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Productivity, Markups, and Reallocation: Evidence From French Manufacturing Firms From 1994 to 2016

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Productivity, Markups, and Reallocation: Evidence from French Manufacturing Firms from 1994 to 2016*†

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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. Firm-level productivity and markups are estimated based on a gross output translog production function using popular estimation methods. I find an aggregate productivity growth of about 34% over the whole period while aggregate markups are found to remain relatively stable. As a key finding the study shows that over time reallocation of sales shares affects differently aggregate productivity and markups: Before 2000 both aggregate productivity and markups are importantly driven by reallocation effects; 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. Policy relevant implications of these dynamics are discussed.

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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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; Edmond et al., 2018; Hopenhayn, 2014). 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.[1] If sales shares shift to more productive producers - which happens when productive units grow faster relative to their competitors and/or when new more efficient firms enter the industry, grow, scrap market shares, and force less efficient firms to shrink and exit the market - the economy as a whole reaches a higher level of allocative efficiency. In that sense, in well-functioning market economies, dynamics in productivity growth are typically related to business dynamism and the reallocation of resources (Foster et al., 2001, 2008; Haltiwanger, 2011; Decker et al., 2014; Haltiwanger, 2021). When sales shares not only shift to more efficient firms but also to high-markup firms, higher allocative efficiency is accompanied by a higher level of aggregate markup which, as mentioned above, might also have negative effects. More problematic, however, is the case when reallocation primarily occurs towards high-markup firms but not to high-productive firms. Then, negative implications through markups are not mitigated through gains in aggregate productivity.

To measure such dynamics, this paper investigates jointly the evolution of aggregate productivity and markups, with a particular attention to the role of reallocation w.r.t. both measures. Subsequently, policy implications for the provided evidence are discussed. For that purpose, I exploit data of French manufacturing firms between 1994 and 2016. The estimation of a gross output translog production function, following Ackerberg et al. (2015), allows to derive firm-level productivity and markups. The latter is obtained by using 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.

Let us consider more closely the relation between productivity and markups. At the firm-level, productivity is closely linked to markups since marginal costs are negatively related to productivity, i.e. an increase in production efficiency is associated with lower marginal costs allowing firms to increase markups. These firms are also very likely to grow faster than their competitors which increases the aggregate of both productivity and markups. In this context, 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. However, as briefly mentioned above, economists also believe that a higher level of markups reduce labor demand and capital investments hampering future productivity improvements (De Loecker et al., 2020; Edmond et al., 2018), and that firms use rents from the markup to increase barriers to entry for potential market entrants (Eeckhout, 2022). This in turn reduces competition, thus, having negative long-run effects on productivity improvements (Aghion et al., 2009). Here, sales shares become reallocated towards higher markup firms, which do not necessarily mirror their relative improvements in efficiency. In other words, firms exploit their dominant market position to the cost of the economy which reduces welfare.

In both described scenarios aggregate markups increase, however, by very different reasons. This has important policy implications: In the first case, where resources become allocated to both high-productivity and high-markup firms, policy interventions targeting high-markup firms' size could have negative effects, since, from a welfare perspective, high-markup firms should even produce more (De Monte and Koebel, 2023; Baqaee and Farhi, 2020). In the second case, instead, where resource reallocation towards high-markup firms is not reflected by their productivity, competition and entry enhancing policies, potentially reducing the size of high-markup firms by fostering reallocation towards smaller but efficient firms, would be beneficial.

While staying descriptive, my results for French manufacturing firms show that there is

[1] Aggregate productivity and markups are usually measured by a sales share weighted average of individual firms' productivity and markups. As will be explained in detail further down, this also allows 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.

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.

The reminder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 and Section 4 introduce the theoretical and empirical framework. Section 5 describes the data and descriptive statistics. Section 6 presents the results of the aggregate productivity and markup decomposition and discusses policy implications. Section 7 provides robustness checks and considers the impact of potential biases. Section 8 finally concludes.

2 Related literature

Productivity, markups, and their relation are vastly treated topics in the field of industrial organization. I present selected studies on that issue in the following.

2.1 Productivity

An important reason why productivity is extensively studied at the firm-level is because it is seen as an important determinant for firms' ability to survive in the market. Well-known industry models such as the ones presented by Jovanovic (1982), Hopenhayn (1992), and Ericson and Pakes (1995) describe the selection process of firms entering, surviving, and exiting the market to be determined by firms' productivity. The hypothesis that entering and surviving firms have higher productivity compared to exiting firms is empirically confirmed by various studies (Fariñas and Ruano, 2005; Wagner, 2010). Moreover, Aghion et al. (2004) and Aghion et al. (2009) show that higher firm entry rates incentivize incumbent firms to increase their productivity, which finally leads to an increase in aggregate productivity growth. That is, a firm's productivity is crucial for its own ability to survive and the process of entry and exits shapes the evolution of the aggregate level of productivity of a given economy or industry.

The best way to measure aggregate productivity is to derive it from individual firms' productivity (Van Biesebroeck, 2008a). In the literature, it is common to measure aggregate productivity by a sales/market share weighted average of firm-level productivity. In addition, Olley and Pakes (1996) show that the weighted average can be decomposed into an unweighted average component and a covariance term between firm's productivity and their market share. That is, an increase in the aggregate measure might be induced by an increase in the average productivity or by the reallocation of market shares. The first term is referred to as the within-change or learning effect and the second one is referred to as the between-change or reallocation effect.[2] In a dynamic setting, when firm entry and exit occurs, it is natural to investigate the impact of firm dynamics on aggregate productivity. Baily et al. (1992), Foster et al. (2001), and more recently Melitz and Polanec (2015) develop decomposition methods that allow to investigate the contribution of the firm groups of survivors, entrants, and exitors on aggregate productivity growth. While there are some differences in measuring the contribution of the firm groups on aggregate productivity growth, all methods measure aggregate productivity by a sales/market share weighted average of firm-level productivity. Many studies show that aggregate productivity growth is considerably impacted by surviving firms' within-change, i.e. by the learning effect, and by the between-change, i.e. market share reallocation among incumbents. Also, the cited literature shows that surviving firms contribute relatively more to aggregate productivity growth compared to entering and exiting firms. Ben Hassine (2019) applies and compares the three methods on French firm-level data from 2000 to 2012. He shows that firms' (average) productivity improvement, i.e. the learning effect, mainly contributes to the aggregate productivity evolution while the reallocation effect of market shares turns out to have a less pronounced effect on the aggregate productivity growth. In terms of the evolution of aggregate productivity, the here presented paper extends the results presented by Ben Hassine (2019) to a longer time period and uses a more flexible estimation approach. Considering only the period 2000-2012, my results go largely in line with Ben Hassine (2019)'s results.

Asturias et al. (2023) apply the productivity decomposition presented by Foster et al. (2001) on manufacturing firms from Chile and Korea and find that, compared to periods of low growth, entering firms have a stronger contribution to aggregate productivity growth during periods of high growth. For the case of the US steel industry, Collard-Wexler and De Loecker (2015) show the important role of reallocation to aggregate productivity growth

[2] Section 4.2 discusses in detail the decomposition of aggregates w.r.t. within/between change as well as firm entry and exit.

by the arrival of a novel and more efficient steel production technology. While the productivity decomposition literature considers resource allocation in terms of output, where misallocation is described as a process where less efficient firms become allocated larger output shares, there is also a vast literature on the misallocation of production inputs. See for instance Restuccia and Rogerson (2008) providing a model that shows that resource allocation in an economy with heterogeneous firms in term of productivity is an important determinant for per capita output and aggregate total factor productivity. In this vein, Hsieh and Klenow (2009) show that if production inputs in China and India were allocated as efficiently as in the US, aggregate productivity would increase by 30%–50% and 40%–60%, respectively.[3]

Another strand of the literature focuses on the overall trend of the evolution of productivity. Recent studies have documented that productivity growth has slowed down. For instance, for the US economy a productivity slowdown from the early 2000s on is measured and discussed by Decker et al. (2017), Gordon (2017), Syverson (2017) and Byrne et al. (2016). Cette et al. (2016) compare the evolution of aggregate productivity growth for UK, Spain, Germany, and France finding slowed productivity growth particularly for the considered southern European countries, which they relate to misallocation provoked by low interest rates in these countries. Investigating the French economy specifically, Cette et al. (2017) find that productivity growth slows down from 2000 on, which is here likewise related to inefficient resource allocation.[4]

