Market Power and Labor Share

Arthur Bauer* and Jocelyn Boussard**

Abstract – Secular trends in market power and labor share have important implications for inequality and allocative efficiency. Studying them requires comprehensive, detailed firm-level data spanning several decades. We leverage a novel database on the universe of French firms between 1984 and 2016 and document a rise in concentration since the early 1990s. Despite a stability of the aggregate labor share, larger firms with lower labor shares gained market shares, especially in industries where concentration increased the most. The markup of the typical firm, considered here as a proxy of its market power, has decreased, but market shares reallocation toward larger firms contributed to an increase in the aggregate markup. In particular, we do not find that the rise in concentration is accompanied by an increase in market power at the top. Finally, we show how taking into account reallocation across firms is essential to understand how the trends in market power have shaped the dynamics of the aggregate labor share in France.

JEL Classification: E10, E23, E25
Keyword: labor share, markups, competition, production function

**Insee and CREST (arthur.bauer@ensae.fr); **European Commission and CREST (boussard.jocelyn@ensae.fr)*

Acknowledgements – We thank the economic studies, archives, and firm-level statistics departments at Insee and in particular Kim Anh Fabre, Pascal Lucas, Christelle Le Borgne and Emmanuel Gros for facilitating our access to and understanding of the data. We thank Elizaveta Archanskaia, Sabien Dobbelaere, Dominique Goux, Maxime Gueuder, Francis Kramarz, Edouard Jousselin, Rémy Lecat, Margarita Lopez-Forero, Jacques Mairesse, Rémi Monin, Ludovic Panon, Sébastien Roux, Olivier Simon, and participants at Insee, Banque de France, ECFIN, Collège de France and CREST Seminars for their useful comments. Finally, we thank also two anonymous reviewers.

Received in October 2018, accepted in April 2020.

Citation: Bauer, A. & Boussard, J. (2020). Market Power and Labor Share. *Economie et Statistique / Economics and Statistics*, 520-521, 125–146.
https://doi.org/10.24187/ecostat.2020.520d.2034

Large and productive superstar firms have been gaining market shares in many advanced economies, and the rise of their market power, measured either through their markup or their profitability, has been the focus of attention in many recent works. De Loecker *et al.* (2020) have documented an increase in top firms' market power in the US that is large enough to have important macroeconomic consequences. They find that the weighted average markup in the United States rose from 21% above marginal cost at the beginning of the 1980s to around 61% now. Autor *et al.* (2020) also document a rise of the weighted average markup in the US. Gutiérrez & Philippon (2018) argue that European markets are more competitive, and exhibit lower levels of concentration, lower excess profits and lower barriers to entry, which raises the question of whether the secular trends mentionned above are specific to the US. We use detailed firm-level administrative data on the universe of French firms to document facts about market power and labor shares in France.

These questions are important for inequality concerns. One of the important macroeconomic implications of a rise in market power is a decline in the aggregate share of income going to workers. Given that there is ample evidence that labor is more evenly distributed than capital (Garbinti *et al.*, 2018; Piketty *et al.*, 2018) or firm ownership (Bauer *et al.*, 2018), a decline in the aggregate labor share is a possible driver of inequality. Important work has shown that the aggregate labor share has indeed been declining in a wide range of countries (Karabarbounis & Neiman, 2014; Elsby *et al.*, 2013; Grossman *et al.*, 2018). Using aggregate data, Barkai (2020) and Boussard & Lee (2020) show that both the labor and capital shares have declined in the United States and many advanced economies, while measures of the profit share have increased. Looking more closely at firm-level data, Kehrig & Vincent (2018) and Autor *et al.* (2020) show that the labor share of the typical firm has actually increased, while the aggregate fall is attributable to reallocation from high- to low-labor share firms.

Market power trends have also important but ambiguous consequences for allocative efficiency. Baqaee & Fahri (2020) show that a reallocation of market shares to high-markup firms as shown in Autor *et al.* (2020) increases efficiency, but an increase in markup dispersion as shown in De Loecker *et al.* (2020) reduces efficiency. Market power also has important but ambiguous dynamic implications: while lower competition may lead firms to under-invest (Gutiérrez & Philippon, 2017), the relationship between competition and innovation depends on the initial level of competition (Aghion *et al.*, 2005).

Understanding the underlying micro-structural transformations behind these aggregate trends is crucial to identify their possible explanations such as changes in the competitive environment and changes in technology. For instance, Bonfiglioli *et al.* (2019) and Panon (2020) show that national firms compete in markets that are increasingly global, which reduces firm-level markups but benefits larger firms, and Melitz (2003) and Mayer *et al.* (2014) show that international competition causes reallocation toward top producers. Recent work (Autor *et al.*, 2020; Van Rennen, 2018) argues that technological change, such as the growth of platform competition in digital markets, may have caused reallocation from small to large firms that could lead to dominance by a small number of firms. Lashkari *et al.* (2019) find that the rise of Information Technology has disproportionately benefited larger firms.

We use France as a laboratory to study the link between variations in industry concentration and firm-level outcomes, and provide evidence on the sources of market power variations. France is an interesting case because the labor share appears to have been stable or increasing over the past decades, in contrast to the US (see Figure I). We document important facts about secular trends in France that are similar to what has been documented for other advanced economies. When we decompose the labor share variations in France since the 1990s, we find that there was an important reallocation of market shares from firms with high labor shares to firms with low labor shares, which tend to be larger. This reallocation is correlated with a rise of industry concentration, measured through a wide range of proxies. However, labor shares have on average increased at all points of the distribution, a development that has offset the effect of reallocation and explains why the aggregate labor share in France was broadly stable over this period.

To assess the extent to which firm-level market power dynamics have played a role in explaining the diverging trends of firm-level labor share in France and the US, as opposed to other explanations like technological change, we estimate firm-level markups and output elasticities using a flexible production function that allows variations in the marginal product of inputs both across firms and time periods. We follow De Loecker & Warzynski (2012) and first estimate firm-level elasticities of value added to labor and capital, and then recover markups by assuming that firms minimize their costs and that labor is a flexible input. We rely on unique and comprehensive administrative data covering the universe of French firms.

Importantly, we find no evidence that the rise in concentration translated into an increase in firm-level market power. We find that there is substantial heterogeneity in markups, and that markups are increasing with firm size. We also find that much of the increase in firm-level labor shares is attributable to decreases in firm-level markups. All in all, high-markup firms gained market shares while the markup of the typical firm decreased, which indicates both an improvement in allocative efficiency and a decrease in firm pricing power. We show that these two facts about reallocation are strongly correlated with the rise in concentration at the industry level.

Our paper contributes to the macroeconomic literature that documents a number of important secular trends that have recently swept across advanced economies. A number of recent papers have documented growing industry concentration and within-industry dispersion in firm outcomes (Andrews *et al.*, 2016; Berlingieri *et al.*, 2017; Song *et al.*, 2018; Card *et al.*, 2013). In parallel, there is a large body of evidence on a global fall in the labor share across many industries (Elsby *et al.*, 2013; Karabarbounis & Neiman, 2014, 2018; Grossman *et al.*, 2018; Barkai, 2020; Boussard & Lee, 2020). We show that concentration and the market power of top firms are not necessarily correlated, even though at the aggregate level the reallocation of market shares toward high-markup firms contributes to a rise in the aggregate markup. Our findings that *(i)* firm-level markups have decreased and *(ii)* reallocation towards high-markup firms (reflecting a rise in concentration) contributes to a rise in the aggregate markup, are consistent with Autor *et al.* (2020). However, in France, the decrease in firm-level markups is larger, and the reallocation effect does not offset it.[1] This difference is also consistent with evidence in Gutiérrez & Philippon (2018) that European markets have become more competitive than US markets.

The rest of the paper is organized as follows. Section 1 presents our theoretical framework, Section 2 presents our strategy for estimating firm-level markups, Section 3 presents the data that we use to implement this strategy, Section 4 documents important changes in the labor share and concentration in France, and Section 5 presents our results on markups in France.

1. Theoretical Framework

In this section, we provide a general theoretical framework to map variations of the aggregate labor share to variations of firm-level market power, input elasticities and market shares. Consider an industry with N firms indexed by i. Consistently with a wealth of evidence and in the spirit of canonical models (Melitz, 2003; Hopenhayn, 1992), we assume that firms have heterogeneous exogenous productivity Ω_{it} and have access to a common production technology $\mathcal{Q}(.)$ defined as $Y_{it} = \mathcal{Q}(\Omega_{it}, L_{it}, K_{it})$, that they use to produce value added Y_{it}, using variable labor input L_{it}, and capital stock K_{it}. We assume that adjusting the capital stock is subject to cost $\mathcal{C}_a(.)$, which depends only on the current and previous levels of capital, and crucially not on variable inputs levels. The sum of discounted costs of the firm is:

$$\mathcal{V}(\mathrm{Z}_{it}) = \min_{\mathrm{X}_{it}} \mathcal{C}(\mathrm{X}_{it}, \mathrm{Z}_{it}) + \beta\mathbb{E}\left[\mathcal{V}(\mathrm{Z}_{it+1})\right]$$
$$\text{s.t } \mathcal{Q}(\Omega_{it}, \mathrm{X}_{it}) = Y_{it}$$

where $\mathcal{C}(.)$ is the total cost of the firm, $\mathrm{X}_{it} = (L_{it}, K_{it})$ refers to inputs, and Z_{it} to variables that are exogenous to the choice of the firm at time t, such as previous year capital stock, productivity and input prices.

The Lagrangian associated with the right-hand side of the Bellman equation is defined as:

$$\mathcal{L}(\mathrm{X}_{it}, \xi_{it}, Y_{it}, \mathrm{Z}_{it}) = W_{it}L_{it} + r_{it}\left(K_{it} + \mathcal{C}_a(K_{it}, K_{it-1})\right) + F_{it} + \beta\mathbb{E}\left[\mathcal{V}(\mathrm{Z}_{it+1})\right] - \xi_{it}\left(\mathcal{Q}(\Omega_{it}, \mathrm{X}_{it}) - Y_{it}\right)$$

where W_{it} is the wage, r_{it} is the user cost of capital, F_{it} is an exogenous fixed cost, and ξ_{it} is the Lagrange multiplier. The first-order conditions at the optimal choice of inputs (X^*_{it} and ξ^*_{it}) imply that:

$$\nabla L\left(\mathrm{X}^*_{it}, \xi^*_{it}, Y_{it}, \mathrm{Z}_{it}\right) = 0 \tag{1}$$

where ∇ denotes the gradient vector of partial derivatives with respect to inputs. Applying equation (1) to the flexible labor input yields the following cost-minimization condition linking the wage and marginal product of labor:

$$\frac{\partial\mathcal{L}}{\partial L}\left(\mathrm{X}^*_{it}, \xi^*_{it}, Y_{it}, \mathrm{Z}_{it}\right) = W_{it} - \xi^*_{it}\frac{\partial\mathcal{Q}}{\partial L}\left(\Omega_{it}, \mathrm{X}^*_{it}\right) = 0$$

The output elasticity with respect to the labor input L, $\theta_{l,it}$, can therefore be expressed at the optimum as:

$$\theta_{l,it} \equiv \frac{L^*_{it}}{Y_{it}}\frac{\partial\mathcal{Q}}{\partial L}\left(\Omega_{it}, \mathrm{X}^*_{it}\right) = \frac{1}{\xi^*_{it}}\frac{W_{it}L^*_{it}}{Y_{it}} \tag{2}$$

1. *Possible interpretations of these difference are that the market power of French firms is more sensitive to the underlying cause, for instance if French firms are more exposed to globalization or to competition on internet platforms than US firms, or if the productivity gap between top French firms and laggards is not as large as for top US firms.*

Using the first order conditions in equation (1) to express the optimal choice of inputs X^*_{it} and ξ^*_{it} as functions of output Y_{it} and exogenous variables Z_{it}, we derive the optimal total cost as a function of output and exogenous variables:

$$\mathcal{C}^*\left(Y_{it}, Z_{it}\right) = \mathcal{C}\left(X^*_{it}\left(Y_{it}, Z_{it}\right), Z_{it}\right)$$

