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Market Power and Labor Share ^{*}

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Abstract

This paper leverages a novel and comprehensive database on French firms from 1966 to 2016 to document important facts about secular trends in market power and labor shares, especially the role of market power in explaining variations of the aggregate labor share, as opposed to other technological factors. To do so, we follow the literature and rely on measures of industry concentration and firm level markups as proxies of market power. We find first that concentration has increased since the beginning of the 1980s in France, that the distribution of labor shares shifted upwards and that those two facts are correlated at the industry level. Second, aggregate markups increased slightly, but firm level markups decreased markedly. We find that the rise of concentration is correlated with a downward shift of the markup distribution, suggesting that the two measures might imperfectly capture different dimensions of market power. Third, larger firms have higher markups and lower labor shares. To sum up, larger firms with lower labor shares and higher markups gained market shares, even more so in industries where firm level labor shares increased and markups decreased most. From a *macro* point of view, the relative stability of the aggregate labor share in France can be decomposed into a small negative contribution of the aggregate markup, and a small positive contribution of aggregate technology, but from a *micro* point of view, reallocation contributed negatively, *firm level* markups contributed positively, and the contribution of technology was negligible.

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1 Introduction

Large and productive superstar firms have been gaining market shares in many advanced economies, and the rise of their market power has therefore been the focus of attention in recent work, especially in the United States where [de Loecker et al. \(2018\)](#) have documented an increase in firm market power that is large enough to have important macroeconomic consequences. According to them, the sales weighted average markup in the United States rose from 21% above marginal cost at the beginning of the 1980s to around 61% now, both because the markup of the largest firm with already highest markup increased, and because those firms gained market shares, which leads us to wonder if the rise of large firms market power is a consequence of the rise in concentration. [Gutiérrez and Philippon \(2018\)](#) argue that European market are more competitive, and exhibit lower levels of concentration, lower excess profits and lower barriers to entry. This provides us with the unique opportunity to study which of the dynamics about concentration, markups and labor share observed in the United States are also present in France, for which we have detailed firm level administrative data.

One of the important macroeconomic implications of the rise of market power is a decline in the aggregate share of income going to workers, and given that labor is more evenly distributed than firm ownership, this has important consequences for the understanding of inequality. Important work has shown that the aggregate labor share has indeed been declining in a wide range of countries. The pattern is well documented in the United States ([Autor et al., 2017](#)), and using aggregate data, [Barkai \(2017\)](#) shows that both the labor share and capital share have been falling in the United States, and that the profit share has been increasing. However, contrary to what [de Loecker et al. \(2018\)](#) imply¹, ([Autor et al., 2017](#); [Kehrig and Vincent, 2017](#)) 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. The macroeconomic welfare implications of the rise of market power described in [de Loecker et al. \(2018\)](#) are however ambiguous: the reallocation of market share to high markup firms is welfare improving, but the increase in markup dispersion is welfare decreasing ([Baqae and Farhi, 2019](#)).

We use France as a laboratory to study the link between variations in market power and labor shares, and rely on measures of industry concentration and markups as proxies of market power. We also aim at assessing the extent to which firm level market power dynamics has played a role in explaining the divergence between firm level labor share in France and the United States, as suggested by [Gutiérrez and Philippon \(2018\)](#), as opposed to other factors like technical change. We rely on a unique and comprehensive administrative data covering the universe of French firms from 1966 to 2016. This data is produced by the French National Institute of Economics and Statistics (INSEE) and contains the information collected in firms tax returns. To sum up, we find that larger firms with lower labor shares and higher markups gained market shares, and that this even more

¹A rise in firm level markup translates into a decrease in firm level labor shares.

true in industries where firm level labor shares increased and markups decreased most. From a *macro* point of view, the relative stability of the aggregate labor share in France can be decomposed into a small negative contribution of the aggregate markup, and a small positive contribution of aggregate technology, but from a *micro* point of view, reallocation contributed negatively, *firm level* markups contributed positively, and the contribution of technology was negligible.

To be more precise, we show that concentration, measured by various shares of top firms and industry sales, increased in France as it did in the United States (Autor et al., 2017). In contrast to the United States however, the labor share in France appears to have been stable over the past decades and recently increasing: there is no clear trend in the aggregate labor share over the 1966–2016 period in France both in national accounts and in our representative sample of firms, and that the labor share in France has started to increase after 2000 (see figure 2). We decompose aggregate labor share variations and show that an important reallocation of market share from firms with high labor share to firms with low labor share contributed negatively to the aggregate labor share, but that the labor share of the typical firm increased markedly, which has more than offset the market reallocation effect in recent years. We find that firms with low labor share tend to be larger, and that the market reallocation towards low labor share is correlated with increases in industry concentration.

Computing firm-level markups and technical change parameters like automation² and returns to scale requires estimating the elasticities of output to production factors. We first estimate firm-level elasticities using both a simplified version of the dynamic panel strategy described in Blundell and Bond (2000) and a proxy variable strategy (Akerberg et al., 2015). We then follow De Loecker and Warzynski (2012) and recover markups by assuming that firms minimize their costs.

We find that there is substantial heterogeneity in markups, and that markups are increasing with firm size. We also find that much of the variations in firm level and aggregate labor shares is attributable to markups, including when we allow automation and returns to scale to vary across time and industries. Lastly, while the aggregate markup increased slightly, we find that high-markup firms gained market shares and that the distribution of markups shifted downwards, which indicates both an improvement in allocative efficiency and a reduction of the distortive effect of markups (Baqee and Farhi, 2019). As for the market reallocation towards low-labor share firms, we also show that market reallocation towards high markup firms is 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). 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 and Neiman,

²We define automation as in Caballero et al. (2017) as the elasticity of output to labor normalized to constant returns to scale. In perfect competition, this is equal to the labor share.

2014, 2018; Barkai, 2017; Grossman et al., 2017). Our paper shows that concentration and firm level market power are not necessarily correlated, even though at the aggregate level the reallocation of market shares toward high-markup firms may contribute to a rise in the aggregate markup. In fact in France, industries which experienced the largest rise in concentration at the top are also industries which experienced the largest fall in firm level markup at the top. Bonfiglioli et al. (2019) show national firms compete in markets that are increasingly global, and Melitz (2003); Melitz and Redding (2014) show that international competition causes reallocation toward top producers.

Diverging trends in France and in the US

A recent literature (Gutiérrez and Philippon, 2018) has emphasized the different competitive environment in Europe and the US. It shows that concentration has increased in the United States while it decreased in Europe.

Using administrative data, we do not observe that concentration has decreased in France, but our findings of decreasing firm level markups are consistent with a more competitive economic environment in France than in the United States. Autor et al. (2017) suggest that an increase in market toughness leads to a rise in concentration, a decrease in firm level markup and an increase in firm level labor shares, consistent with our observations for France.

Diverging trends with estimations based on the Worldscope database

One important difference between de Loecker et al. (2018); de Loecker and Eeckout (2018) and our study is the use of data sources that differs substantially in terms of firms coverage and variable detail. Our sample is more representative of the overall economy than the Compustat and Worldscope data they use, and we do observe different production factors such as employment and capital stock.

One advantage of the French data is that it covers the universe of french firms irrespective of their size or the industries they belong to. Worldscope data, on which de Loecker and Eeckout (2018) rely, contains 70,000 firms across more than 130 countries with around 10,000 firms in the United States. As a result the sample of French firm in this database is likely to be relatively small compared to the over 1 millions of French firms present in our sample on average every year.

Another advantage of the French administrative data is that it allows us to distinguish between the different types of inputs that enter the production function. Compustat data only has limited information on costs and contains wage bill and sales consistently across plants and time only for sectors outside manufacturing (de Loecker et al. (2018)). Our data is therefore better suited for the analysis of aggregated markups by applying the production function estimation techniques commonly used in the recent literature.

Diverging trends with estimations based on the Orbis database

Another work that computes average markups and documents an increase, which contrasts to results presented in this paper, is [Calligaris et al. \(2018\)](#) that rely on the Orbis dataset. This data substantially differs from the administrative data we use. Orbis data is limited to firms above 20 employees for most of the countries, and to the 2000 - 2014 period. Moreover, [Calligaris et al. \(2018\)](#) do not provide estimates specific to France.

The rest of the paper is organized as follows. Section 2 presents our data, Section 3 presents evidence that concentration has increased in France, and that the rise in concentration is correlated with a reallocation of market shares toward low-labor share firms, and Section 4 presents our strategy for estimating firm level markup and for linking between aggregate labor share and firm level markups. Finally, Section 5 concludes.

2 Data

To carry out our empirical analysis we rely on several sources of micro data produced at the French Institute of Statistics and Economic Studies (INSEE) for the purpose of the elaboration of National Accounts, covering the universe of French firms³ spanning the 1966-2016 period. Our sources are collected from the firms' tax forms and provide balance sheet, income, and cost information at the firm level, as well as employment, the 5-digit industry level in which the firm operates, the type of legal entity (from micro-firms and sole proprietorship entities to limited liability companies and corporations) and the tax regime to which it is affiliated (micro-regime, simplified regime, or normal regime). Over this 50-year period, the INSEE methodology for collecting firm-level data from tax forms has changed several times, but the most important changes for the analysis we carry out took place in 1970, 1978, 1984 and 2008 because they affected either the coverage of firms or the firm-level information collected, or both.

From 1966 to 1983, we rely on the "BIC" sources (*Bénéfices Industriels et Commerciaux*) for firms affiliated to the "BIC" normal tax regime, which applies to firms above a certain threshold of size.⁴ Data from 1966 to 1977 had to be recovered from magnetic tapes stored at INSEE, and because some of those extractions failed, the year-by-year coverage of our data over this period varies greatly. This issue is particularly pronounced for firms affiliated to the simplified regime for which we information some years but not others and therefore exclude from our data before 1984. Moreover, because thresholds of size used to define firm legal status have varied from 1966 to 1983 following successive reforms of the "individual firm" status, we also do not consider firms in the normal regime data firms whose legal entity is sole proprietorship. To the best of our knowledge, this is the first paper that makes use of pre-1984 firm level administrative data in France. Finally, with the exception of firm employment which was not included in tax returns before 1970, income

³A firm is defined as a legal unit with a unique SIREN identifying number.

⁴See Appendix A for details.

and balance sheet information information at the firm level is consistent across years.

From 1984 to 2007, we rely on the "SUSE" sources (*Système Unifié de Statistiques d'Entreprises*), gathering information from firms affiliated to the tax regimes "BRN" (*Bénéfice Réel Normal*) and "RSI" (*Régime Simplifié d'Imposition*), which have been used before in the literature (di Giovanni et al., 2014; Caliendo et al., 2015). Those regimes cover the same population of firms as above, but, as of 1984, tax returns provide more detailed information on sales and costs. In particular they isolate, merchandises, which are goods bought and sold by the firm without transformation, from either goods and services produced by the firm or other inputs used by the firm in production. This distinction allows us to construct output and input measures where merchandises is not counted as inputs or outputs of production, but that integrate merchandises resale profit as part of firm's output. Moreover, these sources provide information about variations in inventories which we also take into account to infer output.⁵ This method follows more closely aggregate definitions from National Accounts and reduce mainly the overall output of the retail and wholesale trade sectors.

Starting in 2008, we rely on the "ESANE" sources (*Élaboration des Statistiques Annuelles d'Entreprises*), which result from the unification of the previous "SUSE" data with Annual Surveys of Firms that were conducted each year for broad sectors of industries. From that date on, coverage increased to include the "micro-BIC" regime,⁶ and the perimeter of some firms is redefined⁷.

We focus on market sectors⁸ and exclude agriculture because our sample does not cover well firms in that sector, which are mostly affiliated to a tax regime that is not included in the BIC, BRN and RSI regimes. 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. Finally, we focus on firms with positive value-added and labor costs, as well as positive employment after 1984 to exclude very small firms from the "RSI" and "micro-BIC" regimes whose number could be influenced by tax exemption reforms and whose inclusion would introduce noise in our concentration measures.

Data representativeness

Table 1 shows the representativeness of the data we use to compute the evolution of concentration, labor shares and markups in France. It presents the shares of total employment, value added and investment reported in aggregate data that are accounted for in our sample.⁹ Before 1984, our

⁵Table 4 shows indeed that output and inputs including merchandises are higher. This correction in principle does not affect the measure of value-added, but due to minor gaps in the breakdown of sales across goods, services and merchandise, and in the recorded variation of inventory, some discrepancy appear between the two measures.

⁶An extremely simplified regime introduced in 2008 applicable to very small firms, whose total sales do not exceed 170 K€ if the firm operates within the real estate and trade sectors, or 70 K€ otherwise. This regime has been widely used by free-lance workers who do not report any capital nor employment.

⁷The legal units that are part of a group are brought together below the relevant legal unit, and accounts are consolidated (Deroyon, 2015).

⁸The market sectors are total economy excluding public administrations, healthcare, and education.

⁹At this stage, on top of the selection based on tax regime, legal status, and positive value-added, labor costs, or employment after 1984 constraints, we also exclude firms which reports labor share above 300%. See Appendix A for details about our trimming procedure.

data includes around 150K to 200K non individual firms affiliated to the normal regime per year. Data from years 1967, 1968, 1971, and 1974-1977 is either missing or excluded from the analysis because we were not able to properly retrieve it. Data in 1969 and 1970 includes only 50K firms per year because data on small firms¹⁰ affiliated to the normal regimes is also missing. After 1984, our data includes from 600K to 1M firms affiliated to both the simplified and normal regimes per year. Our data account for around 60% of employment, value-added, and investment before 1984, and after 1984, coverage grows from 81% of employment and 74% of value added during the 1984-1994 period, to 94% of employment, 83% of value-added during the 2008-2016 period, which reflects the growing representativeness of our data among relatively small and unproductive firms in terms of average labour productivity. Investment coverage remained around 73% of investment across years after 1984, which reflects the fact that our data's coverage of relatively large firms who do invest, remained stable over time.

Tables 2 and 3 show the same statistics for two additional sample that we will use in section 4 to estimate industry-level production function parameters. For estimations based on the 1984-2016 sample, we also exclude individual firms, and for estimations based on the 1970-2016, we also exclude firms with sales below 1M constant euros of 2010, as well as years 1966 and 1969 for which we do not have information on firm-level employment. Additionally, we exclude from both samples firms with extreme values of capital per worker, value-added per worker and average gross wage.¹¹ Table 2 presents results for the estimation sample for 1984-2016, while Table 3 presents results for the estimation sample for 1970-2016. In both cases, while the number of firms per year drops significantly, the representativeness of our data remains high.

Overview of the data

Tables 4 and 5 describe the main variables that we use in our analysis. We rely on two different datasets to obtain our results: the first one spans 1966-2016 and contains all non individual firms while the second one spans 1984-2016 and contains all firms. In Sections 3 and 4, aggregate evolution of concentration, labor shares and markups are observed with the first dataset for years before 1984, and with the second one for years after 1984. The variations of concentration, labor share and markups before 1984 therefore do not take into account individual firms¹². The top panels of Tables 4 and 5 describe the main variable for the whole dataset and the bottom panels describe those variables for the estimation samples that we use to retrieve industry-level production function parameters.

The top panel of Table 4 shows that the 1984-2016 data has more than 27M firm-year observations, the average firm's sales level is 2,5M€ , has 14 employees, and capital stock book value of 1,2M€. This data is highly skewed to the right, with 50% of firms having sales below 275K€ , less than 3

¹⁰Firms with less than 20 employees and sales below 2 millions francs in 1966 and 3 millions francs in 1969.

¹¹See Appendix A for details about our trimming procedure.

¹²Table 1 reports the representativeness of the 1984-2016 sample from 1984 onwards, and of the 1966-2016 before 1984.

employees and less than 72K€ in capital stock. The bottom panel shows that excluding individual firms and firms with extreme capital per employee, wage, and labor productivity results in a reduced sample size of almost 18M observations, with bigger firms on average and at the median respectively: average sales are 3.5M€ (resp. 435K€), average number of employee is 19 (resp. 4) and average capital book value is 1.6M€ (resp. 101K€). The same conclusions apply to the 1966-2016 data restricted to non individual firms, with 23M firm-year observations restricted to 6M observations for estimation (see Table 5).

3 Concentration and Labor Share

In this section, we discuss the variation of industry concentration and how it relates to variations in the share of aggregate income going to labor in France from 1966 to 2016. We revisit a number of facts recently uncovered in the US and across other OECD countries. We show that concentration has been increasing in France, but that this increase has been associated with an upward shift in the distribution of labor share, despite an apparent stability of the aggregate labor share.

3.1 Rise in concentration

Figure 1 reports the cumulative change since 1966 in sales weighted average levels of industry concentration of sales, where each concentration index is computed at the 3-digit industry level using firms share of industry total sales. Before 1984, the variations of concentration are computed on the 1966-2016 data which excludes non individual firms. After 1984, they are computed on the 1984-2016 data which includes individual firms. The share of sales of the 1% or 5% biggest firms in each industry sharply barely increased before 1980, and then increased sharply throughout the past three decades, totalling an average of 10 to 15 percentage points across industries since 1966. Figure C.1 in the Appendix provides results with alternative measures of concentration : share of the 1, 4, 10, and 20 largest firms in each industry, and the Herfindahl-Hirschman Index. This measures shows a slight decrease in the 1980s and then shows more modest increase from the middle of the 1990s, of around 2.5 to 6 percentage points from 1990 to 2016.

3.2 Labor share evolution

Figure 2 reports the ratio of total payments to labor, including payroll taxes, to total value-added in the market sectors excluding agriculture, real estate, and finance in the aggregate data provided by the National Accounts at INSEE and in our micro data. The labor share computed from macro data includes a correction of the self-employed share following the methodology described in Jäger (2017a), where the hourly wage of self-employed worker is assumed to be equal to the average hourly

wage of the industry they belong to.¹³ The aggregate labor share in our data is somewhat different from the macro labor share before 2000, where our data reports an increase throughout the 1970s, and then a relative stability until 2000, while the macro data reports a stability before 1980 and then a sharp decrease to levels comparable to our labor share in 2000. Since 2000, both data report an increase in the aggregate labor share. These patterns differ substantially from what has been shown to prevail in the US by Autor et al. (2017).

Following Kehrig and Vincent (2017), we decompose the variations of the aggregate labor share to understand whether they are driven by a variations at the firm level or by composition effects. The top left panel in Figure 3 shows the decomposition of changes in the aggregate labor share over time into a an average within-industry change component, when we keep industry shares of total value-added constant from one period to the next, and an average cross-industry component, when we keep the industry labor shares constant and only consider the contribution of variations in the industry shares of total value-added. This decomposition shows that much of the variations of the labor share in our data are driven by variation within industries, but that industries with higher aggregate labor shares grew more than industries with lower aggregate labor share.

The top right panel further decomposes the within-industry change into an average shift in the distribution of labor shares across firms quantiles of labor share, leaving the distribution of industry market shares constant, and an average reallocation across quantiles.¹⁴ This decomposition shows that the typical industry in France experienced a consistent trend in reallocation of market shares towards low-labor share firms throughout the period, as in the US, contributing to an overall fall in the aggregate labor Share of around 5 percentage points. This negative realloaction effect was accompanied by a rising within-quantile component. While the observed within-quantile upward trend in value-added is of larger magnitude in France, and more than offset the reallocation in recent years, it has also been observed in the US in Kehrig and Vincent (2017).

Finally, the bottom panels in Figure 3 further decomposes the within-quantiles component in order to understand whether this upward shift in the distribution of labor shares is evenly shared across all point of the distribution. In the bottom left panel, we present the within contributions of the bottom 5% (green line), middle 45% and top 50% firms in the labor share distribution. Most of the increase happened in the middle and top of the distributions, while average the labor share of the firms with the lowest labor shares barely contributed. Because contributions to the within-quantile are weighted by the size of firms in each quantile, they may not give a complete picture of the variations experienced by firms in each quantile. In the bottom right panel, we show the average variations across industries of the average labor share for those three groups of quantiles. This panel confirms that the average labor share of firms with the lowest labor shares did not increase at all over the period.

¹³Figure C.2 in the Appendix shows that the imputed total labor share including payments to individual firms is much higher than the salaried worker share but that the variations since the 1980s are not different between those two measures.

¹⁴The decomposition methodology is described in section A.5.

Figure 4 focuses on the 1984-2016 period and presents the variation of the weighted and unweighted mean labor share. The weighted mean labor share is broadly stable over the period, with a U-shaped pattern, but the unweighted mean labor share increases sharply. This finding is consistent with the findings above that the contribution of reallocation, here defined as the difference between the variations of weighted and unweighted mean, is negative.