2.2 Markups

The gap between a firm's output price and its marginal costs is called the markup. In perfectly competitive markets firms are forced to sell their product at marginal costs to persist in the market. Hence, if the price-to-marginal costs ratio is larger than one, the respective economy is considered as lacking in competition where firms detain market power. Since both prices and marginal costs are typically unobserved in firm-level data, markups need to be estimated econometrically. Seminal contributions were provided by Hall (1986, 1988) showing that, under the assumption of cost minimizing firms, average markups can be estimated as the ratio of elasticity of output of any flexible input (an input free of adjustment costs), and the corresponding input revenue share. If this ratio is equal to one output price and marginal cost equalize and, thus, there are no markups.[5] Hall investigates markups at the 2-digit industry-level and finds (average) markups far above one, suggesting a considerable degree of market power and, thus, imperfect competition. Klette (1999) builds on the Hall-framework and finds very low (average) markups among Norwegian manufacturing firms. Likewise inspired by the Hall-framework, De Loecker (2011) and De Loecker and Warzynski (2012) develop and apply what they call the *production-approach*, allowing to estimate markups at the firm-level based on the estimation of a production function. Using data from Slovenian manufacturing firms, De Loecker and Warzynski (2012) find that exporting firms reveal considerably higher level of markups compared to non-exporting firms. Bellone et al. (2016) apply their approach on data of French manufacturing firms. While confirming higher markups for exporting firms, they also find decreasing aggregate markups for the period 1998-2007. Caselli et al. (2018) treat French firm-level data to study determinants for markdowns, i.e. when firms' prices are found to be below marginal costs. They find that markdowns are persistent and name potential candidates to explain them, such as subsidies, strategic behaviour (aggressive price policy to crowd out competitors), uncertainty, and irreversibility (difficulties to liquidate capital). De Loecker et al. (2020) explicitly focus on the evolution of aggregate markups in the US economy and measure a dramatic increase between 1980 and 2016, from 21% to 61% of prices above marginal costs. Their results show that, while the median markup remains relatively constant, the aggregate markup has been driven upwards by the reallocation of sales shares towards few high-markup firms, detaining large market power. De Loecker et al. (2021) argue that both technical innovation and a changing market structure, such as the decline in antitrust enforcement, are crucial determinants for the rise in market power. De Loecker and Eeckhout (2018) extend the analysis of the measurement of aggregate markups to the global economy and find a global increase of about 50 percentage points between 1980 and 2016. For the considered European countries they find increasing markups between 1980 and 2000 and, after a time of minor changes, again from 2010 until 2016. Weche and Wambach (2021), specifically investigating European countries' aggregate markup evolution, find relatively stable aggregate markups for the period between 2007 and 2015. This is also the case in terms of the results reported in my paper, where aggregate markups are relatively stable for the period from 1994 to 2016.

[3]There are various studies applying the Hsieh and Klenow approach: Bellone et al. (2013) do not find such a productivity gap due to misallocation between France and the US. Calligaris et al. (2016) find that if the level of misallocation among Italian firms remained at the level of 1995, in 2013 aggregate productivity would be 18% higher. Ryzhenkov (2016) finds that if the Ukraine manufacturing attained the level of allocative efficiency of the US or E.U., aggregate productivity could be doubled. Also see Restuccia and Rogerson (2013) for a detailed review on this topic.

[4]See also Bellone (2017) for a controversial discussion on that paper.

[5]This approach is presented and discussed more in detail in the following section.

The influential results presented by De Loecker et al. (2020), however, are controversially discussed in the literature. For instance, Traina (2018) contrasts the findings and argues that when representing public firms more accurately in the sample, aggregate markups only increase modestly.[6] Using industry-level data, Hall (2018) finds increasing markups between 1988 and 2015, changes, however, are statistically insignificant. More recently, Doraszelski and Jaumandreu (2021) and Jaumandreu (2022) criticise the production-approach to measure markups arguing that the method is sensitive to the specific product demand functions firms face and that reduced unit variable costs, through investments in fixed costs, should also be reflected in firms' decreasing elasticity of output w.r.t. the used variable input, which in many empirical studies using the production-approach is not included. Results show that employing a factor augmented production production function, allowing to control for decreasing variable costs, results in relatively stable or considerably lower aggregate markups (Demirer, 2020; Jaumandreu, 2022).

A further issue that might provoke serious biases in the estimated of markups is the case when revenue data (deflated by an industry-level price index) is used. Klette and Griliches (1996) already showed that when estimating production functions, the use of revenue data leads to downwards biased output elasticities, which consequently also affects the estimation of markups using the production approach. Bond et al. (2021) show 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 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 demonstrate that instead of output distortions, the obtained markup estimate rather represents input distortions, given inputs are measured in quantities.[7] In contrast, 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. As an attempt to respond to this controversial discussion, Kirov and Traina (2021) develop a framework allowing to fully identify markups based on revenue data only. Their approach relies on a two-step estimation approach of a production function by controlling for fixed effects, while control functions are used to take unobserved markups into account. This yields an unbiased estimator of the output elasticities of the production function and so for the markup using the production approach.

2.3 Relation between productivity and markups

In the literature, markups (or more precisely dispersed markups) are considered as distortions acting against a more efficient economy (Hopenhayn, 2014). That is, assuming that markups are generated by technological advantages that allow firms to produce at lower costs, these firms (at least temporarily) develop a dominant market position also allowing them to set higher prices and so reducing their output quantity, demanding less inputs such as labor and capital, which, from a welfare perspective, misallocates production factors towards less efficient firms. Edmond et al. (2018) focus on the welfare costs of markups and show that these costs are transmitted as markups behave similar to an output tax as well as due to misallocation of input factors implied by markups. Peters (2020) develops a theoretical model where the stationary distribution of markups is determined by what he calls the "churning intensity", described by the rate of creative destruction - i.e. the rate at which less efficient firms are replaced by more efficient ones - relative to the rate at which firms increase markups. In particular, throughout the life-cycle of a product firms increase the related markup until the product will be replaced by a new one, produced by more efficient competitors. By that, the lower the churning intensity, the fatter the tails of the markup distribution, the higher the degree of misallocation and, as a consequence, the lower aggregate productivity. That is, reallocation of sales shares towards higher markup firms throughout the time is beneficial for aggregate productivity as high-markup firms are likely to be highly efficient, too. On the other hand, if there were no markups, those firms would be even bigger, thus a part of potential productivity and welfare increases is missed. By the use of a general equilibrium model Baqaee and Farhi (2020) aim to quantify these effects for the US economy, covering

[6] Note that Traina (2018) refers to an earlier working paper version of De Loecker et al. (2020).

[7] Input distortions refer to firms' market power (measured as markups) in input markets (i.e. input market imperfections), which has received a lot of attention in the literature. Markups in input markets (also called markdowns) are shown to be tightly related to markups in output markets. For instance, Mertens (2020, 2022) derives a measure of input market power that is inversely related to product market power, which is also shown empirically investigating German manufacturing firms. Caselli et al. (2021) builds on this framework to study labor market imperfections using data on French manufacturing firms. They show that, at the aggregate level, firms' markups in output markets contribute negatively over time to labor market imperfections.

the period from 1997 to 2015. They find that resource reallocation from low-markup to high-markup firms accounts for 50% of aggregate productivity growth as these firms were highly productive. However, they also show that markups hamper aggregate productivity growth as high-markup firms remain too small (i.e. demanding less inputs and producing less by optimally choosing the markup), hence, if markups were eliminated, aggregate productivity would increase by 15%.

The here presented 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. In particular, while between 1994 and 2000 both aggregate measures increases as sales shares become allocated to higher productive and higher markups firms, post-2000 reallocation dynamics to both measures becomes disconnected, i.e. sales shares become only reallocated to high-markup firms but not to high-productivity firms.

3 Theoretical background

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 production function

$$Y_{nt} = F(X_{nt}^V, X_{nt}^F, \Omega_{nt}), \tag{1}$$

where X_{nt}^V and X_{nt}^F denote, for simplicity, one *variable* and one *fixed* input factor, and Ω_{nt} is related to total factor productivity (TFP). *Variable* inputs, such as materials, might be *adjusted* at t, whereas *fixed* inputs, such as capital, are assumed to be *predetermined*, i.e. optimally chosen by the firm prior to t.

