006
2003	1.225	1.239	70.04	1.196	74.53	0.038	0.098	-0.062	1.203	29.96	-0.009	1.214	25.47	-0.005	-0.014
2004	1.207	1.211	68.33	1.206	70.42	0.013	0.084	-0.066	1.183	31.67	-0.011	1.178	29.58	0.008	-0.003
2005	1.154	1.219	54.58	1.246	61.57	0.020	0.050	-0.025	1.019	45.42	-0.112	1.123	38.43	0.047	-0.065
2006	1.145	1.211	53.90	1.248	59.16	0.012	0.046	-0.035	1.012	46.10	-0.114	1.128	40.84	0.049	-0.066
2007	1.142	1.214	53.20	1.247	57.35	0.015	0.026	-0.012	1.006	46.80	-0.120	1.135	42.65	0.048	-0.072
2008	1.233	1.260	56.34	1.247	55.40	0.062	0.099	-0.035	1.135	43.66	-0.076	1.138	44.60	0.049	-0.027
2009	1.298	1.346	55.27	1.245	51.37	0.151	0.184	-0.038	1.176	44.73	-0.098	1.143	48.63	0.049	-0.049
2010	1.228	1.282	53.27	1.239	49.58	0.088	0.104	-0.020	1.115	46.73	-0.099	1.151	50.42	0.045	-0.055
2011	1.194	1.260	51.64	1.226	46.69	0.067	0.055	0.010	1.088	48.36	-0.099	1.166	53.31	0.032	-0.067
2012	1.210	1.277	53.86	1.214	47.60	0.086	0.075	0.009	1.106	46.14	-0.090	1.171	52.40	0.023	-0.067
2013	1.218	1.311	47.89	1.221	46.05	0.119	0.126	-0.011	1.106	52.11	-0.122	1.167	53.95	0.029	-0.093
2014	1.217	1.314	47.02	1.216	45.07	0.124	0.119	0.000	1.108	52.98	-0.122	1.171	54.93	0.025	-0.098
2015	1.217	1.335	45.35	1.218	44.10	0.145	0.163	0.006	1.095	54.65	-0.147	1.169	55.90	0.028	-0.119
2016	1.189	1.313	45.15	1.222	42.79	0.121	0.133	0.011	1.062	54.85	-0.154	1.169	57.21	0.030	-0.124

Source: FICUS/FARE database, own calculations.  $t$  refers to the respective year, while  $t - k$  always refers to the initial year 1994. Contributions of survivors and net entry are, hence, always w.r.t. 1994.  $\Phi_G$  and  $S_G$  with  $G = \{S, E, X\}$  denotes aggregate markup and sales share of the group of survivors, entrants, and exitors.  $S_G$  are given in percent.

## D Cobb-Douglas production function specification

Table [D1](#) presents the estimated coefficients of a Cobb-Douglas (CD) production function along with the resulting returns to scale. Analogously to the employed TL production function presented in the paper, the CD production function is estimated for each 2-digit industry separately. As discussed in the paper, the CD specification is estimated for sake of comparison of aggregate productivity and markups w.r.t. results derived from a TL specification.