At the optimum, the Lagrangian is equal to total cost, and from the envelop theorem it follows that the marginal cost is equal to the Lagrange multiplier ξ^*_{it}:

$$\frac{\partial \mathcal{C}^*}{\partial Y}\left(Y_{it}, Z_{it}\right) = \frac{\partial \mathcal{L}^*}{\partial Y}\left(Y_{it}, Z_{it}\right)$$
$$= \frac{\partial \mathcal{L}}{\partial Y}\left(X^*_{it}, \xi^*_{it}, Y_{it}, Z_{it}\right) = \xi^*_{it}$$

Dropping for simplicity the superscript * to denote optimal variables, we define the markup as the ratio of the firm's output price P_{it} to its marginal cost:

$$\mu_{it} = \frac{P_{it}}{\xi_{it}} \tag{3}$$

The markup captures the degree of pricing power of the firm, and is a widely used measure of firm-level market power. As noted by De Loecker & Warzynski (2012), this expression is robust to various static price setting models, and does not depend on any particular form of price competition among firms. The markup itself will, however, depend on the specific nature of competition among firms. Moreover, it follows from equations (2) and (3) that the markup is defined as the elasticity of output with respect to the labor input, divided by the share of this labor costs in total firm revenue, *i.e* the labor share λ_{it}:[2]

$$\mu_{it} = \theta_{l,it} \frac{P_{it} Y_{it}}{W_{it} L_{it}} \equiv \frac{\theta_{l,it}}{\lambda_{it}} \tag{4}$$

In what follows, we map the aggregate labor share into firm level markups, and the output[3] elasticity of labor. First, we define the aggregate labor share Λ_t as the value added weighted average of firm-level labor shares:

$$\Lambda_t \equiv \frac{\sum_i W_{it} L_{it}}{\sum_i P_{it} Y_{it}} = \sum_i S_{it} \lambda_{it} \tag{5}$$

where $S_{it} = \frac{P_{it} Y_{it}}{\sum_i P_{it} Y_{it}}$ is the market share of firm i.

From equation (4) we know that the labor share is the product of the output elasticity of labor and the inverse markup:

$$\lambda_{it} = \theta_{l,it} \mu^{-1}_{it} \tag{6}$$

We decompose the output elasticity of labor $\theta_{l,it}$ into a component stemming from returns to scale, which tells us how much output expands when all inputs increase proportionally, and a component stemming from the labor intensity of the production process relative to capital:

$$\theta_{l,it} = \underbrace{\theta_{l,it} / \left(\theta_{l,it} + \theta_{k,it}\right)}_{\text{Labor intensity}} \times \underbrace{\left(\theta_{l,it} + \theta_{k,it}\right)}_{\text{Returns to scale}} \equiv \alpha_{it} \gamma_{it} \tag{7}$$

noting that when α_{it} is high the production process is intensive in labor relative to capital. It follows from equations (5), (6) and (7) that the aggregate labor share can be expressed as a function of firm level labor intensity, returns to scale, and markups:

$$\Lambda_t = \sum_i S_{it} \alpha_{it} \gamma_{it} \mu^{-1}_{it} \tag{8}$$

We compute the aggregate markup M_t as the value added weighted harmonic average of firm-level markups:

$$M_t \equiv \left[\frac{\sum_i P_{it} Y_{it} \mu^{-1}_{it}}{\sum_i P_{it} Y_{it}}\right]^{-1} = \left[\sum_i S_{it} \mu^{-1}_{it}\right]^{-1}$$

2. Estimation Procedure

In this section, we describe the procedure to recover estimates of firm-level output elasticities of labor and capital; together with firm-level labor and market shares observed in the data, this allows us to compute the contribution of markups, labor intensity, and returns to scale to the aggregate labor share.[4]

To recover markup from production data, we rely on equation (4). This framework is particularly convenient to analyze the evolution of markups in the long run because it does not require observing consumer-level attributes to estimate demand elasticities. Second, it makes no assumption on firms pricing behavior and competition environment. It only requires two assumptions: firms minimize production cost and freely adjust at least one variable input.

We can directly observe firm-specific input shares in production data, but output elasticities are unobserved. Because these elasticities can vary across time and firms, we estimate a flexible production function, with a minimum number of parametric restrictions. In what follows, we assume that firms belonging to a particular industry j share the same technology $f_j(.)$, using labor and capital to generate value added. Moreover, we assume that productivity is Hicks-neutral and evolves according to an AR(1)

2. It is important to note that equation (4) only applies to inputs that are freely adjustable, at least at the margin and that input prices are exogeneous to the firm choices. Section C2 in the Online Appendix discusses the sign of the wedges that arise from relaxing one of these assumptions. Link to the Online Appendices at the end of the article.

3. Actually, the value added. The two terms are used interchangeably hereafter.

4. We abstract from input-output linkages by considering value added production function. Baqaee & Fahri (2020) show that input-output linkages are important for the propagation of productivity shocks, and Grassi (2017) shows that they matter for market power in the case oligopolistic competition.

Markov process. For firm i in industry j, our empirical model is given by:

$$y_{it} = f_j\left(k_{it}, l_{it}\right) + \omega_{it} + \varepsilon_{it} \tag{9}$$

$$\omega_{it} = \rho_{jt}\omega_{it-1} + \eta_j + \nu_j t + \xi_{it} \tag{10}$$

where y_{it} stands for the logarithm of value added of firm i at time t, and l_{it} and k_{it} are the logarithms of employment and capital stock. Productivity ω_{it} is Hicks-neutral, ε_{it} is an i.i.d measurement error, and ξ_{it} is the i.i.d innovation to productivity. Steady-state productivity η_j and time trend ν_j are common across firms in industry j in period t.

One issue that prevents us for simply running Ordinary Least Squares (OLS) on equation (9) is that we do not observe productivity ω_{it} but firms have information about their productivity when they choose their inputs. ω_{it} is therefore correlated with k_{it} and l_{it} and OLS estimates are biased. In what follows, we make the following standard assumptions regarding the timing of firm decisions:

Assumption 1 (Information Set) – The firm's information set at t, i.e. I_t, includes current and past productivity shocks $\left\{\omega_{i\tau}\right\}_{\tau=0}^{t}$ but does not include future productivity shocks $\left\{\omega_{i\tau}\right\}_{\tau=t+1}^{+\infty}$. Measurement errors μ_{it} satisfy $\mathbb{E}\left[\mu_{it} \mid I_t\right] = 0$. The productivity process defined in equation (10) is known to firms and stochastically increasing in ω_{it-1}.

Assumption 2 (Input Choices) – Labor and capital inputs used at time t are chosen with information set I_t.

These assumptions are straightforward: firms do not observe ω_{it} until time t, but the Markov process defines what the firm knows about the distribution of future productivity shocks. To control for unobserved productivity, we rely on an approach usually called dynamic panel estimation (Blundell & Bond, 2000). We use the AR(1) structure of the productivity process to write current value added as:

$$y_{it} = \rho_{jt} y_{it-1} + \left(f_j\left(k_{it}, l_{it}\right) - \rho_{jt} f_j\left(k_{it-1}, l_{it-1}\right)\right) + \eta_j$$
$$- \nu_j t + u_{it}$$

where the composite error $u_{it} = \xi_{it} + \varepsilon_{it} - \rho\varepsilon_{it-1}$ is zero mean conditional on information set I_{t-1}, by assumptions 1 and 2. Conditioning on a set of instruments included in I_{t-1}, we recover the parameters of the production function and productivity process with a GMM two-step estimation. Our moment conditions can be written as:

$$E\left[u_{it} \mid I_{t-1}\right] = E\Big[y_{it} - \rho_{jt} y_{it-1} - \left(f_j\left(k_{it}, l_{it}\right)\right.$$
$$\left. - \rho_{jt} f_j\left(k_{it-1}, l_{it-1}\right)\right) - \eta_j - \nu_j t \mid I_{t-1}\Big] = 0 \tag{11}$$

We assume that technology $f_j(.)$ in sector j is a translog production function of capital and labor:

$$f_j\left(k_t, l_t\right) = \beta_{l,jt} l_{it} + \beta_{k,jt} k_{it} + \beta_{ll,jt} l_{it}^2 + \beta_{kk,jt} k_{it}^2$$
$$+ \beta_{lk,jt} l_{it} k_{it}$$

and we use past values ω_{it-1}, l_{it-1}, m_{it-1}, k_{it-1} and higher order combinations of those terms, a time trend t and a constant as instruments in equation (11). From the estimates of the parameters of the production function, we compute the firm-level output elasticity of labor and capital for firm i in year t as:

$$\theta_{l,it} = \beta_{l,j} + 2\beta_{ll,j} l_{it} + \beta_{lk,j} k_{it}$$

$$\theta_{k,it} = \beta_{k,j} + 2\beta_{kk,j} k_{it} + \beta_{lk,j} l_{it}$$

From equation (7), we retrieve firm-level labor intensity and returns to scale.

Previous studes estimating markups with production data have often estimated production functions on the proxy variable method. This method relies on a non-parametric estimation of unobserved productivity ω_{it} from observed variables using the assumption that some proxy variable, either investment (Olley & Pakes, 1996) or intermediate input demand (Levinsohn *et al.*, 2003; Ackerberg *et al.*, 2015), is an invertible function only of other inputs and productivity. However, this approach is not valid if the proxy variable is also a function of some unobserved shock, such as an input cost shock to all inputs, or a demand shock. Let us define intermediate input demand m_{it} as a function of capital, labor, productivity, and some unobserved shock d_{it}:

$$m_{it} = m\left(\omega_{it}, k_{it}, l_{it}, d_{it}\right)$$

Assuming that this function is invertible in ω_{it} and using equation (9), one can write value added y_{it} as an unknown function of inputs and the unobserved shock:

$$y_{it} = f_j\left(k_{it}, l_{it}\right) + \omega\left(m_{it}, k_{it}, l_{it}, d_{it}\right) + \varepsilon_{1,it}$$
$$= g\left(m_{it}, k_{it}, l_{it}, d_{it}\right) + \varepsilon_{1,it}$$

Ignoring the unobserved shock, and using assumption (1) that ε_{it} is independant from input choices, we can obtain a non parametric estimate $\hat{g}_{it}$ of $g(.)$ that is a high-order polynomial in m_{it}, k_{it}, and l_{it}, but not of d_{it}:

$$y_{it} = \hat{g}_{it} + \hat{\varepsilon}_{it}$$

where the residuals $\hat{\varepsilon}_{it}$ are correlated with d_{it}. In practice, when we apply this procedure, we find that the residuals are not i.i.d. As Doraszelski & Jaumandreu (2019) have recently discussed, d_{it}, as ω_{it}, should also be recognized as potentially correlated with the error term. If so, the instruments used in the second stage of the proxy variable method are not consistent.

3. Data

To carry out our empirical analysis we rely on several sources of micro data produced by the French Institute of Statistics (Insee), covering the universe of French firms spanning the 1984-2016 period. These data are, among other uses, one of the main sources of the elaboration of national accounts. Our sources are gathered out of the universe of firms' tax returns and provide balance sheet, income, and cost information at the firm level, as well as employment, the industry in which the firm operates, the type of legal entity (micro-firms, sole proprietorship entities, or limited liability companies and corporations) and the tax regime to which it is affiliated (micro-regime, simplified regime, or normal regime).

From 1984 to 2007, we rely on the SUSE sources (*Système Unifié de Statistiques d'Entreprises*), gathering information from firms affiliated to two tax regimes, the BRN regime (*Bénéfice Réel Normal*) and RSI regime (*Régime Simplifié d'Imposition*). These files allow to distinguish between payments to labor, material inputs, other intermediary inputs, and investment, and provide information of the book value of capital of the firm and total employment. Hence, they have been widely used in previous research (di Giovanni *et al.*, 2014; Caliendo *et al.*, 2015).