In the field of industrial organization, production functions are extensively employed to study firms' production behavior. For instance, from production functions output elasticities w.r.t. different inputs can be derived and studied, as well as firm-level productivity that is widely employed for efficiency analysis. Moreover, as already mentioned, based on Hall (1986, 1988), De Loecker and Warzynski (2012) provide by the production-approach a method to derive firm-level markups from the estimation of a production function. More precisely, they assume firms to behave cost minimizing, which yields the objective Lagrangian function, given by

$$\mathcal{L}\left(X_{nt}^V, X_{nt}^F, \lambda_{nt}\right) = P_{nt}^V X_{nt}^V + P_{nt}^F X_{nt}^F - \lambda_{nt}\left(Y_{nt} - F(\cdot)\right), \tag{2}$$

where P_{nt}^V and P_{nt}^F denote the prices for the variable and fixed inputs. λ_{nt} represents the shadow price, i.e. the change in costs if the production level changes by one unit, in other words, the marginal cost of a change in output. $F(\cdot)$ represents the production technology from (1). The first order conditions (FOC) yield

$$\frac{\partial \mathcal{L}}{\partial X_{nt}^V} = P_{it}^V - \lambda_{nt}\frac{\partial F(\cdot)}{\partial X_{nt}^V} = 0. \tag{3}$$

The last expression can also be written by

$$\theta_{nt}^V = \frac{\partial F(\cdot)}{\partial X_{nt}^V}\frac{X_{nt}^V}{Y_{nt}} = \frac{1}{\lambda_{nt}}\frac{P_{nt}^V X_{nt}^V}{Y_{nt}}, \tag{4}$$

where θ_{nt}^V is the output elasticity w.r.t. the variable input. Defining the markup by $\mu_{nt} = P_{nt}/\lambda_{nt}$, i.e. output price over marginal cost, and insert the expression into the previous equation, we obtain an expression for the markup by

$$\theta_{nt}^V = \frac{\mu_{nt}}{P_{nt}}\frac{P_{nt}^V X_{nt}^V}{Y_{nt}} \Longleftrightarrow \mu_{nt} = \frac{\theta_{nt}^V}{a_{nt}^V}, \tag{5}$$

where $a_{nt}^V = (P_{nt}^V X_{nt}^V)/(P_{nt}Y_{nt})$ denotes the output share of the variable input. That is, a firm's markup is defined by the ratio of output elasticity w.r.t. the variable input and the according input share.

4 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.

4.1 Production function estimation

Empirically, I approximate the production function from equation (1) by a *gross output translog* (TL) production function, given by

$$y_{nt} = \alpha_0 + \sum_i \alpha_i x^i_{nt} + \frac{1}{2}\sum_{ij} \alpha_{ij} x^i_{nt} x^j_{nt} + \omega_{nt} + \epsilon_{nt}, \tag{6}$$

lower case letters denote logs, where gross output production is supposed to be given by $y_{nt} = \log(Y_{nt}) + \epsilon_{nt}$, and x^i_{nt} with $i = (k, l, m)$ denotes the input factors capital, labor, and intermediary products (materials), ω_{nt} represents the log-level of TFP, and ϵ_{nt} an *iid* shock.[8] TFP is unobserved by the econometrician and as such a residual of the production function. However, its decomposition from ϵ_{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, ϵ_{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 $K_{nt} = \exp\left(x^k_{nt}\right)$ 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 ω_{nt}. Instead, materials are supposed to be flexible, and hence adjustable w.r.t. ω_{nt}. Input markets are supposed to be exogenous, i.e. firms do not detain any market power in the respective markets.[9] As extensively discussed in many studies such as Olley and Pakes (1996) (OP, henceforth), Levinsohn and Petrin (2003) (LP), Ackerberg 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^m_{nt}) as a function of the productivity shocks ω_{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 (6) in the LP spirit and proceed very similar to ACF.[10] 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 $x^m_{nt} = h(x^k_{nt}, x^l_{nt}, \omega_{nt}, c_{nt})$, 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^m_{nt} in ω_{nt}. This assumption implies invertibility of h in ω_{nt}, yielding $\omega_{nt} = h^{-1}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt})$, which is then substituted into equation (6) to obtain

$$\begin{aligned} y_{nt} &= \alpha_0 + \sum_i \alpha_i x^i_{nt} + \frac{1}{2}\sum_{ij} \alpha_{ij} x^i_{nt} x^j_{nt} + h^{-1}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt}) + \epsilon_{nt} \\ &= f(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt}) + \epsilon_{nt}. \end{aligned} \tag{7}$$

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 $\hat{f}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt})$, 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 ω_{nt}, which is assumed to be a first order Markov process, where firm entry and exit is allowed to impact the productivity i.e.,

$$\omega_{nt} = g\left(\omega_{n,t-1}, e^-_{nt}\right) + \xi_{nt}, \tag{8}$$

where $g(\cdot)$ defines the productivity process, $e^-_{nt} = 1$ if a firms exits in the subsequent period and zero else, which is included to control for self-selected exit (Olley and Pakes, 1996), and ξ_{nt} is an *iid* error term with $E(\xi_{nt}|\omega_{n,t-1}, e^-_{nt}) = 0$.[11] From equation (7) it follows that

$$\widehat{\alpha_0 + \omega_{nt}}(\alpha) = \hat{f}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt}) - \sum_i \alpha_i x^i_{nt} + \frac{1}{2}\sum_{ij} \alpha_{ij} x^i_{nt} x^j_{nt}, \tag{9}$$

where $\alpha = (\alpha_i,\ \alpha_{ij})$ with $i = \{k, l, m\}$. The innovations in ω_{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

[8] That is, gross output production is allowed to contain measurement errors that are, along with unanticipated shocks to production, comprised in ϵ_{nt} (De Loecker and Warzynski, 2012).

[9] 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).

[10] Also see De Loecker and Warzynski (2012) for a further application.

[11] See Appendix A.2 for the definition of firm exit.

dummy. Then, for some initial values for the parameters, α can be estimated by a search over the space of the parameters in α, imposing the moment conditions[12,13]

$$E\left[\hat{\xi}_{nt}(\alpha)\mathbf{x}_{nt}\right] = 0, \tag{10}$$

with $\mathbf{x}_{nt} \equiv (x^k_{nt}, x^l_{nt}, x^m_{n,t-1}, (x^k_{nt})^2, (x^l_{nt})^2, (x^m_{n,t-1})^2, x^l_{nt}, x^k_{nt}, x^m_{n,t-1}, x^k_{nt}, x^m_{n,t-1}, x^l_{n,})'$. Note that the moment conditions are derived from the first order Markov assumption (given in equation (8)), implying orthogonality between the production input factors and the innovation to productivity, ξ_{nt}.

I rewrite these conditions as

$$E\left[d(\alpha, x_{nt})\right] = 0, \tag{11}$$

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

$$\widehat{\alpha} = \arg\min_{\alpha} \overline{d}(\alpha)' W \overline{d}(\alpha), \tag{12}$$

where W is a $L \times L$ optimal weighting matrix, given by the inverse of the covariance matrix of $d(\alpha, x_{nt})$,[14] and

$$\overline{d}(\alpha) = \frac{1}{N}\sum_{n=1}^{N}\frac{1}{T_n}\sum_{t=1}^{T_n} d(\alpha, x_{nt}), \tag{13}$$

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

4.1.1 Firm-level productivity

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

$$\hat{\omega}_{nt} = y_{nt} - \sum_i \hat{\alpha}_i x^i_{nt} + \frac{1}{2}\sum_{ij}\hat{\alpha}_{ij} x^i_{nt} x^j_{nt} - \hat{\epsilon}_{nt}, \tag{14}$$

where $\hat{\epsilon}_{nt} = y_{nt} - \hat{f}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt})$.

4.1.2 Firm-level markups

According to equation (5), markups can be estimated by the ratio of the output elasticity w.r.t. the variable input materials and its input share, given by

$$\hat{\mu}_{nt} = \frac{\hat{\theta}^M_{nt}}{\hat{a}^M_{nt}}, \tag{15}$$

where the output elasticity w.r.t materials, $\hat{\theta}^M_{nt}$, is obtained by[15]

$$\hat{\theta}^M_{nt} = \frac{\partial y_{nt}}{\partial x^i_{nt}} = \hat{\alpha}_m + \hat{\alpha}_{mm} x^m_{nt} + \hat{\alpha}_{km} x^k_{nt} + \hat{\alpha}_{lm} x^l_{nt}. \tag{16}$$

The input share of materials, generally expressed by $a^M_{nt} = (P^M_{nt} M_{nt})/(P_{nt} Y_{nt})$, 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 ϵ_{nt} is the error from the regression equation (7), De Loecker and Warzynski (2012) propose to correct and estimate the input share by

$$\hat{a}^M_{nt} = \frac{P^M_{nt} M_{nt}}{P_{nt}\frac{\tilde{Y}_{nt}}{\exp(\hat{\epsilon}_{nt})}}. \tag{17}$$

[12] The choice of the instruments in the moment equation (10) 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^k_{nt}, x^l_{nt}, and $x^m_{n,t-1}$ (as well as higher orders and combinations of them), that should be orthogonal to the shocks in innovation, given by ξ_{nt}.

[13] As initial values I use the estimated coefficients of an OLS regression of y_{nt} on all explanatory variables of the gross output production function.

[14] Here, the covariance matrix of $d(\alpha, x_{nt})$ is estimated in a first step, using (12) while setting W to the $L \times L$ identity matrix.

[15] 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. $\widehat{RS}_{nt} = \hat{\theta}^K_{nt} + \hat{\theta}^L_{nt} + \hat{\theta}^M_{nt}$.