3.3 Labor share and concentration

In this section, we ask whether the observed rise in concentration is correlated with the labor share variations within industries. To that end we estimate the industry-level relationship between the medium to long run changes in concentration and moments of the labor share distribution. We run the following regressions:

$$\Delta\lambda_{jt}^m = \Delta Conc_{jt} + \nu_t + \epsilon_{jt}, \quad (1)$$

where $\Delta\lambda_{jt}^m$ represents the 5 or 10 year change of a given moment m of industry j labor share distribution, where we consider five different moments: the value-added weighted mean labor share, the unweighted mean labor share and the 25th, 50th and 75th percentiles of the labor share distribution. $\Delta Conc_{jt}$ is the 5 or 10 year change of sector j concentration level, proxied by the top 1% of top 5% share of sales and ν_t is a set of time fixed-effects that control for year-specific shocks.

The first two panels of Table 6 present the results of these regressions. The first two columns report the correlation between changes in weighted mean labor share and concentration. We find that those two measures are negatively correlated, as documented by Autor et al. (2017), meaning that industries where concentration increased the most are also those where the aggregate labor share decreased the most. If we look at all the other moments of the distribution however, we find that the shift in the distribution of labor shares is positively correlated with concentration. This means that when industries where concentration increased the most are also those where the distribution of labor shares shifted upward. This correlation is present at all points of the labor share distribution, but is more pronounced at the lower tail.

3.4 Labor share and size

The negative contribution of reallocation to the evolution of aggregate labor shares, combined with the rise in concentration, is consistent with prior work that focused on developments in the US. To reconcile those two facts and the finding that they are correlated, we show that there is a negative correlation between labor share and firm size in France, as in the US. We run the following regression:

$$\lambda_{it} = FE_{size_{it}} + \nu_{it} + \epsilon_{it}, \quad (2)$$

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

Figure 5 presents the results of these regression. Relative to 5-10 employee firms, larger firms tend to report lower labor share (either in value added or sales) even after controlling for industry and year fixed effects. This decreasing relationship is monotonic, at all levels of employment.

This decreasing relationship between firm size and labor share help also reconcile section 3.3 results: in industries where concentration increases more the weighted mean labor share decreases more while different quantile of the industry level distribution of the labor share increases more. The reallocation effect due to rising concentration, drives the change in the weighted mean labor share, as larger firms who gain market shares have low labor shares.

That these developments are also correlated with a rise in firm level labor shares is a new and interesting finding. In the next section, we investigate firm level market power, proxied by the markup of prices to marginal costs, to understand the variations in the labor share of the firm.

4 Markups

4.1 Recovering Markups from Production Data

In this section we discuss the identification procedure used to estimate firm level markups in France from 1970 to 2016, which relies on the estimation of the elasticities of output to variable inputs. We compare results across four main specifications of the production function and use the estimated elasticities to compute markups for all firms in our data.

To recover markup from production data, we rely on a framework recently proposed by [De Loecker and Warzynski \(2012\)](#). First, the procedure 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 with respect to the pricing behavior of firms and how firms compete. The assumptions required are that firms minimize their cost of production and do so by freely adjusting at least one variable input.

Consider an industry with N firms indexed by i . Firms have heterogeneous productivity Ω_{it} and have access to a common production technology $\mathcal{Q}(\cdot)$. In each period t , firm i minimizes the cost of producing Y_{it} by choosing the level of inputs used in production, under the constraint that :

$$Y_{it} = \mathcal{Q}(\Omega_{it}, L_{it}, M_{it}, K_{it}), \quad (3)$$

where L_{it} and M_{it} , respectively labor and intermediary inputs, are variable inputs, and the capital stock K_{it} is costly to adjust. We assume that adjusting capital is subject to cost $\mathcal{C}_a(\cdot)$, which depends on the previous level and current level of capital only, and crucially not on variable inputs levels. We write $\mathcal{C}(\cdot)$ the total cost of the firm. The within-time period Lagrangian, conditional

on previous capital level, associated to the cost minimization problem of choosing inputs $\mathbf{X}_{it} = (L_{it}, M_{it}, K_{it})$ under the constraint of producing output Y_{it} can be written as:

$$\begin{aligned}\mathcal{L}(\mathbf{X}_{it}, Y_{it}, \xi_{it}, \mathbf{Z}_{it}) &= \mathcal{C}(\mathbf{X}_{it}, \mathbf{Z}_{it}) - \xi_{it}(\mathcal{Q}(\Omega_{it}, \mathbf{X}_{it}) - Y_{it}) \\ &= P_{it}^L L_{it} + P_{it}^M M_{it} + r_{it} K_{it} \\ &\quad + \mathcal{C}_a(K_{it}, K_{it-1}) + F_{it} - \xi_{it}(\mathcal{Q}(\Omega_{it}, \mathbf{X}_{it}) - Y_{it}),\end{aligned}\tag{4}$$

where P_{it}^M is the wage, P_{it}^L is the price of intermediary inputs, r_{it} is the user cost of capital, F_{it} is an exogenous fixed cost, ξ_{it} is the Lagrange multiplier, and \mathbf{Z}_{it} gathers variables that are exogenous to the optimisation problem at time t , namely previous year capital, current productivity and input prices. The first-order conditions at the optimal choice of inputs \mathbf{X}_{it}^* and ξ_{it}^* are that:

$$\nabla \mathcal{L}(\mathbf{X}_{it}^*, Y_{it}, \xi_{it}^*, \mathbf{Z}_{it}) = 0,\tag{5}$$

where ∇ denotes the gradient vector of partial derivatives with respect to inputs. In the case of any of the two variable inputs $V \in \{L, M\}$, this yields the following relationship between the input price and marginal product of that input:

$$\frac{\partial \mathcal{L}}{\partial V}(\mathbf{X}_{it}^*, Y_{it}, \xi_{it}^*, \mathbf{Z}_{it}) = P_{it}^V - \xi_{it}^* \frac{\partial \mathcal{Q}}{\partial V}(\Omega_{it}, \mathbf{X}_{it}^*, \cdot) = 0.\tag{6}$$

The output elasticity with respect to input V , $\beta_{v,it}$, can therefore be expressed at the optimum as:

$$\beta_{v,it} \equiv \frac{V_{it}^*}{Y_{it}} \frac{\partial \mathcal{Q}}{\partial V}(\Omega_{it}, \mathbf{X}_{it}^*) = \frac{1}{\xi_{it}^*} \frac{P_{it}^V V_{it}^*}{Y_{it}}.\tag{7}$$

Using the first order conditions in equation 5 to express optimal choice of inputs \mathbf{X}_{it}^* and ξ_{it}^* as functions of output Y_{it} and exogenous variables \mathbf{Z}_{it} , and using the definition of total cost in equation 4, we derive the optimal cost function:

$$\mathcal{C}^*(Y_{it}, \mathbf{Z}_{it}) = \mathcal{C}(\mathbf{X}_{it}^*(Y_{it}, \mathbf{Z}_{it}), \mathbf{Z}_{it}) = \mathcal{L}(\mathbf{X}_{it}^*(Y_{it}, \mathbf{Z}_{it}), Y_{it}, \xi_{it}^*(Y_{it}, \mathbf{Z}_{it}), \mathbf{Z}_{it}) \equiv \mathcal{L}^*(Y_{it}, \mathbf{Z}_{it}).\tag{8}$$

The envelop theorem yields that the marginal cost at the optimum is equal to the Lagrange multiplier at the optimum ξ_{it}^* :

$$\frac{\partial \mathcal{C}^*}{\partial Y}(Y_{it}, \mathbf{Z}_{it}) = \frac{\partial \mathcal{L}^*}{\partial Y}(Y_{it}, \mathbf{Z}_{it}) = \frac{\partial \mathcal{L}}{\partial Y}(\mathbf{X}_{it}^*(Y_{it}, \mathbf{Z}_{it}), Y_{it}, \xi_{it}^*(Y_{it}, \mathbf{Z}_{it}), \mathbf{Z}_{it}) = \xi_{it}^*(Y_{it}, \mathbf{Z}_{it}).\tag{9}$$

Dropping from now on the superscript $*$ to denote optimal variables, we define the markup as the ratio of the output price of the firm to the marginal cost:

$$\mu_{it} = \frac{P_{it}}{\xi_{it}}. \quad (10)$$

It follows from equations 6 and 10 that the markup is defined as the elasticity of output with respect to a variable input, divided by the share of this input cost in total firm revenue:

$$\mu_{it} = \beta_{v,it} \frac{P_{it} Y_{it}}{P_{it}^V V_{it}}. \quad (11)$$

Cost shares are directly observable in the data, but elasticities of output to variable inputs are not. Because these elasticities can vary across time and firms, identification requires making parametric assumptions about the production function that a firm uses. In what follows, we assume that the production function of a given industry is a Cobb-Douglas function of inputs, thereby assuming that the elasticity heterogeneity across firms is a reflection of heterogeneity of production processes across industries. We rely on two main specifications of the production function, one where value-added is a Cobb-Douglas function of labor and capital and one where gross output is a Cobb-Douglas function of labor, capital, and intermediary inputs. Output or value-added at time t of firm i belonging to industry j is therefore given by:

$$\begin{cases} y_{it} = \beta_k^j k_{it} + \beta_l^j l_{it} + \omega_{it}, & \text{(Value Added)} \\ y_{it} = \beta_k^j k_{it} + \beta_l^j l_{it} + \beta_m^j m_{it} + \omega_{it}, & \text{(Gross Output)} \end{cases}$$

where y_{it} stands for the logarithm of value-added or gross output of firm i at time t , and l_{it} , k_{it} , and m_{it} are the logarithms of employment, capital stock, and intermediary inputs respectively, and ω_{it} stands for total factor productivity. We then estimate output elasticities β_l^j , β_k^j , and β_m^j that are constant across time, or let the elasticities vary across time periods and estimate the two production functions over rolling 12-year windows.

To recover firm-level markups therefore requires consistent estimates of the following notation equation, either in output or value-added:

$$y_{it} = \beta^j X_{it} + \omega_{it}, \quad (12)$$

where X_{it} gathers the constant and all inputs to production, and industry j specific β^j gathers the associated elasticities. One issue that prevents us for simply running Ordinary Least Squares (OLS) is that firms typically observe ω_{it} when choosing inputs, or predict it using the information set available at time $t-1$ I_{t-1} . We follow a simplified version of the dynamic panel specification of (Blundell and Bond, 2000), close to proxy variable methods proposed by Olley and Pakes (1996); Levinsohn and Petrin (2003); Akerberg et al. (2015)¹⁵, and assume that productivity evolves according to an AR(1) process with innovation ϵ_{it} , a constant μ^j which determines the long-run

¹⁵See Appendix for results with the proxy variable method of Akerberg et al. (2015)

steady-state productivity level of firms in industry j , and a linear trend μ^j :

$$\omega_{it} = \rho^j \omega_{it-1} + \eta^j + \mu^j t + \epsilon_{it}, \quad (13)$$

with the identifying assumption that I_{t-1} does not include time t productivity innovations ϵ_{it} . Using equation 13, equation 12 becomes

$$y_{it} - \rho y_{it-1} = \beta^j \left[X_{it} \rho^j X_{it-1}^- \right] + \epsilon_{it}, \quad (14)$$

which generates one-stage GMM estimates $\hat{\beta}^j$ and $\hat{\beta}^j$ separately for each industry j (and each sub-period in the case of rolling windows estimations), under the following moment condition:¹⁶

$$\mathbb{E} [\epsilon_{it} | I_{t-1}] = 0. \quad (15)$$

As discussed in [Akerberg et al. \(2015\)](#), on one hand, this approach does not require an assumption about the invertibility of the variable inputs demand function, like in the proxy variable method, and therefore can allow unobserved cost shocks to all inputs. On the other hand, it relies on the linearity of the productivity process. The limited number of instruments at our disposal does not allow a much more complex parameterization of the productivity process, which defeats the purpose of applying the proxy variable identification method. Tables 7 and 8 present results of this estimation procedure applied to a value-added production function, for manufacturing and non manufacturing industries in the 1970-2016 estimation sample, assuming that elasticities remained constant across time periods. For this sample of relatively large firms¹⁷, we find an estimated median value-added elasticity of labor of 0.795 in manufacturing and 0.881 in non manufacturing industries. Tables 9 and 10 present results in the 1984-2016 estimation sample. Including small firms in the estimation sample shifts up point estimates of the labor elasticity, and shifts down point estimates of the capital elasticity. The median value-added elasticity of labor in manufacturing industries is 0.928 and 1.075 in non manufacturing industries.¹⁸

Figures 6 and 7 present the estimated value-added elasticities of labor resulting from this procedure across several sub-period. Industries are ordered according to the value of the labor elasticity in the entire period, displayed in the bottom right panel. There does not appear to be a broad shift in the distribution of elasticities across industries: labor elasticities across time have evolved, but while some industries have become less labor intensive, other have become more labor intensive.¹⁹

Armed with these estimates, we compute four alternative measures of firm-levels markups using equation 11. In the case of a value-added (VA) production function, we define the markup on value-added of firm i in industry j from the value-added elasticity of labor and the share of total

¹⁶We use past values y_{it-1} , l_{it-1} , m_{it-1} , k_{it-1} , a time trend t and a constant 1 as instruments.

¹⁷Non individual firms with sales above 1M constant € of 2010.

¹⁸Tables B.3, B.4, B.5 and B.6 in the Appendix present results in the case of a gross output production function.

¹⁹Figures C.3, C.4, C.5, and C.6 in the Appendix present results in the case of a gross output production function.

labor costs in value-added:

$$\mu_{it}^{\text{VA}} = \frac{\beta_{l,t}^j}{\text{Labor Share of Value-Added}_{it}}, \quad (16)$$

while in the case of a gross output (GO) production function, we define the markup on gross output of firm i in industry j from the output elasticities of both variable inputs and the total share of total labor costs and total intermediary inputs in gross output:

$$\mu_{it}^{\text{GO}} = \frac{\beta_{l,t}^j + \beta_{m,t}^j}{\text{Labor + Intermediary Inputs Share of Gross Output}_{it}}. \quad (17)$$

where $\beta_{l,t}^j$ and $\beta_{m,t}^j$ are either constant and equal to results with the entire period ($\beta_{l,t}^j = \beta_l^j$ and $\beta_{m,t}^j = \beta_m^j$), or equal to the 12-year moving average of rolling windows estimates.²⁰

4.2 Aggregate Markup

In this section we report the variations of the aggregate markup, defined as the value-added weighted average of firm level markups. As for the aggregate labor share, we decompose the variations of the aggregate markup to understand whether they are driven by a variations at the firm level or by composition effects.

Figure 8 reports a the decomposition of aggregate markups obtained from the non rolling value-added estimation. Figure 9 reports the decomposition of aggregate markups obtained from the rolling value-added estimation. In both cases, markups for years 1966-1984 are based on estimation carried on the 1966-2016 estimation sample and for years after 1984 they are based on estimation carried on the 1984-2016 estimation sample.

From the top left panels of both figures, we find that if we look at results from the non rolling estimation the aggregate markup in France was stable in France over the period, while it increased if we look at results from the rolling estimation.

As we have done above for the labor share, the top right panels present the decomposition of aggregate markups into a cross-industry term, a within industry - across quantiles of markups term and finally a within industry - within quantiles of markups term. In both cases, most of the variation is driven by industry level average markups. However the average markup within an industry term hides significant and opposite variations in the within industry-across quantiles and the within-industry-within quantiles terms. We find that reallocation term contributed to a rise in the aggregate markup and that the markup of a typical firm was stable or slightly rising since 1984, but decreasing before 1984. The bottom panels show the variations and contributions of firm level markup at different points of the distribution of markups. We find that most of the fall in

²⁰Results with the proxy variable method are not markedly different from results with the method described here, see Tables B.7 and B.7 in the Appendix.

firm level markups happened at in the top half of the markup distribution.²¹

Figures 10 and 11 focus on the 1984-2016 period and presents the variation of the weighted and unweighted mean markup in both estimations. The weighted mean markup is broadly stable (non rolling estimation) or increasing (rolling estimation) over the period, with an inverted U-shaped pattern, but the unweighted mean markup decreases sharply in both cases. This finding is consistent with the findings above that the contribution of reallocation, here defined as the difference between the variations of weighted and unweighted mean, is positive.²²

4.3 Industry and Firm Level Markups

To explain this positive contribution of reallocation to aggregate markups, we follow the same steps as in Section 3 with the labor share and investigate the link between markup and concentration at the industry level, and between markup and firm size..

First of all, Table 11 presents industry level correlations of various moments of the markup distribution on sector level concentration. The first two columns exhibit a strong positive correlation between aggregate markup and concentration, meaning that industries where concentration increases the most are also those where the aggregate markup increased the most. However, the rise in concentration is not associated with an upward shift in the distribution of markup. In fact, for markup based on rolling estimations, the correlation between concentration and sector level unweighted mean, 25th, 50th or 75th percentiles is negative and significant. This correlation seems to be stronger for highest markups, meaning that top markups fall most in industries where concentration increases most.

To further explore this negative within sector correlation between firm level markup and concentration, we look at broad sectors to see if this pattern is driven by a specific industry. Figures 12 and 13 show that a rise in concentration is indeed rarely associated with a rise in median markups: in the construction, retail and wholesale trade, transportation, and food and accomodation sectors, concentration increased but the median markup decreased.

As for the labor share, we investigate whether markups are increasing with firm size, which would explain our finding that the rise in concentration is positively correlated with aggregate markups but not with firm level markups. We run the following regressions:

$$\mu_{it} = FE_{size_{it}} + \nu_{it} + \epsilon_{it}, \quad (18)$$

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

²¹Figures C.7 and C.8 in the Appendix present results from gross output estimation which are consistent with those obtained from value-added estimation.

²²Figures C.9 and C.10 in the Appendix present results obtained from the proxy variable method from Akerberg et al. (2015), and are similar to results described here.

Figures 14 and 15 report results for both the non rolling and rolling markups. We show that relative to 10-20 employee firms, larger firms tend to report larger markup even after controlling for industry and year fixed effects. This increasing relationship is well observed at all levels of employment, and both for markups obtained with the non rolling and rolling estimations.

4.4 The Link between Firm Level Markup and Aggregate Labor Share

In this section, we go back to the aggregate labor share and aim at explaining its variations: are they driven by markups - i.e. are labor shares increasing because markups are decreasing? - or by technology - i.e. are labor shares increasing because production processes are *more* labor intensive, or *less* automated?

At the firm level, we document a clear relationship between the evolutions of the labor share and markups in France, as de Loecker et al. (2018) find in the US. We estimate the following equation:

$$\log(\mu_{it}) = \log(\lambda_{it}^{\text{Sales}}) + \nu_{it} + \epsilon_{it}, \quad (19)$$

where ν_{it} is a set of fixed effects and $\lambda_{it}^{\text{Sales}}$ is the share of labor costs in firm i total sales.