From 2008, we rely on ESANE (*Élaboration des Statistiques Annuelles d'Entreprises*), a dataset that results from the unification of the previous SUSE data and the Annual Surveys of Firms that were conducted each year for broad sectors of industries. Because there is some overlap of information between tax returns and surveys, Insee applies an algorithmic process to reconcile diverging information. To construct our panel of firms we exclude from the post-2008 data firms affiliated to the micro-BIC regime.[5] Moroever, we restrict our analysis to legal units with a unique and valid identifier number.[6]

We focus on market sectors, excluding agriculture because our sample does not cover well firms in that sector.[7] We also exclude real estate and finance, because we focus on the production side of value added distribution among workers and owners of capital and firms. There are 5.7 million firms in our sample, 3.7 million of which have at least one employee. Finally, we rely on industry-level data from KLEMS (Van Ark, 2017) for information on investment and output prices to compute deflated values for value added and capital stocks. Others details on the data are provided in Appendix 1.

3.1. Overview of the Data

Table 1 describes the main variables that we use in our empirical analysis. Our sample of 3.7 million firms with at least one employee spans over 33 years, and contains 27 millions firm-year observations. The average sales are 2.6 million euros, the average number of employees is 14, and the average value of the capital stock is 1.3 million euros. These data are highly skewed: the median level of sales is 285 thousand euros, median number of employees is 3, and median capital stock is 76 thousand euros. This reflects the fact that our data are nearly exhaustive and include many small firms. For firms that report non missing investment, the average reported value is 185 thousand euros, and the median investment is 4 thousand euros, which also partly reflects the fact that investment is lumpy.[8] The average labor share in our sample, computed as the ratio of the sum of the wage bill and payroll taxes to value added, is 75%, close to the median at 74%.[9]

3.2. Aggregate Labor Share

Figure I reports the ratio of compensation of employees, including payroll taxes, to total value added in the macro and micro data, from 1984 to 2016. The aggregate labor share in our sample is lower than the average firm-level labor share. As discussed below in Section 4, larger firms have a lower labor share, which brings down the weighted average labor share. In the sample of firms with at least one employee on which we rely in the rest of the paper, the aggregate labor share decreases from 69.3% in 1984 to 64.7% in 2000, and then increases back to a level close to its initial level, reaching 69.1% in 2016.

5. *An extremely simplified regime introduced in 2008 applicable to very small firms, whose total sales do not exceed 170 thousand euros if the firm operates within the real estate and trade sectors, or 70 thousand euros otherwise. This regime has been widely used by free-lance workers who do not report any capital nor employees.*

6. *A firm is defined as a legal unit with a unique SIREN identifying number. In ESANE, legal units belonging to the same conglomerate are brought together and their accounts are consolidated (Deroyon, 2015). We do not consolidate and keep the underlying legal units as separate firms.*

7. *The market sectors are total economy excluding public administrations, healthcare, and education. The low coverage of agriculture is due to the fact that firms of this sector are mostly affiliated to a tax regime that is not included in the micro-BIC, BRN and RSI regimes.*

8. *The mean of the average firm investment across years is 140 thousand euros and the median of the average firm investment across years is 8 thousand euros.*

9. *Section C1 in the Online Appendix shows that our data is very representative of the market economy, accounting for 87% of total labor costs, 84% of total value added, with little variations over time.*

Table 1 – **Summary statistics**

	Observations	Mean	Median	St.dev
Sales	27,543,090	2,642.6	284.6	77,556.3
Gross output	27,517,472	1,818.5	203.7	69,157.5
Value added	27,517,472	730.0	111.3	32,121.5
Labor costs	27,517,428	507.8	81.0	18,092.5
Labor share	27,334,884	75.1	74.1	33.6
Employment	27,360,292	14.1	3.0	471.6
Intermediary inputs	27,517,477	1,088.5	80.2	46,270.4
Investment	19,814,136	185.1	4.0	19,200.4
Capital book value	27,507,848	1,305.8	76.0	168,003.0

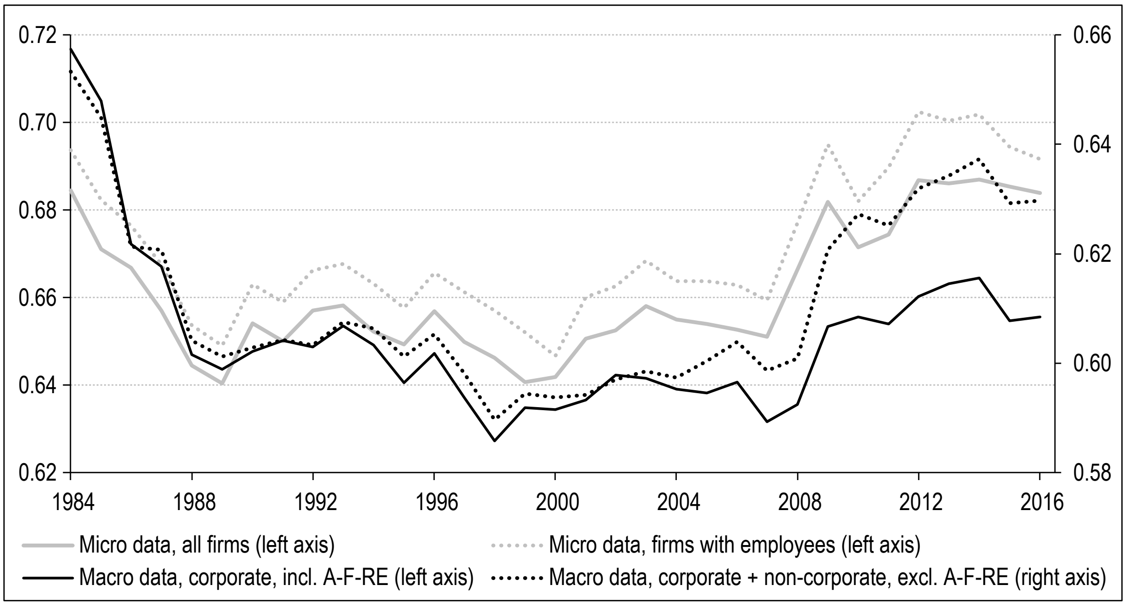
Note: This table presents the main descriptive statistics for the firms in the sample. Values are in thousand euros, except employment which is the number of full-time equivalent salaried workers and the labor share expressed in percentage of value added.
Sources and coverage: Insee, SUSE and ESANE. The sample includes all firms with non zero employment in the corporate market sectors, excluding agriculture, finance and real estate..

The aggregate level is on average 67.1% over the period. Aggregate data in principle also includes firms that have no employee, and doing so in our micro data decreases the aggregate level of the labor share by around 1 percentage point: it stands at 66.1% of value added on average over the period, and has the same U-shaped trajectory. This aggregate pattern differs substantially from the decrease of the labor share in the US, discussed by Autor *et al.* (2020), Kehrig & Vincent (2018), while others have argued that France, as many advanced economies, also experienced a secular decrease in the labor share (see e.g Grossman *et al.*, 2018; Karabarbounis & Neiman, 2014). Because of the U-shaped trajectory of the labor share, both in the micro and macro data, we find that conclusions of a secular decline in France are misguided.

Since our sample excludes agriculture, real estate, and finance, there is no available aggregate data for France for this particular sample; however, the aggregate labor share in our data closely matches the aggregate patterns of the labor share that can be measured for similar spheres of activity, both in levels and in variations.

French national accounts provide detailed operating accounts for spheres that are larger than our data in various dimensions. Figure I reports the labor share of the entire corporate sector, including corporations operating in the agriculture, real estate, and finance. Before 2000, the average level of the labor share in the corporate sector, reported by Insee, is the same as the aggregate labor share in our sample including firms with no employees (65.4%). It starts from

Figure I – **Aggregate labor share in France, 1984-2016**



Note: The figure reports the ratio of employee compensation, including payroll taxes, to total value added in the market sectors in France. See Section 3 for details on the different measures.
Sources and coverage: See Table 1.

a slightly higher level in 1984 (71.6%) than our sample estimate (68.4%) and reaches a slightly lower level in 2000 (63.4% as opposed to 64.1% in our sample). After 2000, however, the corporate labor share rises by 2 percentage points, but the labor share in our sample rises by 4 percentage points.

Figure I also reports the total labor share (corporate and non-corporate) excluding agriculture, real estate, and finance. The non-corporate sector is mainly composed of self-employed workers with few salaried workers. As a result, the total labor share reported by Insee is lower – on average 61% over the period, against 66.1% in our data with all firms. Nevertheless, after 2000, and despite this difference in levels, the rise of the total labor share measured with the same industry composition as our data matches the 4 percentage point increase that we observe in our data. One possible explanation of the divergence between the observed labor share of the corporate sector and that of the market economy excluding agriculture, real estate, and finance, as Cette *et al.* (2019) discuss, is that the growing share of the real estate sector, which has a labor share close to zero in total value added contributes negatively to the aggregate labor share of the corporate sector, especially during the housing boom years after 2000.

4. Labor Share and Concentration

In this section, we revisit some important facts about concentration and labor shares in the French context. In particular, we find that the rise in concentration in France is associated with an increase in firm-level labor shares, and a reallocation of market shares towards large and low-labor-share firms.

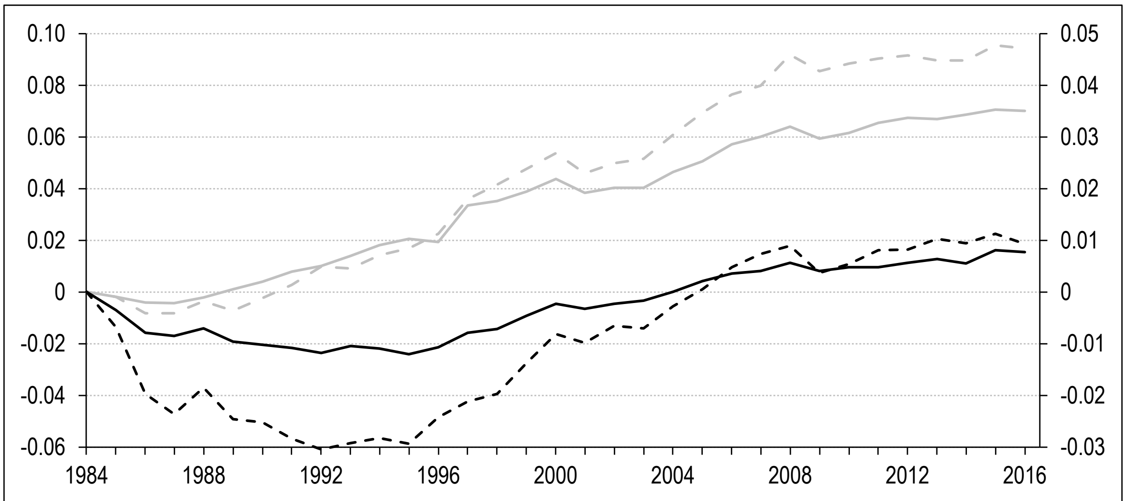
4.1. Rise in Concentration

Figure II reports the cumulative change since 1984 in sales weighted average levels of industry concentration indexes, where each index measures concentration of sales at the 3-digit national industry level. The share of sales of the 1% or 5% largest firms in each industry increased sharply on average since 1984, by 9 and 7 percentage points respectively. The concentration ratios, defined as shares of the 4 and 20 largest firms in each industry, followed a different pattern before 1995 but have increased by close to 4 percentage points each on average since 1995.[10]

Overall, we find that concentration ratios and top shares have increased in more than half of the 211 industries since 1995: the median increase of both concentration ratios is 2 percentage points, and the median increases of the top 1% and 5% shares are 4 and 5 percentage points

10. The median 3-digit industry has around 900 firms in a given year, but because 25% of the industries have more than 5,000 firms, and 25% have less than 200 firm, the number of firms in the top 1% and 5% differs greatly from one industry to the next. The median size of the 3-digit manufacturing industry is around 500 and the median size of the 3-digit non-manufacturing industry is 3,600.