4.1.3 Discussion

Obviously, the crux of estimating firm-level productivity and markups is the specification and estimation of the production function. In the literature, the most applied production function specification is the Hicks-neutral Cobb-Douglas (CD) production function (Bellone, 2017; Traina, 2018; Ben Hassine, 2019). De Loecker et al. (2020) also employ a CD specification, however, with time-varying coefficients, for a given 2-digit industry. In particular, De Loecker et al. (2020) use a five-year rolling window around the year at which the production function is estimated. That is, their specification allows for a flexible production technology over time. Such a specification is nonetheless likely to suffer from misspecification by neglecting higher order polynomials, i.e., neglecting non-linearity in the data.

The main motivation why I use a TL specification is to allow for more flexibility compared to the CD specification, that is allowing to relax the assumption of constant output elasticities. However, I suppose that the time varying component of the technology is fully encompassed by the additive technological change term ω_{nt}, as the production function coefficients are not time-varying. In doing so, firm-level elasticity only changes through a change in the firm's input mix but not through changing technology parameters. Generally, there are two ways to take the time dimension into account: First, rolling-window estimation, second modelling the time trend explicitly. Rolling window estimation has the drawback that not all periods can be used which I see as a larger disadvantage in my case (Zanin and Marra, 2012). The second option, to model the time trend, adds a considerable number of parameters which is numerically burdensome to be estimated as the TL production function already includes a relatively high number of parameters. Generally, assuming any parametric functional form of the production function might suffer from misspecification. To prevent from such model misspecification, novel techniques to estimate the production function nonparametrically would certainly improve and generalize my approach (Gandhi et al., 2020; Demirer, 2020; Malikov et al., 2020). In this vein, Demirer (2020) argues that assuming a Hicks-neutral production function, i.e. implying no unobserved heterogeneity in firms' output elasticity, also leads to biased estimates, which, as he illustrates, considerably translates into biased estimates of firms' markup. The author, therefore, suggests to employ a non-neutral (factor-augmented) production technology.[16]

Morlacco (2020) argues to focus as base-line model on the CD production function, as a TL specification leads to outliers in the markup measures, distorting further analysis. To handle this issue on outliers in the markup measures, I winsorize the distribution of markups at the $1th$ and $99th$ percentile, which already eliminates important outliers (Hastings et al., 1947).

Concerning the choice of materials as flexible input, in the most applications of the production approach to measure firm-level markups, labor is used as flexible input. Generally, the decision about which input can be viewed as flexible or fixed should adapt to the specific economic context. Here, considering labor beside capital as fixed input, is, in my view, more appropriate to the French labor market characteristics. This leaves only materials as a flexible input, which I use for the estimation of markups.[17]

A limit of my approach is that I only have access to firm-level revenue (output) and expenditure (inputs) data, which is deflated by 2-digit price indices. That is, potential price variations among firms in both output and inputs are not taken into account. However, if price differences in output and input markets are correlated with the optimal choice of firms' output and input, the estimated coefficients of the production function suffer from the output/input price bias, affecting the estimates of both productivity and markups (De Loecker et al., 2016; Klette and Griliches, 1996). Consider first the input price bias, as mentioned above, my study relies on the assumption that there is no price variation in input markets, i.e. firms are price takers, without monopsony power. By this admittedly strong assumption due to data restrictions we do not have to be concerned about the input price bias. Of course, I need to assume variation in output prices across producers. In this study, to measure reallocation, I am mainly interested in the correlations between firm-level productivity/markups and sales shares. Hence, the question is whether the main results presented in this study are severely affected by the output price bias. Section 7 will discuss this aspect among others in more detail.

4.2 Decomposition approach of aggregate productivity and markups

Once firm-level productivity and markups are estimated, we can build aggregates of both measures by a weighted average of individual firms' productivity/markups, here weighted by firms' sales shares. More formally, let ϕ_{nt} represent an individual firm's productivity/markup

[16] See Doraszelski and Jaumandreu (2018) and Chen (2017) for more discussions on non-neutral production functions and their estimation.

[17] It is noteworthy to mention that even in markets in which both labor and materials could be considered as flexible inputs, using either labor or materials for the estimation of markups leads to substantially different outcomes (Raval, 2019).

measure at t and let s_{nt} denote its sales share. As shown by Olley and Pakes (1996), the aggregate measure Φ_t can then be decomposed by

$$\Phi_t = \sum_{n}^{N_t} s_{nt}\phi_{nt} = \bar{\phi}_t + \sum_{n}^{N_t} \left(s_{nt} - \bar{s}_t\right)\left(\phi_{nt} - \bar{\phi}_t\right). \tag{18}$$

The first equality simply defines the aggregate measure as a weighted average. The second equality decomposes the weighted average into an unweighted average, $\bar{\phi}_t$, and a covariance term between firms' productivity/markup and the sales share. Aggregate growth between two periods is obtained taking the first difference, i.e. $\Delta\Phi = \Phi_t - \Phi_{t-k}$. Aggregate growth is, hence, transmitted by two reasons: (i) if firms' unweighted average changes, called the *within change*, and (ii) if the covariance between productivity/markups and sales share changes, called the *between change* - also referred to the process of *reallocation* w.r.t. firms' productivity. Melitz and Polanec (2015) extend the Olley-Pakes decomposition taking into account firm entry and exit. They show that, in this case, the aggregate growth can be separated into the contribution of the three firm groups of surivors, entrants and exitors, given by

$$\begin{aligned}\Delta\Phi &= \underbrace{(\Phi_{S,t} - \Phi_{S,t-k})}_{\text{Survivors}} + \underbrace{S_{E,t}(\Phi_{E,t} - \Phi_{S,t})}_{\text{Entrants}} + \underbrace{S_{X,t-k}(\Phi_{S,t-k} - \Phi_{X,t-k})}_{\text{Exitors}} \\ &= \Delta\bar{\phi}_S + \Delta N_S cov_S + S_{E,t}(\Phi_{E,t} - \Phi_{S,t}) + S_{X,t-k}(\Phi_{S,t-k} - \Phi_{X,t-k})\end{aligned} \tag{19}$$

where $S_{Gt} = \sum_{n \in G} s_{nt}$ denotes the aggregate sales share of a group G with $G = (E, S, X)$ the indexes referred to the group of entrants, survivors, and exitors.[18] 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 exitors, 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. $\Phi_{E,t} - \Phi_{S,t} > 0$ $(\Phi_{S,t-k} - \Phi_{X,t-k} > 0)$.[19]

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. $\overline{\Phi} = (\Phi_t - \Phi_{t-k})/2$), while FHK use the measured overall aggregate level at the first period (i.e. Φ_{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 $\overline{\Phi}$ (GR) and Φ_{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 undermeasurment of the contribution of the groups of surviving and exiting firms.

A further aspect discussed in the literature concerns the used individual weight when 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. (2018) 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 bellow.

[18]See Section 5.1.2 for the definition of firm survival, entry, and exit.
[19]See Online Appendix C.1 for more details on the derivation of the DOPD approach.

5 Data, variables, and descriptive statistics

5.1 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.[20] 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.[21] 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 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[a]

Sector[b]	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

[a] Source: FICUS/FARE database.
[b] Statistical classification of economic activities in the European Community, Rev. 2 (2008).

5.1.1 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.

5.1.2 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'

[20] 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.

[21] 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").

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.[22] 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.[23]

5.2 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 entry/exit rates.[24] Figure 1 shows the

Table 2: Summary statistics w.r.t. firm size : averages from 1994-2016[a]

Size group[b]	# of firms	Share of firms	Share of empl.	Share of sales	Entry rate	Exit rate	Age
5-<10	12410	33.53	3.75	2.15	5.51	5.27	17.03
10-<20	9228	24.94	5.63	3.41	4.49	4.89	19.89
20-<50	8908	24.07	12.50	9.00	3.36	3.75	23.09
50-<100	2927	7.91	9.04	6.91	3.04	3.63	25.90
100-<200	1793	4.85	11.04	9.35	2.84	3.33	27.20
200-<500	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

[a] Source: FICUS/FARE database, own calculations. All figures represent averages over the whole period 1994-2016. Shares and rates are given in %.
[b] Size group is given in terms of number of employees.

evolution of aggregate production and inputs. Here, aggregates are measured by the sum of the respective variable over all firms, where the initial year 1994 represents 100. The figure shows

[22] 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).

[23] See Appendix A.2, Figure A1 showing the frequencies of observed consecutive years of firm inactivity.

[24] See Appendix A.1 for a similar table w.r.t. the 2-digit sectors instead of firm size.

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.

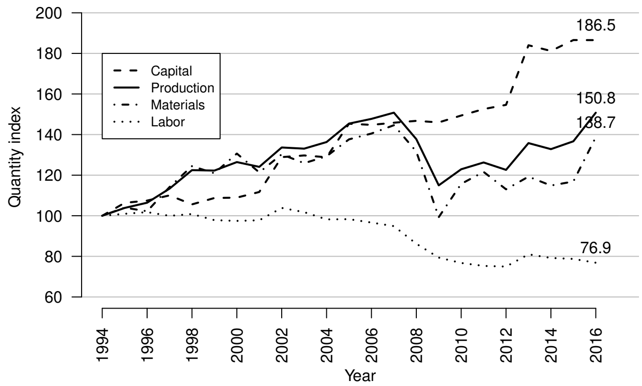

Figure 1: Aggregate production and inputs over time. Source: FICUS/FARE database, own calculations.