Table 12 presents the results with markups obtained from non rolling estimation and Table 13 presents the results with markups obtained from rolling estimation. Both tables yield really similar results. In all cases, the correlation between firm level labor share and markup is negative. Importantly, the last column of Table 13 shows that the increase of the labor share at the firm level is correlated with a decrease in firm-level markup.²³

At the aggregate level, we map the aggregate labor share into firm level markups, returns to scale and automation. First, the aggregate labor share Λ_t is the value-added share weighted average of firm level labor shares:

$$\Lambda_t \equiv \frac{\sum_i P_{it}^L L_{it}}{\sum_i P_{it} Y_{it}} = \sum_i S_{it} \lambda_{it}, \quad (20)$$

where $S_{it} = \frac{P_{it} Y_{it}}{\sum_i P_{it} Y_{it}}$ is the market share of total value-added of firm i , and $\lambda_{it} = \frac{P_{it}^L L_{it}}{P_{it} Y_{it}}$ is the labor share in value-added of firm i . Then, from equation 11 we know that the labor is the product of the output elasticity of labor and the inverse markup:

$$\lambda_{it} = \beta_{l,it} \mu_{it}^{-1}. \quad (21)$$

Finally, we can decompose the output elasticity of labor $\beta_{l,it}$ into a component stemming from returns to scale, which tells us how much output expands when all inputs increase proportionally,

²³Tables B.10 and B.11 in the Appendix present results with markups estimated with the proxy variable method.

and a component stemming from labor-intensity of the production process relative to other inputs, which we call automation:

$$\beta_{l,it} = \underbrace{\beta_{l,it} / \sum_f \beta_{f,it}}_{\text{Automation}} \underbrace{\sum_f \beta_{f,it}}_{\text{Returns to Scale}} = \alpha_{it} \gamma_{it}, \quad (22)$$

noting that when α_{it} is high automation is low. It follows from equations 20, 21, and 22 that the aggregate labor share can be expressed as a function of firm level automation, returns to scale, and markups:

$$\Lambda_t = \sum_i S_{it} \alpha_{it} \gamma_{it} \mu_{it}^{-1}. \quad (23)$$

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 :

$$\mathbb{E}_t^{\text{NR}}[Z] \equiv \sum_i S_{it} Z_{it}, \quad (24)$$

where NR stands for "ignoring reallocation". In a second exercise, we isolate the reallocation contribution and write the unweighted average mean for a given variable Z :

$$\mathbb{E}_t^{\text{WR}}[Z] \equiv \frac{1}{N_t} \sum_i Z_{it}, \quad (25)$$

where N_t is the total number of firms and WR stands for "with reallocation". Equation 23 can be rewritten using the definition 24, which gives a decomposition of the aggregate labor share into aggregate automation, aggregate returns to scale and aggregate markup:

$$\Lambda_t = \mathbb{E}_t^{\text{NR}}[\alpha \gamma \mu^{-1}] = \mathbb{E}_t^{\text{NR}}[\alpha] \times \mathbb{E}_t^{\text{NR}}[\gamma] \times \mathbb{E}_t^{\text{NR}}[\mu^{-1}] + \text{COV}_t^{\text{NR}}, \quad (26)$$

or using the definition 25, 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 automation, returns to scale and markup:

$$\Lambda_t = \left(\mathbb{E}_t^{\text{NR}}[\alpha \gamma \mu^{-1}] - \mathbb{E}_t^{\text{WR}}[\alpha \gamma \mu^{-1}] \right) + \mathbb{E}_t^{\text{WR}}[\alpha] \times \mathbb{E}_t^{\text{WR}}[\gamma] \times \mathbb{E}_t^{\text{WR}}[\mu^{-1}] + \text{COV}_t^{\text{WR}}, \quad (27)$$

where in both cases COV_t^{R} , $\text{R} \in (\text{NR}, \text{WR})$ gathers all of the covariance terms, meaning that it is positive when firms that have low levels of automation also have high returns to scale and low

markups.²⁴ Defining \overline{X}_t and $\Delta X_t = (X_t - X_{t-1})$ as:

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

we can decompose the variation of the product of expectations in equations 26 and 27 into contributions of the variation in automation, returns to scale and markups:

$$\begin{aligned} \Delta \mathbb{E}_t^R[\alpha] \times \mathbb{E}_t^R[\gamma] \times \mathbb{E}_t^R[\mu^{-1}] &= \underbrace{\frac{\Delta \mathbb{E}_t^R[\alpha]}{3} \left(\overline{\mathbb{E}_t^R[\gamma] \times \mathbb{E}_t^R[\mu^{-1}]} + 2\overline{\mathbb{E}_t^R[\gamma]} \times \overline{\mathbb{E}_t^R[\mu^{-1}]} \right)}_{\text{Contribution of Automation}} \\ &+ \underbrace{\frac{\Delta \mathbb{E}_t^R[\gamma]}{3} \left(\mathbb{E}_t^R[\alpha] \times \mathbb{E}_t^R[\mu^{-1}] + 2\overline{\mathbb{E}_t^R[\alpha]} \times \overline{\mathbb{E}_t^R[\mu^{-1}]} \right)}_{\text{Contribution of Returns to Scale}} \\ &+ \underbrace{\frac{\Delta \mathbb{E}_t^R[\mu^{-1}]}{3} \left(\overline{\mathbb{E}_t^R[\alpha] \times \mathbb{E}_t^R[\gamma]} + 2\overline{\mathbb{E}_t^R[\alpha]} \times \overline{\mathbb{E}_t^R[\gamma]} \right)}_{\text{Contribution of Markups}}, \end{aligned} \quad (28)$$

for both $R \in (\text{NR}, \text{WR})$. By adding to the decomposition in equation 28 the variation of the covariance term and of the reallocation term if $R = \text{WR}$, we obtain the decomposition of the variation of the aggregate labor share $\Delta \Lambda_t$.

Figure 16 presents the results of the decomposition ignoring reallocation, when we estimate the markup using the value-added non rolling production function, from 1984 to 2016. The total variation of the aggregate labor share from 1984 to 2016 is small and positive. Ignoring the role of reallocation, aggregate markups have contributed negatively to the aggregate labor share, which is consistent with evidence above that the aggregate markup has been increasing over the period. The sum of the contributions of automation and returns to scale, in other words the contribution of weighted average output elasticity of labor, is slightly positive. Given that the estimation is non rolling, this means that industries with higher output elasticities of labor have grown more than industries with lower output elasticities of labor.

Figure 17 presents the results of the decomposition isolating the contribution of reallocation. The contribution of reallocation is negative and very significant, as we have already showed in figure

²⁴For each $R \in (\text{NR}, \text{WR})$, this quantity is defined by:

$$\begin{aligned} \text{COV}_t^R &= \text{cov}_t^R(\alpha, \gamma, \mu^{-1}) + \mathbb{E}_t^R[\alpha] \text{cov}_t^R(\gamma, \mu^{-1}) \\ &+ \mathbb{E}_t^R[\gamma] \text{cov}_t^R(\alpha, \mu^{-1}) + \mathbb{E}_t^R[\mu^{-1}] \text{cov}_t^{\text{NR}}(\alpha, \gamma), \end{aligned}$$

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

$$\text{cov}_t^{\text{NR}}((X^s)_{s \in S}) = \mathbb{E}_t^{\text{NR}} \left[\prod_{s \in S} (X_t^s - \mathbb{E}_t^{\text{NR}}[X^s]) \right].$$

4, and is entirely offset by the contribution of unweighted markups. In other words, the markup of the typical firm has decreased over the period, but because of the market reallocation towards high-markup / low-labor share firms, the aggregate markup has slightly increased and the aggregate labor has not increased much.

Figures 18 and 19 present the same decompositions using the value-added rolling production function. In this specification, which allows output elasticities to vary across time, the contribution of aggregate automation is much higher, meaning that not only did industries with higher output elasticities of labor grow more, but the output elasticity of the average industry also increased. Compared with the non rolling estimates, some of the fall in firm level markup is therefore re-interpreted as a fall in *average* automation, which we interpret here as a consequence of the rise of services in France. Figure 19 shows that the contribution of the unweighted markup remains positive and significant, and the finding that the markup of the typical firm has decreased stands.²⁵

5 Conclusion

In this paper, we find no evidence of a rise in market power at the firm level in France : firm level markups decreased, especially at the top, while firm level labor shares decreased. These facts are however correlated with an important reallocation of market shares towards low-labor share and high-markup firms. Because those firms tend to be larger, this reallocation translates into a rise in concentration.

The simultaneous rise in concentration and fall in firm level markups raises questions about the interpretation of concentration that goes beyond the French case. One channel than could possibly explain both the reallocation of market shares towards large firms and the within-firm increase in the labor share of income is an increase in winner-take-most competition level, as in Autor et al. (2017): as consumers become more sensitive to firm prices, more productive and bigger firms gain market share but a given firm market power decreases. The source of this increase in competition could be international competition, as argued by Bonfiglioli et al. (2019).

An important limit of this analysis is that the estimated markup is highly dependent on the parametric assumptions made regarding the production function. Further research is needed to fully take into account firm heterogeneity in production processes even within narrowly defined industries.

²⁵Figures C.11 to C.14 present the variations of the weighted and unweighted means of automation and returns to scale, according to both non rolling and non rolling estimation.

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6 Tables

Table 1: Data Representativeness, 1966-2016

	Obs	Employment		Value Added (excl Merch)		Value Added (incl Merch)		Investment	
	per year	per year		per year		per year		per year	
	(Nb)	Total (K Persons)	Share (%)	Total (M €)	Share (%)	Total (M €)	Share (%)	Total (M €)	Share (%)
1966	152,884					25,634	55	3,435	
1969	48,733					34,464	55	4,546	
1970	51,074	7,045	64			33,658	48	5,145	
1972	150,127	7,309	65			46,652	53	9,660	
1973	155,303	7,388	64			54,994	54	11,445	
1978-1983	201,604	7,733	65			189,091	63	30,264	61
1984-1994	612,065	9,638	81	386,681	74	380,078	73	65,792	73
1995-2007	881,960	11,878	89	639,883	80	630,295	78	107,014	74
2008-2016	1,060,160	13,234	94	862,980	83	854,723	82	149,194	73

Note: This table presents the share of aggregate employment, value-added and investment that our sample accounts for over the whole period. Output, input and value-added (incl. Merch) measures include the gross sale and purchase value of merchandise. Output, input and value-added (excl. Merch) measures only include merchandise resale profit in output and value-added (see Section 2). Pre-1978 data on aggregate investment by industry is not available on INSEE's website. Sample is firms in the market sectors, excluding agriculture, finance and real estate. Before 1984, it includes all non-individual firms with positive value-added, sales, and labor costs. From 1984, it includes all firms with positive value-added, employment, and labor costs.

Table 2: Representativeness, Estimation Sample 1984-2016

	Obs	Employment		Value Added (excl Merch)		Value Added (incl Merch)		Investment	
	per year	per year		per year		per year		per year	
	(Nb)	Total (K Persons)	Share (%)	Total (M €)	Share (%)	Total (M €)	Share (%)	Total (M €)	Share (%)
1984-1994	345,137	8,662	72	342,933	66	336,705	65	61,050	68
1995-2007	595,261	10,909	81	560,660	70	552,119	69	96,290	67
2008-2016	712,554	12,415	88	742,473	71	734,609	70	117,853	58

Note: This table presents the share of aggregate employment, value-added and investment that our sample accounts for over the whole period. Output, input and value-added (incl. Merch) measures include the gross sale and purchase value of merchandise. Output, input and value-added (excl. Merch) measures only include merchandise resale profit in output and value-added (see Appendix 2). Sample is non-individual firms in the market sectors, excluding agriculture, finance and real estate, with positive value-added, employment and labor costs. See more details about our trimming procedure in Section A.

Table 3: Representativeness, Estimation Sample 1970-2016

	Obs	Employment		Value Added (excl Merch)		Value Added (incl Merch)		Investment	
	per year	per year		per year		per year		per year	
	(Nb)	Total (K Persons)	Share (%)	Total (M €)	Share (%)	Total (M €)	Share (%)	Total (M €)	Share (%)
1970	42,355	6,475	59			31,973	45	4,932	
1972	60,913	6,542	58			43,281	50	9,333	
1973	64,985	6,730	58			51,183	51	11,352	
1978-1983	89,147	7,020	59			174,307	58	28,290	57
1984-1994	125,958	7,668	64	322,749	62	322,303	62	58,419	65
1995-2007	185,339	9,354	70	525,482	65	523,019	65	96,193	66
2008-2016	215,289	10,690	76	701,467	67	700,252	67	122,135	60

Note: This table presents the share of aggregate employment, value-added and investment that our sample accounts for over the whole period. Output, input and value-added (incl. Merch) measures include the gross sale and purchase value of merchandise. Output, input and value-added (excl. Merch) measures only include merchandise resale profit in output and value-added (see Appendix 2). Pre-1978 data on aggregate investment by industry is not available on INSEE's website. Sample is non-individual firms in the market sectors, excluding agriculture, finance and real estate, with positive value-added, employment and labor costs, excluding years where coverage is unstable (1971, 1974-1977 and 1979). See more details about our trimming procedure in Section A.

Table 4: Summary Statistics, 1984-2016

	Obs. (Nb)	Mean	Median	Sd
Data : 1984 - 2016				
Sales	27,739,630	2,554.200	275.000	75,725.139
Gross Output (excl. Merch)	27,739,630	1,763.934	197.830	67,200.162
Gross Output (incl. Merch)	27,739,630	2,568.018	275.475	77,023.228
Intermediary Inputs (excl. Merch.)	27,739,630	1,030.731	75.836	43,753.087
Intermediary Inputs (incl. Merch.)	27,739,630	1,844.606	148.456	55,171.820
Value-Added (excl. Merch.)	27,739,630	733.203	110.000	31,479.228
Value-Added (incl. Merch.)	27,739,630	723.413	107.629	31,421.826
Labor Costs	27,739,630	493.964	77.143	17,999.498
Labor Share	27,739,630	0.736	0.726	0.332
Employment	26,562,521	14.288	3.000	478.345
Investment	19,396,166	178.264	4.226	17,770.174
Capital Book Value	27,732,334	1,249.302	72.000	165,310.926
Estimation Sample : 1984 - 2016				
Sales	17,947,892	3,565.971	435.090	84,648.185
Gross Output (excl. Merch)	17,947,892	2,455.190	311.000	74,818.364
Intermediary Inputs (excl. Merch.)	17,947,892	1,466.600	126.421	47,601.176
Value-Added (excl. Merch.)	17,947,892	988.590	164.492	35,850.748
Labor Costs	17,947,892	713.621	132.000	22,294.764
Employment	17,947,892	19.436	4.000	579.594
Investment	14,720,648	202.708	6.358	19,556.959
Capital Book Value	17,947,892	1,650.196	101.000	197,279.430
Labor Share	17,947,892	0.934	0.818	1.453

Note: This table presents the main descriptive statistics of the variables that enter the estimation of the production function. Both panels include firms in the market sectors excluding agriculture, finance and real estate. Top panel is restricted to firms with positive value-added, employment, and labor costs. Bottom panel is the trimmed estimation sample, with non individual firms (see more details about our trimming procedure in Appendix A). Output, input and value-added (incl. Merch) measures include the gross sale and purchase value of merchandise. Output, input and value-added (excl. Merch) measures only include merchandise resale profit in output and value-added (see Section 2).

Table 5: Summary Statistics, 1966-2016

	Obs. (Nb)	Mean	Median	Sd
Data : 1966 - 2016				
Sales	23,489,296	3,049.417	322.700	82,102.877
Gross Output (incl. Merch)	23,489,296	3,066.178	323.420	83,536.528
Value-Added (incl. Merch.)	23,489,296	876.556	123.404	34,525.940
Intermediary Inputs (incl. Merch.)	23,489,296	2,189.621	173.792	59,014.746
Labor Costs	23,489,296	594.930	97.372	19,763.982
Labor Share	23,489,296	0.827	0.807	0.400
Employment	23,056,398	17.783	3.000	544.988
Investment	19,530,817	182.315	3.811	18,150.541
Capital Book Value	23,483,253	1,504.921	70.052	180,921.205
Estimation Sample : 1970 - 2016				
Sales	6,257,388	10,257.172	1,995.105	153,477.790
Gross Output (incl. Merch)	6,257,388	10,312.973	1,999.450	156,339.244
Intermediary Inputs (incl. Merch.)	6,257,388	7,520.991	1,301.000	110,981.640
Value-Added (incl. Merch.)	6,257,388	2,791.982	629.970	63,898.385
Labor Costs	6,257,388	1,932.787	492.000	38,203.686
Employment	6,257,388	55.933	16.000	1,043.427
Investment	6,227,684	502.773	23.020	31,683.854
Capital Book Value	6,257,388	5,056.423	356.426	345,254.761

Note: This table presents the main descriptive statistics of the variables that enter the estimation of the production function. Both panels include firms in the market sectors excluding agriculture, finance and real estate. Top panel is restricted to non individual firms with positive value-added, employment, and labor costs. Bottom panel is the trimmed estimation sample, with non individual firms with sales higher than 1M constant euros of 2010 (see more details about our trimming procedure in Appendix A). Output, input and value-added (incl. Merch) include the gross sale and purchase of merchandise (see Section 2).

Table 6: Correlations Between Variations in Concentration and in the Distribution of Labor Shares

	Weighted Mean		Unweighted Mean		25th Percentile		Median		75th Percentile	
Labor Share, 5-Year Change										
Top 1% Share	-0.1034 (0.0633)		0.0428 (0.0321)		0.0717 (0.0326)		0.0528 (0.0256)		0.0150 (0.0265)	
Top 5% Share	-0.3774 (0.1075)		0.1763 (0.0638)		0.2214 (0.0872)		0.1360 (0.0555)		0.1186 (0.0437)	
Observations	756	756	756	756	756	756	756	756	756	756
R2	0.1697	0.2002	0.2875	0.2990	0.2275	0.2379	0.2070	0.2106	0.2455	0.2560
Labor Share, 10-Year Change										
Top 1% Share	-0.1882 (0.0459)		0.0817 (0.0316)		0.1551 (0.0396)		0.1021 (0.0277)		0.0231 (0.0241)	
Top 5% Share	-0.4691 (0.0561)		0.2664 (0.0425)		0.3446 (0.0658)		0.2212 (0.0406)		0.1504 (0.0278)	
Observations	621	621	621	621	621	621	621	621	621	621
R2	0.1609	0.2156	0.2252	0.2687	0.1686	0.1937	0.1527	0.1672	0.1651	0.1962

Note: Each estimate is the result of a regression. Regressions are carried at the NA38 sector classification level. The dependent variable is the change in a moment of the distribution of labor shares in a given sector. Labor share is defined as the ratio of the sum of workers' compensation and taxes paid on labor over value added. The independent variable reports changes of two measures of concentration, based on firms share of sales. The estimation method in all columns is OLS, with time fixed effect. Sample is restricted to years 1984-2016.

Table 7: Value Added Production Function Estimation, Estimation Sample 1970-2016, Manufacturing Sectors

	β_l	β_k	η	μ	ρ	N
Mining	0.635 (0.023)	0.356 (0.017)	1.018 (0.037)	-0.007 (0.000)	0.728 (0.008)	24,290
Food products	0.774 (0.006)	0.233 (0.004)	0.937 (0.011)	0.001 (0.000)	0.661 (0.004)	183,251
Textiles	0.734 (0.007)	0.183 (0.005)	0.917 (0.014)	0.004 (0.000)	0.672 (0.004)	104,826
Wood, paper and printing	0.901 (0.007)	0.104 (0.005)	0.856 (0.011)	0.007 (0.000)	0.659 (0.004)	152,951
Coke and refined petroleum	0.642 (0.231)	0.354 (0.153)	0.543 (0.097)	-0.000 (0.001)	0.811 (0.021)	2,014
Chemicals	0.825 (0.015)	0.198 (0.010)	0.840 (0.020)	0.007 (0.000)	0.660 (0.007)	38,174
Pharmaceuticals	0.964 (0.053)	0.121 (0.044)	0.570 (0.040)	0.003 (0.001)	0.783 (0.012)	9,148
Rubber and plastic products	0.745 (0.007)	0.235 (0.006)	0.634 (0.011)	0.006 (0.000)	0.715 (0.004)	115,801
Basic Metals	0.827 (0.004)	0.135 (0.003)	1.262 (0.012)	0.003 (0.000)	0.601 (0.004)	230,857
Computers and electronics	0.871 (0.014)	0.126 (0.010)	0.168 (0.010)	0.023 (0.001)	0.669 (0.007)	42,629
Electrical equipments	0.795 (0.018)	0.171 (0.013)	0.794 (0.023)	0.006 (0.000)	0.709 (0.008)	26,678
Machinery and equipments	0.907 (0.007)	0.089 (0.005)	1.237 (0.015)	0.013 (0.000)	0.527 (0.006)	84,764
Transport equipments	0.864 (0.011)	0.155 (0.008)	1.333 (0.029)	0.003 (0.000)	0.557 (0.009)	35,424
Other manufacturing products	0.938 (0.006)	0.048 (0.005)	1.009 (0.012)	0.008 (0.000)	0.665 (0.004)	144,921
Gas and electricity	0.725 (0.022)	0.245 (0.017)	0.731 (0.051)	0.004 (0.001)	0.755 (0.017)	5,106
Water supply and waste	0.737 (0.008)	0.222 (0.006)	1.285 (0.027)	-0.003 (0.000)	0.650 (0.007)	43,651

Note: This table presents the results of value-added based non rolling estimation in the estimation sample for 1970-2016, by NA38 manufacturing sector.

Table 8: Value Added Production Function Estimation, Estimation Sample 1970-2016, Non Manufacturing Sectors

	β_l	β_k	η	μ	ρ	N
Construction	0.876 (0.003)	0.071 (0.002)	1.689 (0.009)	-0.002 (0.000)	0.601 (0.002)	678,575
Wholesale and retail trade	0.869 (0.001)	0.086 (0.001)	1.318 (0.004)	0.005 (0.000)	0.604 (0.001)	2,092,776
Transportation	0.881 (0.005)	0.101 (0.003)	0.730 (0.009)	0.002 (0.000)	0.775 (0.003)	273,378
Accommodation and food services	0.772 (0.004)	0.178 (0.003)	1.025 (0.012)	-0.004 (0.000)	0.732 (0.003)	191,706
Publishing and motion pictures	0.997 (0.011)	0.093 (0.007)	1.063 (0.017)	0.001 (0.000)	0.701 (0.004)	76,281
Telecommunications	0.929 (0.040)	0.168 (0.023)	0.092 (0.033)	0.020 (0.001)	0.720 (0.014)	6,663
ICT	0.974 (0.007)	0.044 (0.005)	1.029 (0.020)	0.004 (0.000)	0.707 (0.005)	70,594
Legal, accounting and engineering	0.947 (0.006)	0.028 (0.004)	1.274 (0.013)	-0.001 (0.000)	0.711 (0.003)	256,744
Scientific research	0.985 (0.039)	0.053 (0.027)	0.949 (0.064)	-0.001 (0.001)	0.754 (0.014)	7,840
Advertising and market research	0.892 (0.011)	0.067 (0.008)	0.906 (0.019)	0.003 (0.000)	0.754 (0.004)	69,733
Administrative and support	0.794 (0.003)	0.168 (0.002)	1.039 (0.011)	-0.003 (0.000)	0.747 (0.002)	271,086

Note: This table presents the results of value-added based non rolling estimation in the estimation sample for 1970-2016, by NA38 non manufacturing sector.