Figure II – **Cumulative change in sales concentration**



Note: The cumulative change in sales concentration is measured across 3-digit industries. Industry changes in concentration are weighted by the share of each industry in total sales.
Sources and coverage: See Table 1.

respectively.[11] These results are consistent with evidence across the US and other OECD countries (CEA, 2016; Autor *et al.*, 2020; Andrews *et al.*, 2016).

4.2. Reallocation of Labor Shares

We build on Kehrig & Vincent (2018) and decompose the variations of the aggregate labor share to understand whether they are driven by variations at the firm level or by composition effects. Figure III reports, for each decile of labor share, the value-added-weighted average labor share and the share of industry value added of firms in that decile, in the first and last five years of the sample. Firms in the lowest decile of labor share accounted for 12% of their industry value added before 1990, compared to 16% in after 2010. The rise in industry shares is verified for four out of the five lowest deciles of labor share, while all five highest deciles of labor share accounted for less of industry value added in 2011-2016 than in 1984-1989. The lines illustrate how the raw distribution of labor shares has shifted upwards: the average labor share of each decile is higher in after 2010 than before 1990. The vertical bars illustrate how low labor share firms gained market share in the last 30 years.

To quantify how these dynamics affect the aggregate labor share, we compute the contributions of industry reallocation, firm reallocation, and firm labor shares to the variations of the aggregate labor share.[12] Figure IV reports the results of this decomposition. Reallocation across industries plays only a minor role in aggregate labor share variations. However, reallocation towards low-labor-share firms contributed to an accumulated 5 percentage points decrease of the aggregate labor share since 1984. This was offset by the upward shift in the labor share distribution, that contributed to a rise of the aggregate labor share of 5 percentage points.

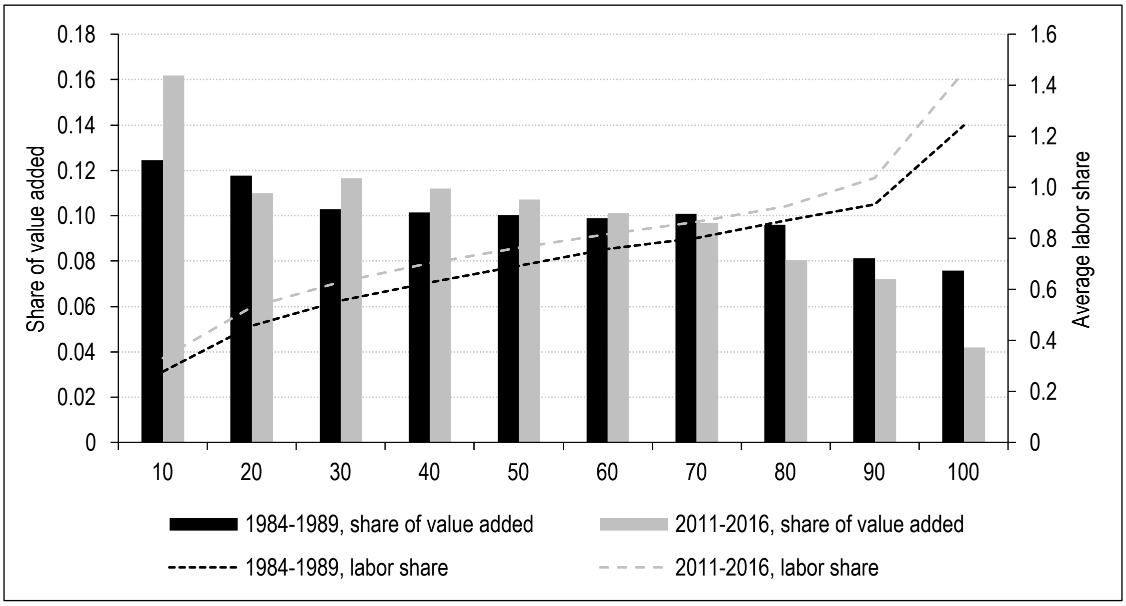
As emphasized by Kehrig & Vincent (2018), this decomposition groups firms into labor shares quantiles, which allows us to compare two static equilibria. It is conceptually distinct from standard within and between firm decompositions, because it abstracts from the contributions of firms' entry and exit. We focus on long term shifts in the joint distribution of labor and value added shares, not on the role of entry nor on the trajectories of specific firms (Section C3 in the Online Appendices discusses firm-level trends).

4.3. Correlation of Rise in Concentration and Reallocation of Labor Shares

We now show that variations in industry concentration are related to these labor share trends. We estimate the industry-level relationship between

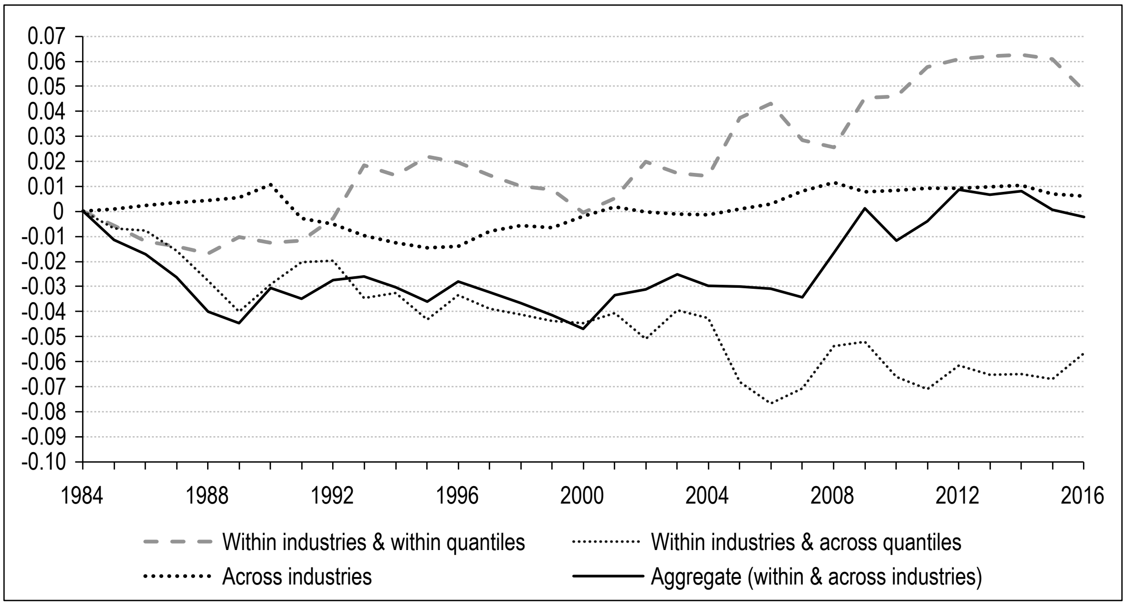
11. Section C5 in the Online Appendices discusses the results in manufacturing and non-manufacturing.
12. The details of decomposition are presented in Appendix 2.

Figure III – **Distributions of labor shares and value added**



Note: Dashed lines correspond to the raw cross-firm distribution of labor shares (scale on the right-hand axis). Vertical bars reflect the share of industry value added of firms in each unweighted decile of labor share (scale on the left-hand axis). To account for industry-specific differences in the joint distributions of labor share and value added, these distributions are averaged across 3-digit industries using value added weights in a given year, and averaged across 5 year periods.
Sources and coverage: See Table 1.

Figure IV – **Decomposition of the aggregate labor share**



Note: The decomposition of the aggregate labor share is described in Appendix 2. Quantiles of labor share are calculated each year within 3-digit industries.
Sources and coverage: See Table 1.

changes in concentration and changes in labor share. We run the following regression:

$$\Delta\lambda_{jt} = \psi_{\lambda}\Delta Conc_{jt} + FE_t + \varepsilon_{jt} \qquad (12)$$

where $\Delta Conc_{jt}$ is the 10-year change of sector j concentration level, proxied by the top 1% and top 5% share of sales, FE_t is a set of time fixed-effects that control for year-specific shocks, and $\Delta\lambda_{jt}$ is the 10 year change in industry j labor share.

Table 2 reports the results. The first two columns show that variation of industry concentration are negatively correlated with variation of industry labor shares. This relationship is significant and holds for all proxies of concentration. We find that a 10 percentage point rise in concentration is associated with a 0.7 to 1.1 decline in the weighted average labor share of the industry. These results are similar to those documented in the US (Autor *et al.*, 2020).

We then consider two components of the 10-year change of the labor share: the cross-quantile contribution to the labor share variation discussed in the previous paragraph, and the evolution of the average labor share of the 5% firms with the lowest labor share within each industry. We

Table 2 – **Correlations between variations in industry-level concentration and labor shares**

	Industry labor share		Across labor share quantiles		Within low labor share quantiles	
Top 1% share	-0.0777		-0.0457		0.0097	
	(0.0123)		(0.0112)		(0.0099)	
Top 5% share		-0.1102		-0.1288		0.0092
		(0.0167)		(0.0150)		(0.0135)
Observations	4,666	4,673	4,665	4,660	4,661	4,664
R2	0.0341	0.0347	0.0290	0.0405	0.0281	0.0292
4 largest shares	-0.0728		-0.0602		0.0772	
	(0.0147)		(0.0133)		(0.0119)	
20 largest shares		-0.1113		-0.1196		0.0615
		(0.0168)		(0.0152)		(0.0137)
Observations	4,649	4,648	4,645	4,645	4,651	4,650
R2	0.0320	0.0388	0.0325	0.0401	0.0366	0.0340

Note: Each estimate is the result of OLS estimation at the 3-digit industry with year fixed-effects. The dependent variable in columns "Industry labor share" is the long-term change of the industry aggregate labor share, defined as the ratio of the sum of firm level compensation and taxes paid on labor over the sum of firm level value added in that industry. The dependant variable in columns "Across labor share quantiles" and "Within low labor share quantiles" are the corresponding contributions to the industry aggregate labor share according to the decomposition described in Appendix 2, where low quantiles are the bottom 5%. The independent variables are the changes in the share of sales for the top 1%, top 5%, 4 largest and 20 largest firms.
Sources and coverage: See Table 1.

use these components as dependent variables in equation (12).

We find that larger increases in concentration are associated with a more negative contribution of value added share reallocation to the aggregate labor share. All coefficients are negative and significant. We also find a positive correlation between change in concentration and change in the average labor share of low labor share firms, defined as firms with a labor share in the bottom 5% of their 3-digit industry. These firms are sometimes referred to in the literature as 'hyper-productive' (Kehrig & Vincent, 2018) or 'superstar' firms (Autor *et al.*, 2020). As we will show next, firms with low labor shares also tend to be larger in our sample. These results suggest that the negative correlation between labor share and concentration is not driven by a decrease in the labor share of 'superstar' firms as they gain market shares.

4.4 Labor Share and Firms' Size

In fact, we show that the negative correlation between reallocation towards low labor share firms and concentration is largely driven by a monotically decreasing relationship (on average) between labor share and firm size. We run the following regression:

$$\lambda_{it} = FE_{size_{it}} + FE_{jt} + \varepsilon_{it} \qquad (13)$$

where $FE_{size_{it}}$ is a set of dummies indicating the size class of firm i in industry j in terms of employment at time t, FE_{jt} is a set of interacted fixed effects at the 3-digit industry j and year level.

Figure V presents the results of this regression, considering labor share in value added and in gross output. Relative to 10-20 employee firms, larger firms tend to report lower labor shares even after controlling for industry and year fixed effects. This decreasing relationship is monotonic, at all levels of employment. Labor shares of firms with 50 to 100 employees tend to be 2 percentage points lower than labor shares of 10 to 20 employees firms of the same industry at the same year. For firms with 2,500 to 5,000 employees the gap rises to 5 percentage points considering labor share in value added and to 7 percentage points considering labor share in gross ouput.