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 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.[25]

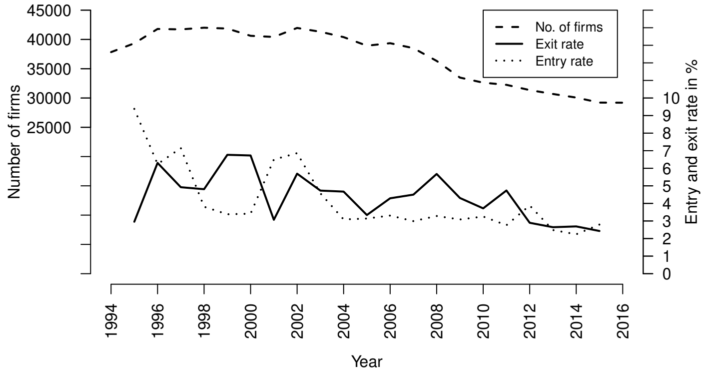

Figure 2: The evolution of the number of firms and the entry and exit rate. Source: FICUS/FARE database, own calculations.

6 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.[26] Related policy implications are discussed subsequently.

[25]See Appendix A.2 for a detailed description of the measurement of firm entry and exit on a yearly basis.

[26]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.

6.1 Empirical decomposition of aggregate productivity

To measure and decompose aggregate productivity growth, the DOPD presented in equation (19) 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 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).[27] Next, the DOPD

Table 3: Aggregate productivity growth (DOPD) over all firms[a]

Period	Total Growth[b]	Contribution Survivors: Within	Contribution Survivors: 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

[a] 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.

[b] The total growth in aggregate productivity is the sum of the contributions of survivors, entrants and exitors.

approach is applied by keeping 1994 as initial year of reference. That is, the contributions to the 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%.[28] 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

[27]See Online Appendix C.2, Table C1 for the measures of aggregate market share and productivity of the different groups and periods.

[28]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 $\Phi_{1995} = 0.556$. 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.

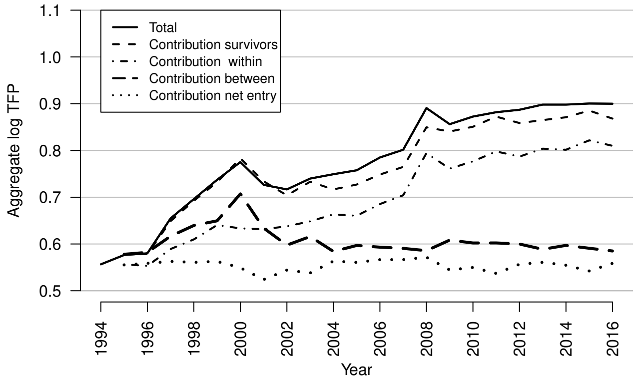

Figure 3: Aggregate log productivity decomposition. Source: FICUS/FARE database, own calculations.

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%).[29] 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 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 reallocation 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).

6.2 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

[29]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.

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 increases 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%.[30]

Table 4: Aggregate markup growth (DOPD) over all firms[a]

Period	Total Growth[b]	Contribution Survivors Within	Between	Contribution Entrants	Contribution Exitors
$1994-1998$	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

[a] 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.

[b] The total growth in aggregate markup is the sum of the contributions of survivors, entrants and exitors.

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, declining in 2015 (2016) to about 1.22 (1.19).[31] 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).

[30] See Online Appendix C.3, Table C3 for the measures of aggregate market share and markups of the different groups and periods.

[31] Also see Bellone et al. (2016) who find for the French manufacturing a similar pattern of decreasing markups for the period 1998-2007.

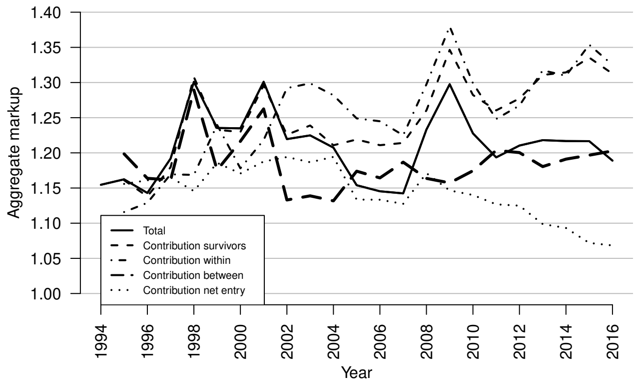

Figure 4: Aggregate markup decomposition. Source: FICUS/FARE database, own calculations.

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 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.[32] Generally, as Bond et al. (2021) and De Ridder et al. (2022) hint to the fact that the production approach based on revenue data is uninformative w.r.t. the estimated level of markups, the here presented results of its evolution over time should be considered with caution.[33]

6.3 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 where 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 firms contributed to maintain a certain level of the aggregate markup, especially towards the end of the sample period. In

[32] See Online Appendix C.3, Table C4 for exact figures.

[33] See Section 7 where the robustness of the provided results will be discussed in more detail.

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 (Baqaee and Farhi, 2020; De Monte and Koebel, 2023). 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, is 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.

7 Robustness and the impact of potential biases

In this section I present robustness checks concerning the estimation of aggregate productivity and markups. In particular, the statistical validity of the aggregate measures is investigated by providing confidence intervals, while a different production function specification and aggregation method is employed for further checks. Finally, I discuss the impact of potential biases to the results.

7.1 Statistical validity

Appendix B.2, Figure B1 shows the evolution of total aggregate productivity (based on the approach described above) along with the 95% confidence interval (CI). The estimated aggregate productivity always lies within the 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 CI is closely located around the weighted average. Likewise, Appendix B.3, Figure B3 shows the 95% CI for aggregate markups, where the weighted average always lies within the CI, which lower and upper bounds closely follow the evolution of the aggregate markup, implying statistically viable measures. For some years, such as for 2005 to 2007, the lower bound of the 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.

7.2 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.[34] Appendix B.2.2, Figure B2 illustrates 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. 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

[34] The estimation procedure of the CD production function is presented in Appendix B.1.

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). Appendix B.3, Figure B4 shows that markups based on the TL production function are comparatively more stable over time and lie at a lower level. 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. To check the aggregate markup on its sensitivity w.r.t. the output elasticity, De Loecker et al. (2020) fix the output elasticity (in their case w.r.t. labor) to 0.85 and find much less sensitivity of the aggregate markup compared my experiment. However, their (time-varying) CD specification is already relatively close to the counterfactual experiment when fixing the output elasticity to 0.85, which therefore might result in less differences in the aggregate measures compared to my case. Jaumandreu (2022) argues that using a Cobb-Douglas production function does not enable to take into account firms' investment in fixed costs, which would translate into a reduction in variable costs and a reduced output elasticity w.r.t. the flexible input (also see De Monte and Koebel (2023) for more details on that issue). 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.

7.3 Aggregation method

For markups only, I compare aggregate markups based on sales-weighted and total cost-weighted average (both derived from the translog production function) as suggested by De Loecker et al. (2020). The results are shown in Appendix B.3, Figure B5, where both weighting methods produce very similar and close patterns, suggesting that the weight in use does not substantially matter in this case.

7.4 Impact of potential biases

As already mentioned in section 4.1.3, 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, they 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, Hashemi et al. (2022) show that using the production approach with revenue data does not provide informative measures for the level of markups. While De Ridder et al. (2022) agree with that, they also demonstrate that the distribution of markups resulting from a revenue-based estimation is informative, 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.[35] 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 that the output measurement error, which is taken into account through the first step of the estimation of the production function, plays a fare more important role compared to occurring output price bias.[36] Similar to the case of productivity, the authors find a high correlation between revenue-based and quantity-based markups (ranging between 0.41 and 0.82, depending on the estimation approach of the production function). Further, De Ridder et al. (2022) empirically illustrate that the aggregate level of revenue- and quantity-based (sales-weighted) measures behave relatively similar for most 2-digit industries. Unfortunately, their study does not continue by a comparison of aggregate markup decomposition, such as performed by Foster et al. (2008) for the case of quantity- and revenue-based productivity. However, due to the high correlation between quantity- and revenue-based markups, I expect that general patterns of reallocation dynamics, measured by the change in the correlation between firms' markups and sales shares, will be uncovered.