Table 9: Value Added Production Function Estimation, Estimation Sample 1984-2016, Manufacturing Sectors

	β_l	β_k	η	μ	ρ	N
Mining	0.771 (0.022)	0.298 (0.015)	0.947 (0.030)	-0.009 (0.000)	0.732 (0.007)	35,539
Food products	0.907 (0.004)	0.182 (0.003)	0.923 (0.006)	0.002 (0.000)	0.653 (0.002)	502,066
Textiles	0.928 (0.008)	0.150 (0.006)	0.558 (0.008)	0.006 (0.000)	0.749 (0.003)	181,885
Wood, paper and printing	1.000 (0.005)	0.074 (0.004)	0.783 (0.007)	0.009 (0.000)	0.691 (0.002)	348,488
Coke and refined petroleum	0.786 (0.125)	0.261 (0.082)	0.926 (0.106)	-0.007 (0.002)	0.744 (0.027)	1,797
Chemicals	0.953 (0.018)	0.145 (0.012)	0.744 (0.019)	0.006 (0.000)	0.724 (0.006)	50,683
Pharmaceuticals	1.037 (0.047)	0.109 (0.035)	0.625 (0.045)	0.005 (0.001)	0.752 (0.014)	9,246
Rubber and plastic products	0.861 (0.007)	0.178 (0.005)	0.691 (0.010)	0.007 (0.000)	0.715 (0.003)	183,208
Basic Metals	0.888 (0.004)	0.119 (0.003)	1.074 (0.009)	0.004 (0.000)	0.654 (0.003)	422,127
Computers and electronics	1.000 (0.012)	0.072 (0.009)	0.372 (0.009)	0.024 (0.000)	0.689 (0.005)	74,546
Electrical equipments	0.989 (0.017)	0.062 (0.012)	0.894 (0.022)	0.006 (0.000)	0.712 (0.007)	41,645
Machinery and equipments	0.987 (0.009)	0.063 (0.006)	1.015 (0.014)	0.010 (0.000)	0.653 (0.004)	124,455
Transport equipments	0.961 (0.013)	0.097 (0.010)	1.074 (0.025)	0.002 (0.000)	0.661 (0.007)	52,725
Other manufacturing products	1.003 (0.004)	0.034 (0.003)	1.074 (0.007)	0.007 (0.000)	0.671 (0.002)	409,862
Gas and electricity	0.886 (0.018)	0.217 (0.016)	0.756 (0.038)	0.002 (0.001)	0.737 (0.011)	12,089
Water supply and waste	0.900 (0.007)	0.155 (0.005)	1.076 (0.019)	-0.003 (0.000)	0.691 (0.005)	75,945

Note: This table presents the results of value-added based non rolling estimation in the estimation sample for 1970-2016, by NA38 manufacturing sector.

Table 10: Value Added Production Function Estimation, Estimation Sample 1984-2016, Non Manufacturing Sectors

	β_l	β_k	η	μ	ρ	N
Construction	0.971 (0.001)	0.060 (0.001)	1.585 (0.004)	-0.003 (0.000)	0.597 (0.001)	2,543,929
Wholesale and retail trade	1.075 (0.001)	0.060 (0.001)	0.926 (0.002)	0.004 (0.000)	0.697 (0.001)	4,981,422
Transportation	0.931 (0.002)	0.096 (0.002)	1.069 (0.006)	0.003 (0.000)	0.665 (0.002)	634,507
Accommodation and food services	0.926 (0.002)	0.159 (0.001)	1.261 (0.004)	-0.002 (0.000)	0.586 (0.001)	1,565,461
Publishing and motion pictures	1.213 (0.006)	0.021 (0.004)	1.204 (0.010)	0.004 (0.000)	0.631 (0.002)	214,197
Telecommunications	1.254 (0.027)	0.025 (0.016)	0.373 (0.022)	0.025 (0.001)	0.661 (0.009)	16,195
ICT	1.156 (0.004)	-0.017 (0.003)	1.309 (0.010)	0.006 (0.000)	0.615 (0.003)	245,807
Legal, accounting and engineering	1.112 (0.002)	-0.002 (0.002)	1.487 (0.005)	-0.001 (0.000)	0.630 (0.001)	1,087,476
Scientific research	1.120 (0.020)	-0.012 (0.013)	1.309 (0.037)	-0.001 (0.001)	0.652 (0.008)	18,965
Advertising and market research	1.160 (0.005)	0.008 (0.004)	1.057 (0.009)	0.006 (0.000)	0.669 (0.002)	283,846
Administrative and support	0.937 (0.002)	0.130 (0.001)	1.135 (0.005)	-0.003 (0.000)	0.679 (0.001)	842,258

Note: This table presents the results of value-added based non rolling estimation in the estimation sample for 1984-2016, by NA38 non manufacturing sector.

Table 11: Correlations Between Variations in Concentration and in the Distribution of Markup

	Weighted Mean		Unweighted Mean		25th Percentile		Median		75th Percentile	
Markup, 5-Year Change										
Top 1% Share	0.5290 (0.2431)		-0.2541 (0.0819)		-0.0316 (0.0336)		-0.1864 (0.0895)		-0.3772 (0.1285)	
Top 5% Share	2.0680 (0.4435)		-0.7047 (0.1900)		-0.1959 (0.0584)		-0.3569 (0.1335)		-0.9332 (0.3127)	
Observations	756	756	756	756	756	756	756	756	756	756
R2	0.0392	0.0783	0.1933	0.2023	0.1953	0.2067	0.0484	0.0479	0.1224	0.1267
Markup, 10-Year Change										
Top 1% Share	0.6426 (0.2382)		-0.5246 (0.0994)		-0.0596 (0.0339)		-0.3494 (0.0923)		-0.8389 (0.1728)	
Top 5% Share	2.1458 (0.3429)		-1.0462 (0.1360)		-0.2433 (0.0372)		-0.5471 (0.0877)		-1.5448 (0.2332)	
Observations	621	621	621	621	621	621	621	621	621	621
R2	0.0355	0.0909	0.1862	0.2019	0.1347	0.1652	0.0563	0.0527	0.1084	0.1135
Rolling Markup, 5-Year Change										
Top 1% Share	0.9811 (0.3560)		-0.1330 (0.1147)		0.0499 (0.0573)		-0.1238 (0.1289)		-0.3162 (0.1724)	
Top 5% Share	2.2070 (0.4700)		-0.4997 (0.1881)		-0.0503 (0.0691)		-0.1758 (0.1435)		-0.7314 (0.3113)	
Observations	744	744	744	744	744	744	744	744	744	744
R2	0.0748	0.0936	0.1616	0.1677	0.2408	0.2399	0.0557	0.0553	0.1106	0.1135
Rolling Markup, 10-Year Change										
Top 1% Share	1.0378 (0.3045)		-0.4780 (0.1421)		-0.0328 (0.0585)		-0.3264 (0.1263)		-0.8515 (0.2235)	
Top 5% Share	2.1459 (0.4178)		-0.9068 (0.1604)		-0.1462 (0.0675)		-0.4368 (0.1209)		-1.4215 (0.2631)	
Observations	609	609	609	609	609	609	609	609	609	609
R2	0.0750	0.0944	0.1334	0.1414	0.2415	0.2453	0.0722	0.0684	0.0894	0.0907

Note: Each estimate is the result of a regression. Regressions are carried at the NA38 sector classification level. The dependent variable is the change in a moment of the distribution of markups in a given sector. Markup on value-added is based on estimates of the labor elasticity coefficient β_l from value-added based non rolling estimation in the top two panels, and rolling estimation in the bottom two panels, in the estimation sample for 1984-2016. The independent variable reports changes of two measures of concentration, based on firms share of sales. The estimation method in all columns is OLS, with time fixed effect.

Table 12: Correlation Between Labor Share and Non Rolling Markup on Value-Added

	(1) No FE	(2) Year FE	(3) Year and Industry FE
Labor Share (Log)	-0.5377 (0.0001)	-0.5359 (0.0005)	-0.5359 (0.0005)
Observations	26,823,776	26,823,776	26,823,776
R2	0.3595	0.3720	0.3720

Note: Markup on value-added is based on estimates of the labor elasticity coefficient β_l from value-added based estimation on the 1984-2016 sample. Labor share is defined as the logarithm of the ratio of worker compensation and taxes paid on labor over value added.

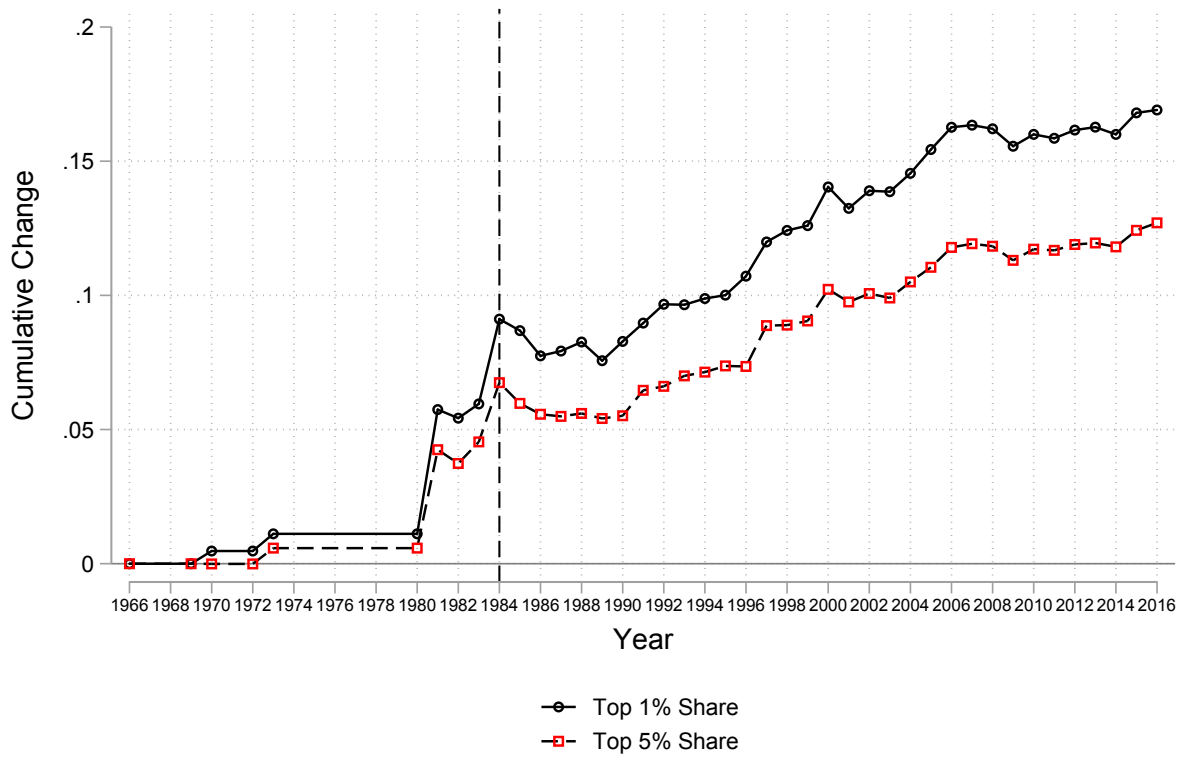
Table 13: Correlation Between Labor Share and Rolling Markup on Value-Added

	(1) No FE	(2) Year FE	(3) Year and Industry FE	(4) Firm FE
Labor Share (Log)	-0.5375 (0.0001)	-0.5363 (0.0005)	-0.5363 (0.0005)	-0.6643 (0.0005)
Observations	26,822,359	26,822,359	26,822,359	26,228,581
R2	0.3597	0.3693	0.3693	0.7925

Note: Markup on value-added is based on estimates of the labor elasticity coefficient β_l from value-added based rolling estimation carried on the 1984-2016 sample. Labor share is defined as the logarithm of the ratio of worker compensation and taxes paid on labor over value added.

7 Figures

Figure 1: Cumulative Change in Concentration



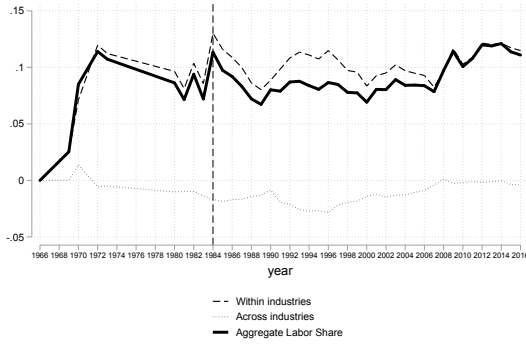
Note: This figure reports the cumulative change since 1966 of the sales weighted average level of concentration in sales across each 2-digit industry. Sample is firms in the market sectors, excluding agriculture, finance and real estate. Before 1984, it includes all non-individual firms with positive value-added, sales, and labor costs. From 1984, it includes all firms with positive value-added, employment, and labor costs.

Figure 2: Aggregate Labor Share in France, 1966-2016.

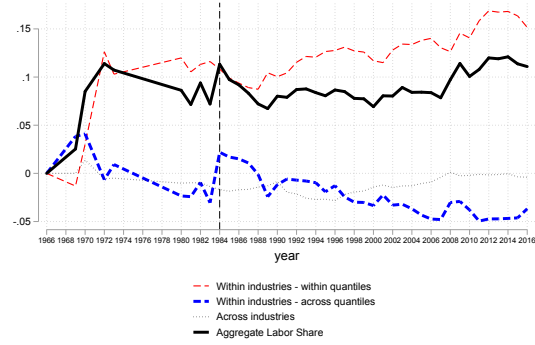


Note: This figure reports the ratio of total payments to labor, including payroll taxes, to total value-added in the market sectors, excluding agriculture, finance and real estate. Macro labor share is corrected for the self-employed share following [Jäger \(2017b\)](#). Micro labor share is the ratio of workers' compensation and taxes paid on labor over value added. Before 1984, micro data includes all non-individual firms with positive value-added, sales, and labor costs. From 1984, micro data includes all firms with positive value-added, employment, and labor costs.

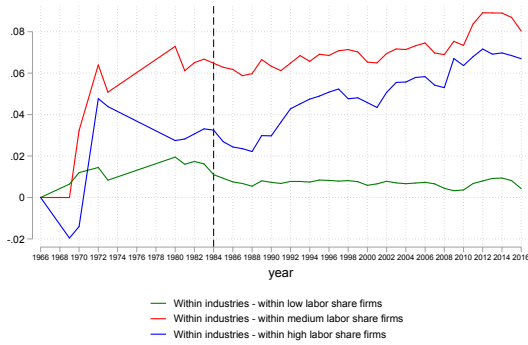
Figure 3: Decomposition of Aggregate Labor Share, 1966-2016



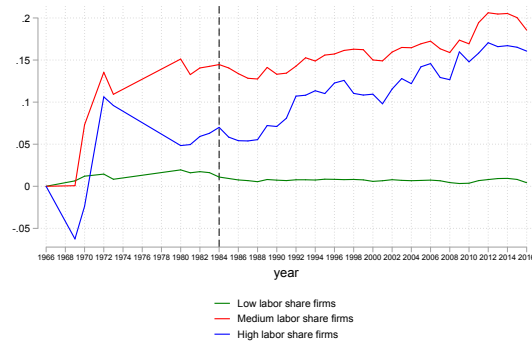
(a) Within/Cross Industries



(b) Within/Cross Quantiles



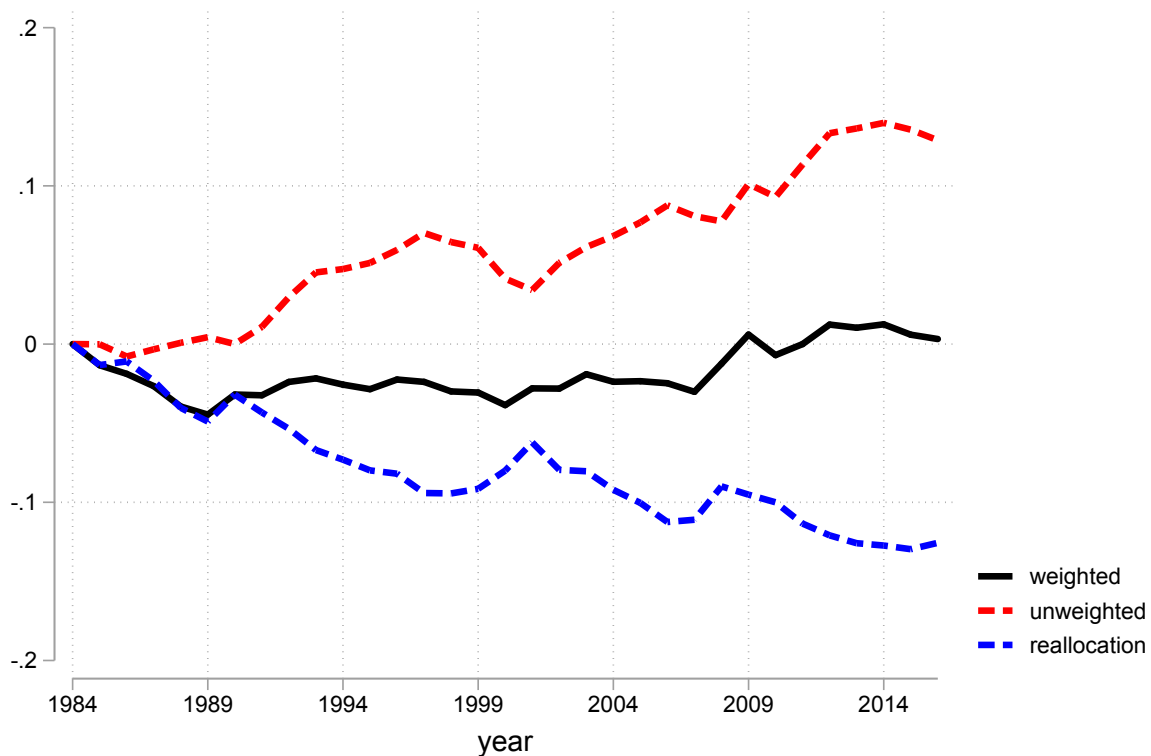
(c) Within Quantiles Contributions



(d) Average Variations

Note: This figures reports the decomposition of the aggregate labor share in our micro data. Decomposition is described in section A.5. Quantiles of labor share are calculated each year within 2-digit industries. Sample is firms in the market sectors, excluding agriculture, finance and real estate. Before 1984, it includes all non-individual firms with positive value-added, sales, and labor costs. From 1984, it includes all firms with positive value-added, employment, and labor costs.

Figure 4: Weighted and Unweighted Mean Labor Share, 1984-2016



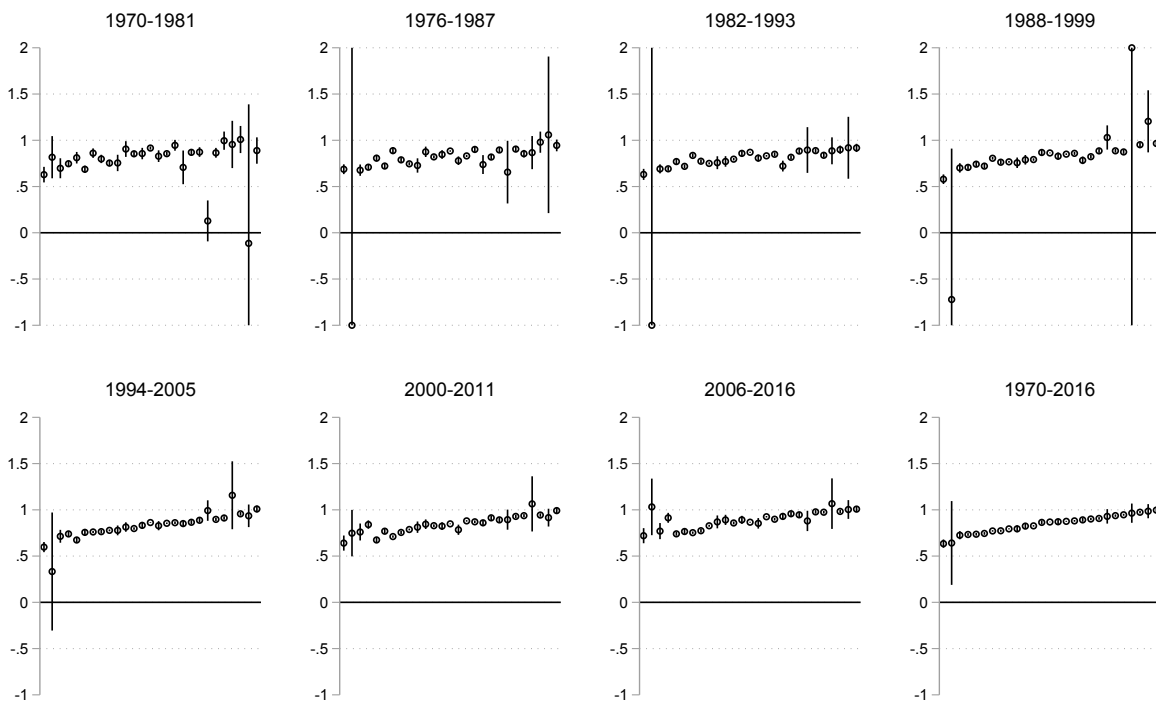
Note: This figure reports the cumulative variations of the weighted and unweighted mean labor share. Reallocation is the difference between the two means. Sample is all firms in the market sectors, excluding agriculture, finance and real estate with positive value-added, employment, and labor costs.