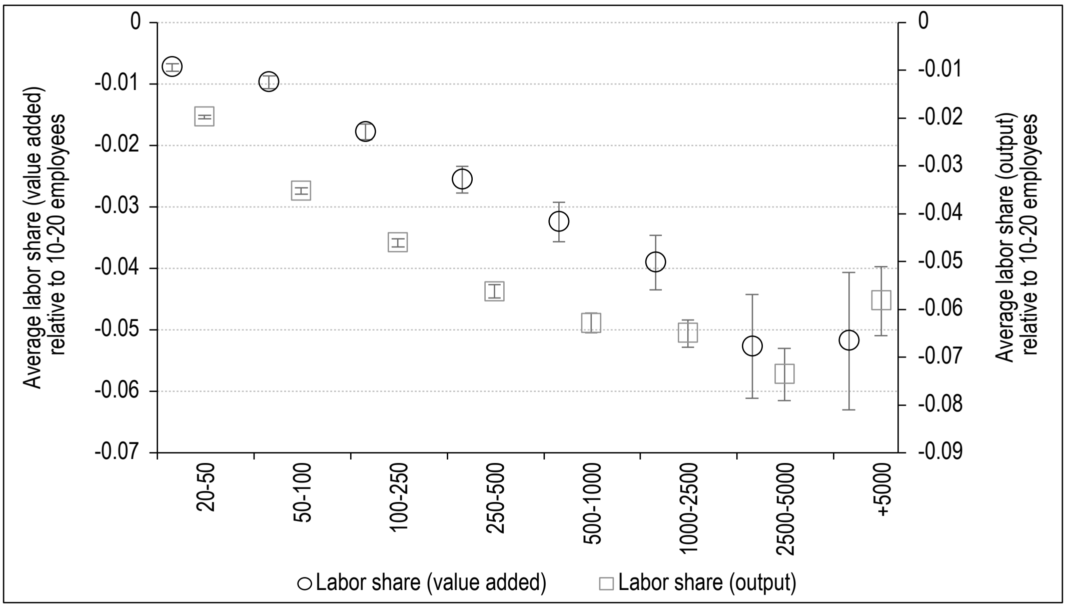
5. Estimation Results

In this section, we first present the results of our estimation procedure, and then show how aggregate and firm-level markups have evolved in France. We document additional facts about market power and concentration, and how variations in market power have contributed to the aggregate labor share, compared to other technological factors.

5.1. Production Function

Table 3 reports the results of rolling estimation of the production function, for the 27 sectors

Figure V – **Labor share by firm size**



Note: The figure reports the conditional average labor share by firm size, with 99% confidence interval. Averages are conditional on a set of flexible fixed effects constructed from the interaction of 3-digit industry codes and year.
Sources and coverage: See Table 1.

Table 3 – **Average output elasticities, rolling estimation**

	θ_l	θ_k	Observations		θ_l	θ_k	Observations
Mining	0.611	0.289	45,698	Gas and electricity	0.697	0.236	22,243
	(0.199)	(0.162)			(0.190)	(0.174)	
Food products	0.754	0.127	1,277,913	Water supply and waste	0.630	0.204	118,249
	(0.052)	(0.104)			(0.178)	(0.146)	
Textiles	0.553	0.135	282,598	Construction	0.611	0.078	4,969,117
	(0.221)	(0.157)			(0.175)	(0.087)	
Wood, paper and printing	0.794	0.044	552,510	Wholesale and retail trade	0.762	0.093	8,502,337
	(0.110)	(0.104)			(0.175)	(0.145)	
Coke and refined petroleum	0.533	0.251	2,472	Transportation	0.840	0.045	988,348
	(0.391)	(0.258)			(0.156)	(0.148)	
Chemicals	0.806	0.163	62,567	Accomodation and food services	0.592	0.181	3,076,031
	(0.143)	(0.122)			(0.174)	(0.133)	
Pharmaceuticals	0.898	0.072	11,657	Publishing and motion pictures	1.077	-0.001	309,540
	(0.359)	(0.286)			(0.245)	(0.215)	
Rubber and plastic products	0.763	0.125	245,896	Telecommunications	1.048	-0.035	25,191
	(0.159)	(0.176)			(0.242)	(0.217)	
Basic Metals	0.719	0.111	545,742	ICT	0.921	0.002	324,622
	(0.128)	(0.095)			(0.140)	(0.140)	
Computers and electronics	0.747	0.095	110,072	Legal, accounting and engineering	0.843	-0.020	1,499,590
	(0.084)	(0.068)			(0.164)	(0.150)	
Electrical equipments	0.766	0.127	50,476	Scientific research	0.856	0.015	30,461
	(0.136)	(0.101)			(0.259)	(0.230)	
Machinery and equipments	0.808	0.094	161,603	Advertising and market research	0.867	-0.067	406,636
	(0.137)	(0.069)			(0.269)	(0.140)	
Transport equipments	0.834	0.121	71,000	Administrative and support services	0.757	0.039	1,401,753
	(0.180)	(0.156)			(0.126)	(0.165)	
Other manufacturing products	0.745	0.042	650,254	Total	0.724	0.086	25,744,576
	(0.129)	(0.080)			(0.193)	(0.143)	

Note: Columns θ_l and θ_k report the average estimated output elasticity with respect to each factor of production for the translog production function for all firms. Standard deviations across firms (not standard errors) of the output elasticities are reported in brackets.
Sources and coverage: See Table 1.

of our data. These estimates are obtained by first estimating the parameters of the production function $\beta_j \in \{\beta_{l,j};\beta_{k,j};\beta_{ll,j};\beta_{kk,j};\beta_{lk,j}\}$ in industry j on 11-year rolling window samples, and then averaging for each firm each year the various estimated output elasticities based on samples that include that year:[13]

$$\beta_{jt}^{rolling} = \frac{1}{11}\sum_{n=-5}^{5}\beta_j^{t+n}$$

where β_j^t is the estimated parameter on the sample restricted to years t-5 to t+5. For the first and last five years of our sample, the average is calculated on fewer estimates. Output elasticities also vary across firms in the same sector. We report, for the different sectors, the average and standard deviation of the elasticities.[14] Because the returns to scale vary across firms, it is possible for many firms in a sector to have increasing returns to scale, while the estimate of the industry average returns to scale is close to 1. On average, the output elasticity of labor in our data is 0.72.

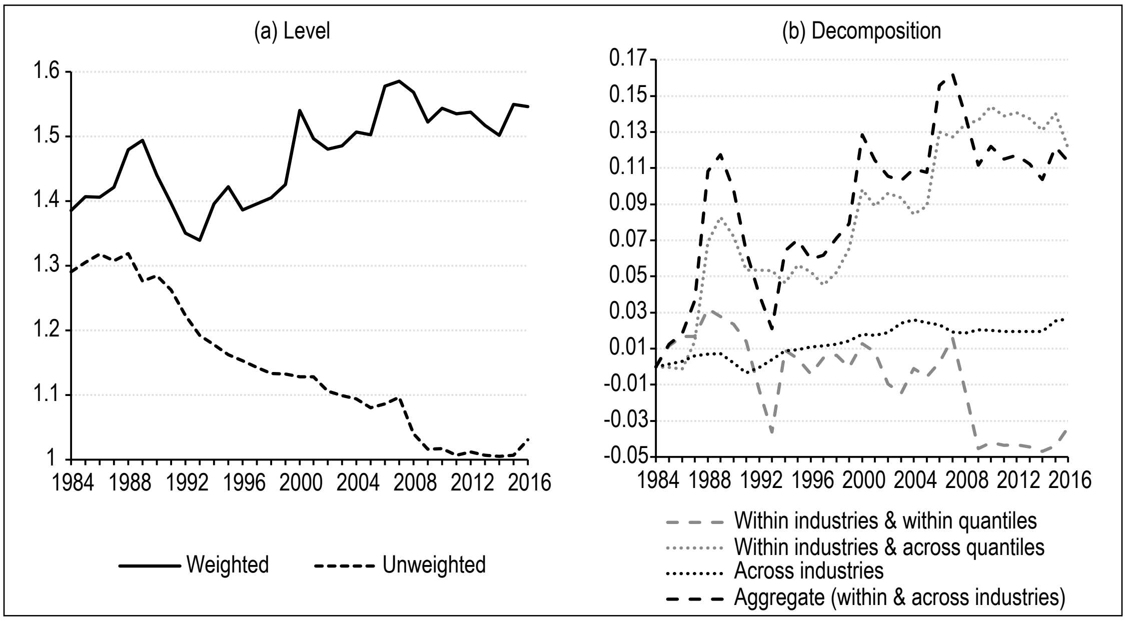
5.2. Aggregate Markup

The left panel of Figure VI reports the variations of the value added weighted and unweighted average markups across all firms in our sample. The unweighted average markup is smaller than the weighted average markup, because firms with larger value added have on average higher markup. We find that the unweighted average markup has decreased in France from 1.3 in 1984 to 1.0 in 2016. The value-added-weighted markup has increased from 1.4 to 1.6.[15]

The right panel of Figure VI shows the decomposition of the aggregate (weighted average) markup into within markup-quantile and

13. We estimate the production for each of the 27 sectors. Each sector includes several 3-digit industries. Section C5 in the Online Appendices reports the results of the non-rolling estimation.
14. We note that a few sectors appear to have negative average capital elasticities or low returns to scale. Section C5 in the Online Appendices reports median output elasticities which are less influenced by outliers.
15. Section C5 in the Online Appendices discusses the results in manufacturing and non-manufacturing. Section C4 of the Online Appendices discusses the results with other estimation methods (non rolling and following the proxy method of Ackerberg et al., 2015).

Figure VI – **Aggregate markup**



Note: The levels of the weighted and unweighted mean markup are based on rolling estimation of a translog value added production function. The decomposition of the aggregate markup is described in Appendix 2. Quantiles of markup are calculated each year within 3-digit industries.
Sources and coverage: See Table 1.

across markup-quantile components. It shows the importance of controlling for industry and disentangling the respective contributions of variations in value added shares holding markup constant or in markup holding value added shares constant to interpret aggregate variation.

The decomposition of the aggregate markup mirrors the decomposition of the aggregate labor share and shows how the within markup-quantile component contributed negatively to the evolution of the aggregate markup, while the cross-quantile component contributed positively. The contribution of reallocation across industries is negligible. Firms with relatively higher markups within narrowly defined industries have been gaining market shares, while the typical firm markup has slightly decreased.

5.3. Markup and Concentration

As for the labor share, we examine whether the observed rise in concentration is correlated with markup variations, on aggregate or along the distribution of markups. To that end we estimate the industry-level relationship between long term changes in concentration and the industry aggregate markup, or the contributions to the aggregate variation. We run the following regression:

$$\Delta\mu_{jt} = \psi_{\mu}\Delta Conc_{jt} + FE_t + \varepsilon_{jt} \qquad (14)$$

where $\Delta\mu_{jt}$ is the 10-year change of sector j aggregate markup level, or one of its contributions according to the decomposition described in Appendix 2.

Table 4 reports the results of the estimation of equation (14). The first two columns show that there is a positive and significant long-term relationship between the evolution of the aggregate markup and the evolution of concentration at the 3-digit industry level. This relationship is significant and holds for all proxies of concentration.

Next, as for the labor share, we ask whether this result is driven by a correlation between the rise in concentration and the shift in value added shares from low to high markup firms. The coefficients of the third and fourth columns of Table 4 are the results of regressions described in equation (14) where the dependent variable is the cross-quantile component to the evolution of aggregate markup, while in the last two columns the dependent variable is the within-quantile component of firms high markups, defined as firms with a markup in the top 5% of their 3-digit industry.They show a positive correlation between the rise in concentration and the cross-quantile component of the evolution of the aggregate markup. As for the labor share, this means that the cross-quantile component contributed more to the rise in markup in those industries that have become more concentrated at the top.