8 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 Ackerberg 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 (Baqaee and Farhi, 2020; De Monte and Koebel, 2023). 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. Even though Foster et al. (2008) for productivity and De Ridder et al. (2022) for markups showed that estimates based on revenue and quantity production functions highly correlate, the development and use of firm-level price indicators could prevent from such biases (see, for instance, Asker et al. (2019), Morlacco (2020), Mertens (2020, 2022), Hahn (2023)). Second,

[35]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.

[36]See Section 4.1.2 which describes how the measurement error in the output variable is taken into account when estimating markups.

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 (2023) 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 larges 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[a]

2-digit sector[b]	# 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

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

[b] 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)				
$a_{n,t-1}$	a_{nt}	$a_{n,t+1}$	Status at t	Binary firm status variables at t
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.

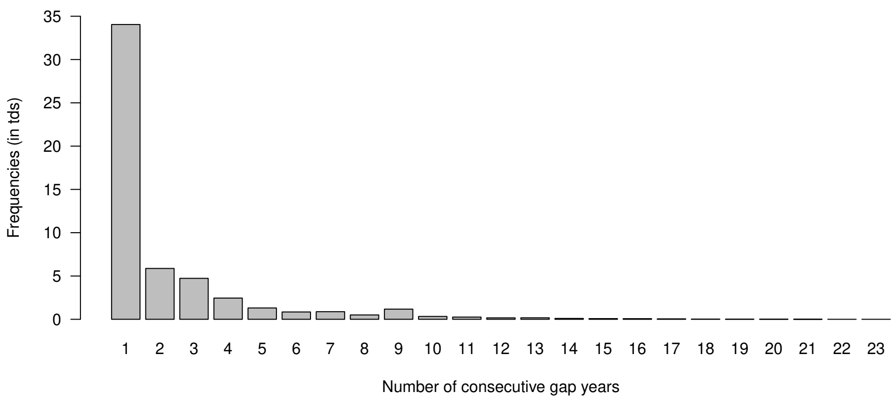

Figure A1: Frequencies of the observed number of consecutive years of inactivity. Source: FICUS/FARE database, own calculations.

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 $e^{-,ESANE}_{nt} = 1$ 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. $e^{-,ESAN}_{ns} = 1$, 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, $e^{-,ESANE}_{nt} = e^{-,ESANE}_{n,t+1} = 1$. To overcome the mentioned issues, I adapt the official variable slightly: Let $e^{-,ESANE\ bis}_{nt} = 1$ 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. $e^{-,ESANE}_{n,t+1} = 1$, 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

	Number of active firms		Number of exitors		
Year (t)	Own def. $\sum_n^{N_t} a_{nt}$	ESANE def. $\sum_n^{N_t} \mathbf{1}_{[e_{nt}^{-,ESANE}=0]}$	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

	0	1
0	90.20	5.92
1	1.73	2.15

b) With ESANE bis exit

	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 α_K, α_L, and α_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 4). 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

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

with $\alpha = \{\alpha_K, \alpha_L, \alpha_M\}$. The innovations in ω_{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 α. 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.

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.

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.

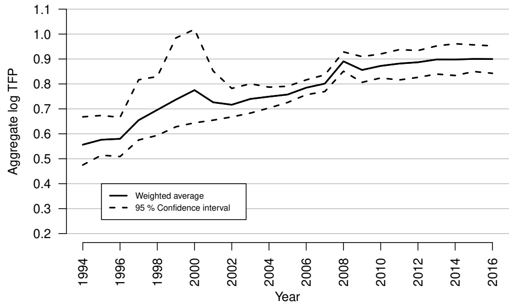

Figure B1: Aggregate productivity with the 95 % confidence interval. The confidence intervals are bootstrapped using 400 replications. Source: FICUS/FARE database, own calculations.

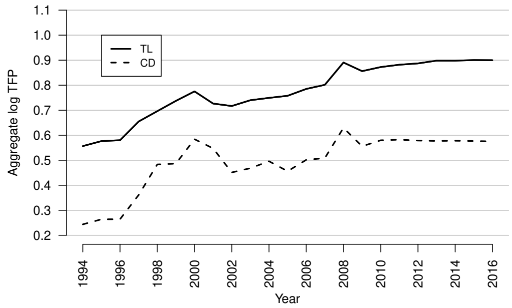

Figure B2: Aggregate log productivity: Translog (TL) vs. Cobb-Douglas (CD) production function. Source: FICUS/FARE database, own calculations.

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

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

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 $\hat{\theta}^M_{nt}$ and $\hat{a}^M_{nt}$. 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 $\hat{\theta}^M_{nt}$, 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, $\hat{\theta}^M_{nt} = \hat{\alpha}_M$ 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.

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

$$C^{tot}_{nt} = P^k_t K_{nt} + P^l_t L_{nt} + P^m_t M_{nt},$$

where P_t denotes the user cost of capital, and P^l_t and P^m_t denote the labor and material price. In order to calculate the user cost of capital, I follow Hall and Jorgenson (1967), i.e., $P^k_t = P^I_t(1+r_t) - P^I_{t+1}(1-\delta_t)$, with P^I_t denoting the price index for investment, available at the 2-digit level, r_t is the long-run rate of interest, and δ_t the annual rate of capital depreciation,

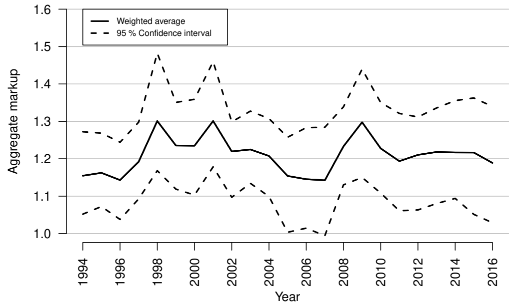

Figure B3: Aggregate markups with the 95 % confidence interval. The confidence intervals are bootstrapped using 400 replications. Source: FICUS/FARE database, own calculations.

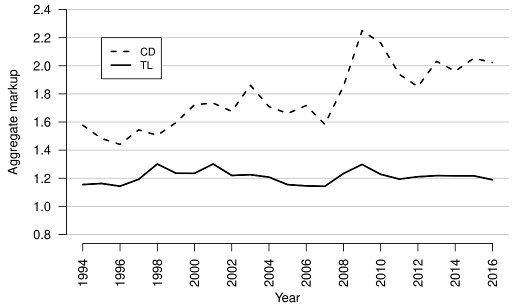

Figure B4: Aggregate markups: Using output elasticity based on translog (TL) vs. Cobb-Douglas (CD) production function. Source: FICUS/FARE database, own calculations.

available at the 2-digit level.[37] 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.[38] A firm's total cost share is then given by $s_{nt}^{C} = C_{nt}^{tot} / \sum_n C_{nt}^{tot}$.

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.

[37]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. δ_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.

[38]The sectoral price data are available at https://www.insee.fr/fr/statistiques/2832666?sommaire=2832834

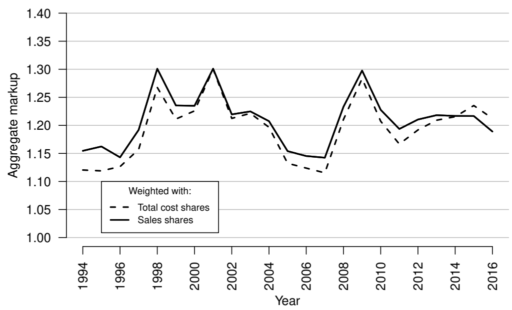

Figure B5: Aggregate markups: Using sales shares vs. total cost shares. Source: FICUS/FARE database, own calculations.

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Online Appendix

Productivity, Markups, and Reallocation: Evidence from French Manufacturing Firms from 1994 to 2016

Enrico De Monte*

January 5, 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 franaise). 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 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

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

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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 2																		
NAF 1	0220	1392	1610	1621	1622	1623	1624	1629	2223	2512	3101	3109	3319	4329	4332	4391	4399	5610	9524	Total
201A	46	0	2060	5	6	22	35	12	0	0	0	7	0	0	25	24	9	5	0	2256
201B	0	0	498	0	0	0	0	0	0	0	0	0	0	17	4	36	24	0	0	579
202Z	0	0	0	108	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	112
203Z	0	7	33	0	15	1880	8	8	41	26	0	41	0	6	1005	386	34	0	0	3490
204Z	0	0	17	0	0	4	857	6	0	0	0	0	35	0	6	0	0	0	0	925
205A	4	16	10	4	0	21	5	1215	0	0	12	317	0	0	87	0	4	10	156	1861
205C	0	0	0	0	0	0	0	86	0	0	0	0	0	0	0	0	0	0	0	86

Source: FICUS/FARE database, own calculations.