Figure 5: Correlation Between Labor Share and Size



Note: This figure reports the conditional average of labor share (the ratio of workers' compensation and taxes paid on labor over either gross output or value added) by firm size, and the 90% confidence interval. Averages are conditional on a set of flexible fixed effects constructed from the interaction of 3-digit industry codes and time dummies.

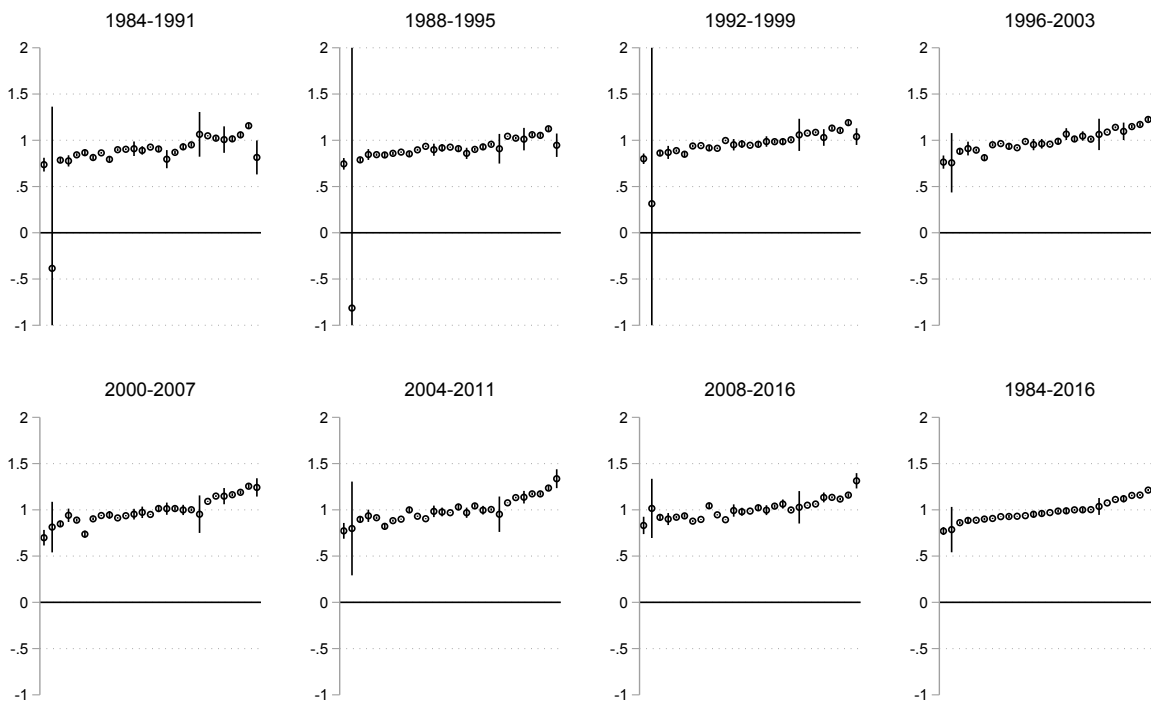
Figure 6: Value Added Production Function Rolling Estimation, Labor Coefficient, 1970-2016



NAF 38

Note: This figure presents estimates of the labor elasticity coefficient β_l from value-added based rolling estimation in the estimation sample for 1970-2016, by NA38 sector, with 5% confidence intervals.

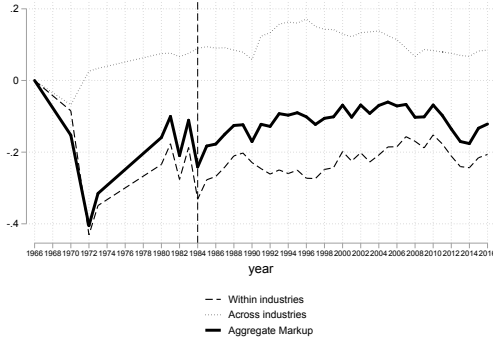
Figure 7: Value Added Production Function Rolling Estimation, Labor Coefficient, 1984-2016



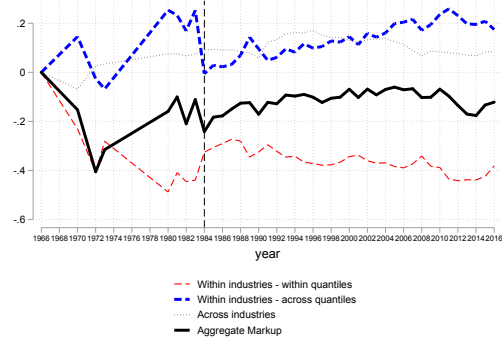
NAF 38

Note: This figure presents estimates of the labor elasticity coefficient β_l from value-added based rolling estimation in the estimation sample for 1984-2016, by NA38 sector, with 5% confidence intervals.

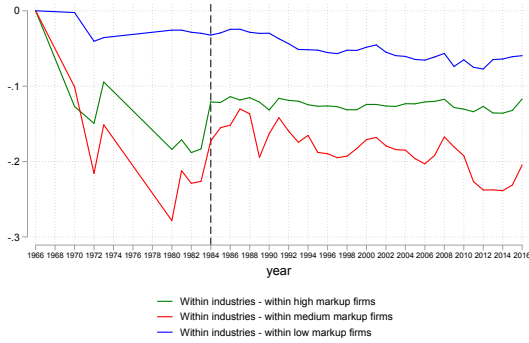
Figure 8: Decomposition of Aggregate Non Rolling Markup on Value-Added, 1966-2016



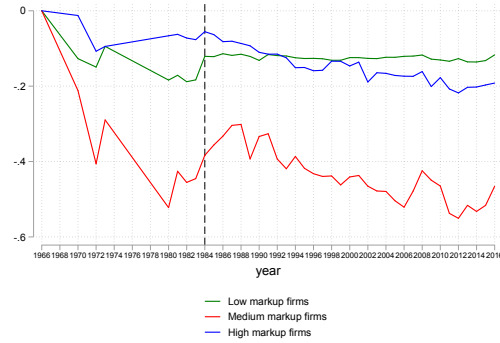
(a) Within/Cross Industries



(b) Within/Cross Quantiles



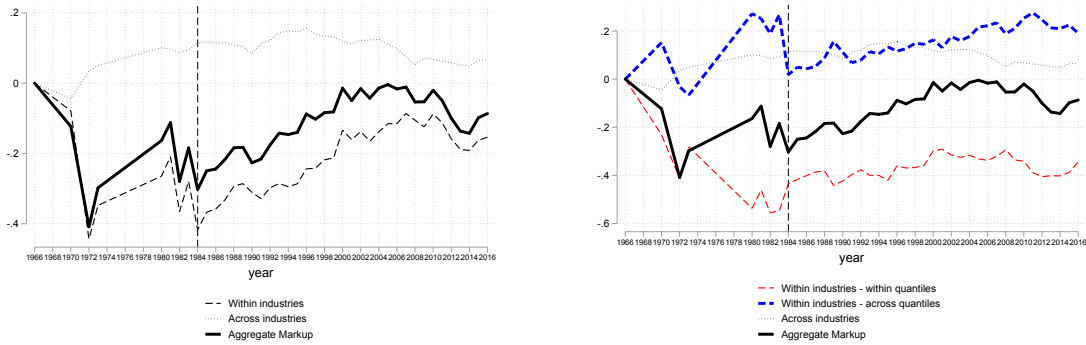
(c) Contributions by Quantiles



(d) Average Variations by Quantiles

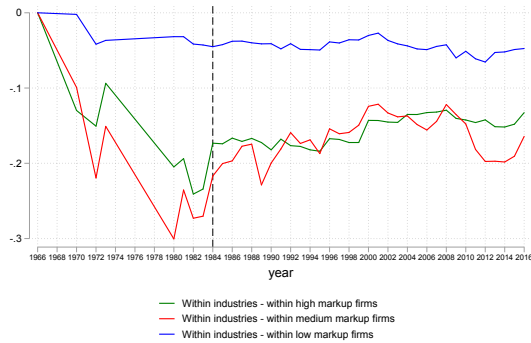
Note: This figures reports the decomposition of the aggregate non rolling markup. Decomposition is described in section A.5. Quantiles of markups are calculated each year within 2-digit industries. Sample is firms in the market sectors, excluding agriculture, finance and real estate. Before 1984, it includes all non-individual firms with positive value-added, sales, and labor costs, and markup is based on estimates of the labor elasticity coefficient β_l from value-added based non rolling estimation in the estimation sample for 1970-2016. From 1984, it includes all firms with positive value-added, employment, and labor costs, and markup is based on estimates of the labor elasticity coefficient β_l from value-added based non rolling estimation in the estimation sample for 1984-2016.

Figure 9: Decomposition of Aggregate Rolling Markup on Value-Added, 1966-2016

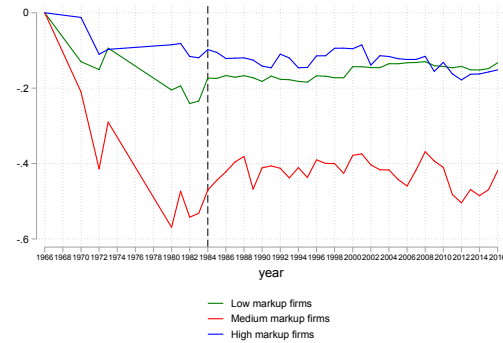


(a) Within/Cross Industries

(b) Within/Cross Quantiles



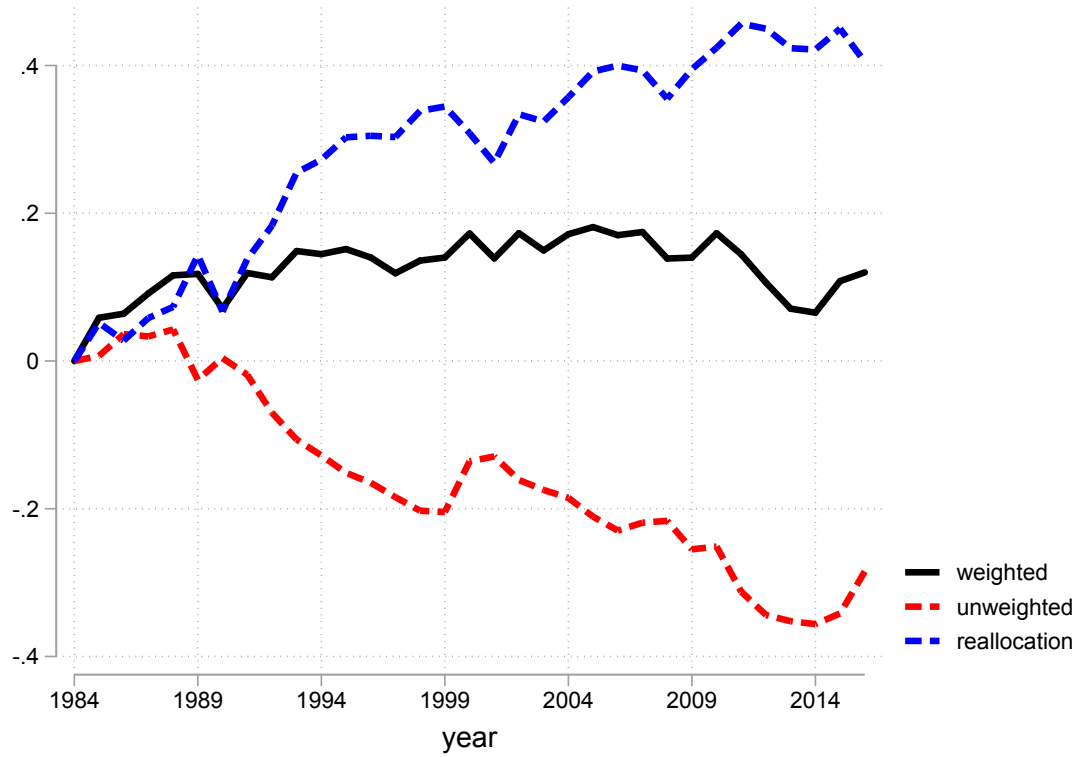
(c) Contributions by Quantiles



(d) Average Variations by Quantiles

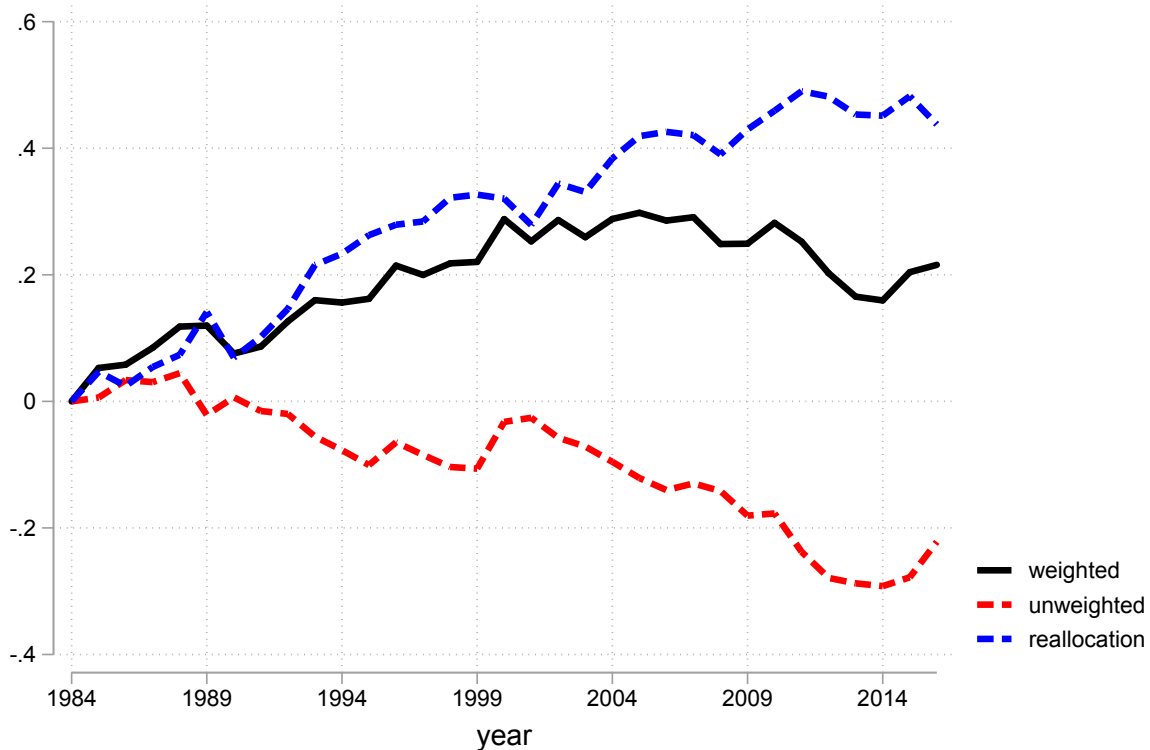
Note: This figures reports the decomposition of the aggregate rolling markup. Decomposition is described in section A.5. Quantiles of markups are calculated each year within 2-digit industries. Sample is firms in the market sectors, excluding agriculture, finance and real estate. Before 1984, it includes all non-individual firms with positive value-added, sales, and labor costs, and markup is based on estimates of the labor elasticity coefficient β_l from value-added based rolling estimation in the estimation sample for 1970-2016. From 1984, it includes all firms with positive value-added, employment, and labor costs, and markup is based on estimates of the labor elasticity coefficient β_l from value-added based rolling estimation in the estimation sample for 1984-2016.

Figure 10: Weighted and Unweighted Mean Markup, Non Rolling Value-Added Estimation



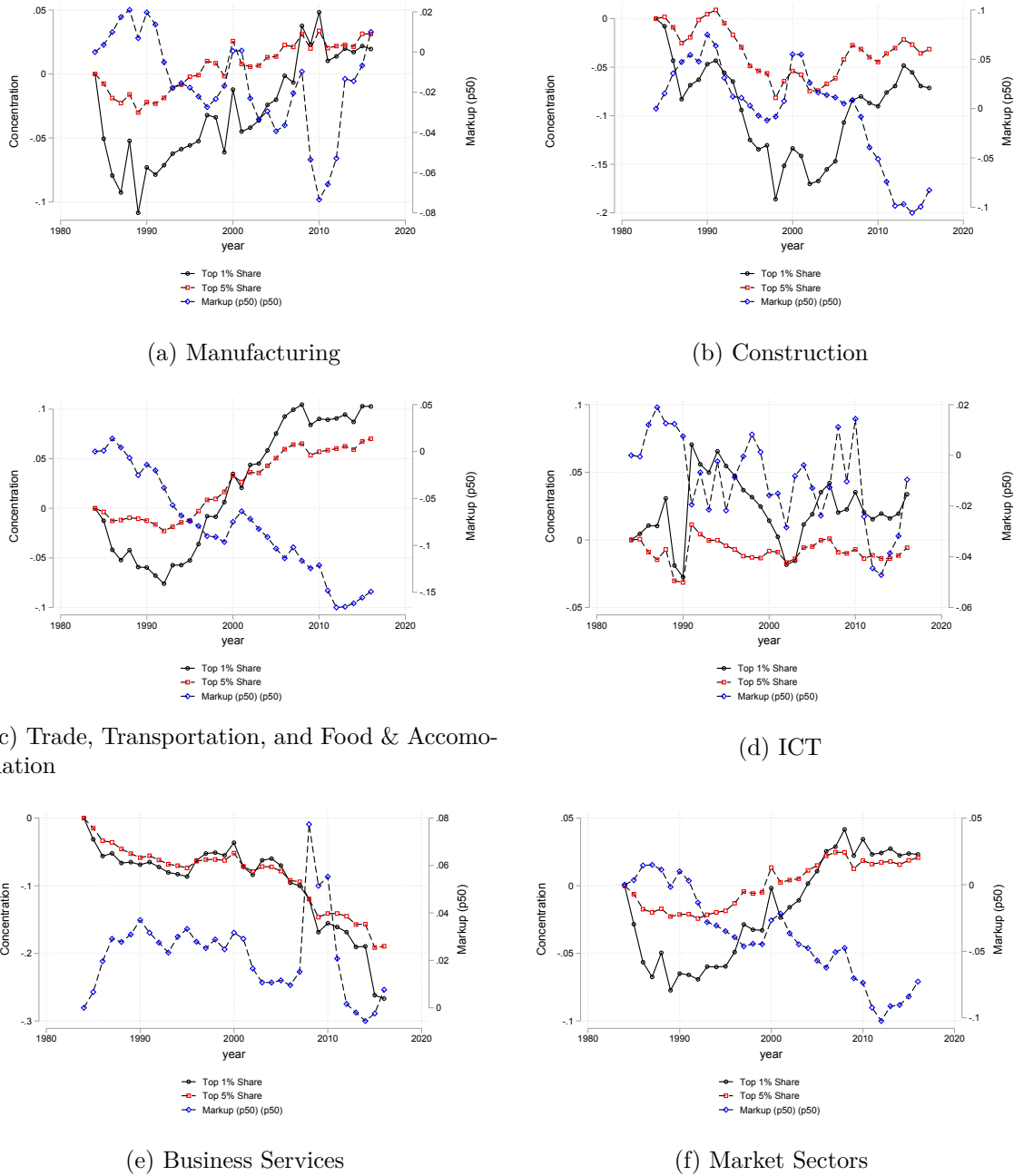
Note: This figures reports the cumulative variations of the weighted and unweighted mean markup on value-added based on non rolling estimation of a value-added production function on the 1984-2016 sample. Reallocation is defined as the difference between the variations in unweighted and weighted mean.