The fifth and sixth columns of Table 4 show no evidence that a rise in concentration is correlated

Table 4 – **Correlations between variations in industry-level concentration and markup**

	Industry markup		Across markup quantiles		Within high markup quantiles	
Top 1% share	0.2640		0.0790		0.0092	
	(0.0257)		(0.0245)		(0.0145)	
Top 5% share		0.3577		0.1460		0.0400
		(0.0353)		(0.0337)		(0.0199)
Observations	4,660	4,660	4,654	4,654	4,663	4,663
R2	0.0569	0.0586	0.0120	0.0140	0.0168	0.0177
4 largest shares	0.2098		0.0995		-0.0536	
	(0.0321)		(0.0298)		(0.0175)	
20 largest shares		0.1702		0.1101		-0.0242
		(0.0372)		(0.0346)		(0.0202)
Observations	4,647	4,646	4,644	4,644	4,650	4,650
R2	0.0482	0.0447	0.0108	0.0112	0.0172	0.0173

Note: Each estimate is the result of OLS estimation at the 3-digit industry with year fixed-effects. The dependent variable in columns "Industry markup" is the long-term change of the industry aggregate markup. The dependant variable in columns "Across markup quantiles" and "Within high markup quantiles" are the corresponding contributions to the industry aggregate markup according to the decomposition described in Appendix 2, where high quantiles are the top 5%. Markups are computed using rolling estimation of a translog production function. The independent variables are the changes of the share of sales of the top 1%, top 5 %, largest 4 and largest 20 firms.
Sources and coverage: See Table 1.

with increases in top markups. The correlations with variations in the top 1% and 5% shares of sales are not significantly positive, the correlations with variations in the shares of the 4 and 20 largest firms are all negative, and significant at the 5% level when concentration is measured with the share of the 4 largest firms.[16] The fact that top markups are not linked with rises in concentration is consistent with theories according to which high productivity firms with higher markups benefit from positive shocks, such as export demand shocks, more than laggard firms, and expand without increasing their markup (see e.g Aghion *et al.*, 2019). However, it is in contrast with results in the US documented by De Loecker *et al.* (2020) where top markups contributed to a third of the overall increase in weighted average markups. Nevertheless, De Loecker *et al.* (2020) do not provide evidence that the rise in top firms' markups is correlated at the industry level with the reallocation component, or with concentration.

5.4. Markup and Size

As for the labor share, we investigate whether markups are increasing with firm size to understand the correlation between the growing share of the largest firms in each industry's total sales and the reallocation of market shares towards high markup firms. To that end, we run the following regression:

$$\mu_{it} = FE_{size_{it}} + FE_{jt} + \varepsilon_{it} \qquad (15)$$

where $FE_{size_{it}}$ is a set of dummies indicating in the size class of firm i in industry j in terms of employment at time t, FE_{jt} is a set of interacted fixed effects at the 3-digit industry j and year level.

Figure VII reports the results of this regression. We find that larger firms have higher estimated markups. Firms with more than 5,000 employees have, on average, markups larger by 30 percentage points than firms with 10 to 20 employees within the same 3-digit industry on the same year. This increasing relationship is well observed at all levels of employment, and both for markups obtained with the non-rolling and rolling estimations.

The markup is defined in equation (4) as the ratio of the output elasticity of labor to the labor share. It is important to note that because the output elasticity of labor vary across firms, the markup is not perfectly correlated with the labor share, and therefore the positive relationship between a firm's markup and its size does not flow directly from the negative relationship between its labor share and its size documented in Section 4.4.

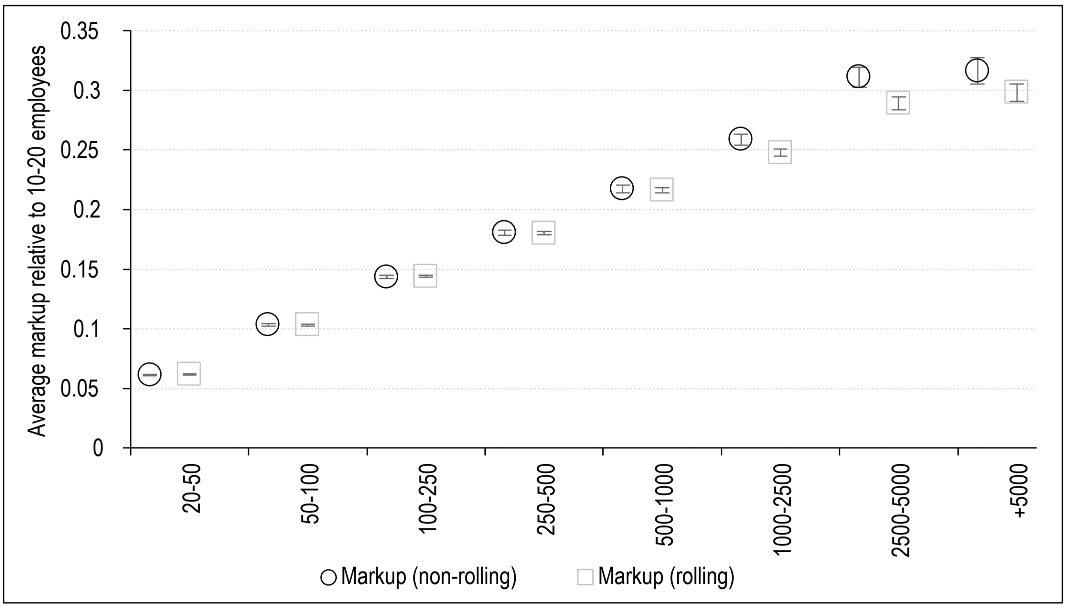
5.5. Link Between Labor Shares and Markups

In this section, we return to the labor share and ask whether variations in firm-level labor share are mainly driven by markups – i.e. are labor shares increasing because markups are decreasing? – or by technology – i.e. are labor shares increasing because production has become more labor intensive?

First, we find that there is a clear negative relationship between firm-level labor shares and markups in France. We run the following regressions:

16. *See Section C5 of the Online Appendix for results limited to manufacturing or non-manufacturing industries.*

Figure VII – **Markup and size**



Note: The figure reports the conditional average markup by firm size, with 99% confidence interval. Averages are conditional on a set of flexible fixed effects constructed from the interaction of 3-digit industry codes and year.
Sources and coverage: See Table 1.

$$\lambda_{it} = \phi\mu_{it} + FE_{ijt} + \varepsilon_{it} \quad (16)$$

where μ_{it} is the markup of firm i in year t, λ_{it} is the labor share, and FE_{ijt} is a set of fixed effect, either industry or firm-level, and year.

Table 5 presents the results of these regressions, and shows that firms with high markup have low labor shares both across industries and across firms within the same industry. We also find that as the markup of the firm grows, its labor share decreases. The absolute value of coefficient ϕ is around 0.3 to 0.5 depending on the estimation: as the markup of the firm increases 10 percentage points, its labor share decreases by 3 percentage points. Finally, as the coefficient of determination of the regression without fixed effects shows, the heterogeneity of markups explains 45% of the heterogeneity of labor shares across firms. The different panels of the table show that this relationship holds statistically and quantitatively for various groups of size.

To extrapolate these firm-level results to the aggregate economy, we need to keep in mind that there is no such a thing as a representative firm in this context. Recall that equations (6) and (7) show that at the level of the individual firm, the labor share is the product of labor intensity, returns to scale and the inverse markup ($\lambda_{it} = \alpha_{it}\gamma_{it}\mu_{it}^{-1}$) but this result does not hold at the aggregate level. From equation (8), we now decompose variations of the aggregate labor share into contributions from labor intensity, returns to scale, and markups, either by taking the "representative firm" approach and computing the contributions of the weighted averages of each component of the aggregate labor share, therefore ignoring the reallocation between firms or, alternatively, by isolating the contribution of reallocation and computing the contributions of the unweighted averages of each component.[17]

The left panel of Figure VIII presents the results of the decomposition for the representative firm. The total variation of the aggregate labor share from 1984 to 2016 is small and positive, and ignoring the role of reallocation, the aggregate markup has contributed negatively to the aggregate labor share, which is consistent with previous evidence that the aggregate markup has increased from 1984 to 2016. The sum of the contributions of labor intensity and returns to scale, in other words the contribution of the weighted average output elasticity of labor, is positive, which would suggest that the French economy has become more 'labor intensive' over the period.

However, taking into account reallocation provides a different picture of underlying determinants of the dynamics of the aggregate labor share in France. The right panel of Figure VIII presents the results of the decomposition isolating the contribution of reallocation. The contribution of reallocation is negative and very large, as we have already showed in Figures IV

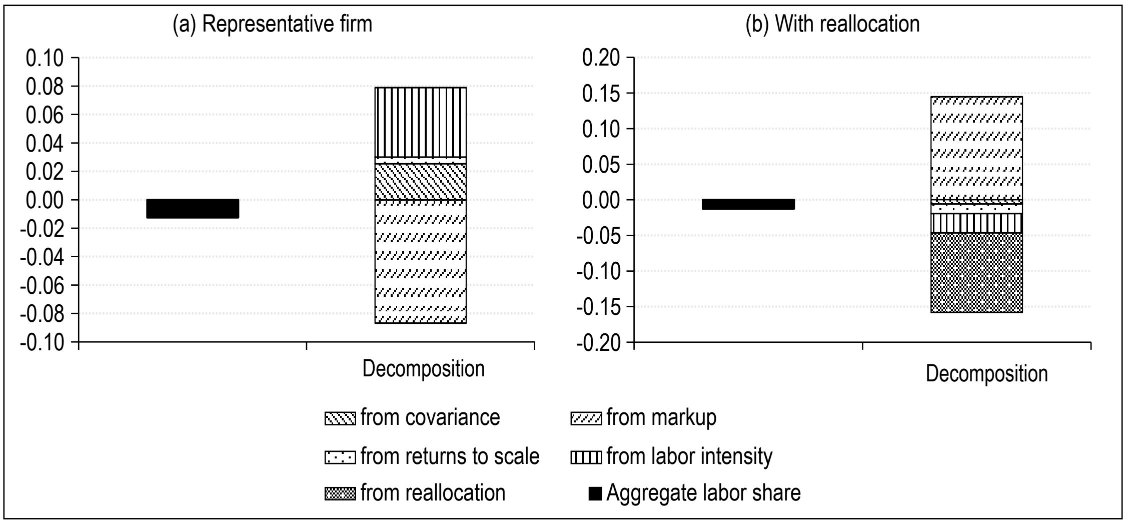
17. See Appendix 3 for details on the decomposition.

Table 5 – **Correlation between labor share and markup**

	Dependent variable: labor share					
	No size threshold			More than 50 employees		
	No FE	Industry FE	Firm FE	No FE	Industry FE	Firm FE
Markup	-0.3173	-0.3520	-0.3370	-0.4070	-0.4351	-0.4797
	(0.0041)	(0.0022)	(0.0027)	(0.0054)	(0.0035)	(0.0044)
Observations	25,554,561	25,554,533	25,092,587	808,003	807,805	789,488
R2	0.407	0.489	0.761	0.493	0.582	0.805
	More than 100 employees			More than 1,000 employees		
	No FE	Industry FE	Firm FE	No FE	Industry FE	Firm FE
Markup	-0.3842	-0.4163	-0.4554	-0.3270	-0.3709	-0.3912
	(0.0053)	(0.0041)	(0.0053)	(0.0050)	(0.0077)	(0.0125)
Observations	398,301	398,018	390,768	26,684	25,305	24,839
R2	0.483	0.594	0.814	0.471	0.710	0.892

Note: Each estimate is the result of OLS estimation of firm level labor share on markups, for four samples: all firms, firms with more than 50 employees, 100 employees, and 1000 employees. Markups are computed using rolling estimation of a translog production function. All columns include year fixed effects. Standard errors are clustered at the 3-digit x year industry level. FE stands for fixed effects.
Sources and coverage: See Table 1.