Table A2: FICUS - FARE: Transitions probabilities

	NAF 2																		
NAF 1	0220	1392	1610	1621	1622	1623	1624	1629	2223	2512	3101	3109	3319	4329	4332	4391	4399	5610	9524	Total
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	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	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	0.04	0.00	0.00	0.00	0.00	1.00
203Z	0.00	0.00	0.01	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	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	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	0.08	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	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	α_K	α_L	α_M	α_{KK}	α_{LL}	α_{MM}	α_{KL}	α_{KM}	α_{ML}	# Obs.	# Firms
Beverages	0.060	0.368	0.661	0.080	-0.019	0.100	0.030	-0.087	-0.021	12743	1330
	(0.0026)	(0.0192)	(0.0328)	(0.0044)	(9e-04)	(0.0048)	(0.0010)	(0.0041)	(0.0010)		
Textiles	0.138	0.157	0.681	0.047	0.168	0.123	-0.023	-0.037	-0.110	31761	3599
	(0.0070)	(0.0076)	(0.0338)	(0.0024)	(0.0081)	(0.0062)	(0.0013)	(0.0014)	(0.0055)		
Wearing apparel	0.137	0.318	0.721	0.028	0.101	0.155	-0.013	-0.022	-0.124	33225	5384
	(0.0079)	(0.0142)	(0.0364)	(0.0013)	(0.0061)	(0.0078)	(0.0012)	(0.0010)	(0.0063)		
Leather/	0.123	0.100	0.759	0.028	0.189	0.120	-0.026	-0.011	-0.132	10553	1337
related products	(0.0065)	(0.0025)	(0.0395)	(7e-04)	(0.0109)	(0.0058)	(0.0016)	(5e-04)	(0.0077)		
Wood/products of	0.134	0.196	0.581	0.015	0.103	-0.034	-0.083	0.052	0.005	50589	5538
wood and cork	(0.0102)	(0.0107)	(0.0286)	(0.0028)	(0.0090)	(0.0024)	(0.0053)	(0.0017)	(0.0034)		
Paper/	0.078	0.238	0.659	0.059	0.126	0.097	-0.013	-0.040	-0.082	19862	1937
paper products	(0.0030)	(0.0095)	(0.0349)	(0.0031)	(0.0068)	(0.0050)	(7e-04)	(0.0016)	(0.0048)		
Printing/reprod.	0.163	0.006	0.735	0.001	0.257	0.074	-0.039	0.015	-0.143	66497	7911
of recorded media	(0.0078)	(0.0015)	(0.0362)	(6e-04)	(0.0126)	(0.0049)	(0.0024)	(9e-04)	(0.0074)		
Chemicals/	0.177	0.130	0.746	0.095	0.168	0.101	-0.035	-0.070	-0.076	28717	3043
chemical products	(0.0093)	(0.0056)	(0.0371)	(0.0046)	(0.0082)	(0.0049)	(0.0016)	(0.0035)	(0.0035)		
Pharma. products/	0.177	0.024	0.790	0.064	0.123	0.102	-0.017	-0.060	-0.065	5902	640
preparations	(0.0097)	(0.0012)	(0.0407)	(0.0034)	(0.0075)	(0.0051)	(0.0014)	(0.0030)	(0.0035)		
Rubber/	0.144	0.128	0.637	-0.010	0.141	0.048	-0.016	0.009	-0.069	55614	5494
plastic products	(0.0078)	(0.0075)	(0.0314)	(0.0012)	(0.0071)	(0.0039)	(0.0013)	(3e-04)	(0.0041)		
Other non-metallic	-0.011	0.561	0.594	0.048	0.008	0.085	0.017	-0.038	-0.063	42255	4792
mineral products	(1e-04)	(0.0275)	(0.0294)	(0.0014)	(9e-04)	(0.0042)	(7e-04)	(0.0013)	(0.0031)		
Basic metals	0.126	0.251	0.622	0.064	0.180	0.107	-0.037	-0.028	-0.109	12978	1354
	(0.0065)	(0.0104)	(0.0318)	(0.0029)	(0.0093)	(0.0052)	(0.0021)	(9e-04)	(0.0056)		
Fabricated metal	0.201	0.257	0.496	0.044	0.149	0.067	-0.034	-0.030	-0.065	191460	19405
products	(0.0100)	(0.0126)	(0.0246)	(0.0022)	(0.0076)	(0.0043)	(0.0023)	(6e-04)	(0.0039)		
Computer/electronic/	0.100	-0.024	0.790	-0.011	0.245	0.096	-0.003	0.013	-0.158	26831	3423
optical products	(0.0056)	(6e-04)	(0.0390)	(0.0013)	(0.0103)	(0.0057)	(8e-04)	(1e-04)	(0.0073)		
Electrical equipment	0.193	0.005	0.719	0.043	0.220	0.123	-0.032	-0.031	-0.124	23439	2602
	(0.0098)	(0.0020)	(0.0345)	(0.0022)	(0.0100)	(0.0061)	(0.0015)	(0.0017)	(0.0056)		
Machinery and	0.182	-0.093	0.778	-0.009	0.309	0.083	-0.058	0.031	-0.147	57187	6446
equipment	(0.0102)	(0.0050)	(0.0403)	(0.0026)	(0.0172)	(0.0054)	(0.0036)	(1e-04)	(0.0087)		
Motor vehicles/	0.246	0.083	0.654	0.070	0.214	0.117	-0.063	-0.033	-0.103	20532	2191
(semi-) trailers	(0.0105)	(0.0054)	(0.0336)	(0.0034)	(0.0101)	(0.0064)	(0.0023)	(0.0017)	(0.0058)		
Other transport	0.166	-0.094	0.832	0.080	0.323	0.110	-0.054	-0.031	-0.160	6656	806
equipment	(0.0090)	(0.0054)	(0.0399)	(0.0026)	(0.0164)	(0.0063)	(0.0021)	(0.0015)	(0.0083)		
Furniture	0.120	-0.021	0.800	0.014	0.192	0.101	-0.030	-0.008	-0.105	32234	4007
	(0.0060)	(0.0015)	(0.0416)	(0.0012)	(0.0108)	(0.0047)	(0.0016)	(3e-04)	(0.0068)		

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

		Input			
Sector	Statistic	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<=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<=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<=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<=0	0.910	0.140	14.230	0.000
Leather/	Elasticity	0.083	0.441	0.521	1.039
related products	MAD	0.013	0.097	0.070	0.031
	Share<=0	0.330	0.410	1.180	0.000
Wood/products of	Elasticity	0.101	0.390	0.555	1.044
wood and cork	MAD	0.031	0.068	0.036	0.015
	Share<=0	5.810	0.030	0.000	0.000
Paper/	Elasticity	0.097	0.404	0.532	1.032
paper products	MAD	0.037	0.048	0.050	0.016
	Share<=0	5.760	0.000	0.230	0.000
Printing/reprod.	Elasticity	0.130	0.480	0.431	1.042
of recorded media	MAD	0.008	0.084	0.049	0.038
	Share<=0	0.000	0.130	0.150	0.000
Chemicals/	Elasticity	0.130	0.371	0.594	1.087
chemical products	MAD	0.063	0.074	0.081	0.033
	Share<=0	8.790	0.620	0.590	0.000
Pharma. products/	Elasticity	0.148	0.265	0.626	1.034
preparations	MAD	0.052	0.058	0.082	0.019
	Share<=0	7.110	1.190	0.260	0.000
Rubber/	Elasticity	0.111	0.395	0.551	1.050
plastic products	MAD	0.012	0.064	0.043	0.022
	Share<=0	0.000	0.020	0.020	0.000
Other non-metallic	Elasticity	0.100	0.464	0.496	1.070
mineral products	MAD	0.034	0.059	0.054	0.026
	Share<=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<=0	4.970	0.330	0.340	0.000
Fabricated metal	Elasticity	0.178	0.545	0.312	1.035
products	MAD	0.029	0.054	0.046	0.027
	Share<=0	0.070	0.000	0.200	0.000
Computer/electronic/	Elasticity	0.119	0.446	0.481	1.048
optical products	MAD	0.026	0.131	0.079	0.045
	Share<=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<=0	2.480	0.370	1.600	0.000
Machinery and	Elasticity	0.048	0.454	0.554	1.046
equipment	MAD	0.029	0.121	0.065	0.049
	Share<=0	17.660	0.400	0.610	0.000
Motor vehicles/	Elasticity	0.101	0.392	0.558	1.045
(semi-) trailers	MAD	0.046	0.077	0.064	0.020
	Share<=0	6.820	0.340	1.420	0.000
Other transport	Elasticity	0.107	0.580	0.429	1.103
equipment	MAD	0.041	0.168	0.126	0.069
	Share<=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<=0	0.240	0.100	0.060	0.000

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

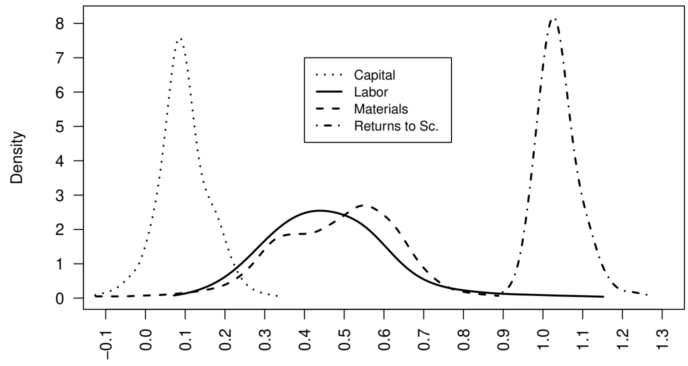

Figure B1: Kernel density estimates of output elasticities and returns to scale. Source: FICUS/FARE database, own calculations.