Figure 11: Weighted and Unweighted Mean Markup, Rolling Value-Added Estimation



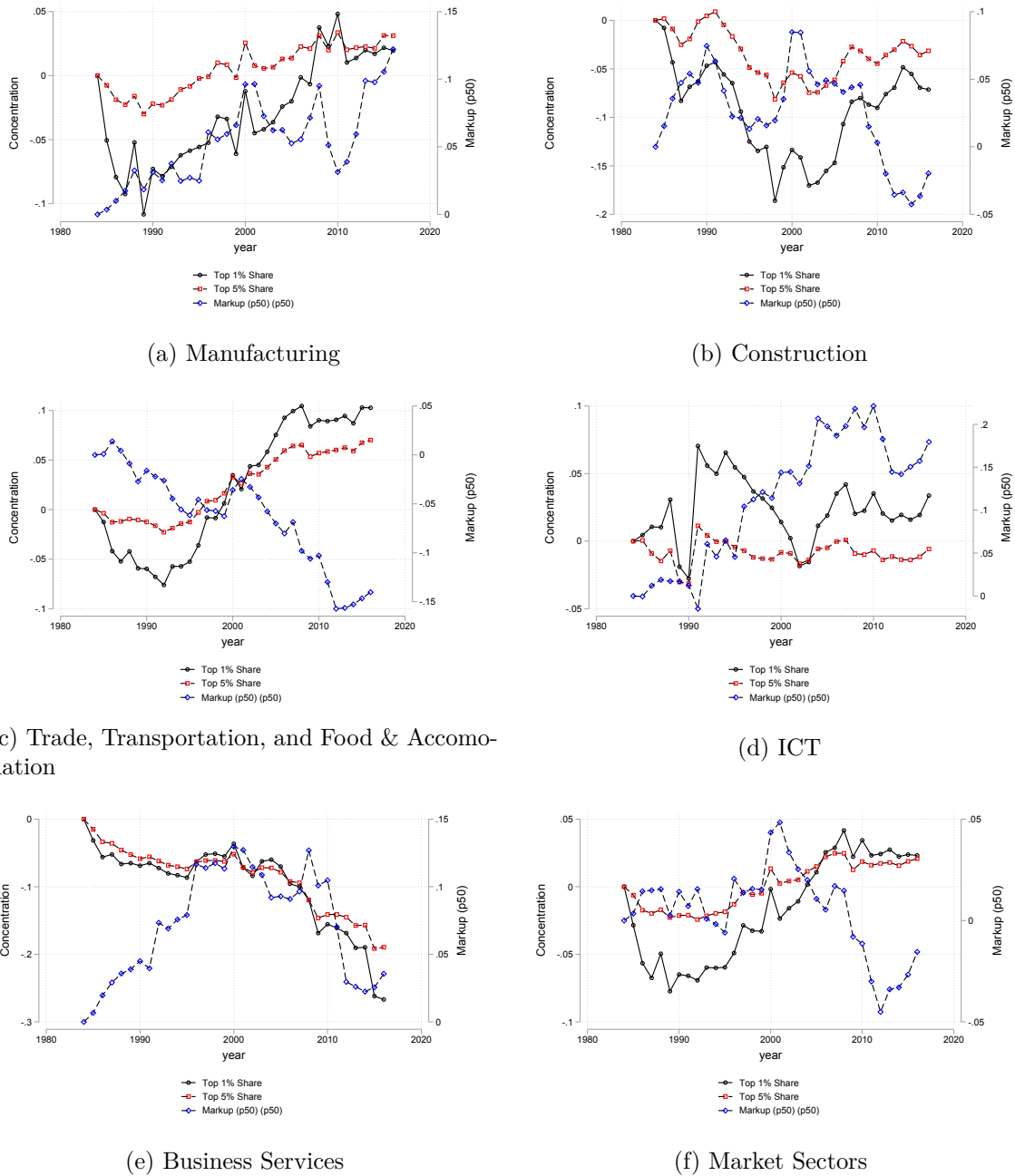
Note: This figures reports the cumulative variations of the weighted and unweighted mean markup on value-added based on rolling estimation of a value-added production function on the 1984-2016 sample. Reallocation is defined as the difference between the variations in unweighted and weighted mean.

Figure 12: Industry Level Median Non Rolling Markups on Value-Added and Concentration, 1984-2016



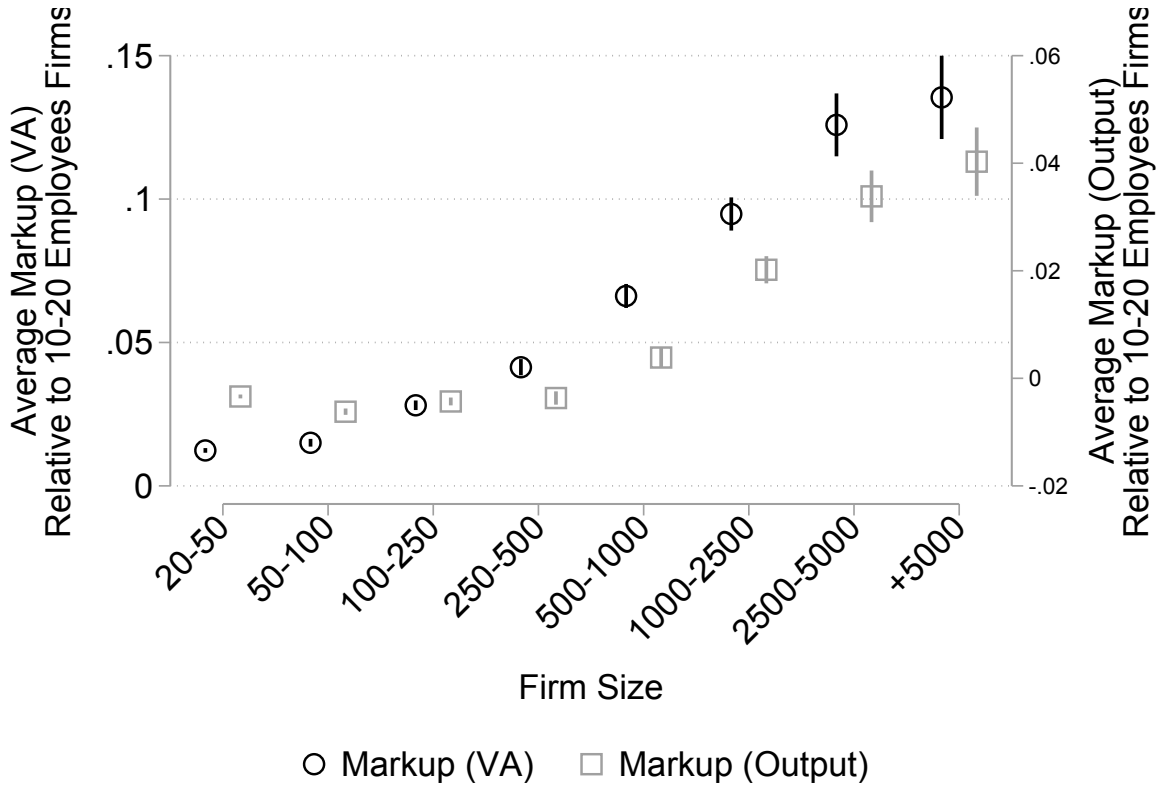
Note: This figure reports the cumulative change since 1984 of average level of concentration in sales, and of the median non rolling markup on value added, across each 2-digit industry by broad sector. Each 2-digit sector's change is weighted by its share of sales in the broader sector. Sample is firms in the market sectors, excluding agriculture, finance and real estate, with positive value-added, employment, and labor costs.

Figure 13: Industry Level Median Rolling Markups on Value-Added and Concentration, 1984-2016



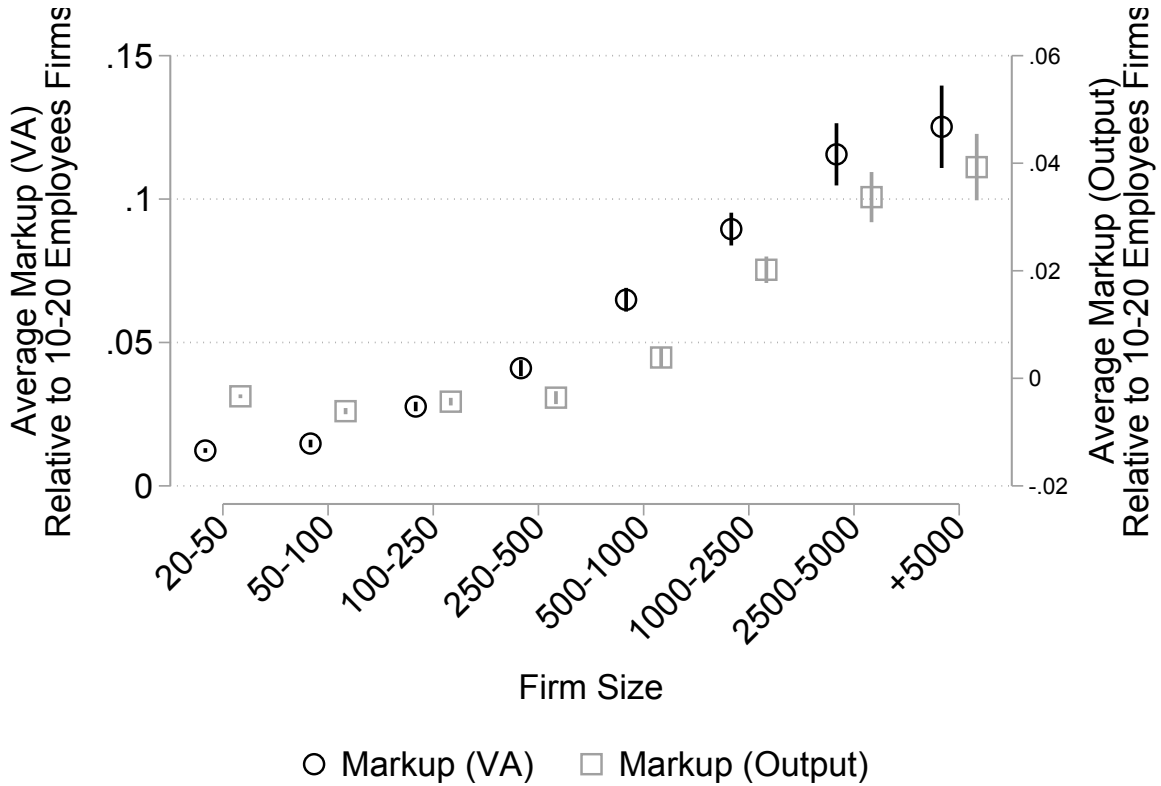
Note: This figure reports the cumulative change since 1984 of average level of concentration in sales, and of the median rolling markup on value added, across each 2-digit industry by broad sector. Each 2-digit sector's change is weighted by its share of sales in the broader sector. Sample is firms in the market sectors, excluding agriculture, finance and real estate, with positive value-added, employment, and labor costs.

Figure 14: Correlation Between Non Rolling Markup and Size



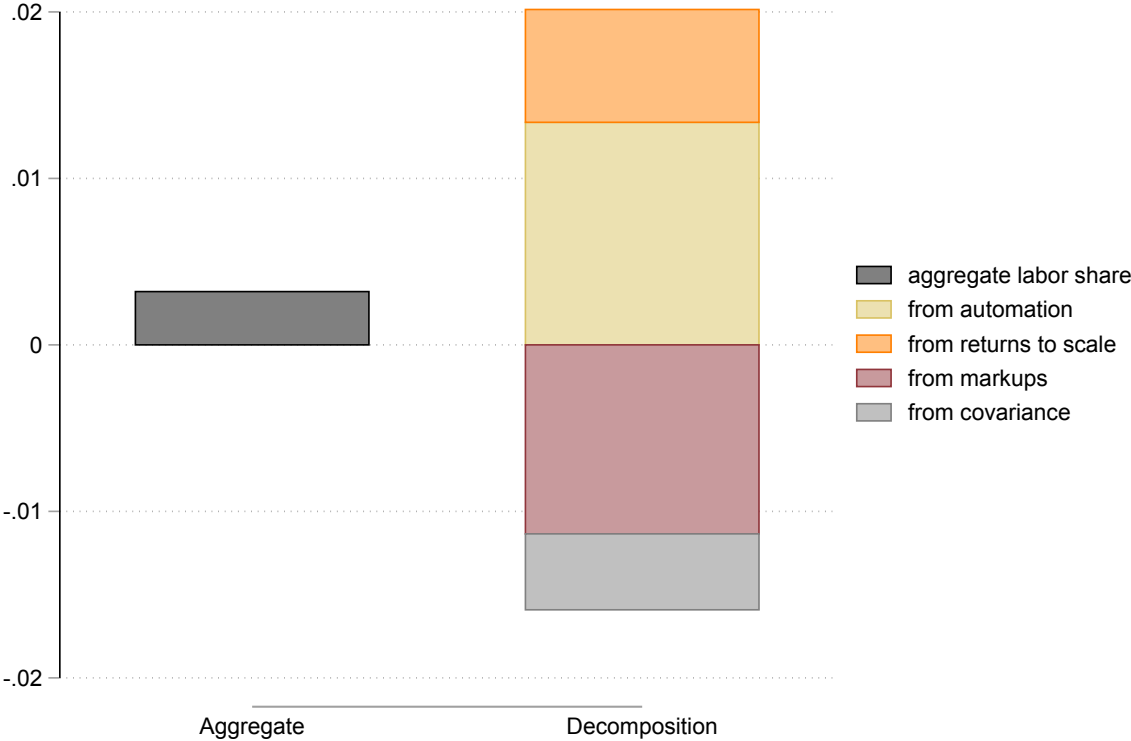
Note: This figure reports the conditional average of non rolling markups by firm size, and the 90% confidence interval. Markup on value-added is based on estimates of the labor elasticity coefficient β_l from value-added based non rolling estimation in the estimation sample for 1984-2016. Markup on output is based on estimates of the sum of labor elasticity coefficient β_l and intermediary input coefficient β_m from output non rolling estimation in the estimation sample for 1984-2016. Averages are conditional on a set of flexible fixed effects constructed from the interaction of 3-digit industry codes and time dummies.

Figure 15: Correlation Between Rolling Markup and Size



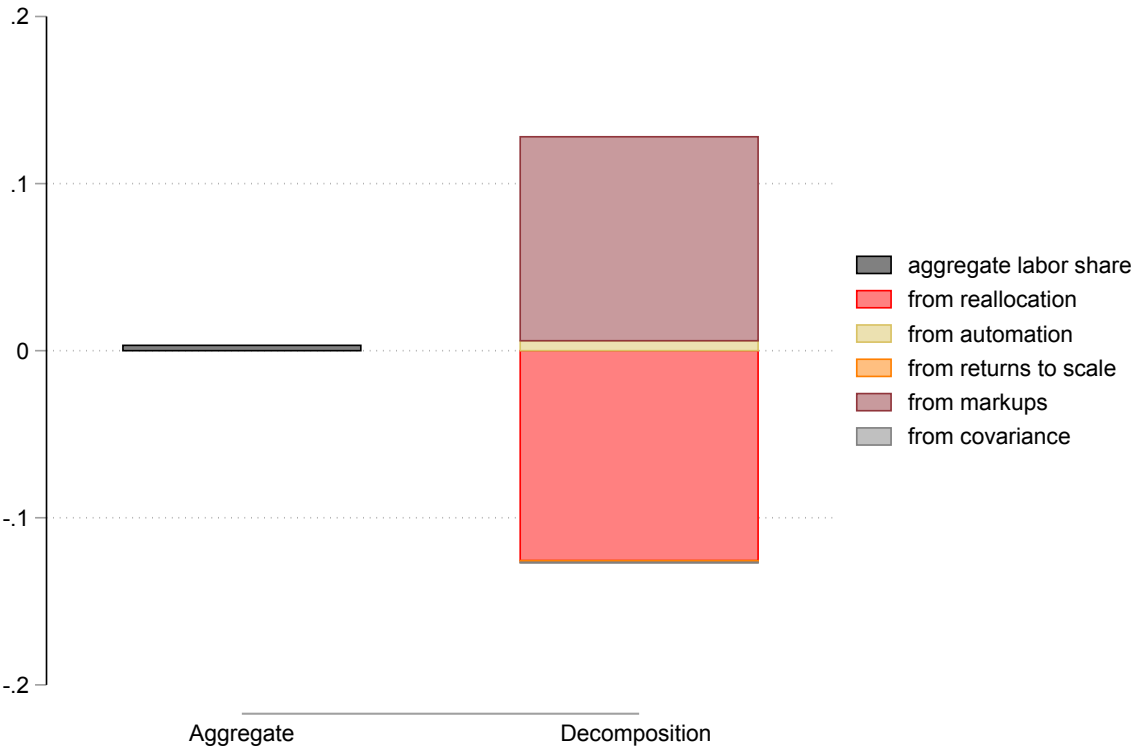
Note: This figure reports the conditional average of rolling markups by firm size, and the 90% confidence interval. Markup on value-added is based on estimates of the labor elasticity coefficient β_l from value-added based rolling estimation in the estimation sample for 1984-2016. Markup on output is based on estimates of the sum of labor elasticity coefficient β_l and intermediary input coefficient β_m from output rolling estimation in the estimation sample for 1984-2016. Averages are conditional on a set of flexible fixed effects constructed from the interaction of 3-digit industry codes and time dummies.

Figure 16: Contributions to the Evolution of the Aggregate Labor Share, Ignoring Reallocation, Non Rolling Value-Added Estimation



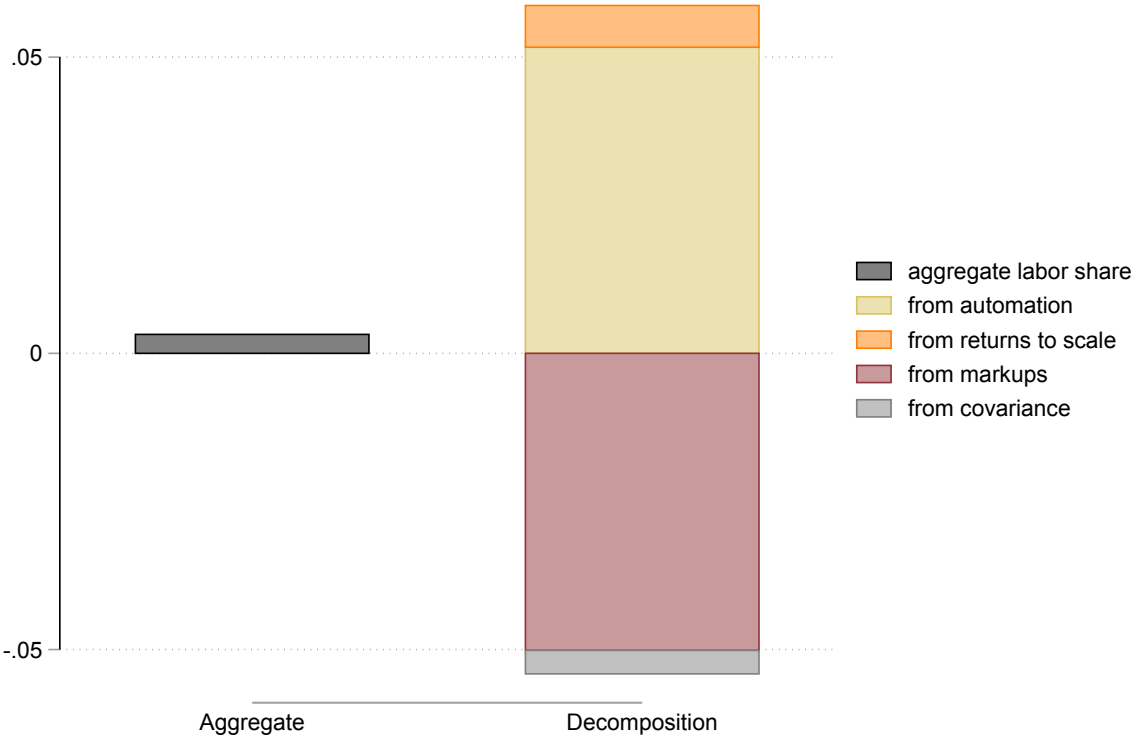
Note: This figures report the decomposition of the variation of the aggregate labor share from 1984 to 2016, ignoring the reallocation term, using non rolling value-added estimates. See section 4.4 for detail.