Figure VIII – **Contributions to the evolution of the aggregate labor share, 1984-2016**



Note: The decomposition of the variation of the agregate labor share is based on translog non-rolling and rolling value added estimation of the production function. See Appendix 3 for details.
Sources and coverage: See Table 1.

and III. Firm-level markups have contributed positively to the aggregate labor share, while firm-level returns to scale and labor intensity had a negative contribution.

* *
*

In this paper, we find no evidence of a rise in firms' market power in France: firm-level markups decreased on average, and the rise in concentration is not correlated with increases in top markups. These facts are however correlated with an important reallocation of market shares towards low-labor share and high-markup firms, which contributed to a rise in the aggregate markup. Because those firms tend to be larger, this reallocation translates into a rise in concentration.

This reallocation of market shares towards large firms is consistent with a wealth of evidence about the increasing differences between firms (Decker *et al.*, 2016a, 2016b, 2016c; Andrews *et al.*, 2016; Karahan *et al.*, 2019). However, the simultaneous rise in concentration and the relative stability of top firm-level markups raises questions about the interpretation of concentration that go beyond the French case. One possible way to explain both the reallocation of market shares towards large firms and the within-firm increase in the labor share would be an increase in winner-take-most competition, as discussed by Autor *et al.* (2020): as consumers become more sensitive to firms' prices, more productive and bigger firms gain market shares but a given firm's market power decreases. The source of this increase in competition could be international competition (Bonfiglioli *et al.*, 2019; Panon, 2020). Since our results hold across broad sectors of the French economy, including non-manufacturing sectors, other factors than international competition could be at play. Technological factors, such as the rise of internet platforms and price comparison websites, may for instance explain why firm-level market power has decreased.

Many predictions of the textbook explanation of a rise in competition are consistent with the evidence provided here. We do not take a stance on the source of market power, and in particular on why there is an increasing relationship between a firm's size and its markup: the price elasticity of demand may decrease with quantity, or large firms may be large enough to influence the equilibrium price, and therefore act strategically. However, in both cases, an increase in competition will have offsetting effects on the markup of large firms: holding size constant, it will tend to decrease their markup, but because of reallocation, these firms will grow and their markup will increase. Qualitatively, it is thus possible to observe a rise in top firms' markups, as De Loecker *et al.* (2020) find for the US, or a stability or decrease, as we find for France. ☐

Link to the Online Appendices: https://insee.fr/en/statistiques/fichier/4997869/ES-520-521_Bauer-Boussard_Online_Appendices.pdf

BIBLIOGRAPHY

Ackerberg, D., Caves, K. & Frazer, G. (2015). Identification Properties of Recent Production Function Estimators. *Econometrica*, 83(6), 2411–2451. https://doi.org/10.3982/ECTA13408.

Aghion, P., Bloom, N., Blundell, R., Griffith, R. & and Howitt, P. (2005). Competition and innovation: an inverted-U relationship. *The Quarterly Journal of Economics*, 120(2), 701–728. https://doi.org/10.1093/qje/120.2.701

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P. J. & Li, H. (2019). A Theory of Falling Growth and Rising Rents. Federal Reserve Bank of San Francisco, *Working Paper* N°2019-11 https://doi.org/10.24148/wp2019-11

Andrews, D., Criscuolo, C. & Gal, P. (2016). The Best versus the Rest: The Global Productivity Slowdown, Technology Divergence across Firms and the Role of Public Policy. *OECD Productivity Working Paper* N°5. https://doi.org/10.1787/63629cc9-en

Autor, D., Dorn, D., Katz, L.F., Patterson, C. & Van Reenen, J. (2020). The Fall of the Labor Share and the Rise of Superstar Firms. *The Quarterly Journal of Economics*, 135(2), 645–709. https://doi.org/10.1093/qje/qjaa004

Baqaee, D.R. & Farhi, E. (2020). Productivity and Misallocation in General Equilibrium. *The Quarterly Journal of Economics*, 135(1), 105–163. https://doi.org/10.1093/qje/qjz030

Bauer, A., Garbinti, B. & Georges-Kot, S. (2018). Financial Constraints and Self-Employment in France, 1945-2014. Insee, *Document de travail* N° G018/08. https://www.insee.fr/en/statistiques/3640484

Barkai, S. (2020). Declining Labor and Capital Shares, *Journal of Finance,* 75(5), 2421–2463. https://doi.org/10.1111/jofi.12909

Berlingieri, G., Blanchenay, P. & Criscuolo, C. (2017), The great divergence(s). *OECD Science, Technology and Industry Policy Papers* N°39, OECD Editions, Paris, https://doi.org/10.1787/953f3853-en.

Blundell, R. & Bond, S.(2000). GMM Estimation with persistent panel data: an application to production functions. *Econometric Reviews*, 19(3), 321–340, 2000. https://doi.org/10.1080/07474930008800475

Bonfiglioli, A., Crinò, R & Gancia, G. (2019). Concentration in International Markets: Evidence from US Imports. CEPR *Discussion Paper* N°13566. https://ssrn.com/abstract=3346357

Boussard, J. & Lee, R. (2020). Competition, Profit Share and Concentration. Insee, *Document de travail* N°G2020/04. https://www.insee.fr/en/statistiques/4651858

Caliendo, L., Monte, F. & Rossi-Hansberg, E. A. (2015). The Anatomy of French Production Hierarchies. *Journal of Political Economy*, 123(4), 1–75. https://doi.org/10.1086/681641

Card, D., Heining, J. & Kline, P. (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics*, 128(3), 967–1015. https://doi.org/10.1093/qje/qjt006

CEA (2016). Benefits of competition and indicators of market power. Council of Economic Advisers, *Issue Brief*, 2016.
https://obamawhitehouse.archives.gov/sites/default/files/page/files/20160414_cea_competition_issue_brief.pdf

Cette, G., Koehl, L. & Philippon, T. (2019). The Labor Schare in the Long Term: A Decline? Economie et Statistique / Economics and Statistics, 510-511-512, 35–51. https://doi.org/10.24187/ecostat.2019.510t.1993

De Loecker, J., Eeckhout, J. & Unger, G. (2020). The Rise of Market Power and the Macroeconomic Implications. *The Quarterly Journal of Economics*, 135(2), 561–644. https://doi.org/10.1093/qje/qjz041

De Loecker, J. & Warzynski, F. (2012). Markups and Firm-Level Export Status. *American Economic Review*, 102(6), 2437–2471. https://doi.org/10.1257/aer.102.6.2437

Decker, R. A., Haltiwanger, J., Jarmin, R. S. & Miranda, J. (2016a). Where has all the skewness gone? The decline in high-growth (young) firms in the U.S, *European Economic Review*, Elsevier, vol. 86(C), pages 4–23. https://doi.org/10.1016/j.euroecorev.2015.12.013

Decker, R. A., Haltiwanger, J., Jarmin, R. S. & Miranda, J. (2016b). The Secular Decline in Business Dynamism in the U. S. *American Economic Review*: Papers & Proceedings, 106(5), 203–207.
http://dx.doi.org/10.1257/aer.p20161050

Decker, R. A., Haltiwanger, J., Jarmin, R. S. & Miranda, J. (2016c). Declining Business Dynamism: What We Know and the Way Forward. *American Economic Review,* 106 (5), 203–07.
http://doi.org/10.1257/aer.p20161050

Deroyon, J. (2015). De nouvelles données issues du profilage des groupes. *In:* Insee Références, *Les entreprises en France*, 39–52. https://www.insee.fr/fr/statistiques/1906511?sommaire=1906539

Di Giovanni, J., Levchenko, A. A. & Méjean, I. (2014). Firms, Destinations, and Aggregate Fluctuations. *Econometrica*, 82(4), 1303–1340. https://doi.org/10.3982/ECTA11041

Doraszelski, U. & Jaumandreu, J. (2019). Using Cost Minimization to Estimate Markups.
https://faculty.wharton.upenn.edu/wp-content/uploads/2019/07/robust_markups20190625.pdf

Elsby, M. W. L., Hobijn, B. & Sahin, A. (2013). The decline of the US labor share. *Brookings Papers on Economic Activity*, Fall(2), 1–63.
https://www.brookings.edu/wp-content/uploads/2016/07/2013b_elsby_labor_share.pdf

Garbinti, B., Goupille-Lebret, J. & Piketty, T. (2018). Income inequality in France, 1900-2014: Evidence from Distributional National Accounts (DINA). *Journal of Public Economics*, 162(C), 63–77.
https://doi.org/10.1016/j.jpubeco.2018.01.012

Gutiérrez, G. & Philippon, T. (2017). Investmentless growth: An empirical investigation. *Brookings Papers on Economic Activity*, Fall(1), 89–190.
https://www.brookings.edu/wp-content/uploads/2018/02/gutierreztextfa17bpea.pdf

Gutiérrez, G. & Philippon, T. (2018). How EU Markets Became Free: A Study of Institutional Drift. National Bureau of Economic Research, *Working Paper* N°24700. https://www.nber.org/papers/w24700

Grassi, B. (2017). IO in I-O: Competition and Volatility in Input-Output Networks.
https://sites.google.com/site/grassibasile/home/research/job-market-paper

Grossman, G. M., Helpman, E., Oberfield, E. & Sampson, T. (2018). The Productivity Slowdown and the Declining Labor Share. Society for Economic Dynamics, *2018 Meeting Paper* N°169.
https://economicdynamics.org/meetpapers/2018/paper_169.pdf

Hopenhayn, H. A. (1992). Entry, Exit, and firm Dynamics in Long Run Equilibrium. *Econometrica*, 60(5), 1127–1150. https://doi.org/10.2307/2951541

Karabarbounis, L. & Neiman, B. (2014). The Global Decline of the Labor Share. *The Quarterly Journal of Economics*, 129(1), 61–103. https://doi.org/10.1093/qje/qjt032

Karabarbounis, L. & Neiman, B. (2018). Accounting for Factorless Income. National Bureau of Economic Research, *Working Paper* N°24404. https://www.nber.org/papers/w24404

Karahan, F. Pugsley, B. & Sahin, A. (2019). Demographic Origins of the Startup Deficit. Federal Reserve Bank of New York, *Staff Reports* N°888.
https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr888.pdf

Kehrig, M. & Vincent, N. (2018). The Micro-Level Anatomy of the Labor Share Decline. National Bureau of Economic Research, *Working Paper* N°25275. https://www.nber.org/papers/w25275

Lashkari, D., Bauer, A. & Boussard, J. (2019). Information Technology and Returns to Scale. Banque de France *Working Paper* N°737, 2019. https://publications.banque-france.fr/en/information-technology-and-returns-scale

Levinsohn, J., Petrin, A. & Levinsohn, J. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *Review of Economic Studies*, 70(2), 317–341. https://doi.org/10.1111/1467-937X.00246

Mayer, T., Melitz, M. J. & Ottaviano, G. I. P. (2014). Market size, competition, and the product mix of exporters. *American Economic Review*, 104(2), 495–536. https://doi.org/10.1257/aer.104.2.495

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6), 1695–1725. https://doi.org/10.1111/1468-0262.00467

Olley, G. S. & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 64(6), 1263–1297. https://doi.org/10.2307/2171831

Panon, L. (2020). Labor Share, Foreign Demand and Superstar Exporters.
https://ludovicrwpanon.github.io/ludovicpanon/JMP_Panon.pdf

Piketty, T., Saez, E. & Zucman, G. (2018). Distributional national accounts: Methods and estimates for the United States. *The Quarterly Journal of Economics*, 133(2), 553–609. https://doi.org/10.1093/qje/qjx043

Song, J, Price, D. J., Guvenen, F., Bloom, N. & von Wachter, T. (2018). Firming Up Inequality. *The Quarterly Journal of Economics*, 134(1), 1–50. https://doi.org/10.1093/qje/qjy025

Van Ark, B. & Jäger, K. (2017). Recent Trends in Europe's Output and Productivity Growth Performance at the Sector Level, 2002-2015. *International Productivity Monitor*, 33(1), 8–23.
http://www.csls.ca/ipm/33/vanArk_Jager.pdf

Van Reenen, J. (2018). Increasing Differences between firms: Market Power and the Macro-Economy. Center for Economic Performance, *Working Paper* N°1576 http://cep.lse.ac.uk/pubs/download/dp1576.pdf

APPENDIX 1

DATA

Industry Codes

Industry classification has changed over the 1985-2016 period. From 1985 to 1993 the classification applicable was the NAP (*Nomenclature d'activités et de produits*). It changed to NAF (*Nomenclature d'activités française*) in 1993, since then revised twice (NAF rév. 1 in 2003, NAF rév. 2 in 2008). There is no one-to-one correspondence between these classifications. As a result we make the choice to map each NAP industry code to its most often associated NAF industry code. Similarly we map each NAF industry code to its most often associated NAF rév. 1 industry code, and each NAF rév. 1 code to its most often associated NAF rév. 2. As a result we are able to associate to each firm for each year its industry code in the NAF rév. 2 classification.