Table D1: Coefficient estimates of the Cobb-Douglas production function

Sector	$\hat{\alpha}_K$	$\hat{\alpha}_L$	$\hat{\alpha}_M$	Returns to scale
Beverages	0.188 (0.006)	0.408 (0.006)	0.533 (0.006)	1.129
Textiles	0.102 (0.003)	0.474 (0.004)	0.418 (0.002)	0.994
Wearing apparel	0.097 (0.004)	0.550 (0.004)	0.378 (0.002)	1.025
Leather/related products	0.139 (0.005)	0.578 (0.007)	0.337 (0.005)	1.054
Wood/products of wood and cork	0.078 (0.003)	0.464 (0.004)	0.499 (0.004)	1.041
Paper/paper products	0.126 (0.004)	0.452 (0.006)	0.479 (0.006)	1.057
Printing/reprod. of recorded media	0.064 (0.003)	0.581 (0.004)	0.368 (0.003)	1.013
Chemicals/ chemical products	0.203 (0.004)	0.396 (0.005)	0.488 (0.004)	1.087
Pharma. products/ preparations	0.138 (0.009)	0.374 (0.016)	0.545 (0.011)	1.057
Rubber/plastic products	0.139 (0.005)	0.431 (0.005)	0.491 (0.006)	1.061
Other non-metallic mineral products	0.139 (0.004)	0.492 (0.004)	0.474 (0.005)	1.105
Basic metals	0.126 (0.005)	0.392 (0.006)	0.492 (0.005)	1.010
Fabricated metal products	0.124 (0.000)	0.553 (0.002)	0.319 (0.001)	0.996
Computer/electronic/optical products	0.135 (0.009)	0.581 (0.010)	0.408 (0.009)	1.124
Electrical equipment	0.108 (0.003)	0.497 (0.005)	0.414 (0.004)	1.019
Machinery and equipment	0.074 (0.003)	0.623 (0.004)	0.364 (0.003)	1.061
Motor vehicles/(semi-) trailers	0.140 (0.005)	0.516 (0.006)	0.408 (0.005)	1.064
Other transport equipment	0.125 (0.016)	0.684 (0.011)	0.313 (0.008)	1.122
Furniture	0.070 (0.003)	0.421 (0.005)	0.524 (0.005)	1.015

Source: FICUS/FARE database, own calculations. Standard errors are bootstrapped using 400 replications and reported in parenthesis.

## E Heterogeneity in aggregate productivity and markup across sectors

To provide some insight into heterogeneity in the aggregate measures among sectors, I compute both aggregate productivity and markups across years, for each of the 2-digit sector separately. Figure E1 illustrates heterogeneity w.r.t. aggregate productivity and shows that there is substantial variation. Some sectors, such as the manufacturing for wearing apparel, reveal an aggregate log productivity of only 0.28, whereas others, such as the manufacturing of other transport equipment, reveals a high productivity, given by 1.20, which is a dramatic difference. Similarly, Figure E2 shows the aggregate markup across sectors. Most sectors are above an aggregate productivity of one, i.e., on average prices are higher compared to marginal costs. Sector 24 (basic metals) and 29 (motor vehicles etc.) show an aggregate markup of somewhat below one. More drastically, sector 30 (other transport equipment) shows an aggregate markup far below one. This is induced by a relatively low (high) estimated output elasticity (output share) w.r.t. materials and a higher share of measured markdowns (share of firms reporting a markup  $< 1$ ), probably weighted by larger sales shares. Caselli et al. (2018) measure for the French manufacturing that about 14% of firms reveal markdowns. I find somewhat smaller share of about 10%.<sup>1</sup>

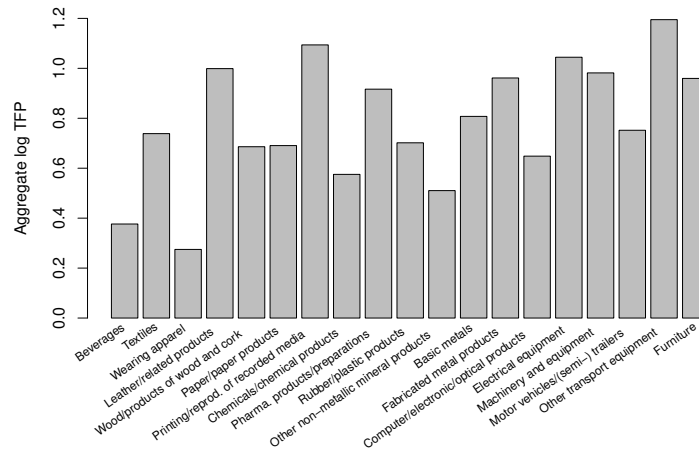


Figure E1: Heterogeneity in aggregate productivity among sectors. Source: FICUS/FARE database, own calculations.

<sup>1</sup>See Appendix B, Table B2, for estimated median elasticities for each sector as well as Appendix F Figure F1, illustrating markdowns per sector.