Figure 17: Contributions to the Evolution of the Aggregate Labor Share, Non Rolling Value-Added Estimation



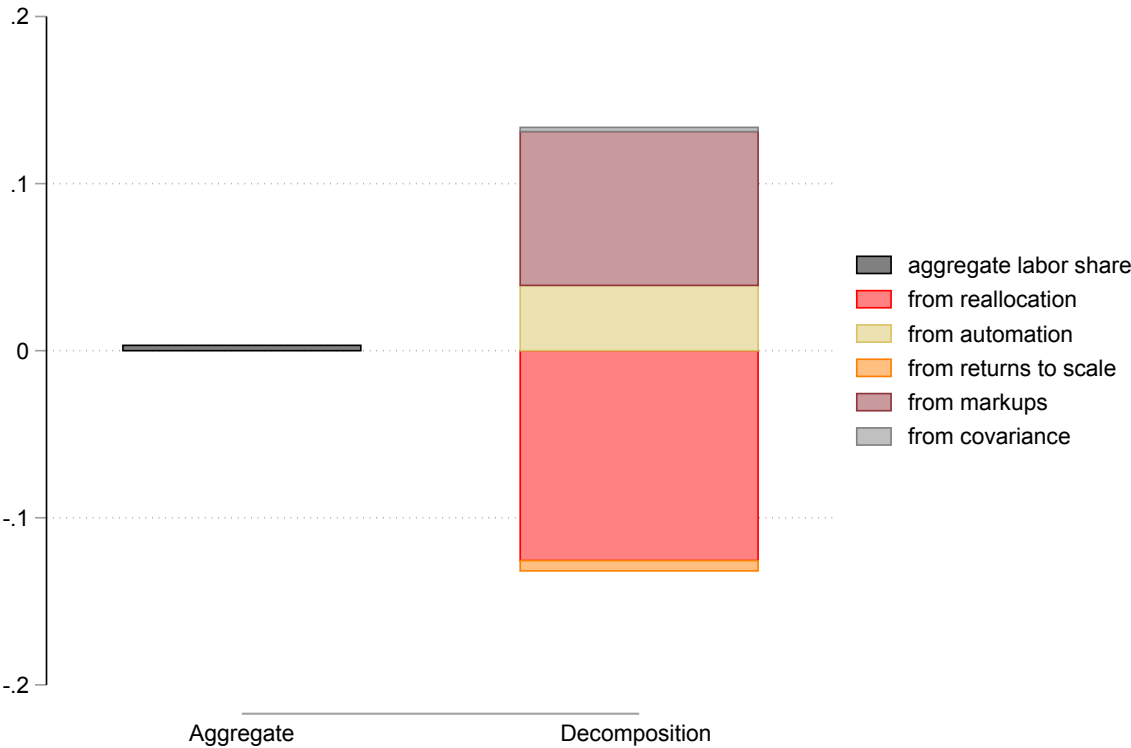
Note: This figures report the decomposition of the variation of the aggregate labor share from 1984 to 2016, including the reallocation term, using non rolling value-added estimates. See section 4.4 for detail.

Figure 18: Contributions to the Evolution of the Aggregate Labor Share, Ignoring Reallocation, Rolling Value-Added Estimation



Note: This figures report the decomposition of the variation of the aggregate labor share from 1984 to 2016, ignoring the reallocation term, using rolling value-added estimates. See section 4.4 for detail.

Figure 19: Contributions to the Evolution of the Aggregate Labor Share, Rolling Value-Added Estimation



Note: This figures report the decomposition of the variation of the aggregate labor share from 1984 to 2016, ignoring the reallocation term, using non rolling value-added estimates. See section 4.4 for detail.

A Data

A.1 Constructing Time Consistent Industry Codes

Industry classification has changed over the 1985-2016 period. From 1985 to 1993 the classification in vigor was the NAP. It changed to NAF in 1993, to NAF rév. 1 in 2003 and finally to 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 association 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. We use this last classification to estimate the production function at the 3-digit level.

A.2 Definition of Production and Value added

Firms tax forms 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. Starting in 1984, all production, inventory variations and cost of inputs are recorded separately for merchandise and other inputs.

Therefore for estimations that dates back no earlier that 1984, we follow definitions from the National Accounts and FICUS database and define output as the sum of sales excluding merchandise, immobilized production and variations in inventory excluding merchandise; and we define intermediary inputs use as the sum of material expenditures and inventory usage, and other external inputs. For estimations that dates back to 1970, we include merchandise both in output and intermediary inputs. While this does not affect much the level of value added, it does affect both the level of output and intermediary inputs, and potentially our estimations with output production functions.

A.3 Input and Output Prices

All our micro data is denominated in current prices, and we do not observe firm level prices of inputs nor output. We deflate nominal values at the 38 sectors level using price indexes for investment and outputs from the September 2018 release of the INSEE Annual National Accounts.

A.4 Trimming procedure

We start from the entire dataset excluding nonmarket sectors, agriculture, real estate and finance, and exclude years 1967, 1968, 1971, and 1974-1977 because data is either missing or excluded from the analysis because we were not able to properly retrieve it. For the 1966-2016 sample, we only keep non individual firms with positive value-added, labor costs, and sales. For the 1984-2016 sample, we only keep firms with positive value-added, labor costs, and employment. In both cases, we also exclude firms which reports labor share above 300%.

For the 1966-2016 estimation sample, we exclude firms with sales above 1M 2010 constant euros. For both estimation samples, we exclude firms with average wage, labor productivity or capital per employee in the top or bottom 0.1%.

A.5 Decomposition

This section details the decomposition method we apply to aggregate labor share and aggregate inverse markups.

Industry level decomposition

Let $k \in \{1, \dots, K\}$ be some industry classification (e.g., 3 digits in micro data), M stands for an aggregate measure we want to decompose the evolution of (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 :

$$\begin{aligned}\Delta X_t &\equiv X_t - X_{t-1}, \quad \bar{X}_t \equiv \frac{1}{2}(X_t + X_{t-1}), \\ \Delta_T X &\equiv X_T - X_0,\end{aligned}$$

where T is the last period and 0 is the first period. Our first decomposition is:²⁶

$$\Delta_T M \equiv \underbrace{\sum_{t=1}^T \sum_k \bar{S}_{kt} \Delta M_{kt}}_{\text{within industry}} + \underbrace{\sum_{t=1}^T \sum_k \Delta S_{kt} \bar{M}_{kt}}_{\text{across industries}}. \quad (29)$$

This allows us to distinguish the extent to which the aggregate variation in markup or labor 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 denote firm quantile. We can write the industry-level measure as

$$M_{kt} \equiv \int_{\underline{y}}^{\bar{y}} S_{kt}(y) M_{kt}(y) dy, \quad (30)$$

where $S_{kt}(y)$ denotes the share of industry- k value added or sales that is in firms of quantile y at time t and $M_{kt}(y)$ denotes the weighted average outcome (labor share or markup) of firms of

²⁶This is simply because:

$$\begin{aligned}\Delta(S_t M_t) &= \bar{S}_t \Delta M_t + \Delta S_t \bar{M}_t \\ \Delta_T(SM) &= \sum_{t=1}^T \Delta(S_t M_t).\end{aligned}$$

quantile y in industry k at time t . We can now decompose²⁷

$$\Delta M_{kt} = \underbrace{\int_{\underline{y}}^{\bar{y}} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy}_{\text{Within quantile}} + \underbrace{\int_{\underline{y}}^{\bar{y}} \Delta S_{kt}(y) \bar{M}_{kt}(y) dy}_{\text{Cross quantile}}. \quad (32)$$

We further decompose the within quantile component into three components: top firms component (for firms with y in the top 1% or 5%), above median component (for firms with y above the median and below the top 5% or 10%) and below median component (for firms with y below the median). Let y^* be the threshold of size for being among the top firms, and y' the median size. We can write

$$\int_{\underline{y}}^{\bar{y}} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy = \underbrace{\int_{\underline{y}}^{y'} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy}_{\text{Within Below Median}} + \underbrace{\int_{y'}^{y^*} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy}_{\text{Within Above Median}} + \underbrace{\int_{y^*}^{\bar{y}} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy}_{\text{Within Top Firms}}. \quad (33)$$

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

1. The cross quantile component:

$$\sum_{t=1}^T \sum_k \bar{S}_{kt} \int_{\underline{y}}^{\bar{y}} \Delta S_{kt}(y) \bar{M}_{kt}(y) dy.$$

2. The within quantile component:

$$\sum_{t=1}^T \sum_k \bar{S}_{kt} \int_{\underline{y}}^{\bar{y}} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy,$$

which can then be further decomposed to

- (a) Within top firms component:

$$\sum_{t=1}^T \sum_k \bar{S}_{kt} \int_{y^*}^{\bar{y}} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy,$$

²⁷As emphasized by [Kehrig and Vincent \(2017\)](#), 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:

$$\Delta M_{kt} \equiv \underbrace{\sum_{i \in \Omega_t^-} \bar{S}_{it} \Delta M_{it}}_{\text{within firm}} + \underbrace{\sum_{i \in \bar{\Omega}_{kt}^-} \Delta S_{it} \bar{M}_{it}}_{\text{cross firm}} + \underbrace{\left(\sum_{i \in \Omega_{kt}^+} S_{it} M_{it} - \sum_{i \in \Omega_{kt-1}^-} S_{it-1} M_{it-1} \right)}_{\text{net entry}}, \quad (31)$$

where again shares are computed within the industry.

(b) Within above median component:

$$\sum_{t=1}^T \sum_k \bar{S}_{kt} \int_{y'}^{y^*} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy,$$

(c) Within below median component:

$$\sum_{t=1}^T \sum_k \bar{S}_{kt} \int_{\underline{y}}^{y'} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy.$$

To take a closer look at outcomes for small firms, we will also display the average variations in those three components across all industries, without weighing them to their industry level contributions :

(a) Average top firms component:

$$\sum_{t=1}^T \sum_k \bar{S}_{kt} \frac{\int_{y^*}^{\bar{y}} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy}{\int_{y^*}^{\bar{y}} \bar{S}_{kt}(y) dy}$$

(b) Average above median component:

$$\sum_{t=1}^T \sum_k \bar{S}_{kt} \frac{\int_{y'}^{y^*} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy}{\int_{y'}^{y^*} \bar{S}_{kt}(y) dy}$$

(c) Average below median component:

$$\sum_{t=1}^T \sum_k \bar{S}_{kt} \frac{\int_{\underline{y}}^{y'} \bar{S}_{kt}(y) \Delta M_{kt}(y) dy}{\int_{\underline{y}}^{y'} \bar{S}_{kt}(y) dy}$$

B Tables

Table B.1: Labor Share and Markup on Valued Added, Firm Level Trends

	Labor Share		
	(1)	(2)	(3)
Trend	0.0075 (0.0000)	0.0080 (0.0000)	0.0075 (0.0000)
Log Employment			0.0075 (0.0003)
Firm FE	Yes	Yes	Yes
Size FE	No	Yes	No
Observations	26,241,148	25,566,453	26,148,089
R2	0.496	0.545	0.499
	Non-Rolling Markup		
	(1)	(2)	(3)
Trend	-0.0170 (0.0000)	-0.0193 (0.0001)	-0.0156 (0.0000)
Log Employment			-0.2075 (0.0006)
Firm FE	Yes	Yes	Yes
Size FE	No	Yes	No
Observations	26,241,148	25,566,453	26,148,089
R2	0.635	0.667	0.646
	Rolling Markup		
	(1)	(2)	(3)
Trend	-0.0148 (0.0000)	-0.0170 (0.0001)	-0.0134 (0.0000)
Log Employment			-0.2053 (0.0006)
Firm FE	Yes	Yes	Yes
Size FE	No	Yes	No
Observations	26,241,148	25,566,453	26,148,089
R2	0.633	0.666	0.645

Note: This table presents the results of regressions of labor share and markup on time trends with firms fixed effects, for the 1984-2016 sample. Markup are based on value added estimation.

Table B.2: Labor Share and Markup on Valued Added, Firm Level Trends, Balanced Panel

	Labor Share		
	(1)	(2)	(3)
Trend	0.0028 (0.0001)	0.0028 (0.0001)	0.0029 (0.0001)
Log Employment			-0.0110 (0.0016)
Firm FE	Yes	Yes	Yes
Size FE	No	Yes	No
Observations	803,814	797,982	803,811
R2	0.357	0.455	0.357
	Non-Rolling Markup		
	(1)	(2)	(3)
Trend	-0.0034 (0.0001)	-0.0036 (0.0001)	-0.0030 (0.0001)
Log Employment			-0.0826 (0.0045)
Firm FE	Yes	Yes	Yes
Size FE	No	Yes	No
Observations	803,814	797,982	803,811
R2	0.576	0.665	0.580
	Rolling Markup		
	(1)	(2)	(3)
Trend	-0.0007 (0.0001)	-0.0010 (0.0001)	-0.0004 (0.0001)
Log Employment			-0.0775 (0.0045)
Firm FE	Yes	Yes	Yes
Size FE	No	Yes	No
Observations	803,814	797,982	803,811
R2	0.572	0.661	0.575

Note: This table presents the results of regressions of labor share and markup on time trends with firms fixed effects, for the 1984-2016 sample. Markup are based on value added estimation. Sample is restricted to the firms are in the sample all years from 1984 to 2016. Those firm account of 20 to 25 % of total value-added.

Table B.3: Output Production Function Estimation, Estimation Sample 1970-2016, Manufacturing Sectors

	β_l	β_k	β_m	η	μ	ρ	N
Mining	0.143 (0.010)	0.095 (0.008)	0.756 (0.011)	0.520 (0.048)	-0.004 (0.000)	0.729 (0.027)	24,290
Food products	0.211 (0.005)	0.015 (0.003)	0.780 (0.003)	0.276 (0.011)	0.000 (0.000)	0.787 (0.010)	183,251
Textiles	0.370 (0.007)	-0.044 (0.006)	0.684 (0.004)	0.351 (0.009)	0.001 (0.000)	0.804 (0.006)	104,826
Wood, paper and printing	0.304 (0.008)	0.011 (0.003)	0.689 (0.005)	0.384 (0.011)	0.002 (0.000)	0.748 (0.009)	152,951
Coke and refined petroleum	0.112 (0.051)	0.047 (0.039)	0.854 (0.024)	0.198 (0.039)	-0.001 (0.000)	0.810 (0.044)	2,014
Chemicals	0.168 (0.007)	0.043 (0.004)	0.791 (0.006)	0.272 (0.014)	0.001 (0.000)	0.743 (0.017)	38,174
Pharmaceuticals	0.128 (0.025)	0.062 (0.018)	0.814 (0.013)	0.198 (0.035)	0.001 (0.000)	0.757 (0.044)	9,148
Rubber and plastic products	0.215 (0.004)	0.043 (0.004)	0.733 (0.006)	0.274 (0.011)	0.002 (0.000)	0.779 (0.012)	115,801
Basic Metals	0.273 (0.004)	0.053 (0.002)	0.651 (0.003)	0.530 (0.009)	0.000 (0.000)	0.717 (0.005)	230,857
Computers and electronics	0.325 (0.012)	0.006 (0.006)	0.677 (0.010)	0.164 (0.006)	0.006 (0.000)	0.757 (0.009)	42,629
Electrical equipments	0.215 (0.010)	0.037 (0.006)	0.737 (0.007)	0.382 (0.020)	0.001 (0.000)	0.727 (0.017)	26,678
Machinery and equipments	0.257 (0.006)	0.024 (0.003)	0.717 (0.004)	0.502 (0.009)	0.002 (0.000)	0.644 (0.008)	84,764
Transport equipments	0.243 (0.009)	0.015 (0.005)	0.749 (0.006)	0.467 (0.017)	0.000 (0.000)	0.690 (0.013)	35,424
Other manufacturing products	0.355 (0.006)	-0.014 (0.003)	0.657 (0.004)	0.447 (0.007)	0.002 (0.000)	0.759 (0.004)	144,921
Gas and electricity	0.188 (0.041)	0.091 (0.017)	0.697 (0.051)	0.168 (0.027)	0.001 (0.000)	0.877 (0.019)	5,106
Water supply and waste	0.219 (0.006)	0.074 (0.004)	0.704 (0.006)	0.417 (0.016)	-0.001 (0.000)	0.765 (0.011)	43,651

Note: This table presents the results of output based non rolling estimation in the estimation sample for 1970-2016, by NA38 manufacturing sector.

Table B.4: Output Production Function Estimation, Estimation Sample 1970-2016, Non Manufacturing Sectors

	β_l	β_k	β_m	η	μ	ρ	N
Construction	0.198 (0.001)	0.016 (0.001)	0.762 (0.001)	0.763 (0.008)	-0.002 (0.000)	0.591 (0.004)	678,575
Wholesale and retail trade	0.127 (0.001)	0.006 (0.000)	0.861 (0.000)	0.334 (0.003)	0.001 (0.000)	0.616 (0.004)	2,092,776
Transportation	0.252 (0.006)	0.031 (0.002)	0.729 (0.004)	0.249 (0.005)	0.001 (0.000)	0.823 (0.006)	273,378
Accomodation and food services	0.295 (0.017)	0.081 (0.002)	0.608 (0.017)	0.513 (0.010)	-0.002 (0.000)	0.771 (0.005)	191,706
Publishing and motion pictures	0.488 (0.017)	0.016 (0.005)	0.564 (0.012)	0.546 (0.012)	0.001 (0.000)	0.763 (0.004)	76,281
Telecommunications	0.248 (0.027)	0.020 (0.010)	0.770 (0.022)	0.039 (0.019)	0.007 (0.001)	0.761 (0.028)	6,663
ICT	0.488 (0.008)	-0.008 (0.004)	0.543 (0.009)	0.516 (0.012)	0.002 (0.000)	0.781 (0.005)	70,594
Legal, accounting and engineering	0.491 (0.006)	-0.034 (0.003)	0.553 (0.004)	0.595 (0.007)	-0.001 (0.000)	0.801 (0.002)	256,744
Scientific research	0.326 (0.032)	-0.026 (0.016)	0.706 (0.023)	0.392 (0.030)	-0.000 (0.000)	0.817 (0.014)	7,840
Advertising and market research	0.401 (0.008)	-0.038 (0.005)	0.659 (0.006)	0.422 (0.011)	0.001 (0.000)	0.794 (0.006)	69,733
Administrative and support	0.476 (0.003)	-0.047 (0.003)	0.625 (0.004)	0.439 (0.006)	-0.001 (0.000)	0.838 (0.003)	271,086

Note: This table presents the results of output based non rolling estimation in the estimation sample for 1970-2016, by NA38 non manufacturing sector.

Table B.5: Output Production Function Estimation, Estimation Sample 1984-2016, Manufacturing Sectors

	β_l	β_k	β_m	η	μ	ρ	N
Mining	0.230 (0.012)	0.066 (0.007)	0.694 (0.012)	0.603 (0.028)	-0.004 (0.000)	0.714 (0.014)	35,539
Food products	0.380 (0.005)	0.065 (0.002)	0.598 (0.004)	0.566 (0.004)	-0.000 (0.000)	0.706 (0.003)	502,066
Textiles	0.449 (0.005)	-0.009 (0.003)	0.597 (0.004)	0.483 (0.007)	0.002 (0.000)	0.757 (0.003)	181,885
Wood, paper and printing	0.473 (0.010)	0.015 (0.002)	0.549 (0.007)	0.560 (0.006)	0.003 (0.000)	0.725 (0.003)	348,488
Coke and refined petroleum	0.211 (0.065)	0.015 (0.032)	0.799 (0.050)	0.378 (0.090)	-0.002 (0.001)	0.760 (0.081)	1,797
Chemicals	0.258 (0.015)	0.029 (0.006)	0.725 (0.013)	0.389 (0.012)	0.001 (0.000)	0.744 (0.009)	50,683
Pharmaceuticals	0.153 (0.032)	0.032 (0.015)	0.820 (0.021)	0.287 (0.041)	0.003 (0.000)	0.712 (0.037)	9,246
Rubber and plastic products	0.293 (0.012)	0.042 (0.006)	0.662 (0.015)	0.430 (0.017)	0.002 (0.000)	0.738 (0.015)	183,208
Basic Metals	0.447 (0.006)	0.043 (0.002)	0.516 (0.004)	0.685 (0.006)	0.001 (0.000)	0.712 (0.002)	422,127
Computers and electronics	0.476 (0.017)	0.020 (0.005)	0.533 (0.014)	0.393 (0.009)	0.010 (0.000)	0.717 (0.005)	74,546
Electrical equipments	0.362 (0.022)	0.016 (0.006)	0.629 (0.018)	0.543 (0.016)	0.002 (0.000)	0.721 (0.010)	41,645
Machinery and equipments	0.436 (0.012)	0.018 (0.003)	0.560 (0.009)	0.641 (0.010)	0.003 (0.000)	0.699 (0.005)	124,455
Transport equipments	0.403 (0.019)	0.032 (0.006)	0.587 (0.015)	0.573 (0.016)	0.001 (0.000)	0.723 (0.007)	52,725
Other manufacturing products	0.606 (0.007)	0.001 (0.002)	0.426 (0.005)	0.774 (0.006)	0.004 (0.000)	0.707 (0.002)	409,862
Gas and electricity	0.146 (0.021)	0.100 (0.007)	0.720 (0.015)	0.412 (0.023)	0.002 (0.000)	0.715 (0.011)	12,089
Water supply and waste	0.281 (0.008)	0.062 (0.003)	0.657 (0.007)	0.601 (0.011)	-0.001 (0.000)	0.702 (0.006)	75,945

Note: This table presents the results of output based non rolling estimation in the estimation sample for 1970-2016, by NA38 manufacturing sector.