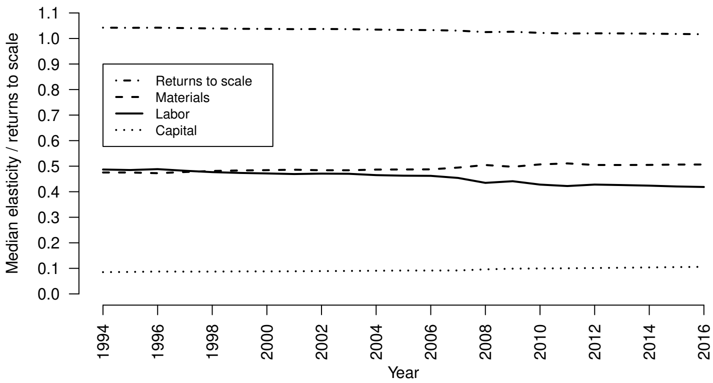

Figure B2: Median output elasticities and returns to scale over time. Source: FICUS/FARE database, own calculations.

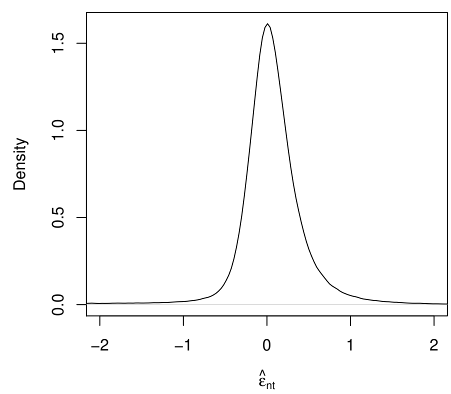

Figure B3: Distribution of residual: production function first stage regression. Source: FICUS/FARE database, own calculations.

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 ϕ_{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

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

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

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

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

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)	Φ_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. Φ_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, Φ_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.

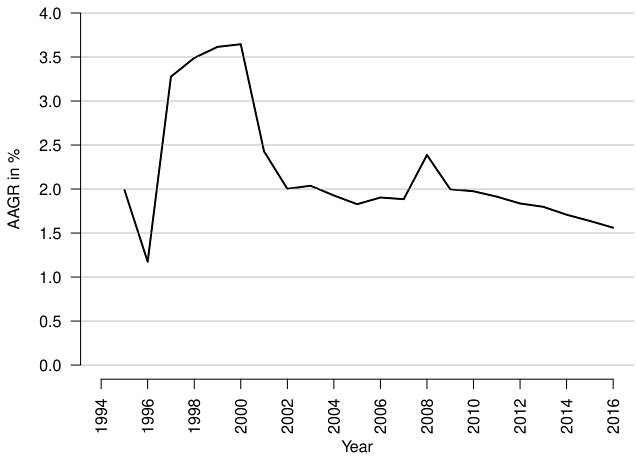

Figure C1: The average annual growth rate (AAGR) of aggregate productivity. Source: FICUS/FARE database, own calculations.

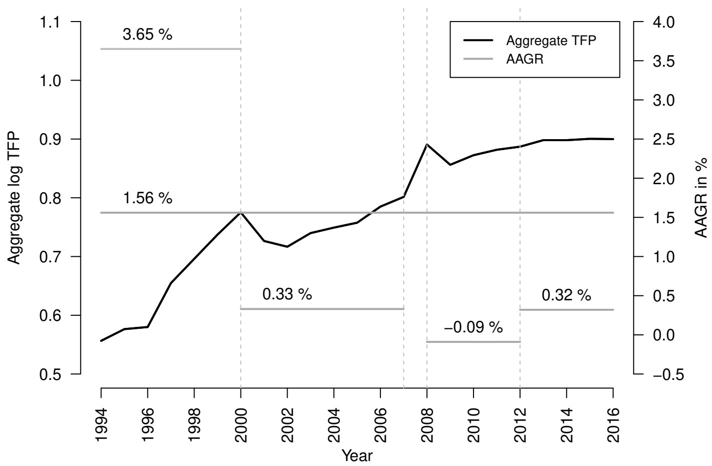

Figure C2: Aggregate productivity and the average annual growth rate (AAGR). Source: FICUS/FARE database, own calculations.

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

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%.[1]

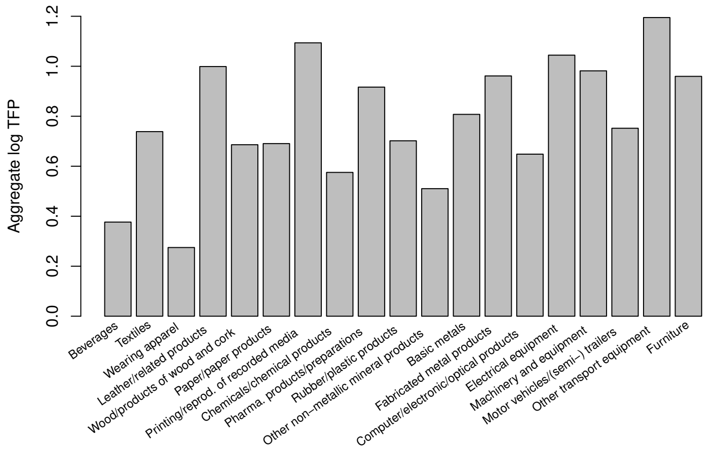

Figure E1: Heterogeneity in aggregate productivity among sectors. Source: FICUS/FARE database, own calculations.

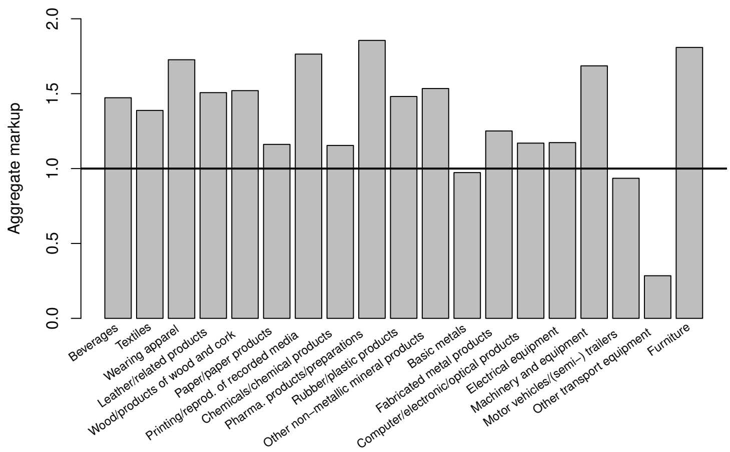

Figure E2: Heterogeneity in aggregate markup among sectors. Source: FICUS/FARE database, own calculations.

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).

[1] See Appendix B, Table B2, for estimated median elasticities for each sector as well as Appendix F Figure F1, illustrating markdowns per sector.

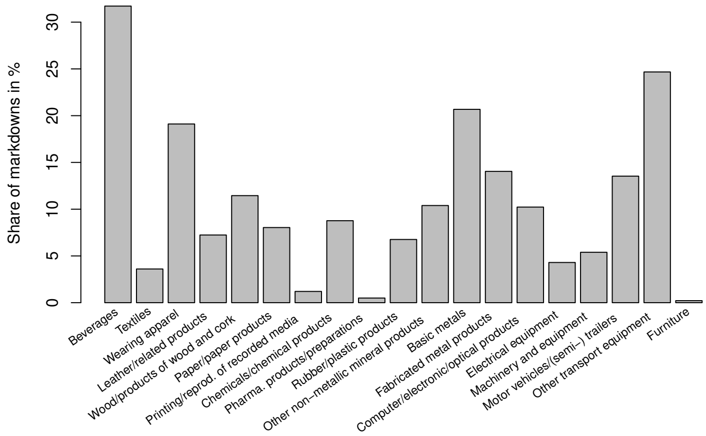

Figure F1: Share of markdowns (share of firms with markup < 1) by sector. Source: FICUS/FARE database, own calculations.

Table F1 provides some descriptive statistics for the estimated output shares w.r.t. capital, labor, and materials, given in the first column by $\hat{a}^K_{nt}$, $\hat{a}^L_{nt}$, and $\hat{a}^M_{nt}$. 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

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

Source: FICUS/FARE database, own calculations.

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