Variable Definitions

Our data provide information on total sales of goods, services and merchandises, as well as variations in inventory and immobilized production. For inputs, they provide the book value of tangible and intangible capital, the wage bill and payroll taxes, and the cost of materials, merchandise, and other intermediary inputs. All data on sales, cost of inventory variations and cost of inputs are recorded separately for merchandise and other inputs. We follow definitions from the National Accounts and define output as the sum of immobilized production, variations in inventory, and sales excluding the cost of merchandise; and we define intermediary inputs use as the sum of material expenditures minus inventory variations, and other external inputs. These definitions mean that gross output includes the net margin on merchandise sold, not gross sales of merchandise. Importantly, our data also include the cost of purchased external services in intermediary inputs. Our micro data are in current prices, and we do not observe firm-level prices of intermediary and capital inputs, nor output prices. We deflate nominal values of gross output, intermediary inputs, and capital stock at the NA38 sectors level using price indexes for investment output, and value added from the September 2018 release of the Insee Annual National Accounts.

Data Cleaning

We exclude micro-firms and profiled enterprises from the 2008-2016 data. Firm-year observations of very high or negative labor shares that stem from very low or negative value added observations relative to the firm average across years are replaced with the average labor share of the firm across years. Concentration measures are computed using sales on the entire sample of firms, labor share decomposition and all subsequent analysis are conducted on the sample of firms with at least one salaried employee. The parameters of the translog production function are estimated using a smaller sample of firms with sales above 1 million, and positive value added, intermediary inputs and capital. We also exclude from the estimation sample firms with wage, labor productivity, or capital per employee in the top or bottom 0.1%.

APPENDIX 2

DECOMPOSITION

The decomposition method presented below is applied to aggregate labor share and aggregate inverse markups.

Industry Level Decomposition

Let $k \in \{1, \cdots, K\}$ be some industry classification (e.g., 3 digits in micro data), M stands for an aggregate measure (labor share or markup). Also, let S_k and M_k stand respectively for the weight of the industry in total value added or total sales, and the industry average measure. Define for any variable X:

$$\Delta X_t \equiv X_t - X_{t-1}, \ \ \bar{X}_t \equiv \frac{1}{2}\left(X_t + X_{t-1}\right)$$

$$\Delta_T X \equiv X_T - X_0$$

where T is the last period and 0 is the first period. Our first decomposition is:[(i)]

$$\Delta_T M \equiv \underbrace{\sum_{t=1}^{T}\sum_{k} \bar{S}_{kt} \Delta M_{kt}}_{\text{within industries}} + \underbrace{\sum_{t=1}^{T}\sum_{k} \Delta S_{kt} \ \bar{M}_{kt}}_{\text{across industries}} \tag{B.1}$$

This allows us to distinguish the extent to which the aggregate variation in markup or labor share is due to a change of industry shares or a within industry variation, irrespective of the sectoral composition of the economy.

Within Industry Decomposition

Next, we focus on changes in the industry-level measure. Our aim is to decompose the changes at the industry level to the changes in the distribution of firm level markup or labor share and the changes in the markup or labor share for the firms of a given quantile. Let $y \in \left[\underline{y};\ \bar{y}\right]$ denote a given level of the labor share or markup. We can write the industry-level outcome as:

$$M_{kt} \equiv \int_{\underline{y}}^{\bar{y}} S_{kt}\left(y\right)\ M_{kt}\left(y\right)\ dy \tag{B.2}$$

where $S_{kt}\left(y\right)$ is the density function. In a discrete version, $S_{kt}\left(y\right)$ is the market shares of firms in industry k with labor share or markup close to y, and $M_{kt}\left(y\right)$ denotes the weighted average outcome (labor share or markup) of firms with outcome close to y in industry k at time t. We can now decompose[(ii)]

$$\Delta M_{kt} = \underbrace{\int_{\underline{y}}^{\bar{y}} \bar{S}_{kt}\left(y\right) \Delta M_{kt}\left(y\right) dy}_{\text{within quantiles}} + \underbrace{\int_{\underline{y}}^{\bar{y}} \Delta S_{kt}\left(y\right) \bar{M}_{kt}\left(y\right) dy}_{\text{across quantiles}} \tag{B.3}$$

We now summarize the within-industry component change in aggregate measure into the following components:

1. The across quantiles component: $\sum_{t=1}^{T}\sum_{k} \bar{S}_{kt} \int_{\underline{y}}^{\bar{y}} \Delta S_{kt}\left(y\right) \bar{M}_{kt}\left(y\right) dy$

2. The within quantiles component: $\sum_{t=1}^{T}\sum_{k} \bar{S}_{kt} \int_{\underline{y}}^{\bar{y}} \bar{S}_{kt}\left(y\right) \Delta M_{kt}\left(y\right) dy$

(i) This is simply because: $\Delta\left(S_t M_t\right) = \bar{S}_t \Delta M_t + \Delta S_t \bar{M}_t$ *and*

$$\Delta_T\left(SM\right) = \sum_{t=1}^{T} \Delta\left(S_t M_t\right)$$

(ii) As emphasized by Kehrig & Vincent (2018) this decomposition is conceptually distinct from standard within and cross firm decompositions. Let Ω_{kt} be the set of firms active in time t, and $\bar{\Omega}_{kt}$ be the set of firms common between time t and $t-1$, Ω_{kt}^{+} the set of new firms at time t, and Ω_{kt}^{-} the set of firms exiting between time t and $t+1$. We can then write:

$$\Delta M_{kt} \equiv \underbrace{\sum_{i \in \Omega_t^{-}} \bar{S}_{it} \Delta M_{it}}_{\text{within firms}} + \underbrace{\sum_{i \in \Omega_{kt}^{-}} \Delta S_{it} \bar{M}_{it}}_{\text{across firms}} + \underbrace{\left(\sum_{i \in \Omega_{kt}^{+}} S_{it} M_{it} - \sum_{i \in \Omega_{kt-1}^{-}} S_{it-1} M_{it-1}\right)}_{\text{net entry}}$$

where again shares are computed within the industry.

APPENDIX 3

LABOR SHARE, MARKUP, AND TECHNOLOGY

In a first exercise, we do not isolate the contribution of reallocation to the aggregate labor share and write the weighted average mean for a given variable Z:

$$\mathbb{E}_t^{RF}[Z] \equiv \sum_i S_{it} Z_{ti} \tag{C.1}$$

where RF stands for "representative firm".

In a second exercise, we take into account the contribution of reallocation and write the unweighted average mean for a given variable Z :

$$\mathbb{E}_t^{WR}[Z] \equiv \frac{1}{N_t} \sum_i Z_{it} \tag{C.2}$$

where N_t is the total number of firms and WR stands for "with reallocation".

Equation (8) can be rewritten using the definition in equation (C.1), which gives a decomposition of the aggregate labor share into the markup, labor intensity and returns to scale of the representative firm:

$$\Lambda_t = \mathbb{E}_t^{RF}\left[\alpha\gamma\mu^{-1}\right] = \mathbb{E}_t^{RF}[\alpha] \times \mathbb{E}_t^{RF}[\gamma] \times \mathbb{E}_t^{RF}\left[\mu^{-1}\right] + COV_t^{RI} \tag{C.3}$$

or using the definition in equation (C.2), which gives a decomposition of the aggregate labor share into a reallocation term, defined by the gap between weighted and unweighted average labor share, and firm-level unweighted average markups, labor intensity and returns to scale:

$$\Lambda_t = \left(\mathbb{E}_t^{RF}\left[\alpha\gamma\mu^{-1}\right] - \mathbb{E}_t^{WR}\left[\alpha\gamma\mu^{-1}\right]\right) + \mathbb{E}_t^{WR}[\alpha] \times \mathbb{E}_t^{WR}[\gamma]: \\ \times \mathbb{E}_t^{WR}\left[\mu^{-1}\right] + COV_t^{WR} \tag{C.4}$$

where in both cases COV_t^R, gathers all of the covariance terms. This term is positive when firms that have high levels of labor intensity also have high returns to scale and low markups. For each $R \in (RF, WR)$, this quantity is defined by:

$$COV_t^R = cov_t^R\left(\alpha,\gamma,\mu^{-1}\right) + \mathbb{E}_t^R[\alpha]\, cov_t^R\left(\gamma,\mu^{-1}\right) \\ + \mathbb{E}_t^R[\gamma]\, cov_t^R\left(\alpha,\mu^{-1}\right) + \mathbb{E}_t^R\left[\mu^{-1}\right] cov_t^{RF}(\alpha,\gamma)$$

where for all set of variables $(X^s)_{s\in S}$:

$$cov_t^{RF}\left((X^s)_{s\in S}\right) = \mathbb{E}_t^{RF}\left[\prod_{s\in S}\left(X_t^s - \mathbb{E}_t^{RF}\left[X^s\right]\right)\right]$$

Defining as above $\overline{X_t}$ and $\Delta X_t = (X_t - X_{t-1})$ as:

$$\overline{X_t} = \frac{1}{2}(X_t + X_{t-1}),\ \Delta X_t = (X_t - X_{t-1})$$

we can decompose the variation of the product of expectations in equations (C.3) and (C.4) into contributions of the variation in automation, returns to scale and markups:

$$\Delta\mathbb{E}_t^R[\alpha] \times \mathbb{E}_t^R[\gamma] \times \mathbb{E}_t^R\left[\mu^{-1}\right] = \tag{C.5}$$

$$= \underbrace{\frac{\Delta\mathbb{E}_t^R[\alpha]}{3}\left(\overline{\mathbb{E}_t^R[\gamma] \times \mathbb{E}_t\left[\mu^{-1}\right]} + 2\overline{\mathbb{E}_t^R[\gamma]} \times \overline{\mathbb{E}_t^R\left[\mu^{-1}\right]}\right)}_{\text{Contribution of labor intensity}} \\ + \underbrace{\frac{\Delta\mathbb{E}_t^R[\gamma]}{3}\left(\overline{\mathbb{E}_t^R[\alpha] \times \mathbb{E}_t^R\left[\mu^{-1}\right]} + 2\overline{\mathbb{E}_t^R[\alpha]} \times \overline{\mathbb{E}_t^R\left[\mu^{-1}\right]}\right)}_{\text{Contribution of returns to scale}} \\ + \underbrace{\frac{\Delta\mathbb{E}_t^R\left[\mu^{-1}\right]}{3}\left(\overline{\mathbb{E}_t^R[\alpha] \times \mathbb{E}_t^R[\gamma]} + 2\overline{\mathbb{E}_t^R[\alpha]} \times \overline{\mathbb{E}_t^R[\gamma]}\right)}_{\text{Contribution of markups}}$$

for $R \in (RF, WR)$. By adding to the decomposition in equation (C.5) the variation of the covariance term and of the reallocation term if $R = WR$, we obtain the decomposition of the variation of the aggregate labor share $\Delta\Lambda_t$.