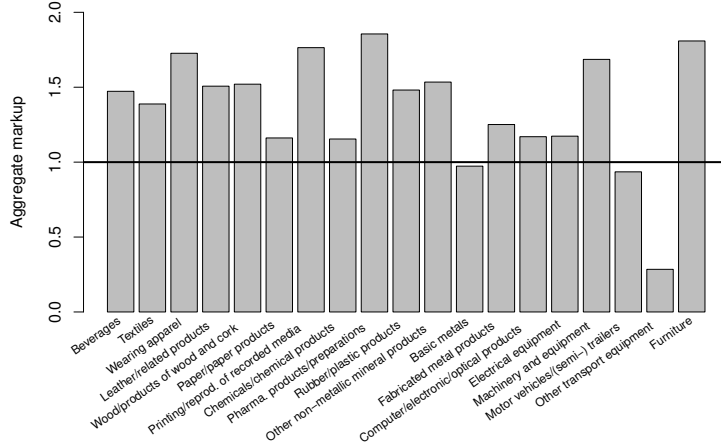


Figure E2: Heterogeneity in aggregate markup among sectors. Source: FICUS/FARE database, own calculations.

## F Further material

Figure F1 illustrates the share of markdowns for each sector. That is, each bar corresponds to the share of firms that reveal prices below the marginal costs, i.e.  $\hat{\mu}_{nt} < 1$ . The sector for beverages exhibits the highest share of markdowns, given by more than 30 %. Other sectors, such as the sector for pharmaceutical products and the manufacture of furniture, only show a share of markdowns slightly larger than zero. These industries also shows the highest aggregate markups (see Figure E2).

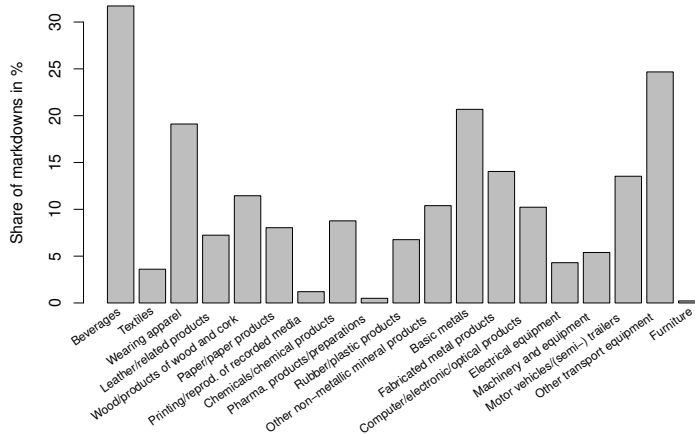


Figure F1: Share of markdowns (share of firms with markup  $< 1$ ) by sector. Source: FICUS/FARE database, own calculations.

Table F1 provides some descriptive statistics for the estimated output shares w.r.t. capital, labor, and materials, given in the first column by  $\hat{a}_{nt}^K$ ,  $\hat{a}_{nt}^L$ , and  $\hat{a}_{nt}^M$ . All shares are estimated analogously to the output share w.r.t. materials, presented in the main text in equation (17). The table shows that among all inputs, the output share w.r.t. capital is the smallest, given with a mean of 7.71%. Here, firms at the 10th (90th) percentile

exhibit an output share w.r.t. capital of 1.42% (15.47%). The highest output share is given for labor, with a mean of 45.35%, which is somewhat higher compared to the mean output share w.r.t. materials, given by 31.55%.

Table F1: Output shares in % w.r.t. inputs over all firms

Output share	Mean	Std Dev	Percentiles		
			P10	P50	P90
$\hat{a}_{nt}^K$	7.71	11.22	1.42	5.26	15.47
$\hat{a}_{nt}^L$	45.35	45.02	17.97	36.55	76.70
$\hat{a}_{nt}^M$	31.55	18.46	8.66	29.95	55.56

Source: FICUS/FARE database, own calculations.

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