Table B.6: Output Production Function Estimation, Estimation Sample 1984-2016, Non Manufacturing Sectors

	β_l	β_k	β_m	η	μ	ρ	N
Construction	0.426 (0.002)	0.008 (0.001)	0.571 (0.001)	0.916 (0.002)	-0.001 (0.000)	0.636 (0.001)	2,543,929
Wholesale and retail trade	0.497 (0.006)	0.044 (0.001)	0.529 (0.004)	0.582 (0.003)	0.002 (0.000)	0.732 (0.001)	4,981,422
Transportation	0.388 (0.004)	0.025 (0.001)	0.595 (0.003)	0.573 (0.004)	0.001 (0.000)	0.724 (0.002)	634,507
Accomodation and food services	0.624 (0.002)	0.077 (0.001)	0.360 (0.002)	1.007 (0.003)	-0.000 (0.000)	0.629 (0.001)	1,565,461
Publishing and motion pictures	0.632 (0.010)	-0.010 (0.002)	0.504 (0.006)	0.800 (0.009)	0.002 (0.000)	0.674 (0.002)	214,197
Telecommunications	0.425 (0.030)	-0.024 (0.007)	0.694 (0.020)	0.351 (0.013)	0.011 (0.000)	0.645 (0.017)	16,195
ICT	0.689 (0.007)	-0.032 (0.002)	0.423 (0.006)	0.931 (0.008)	0.004 (0.000)	0.665 (0.002)	245,807
Legal, accounting and engineering	0.709 (0.003)	-0.034 (0.001)	0.408 (0.002)	1.015 (0.004)	-0.000 (0.000)	0.682 (0.001)	1,087,476
Scientific research	0.470 (0.026)	-0.033 (0.007)	0.601 (0.022)	0.765 (0.027)	-0.000 (0.000)	0.685 (0.009)	18,965
Advertising and market research	0.572 (0.005)	-0.035 (0.002)	0.549 (0.004)	0.690 (0.006)	0.003 (0.000)	0.701 (0.002)	283,846
Administrative and support	0.526 (0.002)	-0.008 (0.001)	0.543 (0.002)	0.717 (0.003)	-0.001 (0.000)	0.727 (0.001)	842,258

Note: This table presents the results of output based non rolling estimation in the estimation sample for 1984-2016, by NA38 non manufacturing sector.

Table B.7: Value Added Production Function Estimation, Estimation Sample 1984-2016, Manufacturing Sectors, Proxy Variable Method

	β_l	β_k	η	μ	ρ	N
Mining	0.714 (0.057)	0.299 (0.039)	0.698 (0.049)	-0.007 (0.000)	0.818 (0.011)	35,539
Food products	0.939 (0.007)	0.136 (0.006)	0.806 (0.009)	0.002 (0.000)	0.726 (0.004)	502,066
Textiles	1.009 (0.025)	0.018 (0.020)	0.517 (0.011)	0.005 (0.000)	0.822 (0.006)	181,885
Wood, paper and printing	1.029 (0.009)	0.025 (0.007)	0.758 (0.010)	0.008 (0.000)	0.732 (0.004)	348,488
Coke and refined petroleum	0.820 (0.082)	0.230 (0.053)	1.307 (0.110)	-0.006 (0.002)	0.641 (0.028)	1,797
Chemicals	0.932 (0.030)	0.131 (0.021)	0.682 (0.029)	0.005 (0.000)	0.771 (0.011)	50,683
Pharmaceuticals	1.244 (0.229)	-0.086 (0.180)	0.472 (0.074)	0.005 (0.001)	0.859 (0.020)	9,246
Rubber and plastic products	0.862 (0.013)	0.146 (0.010)	0.611 (0.015)	0.006 (0.000)	0.777 (0.006)	183,208
Basic Metals	0.880 (0.005)	0.109 (0.004)	1.087 (0.016)	0.004 (0.000)	0.664 (0.005)	422,127
Computers and electronics	0.947 (0.027)	0.083 (0.020)	0.323 (0.014)	0.017 (0.001)	0.785 (0.009)	74,546
Electrical equipments	0.964 (0.032)	0.054 (0.023)	0.757 (0.033)	0.005 (0.000)	0.773 (0.011)	41,645
Machinery and equipments	0.965 (0.012)	0.059 (0.009)	0.981 (0.022)	0.008 (0.000)	0.684 (0.008)	124,455
Transport equipments	0.922 (0.015)	0.110 (0.011)	1.132 (0.040)	0.002 (0.000)	0.655 (0.013)	52,725
Other manufacturing products	0.982 (0.005)	0.028 (0.004)	1.073 (0.012)	0.007 (0.000)	0.686 (0.004)	409,862
Gas and electricity	0.925 (0.062)	0.163 (0.057)	0.445 (0.067)	0.002 (0.001)	0.870 (0.022)	12,089
Water supply and waste	0.873 (0.014)	0.140 (0.011)	0.842 (0.033)	-0.002 (0.000)	0.776 (0.009)	75,945

Note: This table presents the results of value-added based non rolling estimation in the estimation sample for 1984-2016, by NA38 manufacturing sector, using the proxy variable method of [Ackerberg et al. \(2015\)](#).

Table B.8: Value Added Production Function Estimation, Estimation Sample 1984-2016, Non Manufacturing Sectors Proxy Variable Method

	β_l	β_k	η	μ	ρ	N
Construction	0.984 (0.002)	0.026 (0.001)	1.530 (0.005)	-0.002 (0.000)	0.626 (0.001)	2,543,929
Wholesale and retail trade	1.049 (0.002)	0.037 (0.001)	0.947 (0.003)	0.004 (0.000)	0.716 (0.001)	4,981,422
Transportation	0.938 (0.003)	0.065 (0.003)	1.021 (0.009)	0.003 (0.000)	0.702 (0.003)	634,507
Accommodation and food services	0.889 (0.002)	0.164 (0.002)	1.358 (0.006)	-0.003 (0.000)	0.567 (0.002)	1,565,461
Publishing and motion pictures	1.176 (0.008)	0.018 (0.005)	1.263 (0.016)	0.004 (0.000)	0.633 (0.005)	214,197
Telecommunications	1.330 (0.054)	-0.042 (0.033)	0.395 (0.028)	0.022 (0.001)	0.719 (0.016)	16,195
ICT	1.135 (0.006)	-0.022 (0.005)	1.233 (0.018)	0.006 (0.000)	0.652 (0.005)	245,807
Legal, accounting and engineering	1.089 (0.003)	-0.007 (0.002)	1.528 (0.011)	-0.000 (0.000)	0.629 (0.003)	1,087,476
Scientific research	1.124 (0.037)	-0.046 (0.026)	1.082 (0.070)	0.000 (0.001)	0.735 (0.019)	18,965
Advertising and market research	1.170 (0.008)	-0.036 (0.006)	1.003 (0.012)	0.006 (0.000)	0.710 (0.004)	283,846
Administrative and support	0.934 (0.004)	0.076 (0.004)	0.957 (0.011)	-0.003 (0.000)	0.758 (0.003)	842,258

Note: This table presents the results of value-added based non rolling estimation in the estimation sample for 1984-2016, by NA38 non manufacturing sector, using the proxy variable method of [Ackerberg et al. \(2015\)](#).

Table B.9: Correlations Between Variations in Concentration and in the Distribution of Markups on Output

	Weighted Mean		Unweighted Mean		25th Percentile		Median		75th Percentile	
Markup, 5-Year Change										
Top 1% Share	0.3710 (0.3614)		-0.1018 (0.0653)		-0.0101 (0.0092)		-0.0494 (0.0307)		-0.1594 (0.1050)	
Top 5% Share	1.2049 (0.5891)		-0.2019 (0.1531)		-0.0335 (0.0305)		-0.1047 (0.0780)		-0.3258 (0.2251)	
Observations	756	756	756	756	756	756	756	756	756	756
R2	0.1082	0.1372	0.1118	0.1115	0.3283	0.3298	0.1379	0.1382	0.0969	0.0970
Markup, 10-Year Change										
Top 1% Share	0.6326 (0.4436)		-0.2475 (0.1241)		-0.0203 (0.0203)		-0.1110 (0.0615)		-0.3895 (0.1984)	
Top 5% Share	1.4550 (0.6042)		-0.4366 (0.1837)		-0.0792 (0.0336)		-0.2110 (0.1011)		-0.6690 (0.2932)	
Observations	621	621	621	621	621	621	621	621	621	621
R2	0.1203	0.1538	0.1311	0.1325	0.2965	0.3224	0.1562	0.1620	0.1286	0.1280
Rolling Markup, 5-Year Change										
Top 1% Share	0.2117 (0.3600)		-0.2385 (0.1780)		-0.1214 (0.1351)		-0.1755 (0.1488)		-0.3126 (0.2133)	
Top 5% Share	1.0104 (0.6208)		-0.3504 (0.3102)		-0.1501 (0.2421)		-0.2408 (0.2580)		-0.4997 (0.3589)	
Observations	756	756	756	756	756	756	756	756	756	756
R2	0.2208	0.2321	0.2582	0.2538	0.3336	0.3308	0.2901	0.2864	0.2105	0.2063
Rolling Markup, 10-Year Change										
Top 1% Share	0.3866 (0.4099)		-0.4567 (0.2478)		-0.1938 (0.1646)		-0.3056 (0.1892)		-0.6218 (0.3181)	
Top 5% Share	1.2767 (0.5264)		-0.5703 (0.3943)		-0.1854 (0.2616)		-0.3346 (0.3020)		-0.8248 (0.4935)	
Observations	621	621	621	621	621	621	621	621	621	621
R2	0.1929	0.2142	0.2706	0.2521	0.2888	0.2799	0.2829	0.2684	0.2478	0.2271

Note: Each estimate is the result of a regression. Regressions are carried at the NA38 sector classification level. The dependent variable is the change in a moment of the distribution of markups in a given sector. Markup on output is based on estimates of the sum of labor elasticity coefficient β_l and intermediary input coefficient β_m from output based non rolling estimation in the top two panels, and rolling estimation in the bottom two panels, in the estimation sample for 1984-2016. The independent variable reports changes of two measures of concentration, based on firms share of sales. The estimation method in all columns is OLS, with time fixed effect.

Table B.10: Correlation Between Labor Share and Non Rolling Markup

	(1)	(2)	(3)
	No FE	Year FE	Year and Industry FE
Industry: na38 classification			
Labor Share (Log)	-0.5416*** (0.0001)	-0.5398*** (0.0005)	-0.5398*** (0.0005)
Observations	26823776	26823776	26823776
R2	0.3666	0.3796	0.3796

Note: Markup on value-added is based on estimates of the labor elasticity coefficient β_l from value-added based estimation carried on the 1984- 2016 sample using the proxy variable method [Akerberg et al. \(2015\)](#). Labor share is defined as the logarithm of the ratio of workers' compensation and taxes paid on labor over value added. Estimations are run at the firm level. The set of fixed effects included are described in the colum labels.

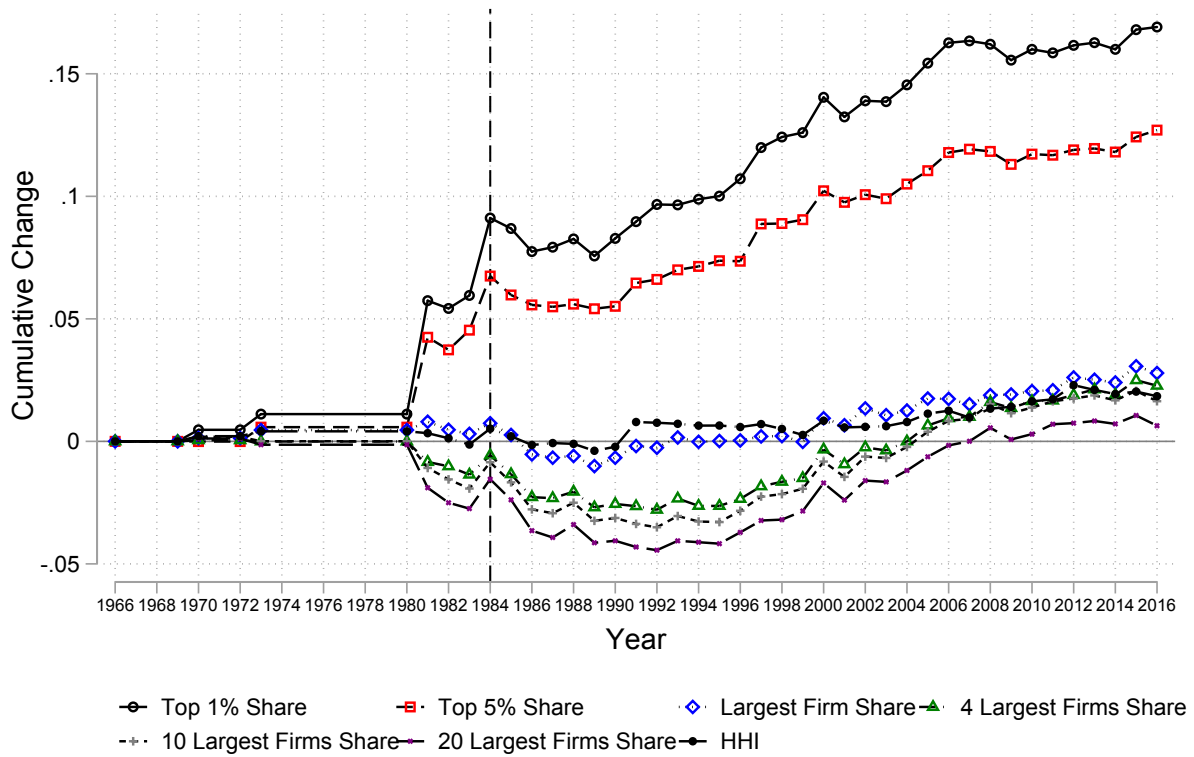
Table B.11: Correlation Between Labor Share and Rolling Markup

	(1)	(2)	(3)	(4)
	No FE	Year FE	Year and Industry FE	Firm FE
Industry: na38 classification				
Labor Share (Log)	-0.5467*** (0.0002)	-0.5444*** (0.0005)	-0.5444*** (0.0005)	-0.6638*** (0.0005)
Observations	26820462	26820462	26820462	26226722
R2	0.3302	0.3461	0.3461	0.7394

Note: Markup on value-added is based on estimates of the labor elasticity coefficient β_l from value-added based rolling estimation carried on the 1984- 2016 sample using the proxy variable method [Akerberg et al. \(2015\)](#). Labor share is defined as the logarithm of the ratio of workers' compensation and taxes paid on labor over value added. Estimations are run at the firm level. The set of fixed effects included are described in the colum labels.

C Figures

Figure C.1: Cumulative Change in Concentration



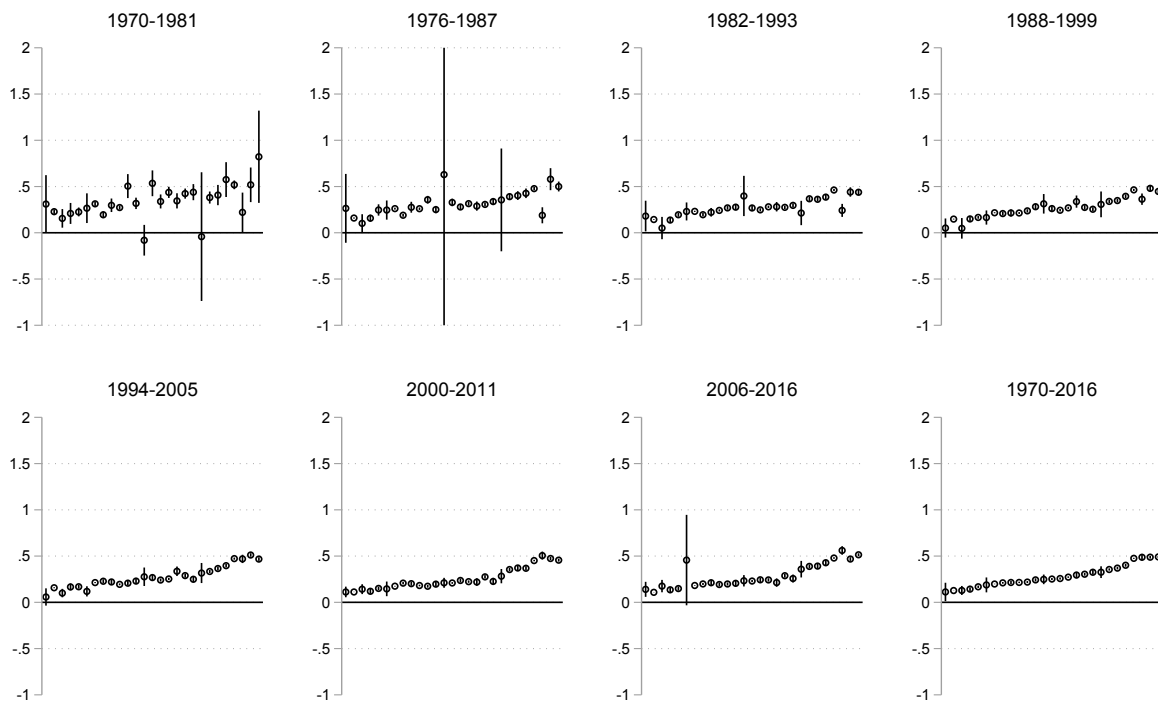
Note: This figure reports the cumulative change since 1966 of the sales weighted average level of concentration in sales across each 2-digit industry. Sample is firms in the market sectors, excluding agriculture, finance and real estate. Before 1984, it includes all non-individual firms with positive value-added, sales, and labor costs. From 1984, it includes all firms with positive value-added, employment, and labor costs.

Figure C.2: Aggregate Labor Share in Macro Data



Note: This figure reports the observed ratio of total salaried employees compensation to total value-added, and the imputed total share where self-employed worker compensation is calculated assuming a constant hourly wage within each A38 industry, in the market sectors excluding agriculture, real estate and finance in France, from INSEE National Accounts data.

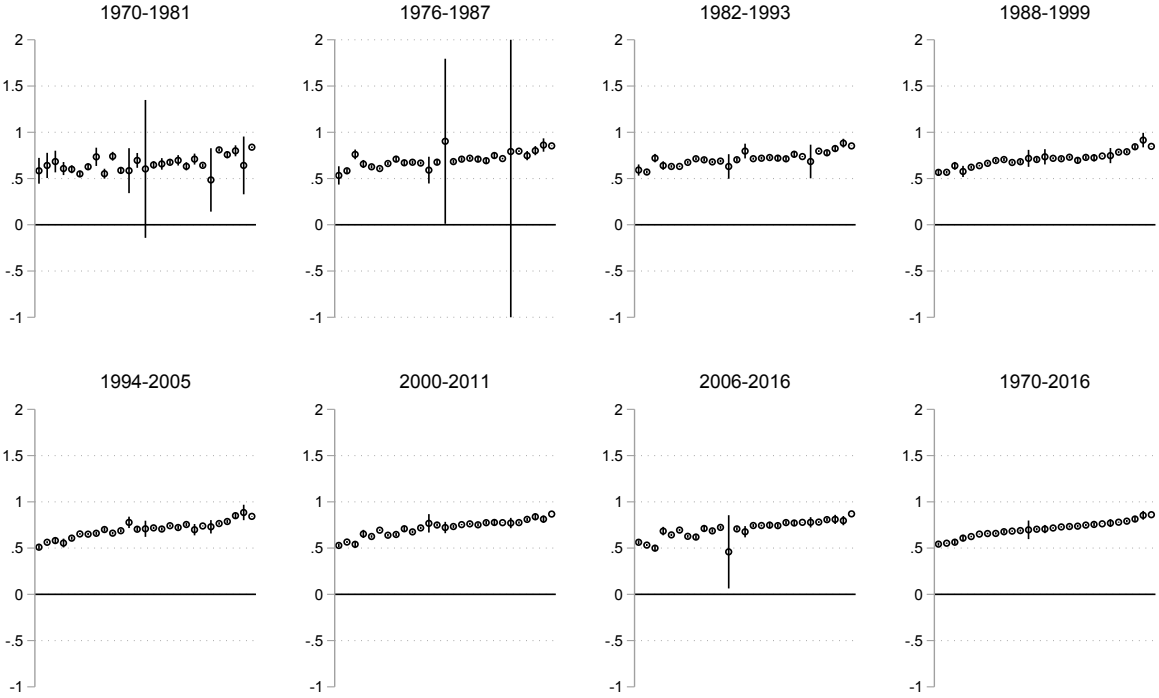
Figure C.3: Output Production Function Rolling Estimation, Labor Elasticity



NAF 38

Note: This figure presents estimates of the labor elasticity coefficient β_l from output based rolling estimation in the estimation sample for 1970-2016, by NAF38 sector, with 5% confidence intervals.

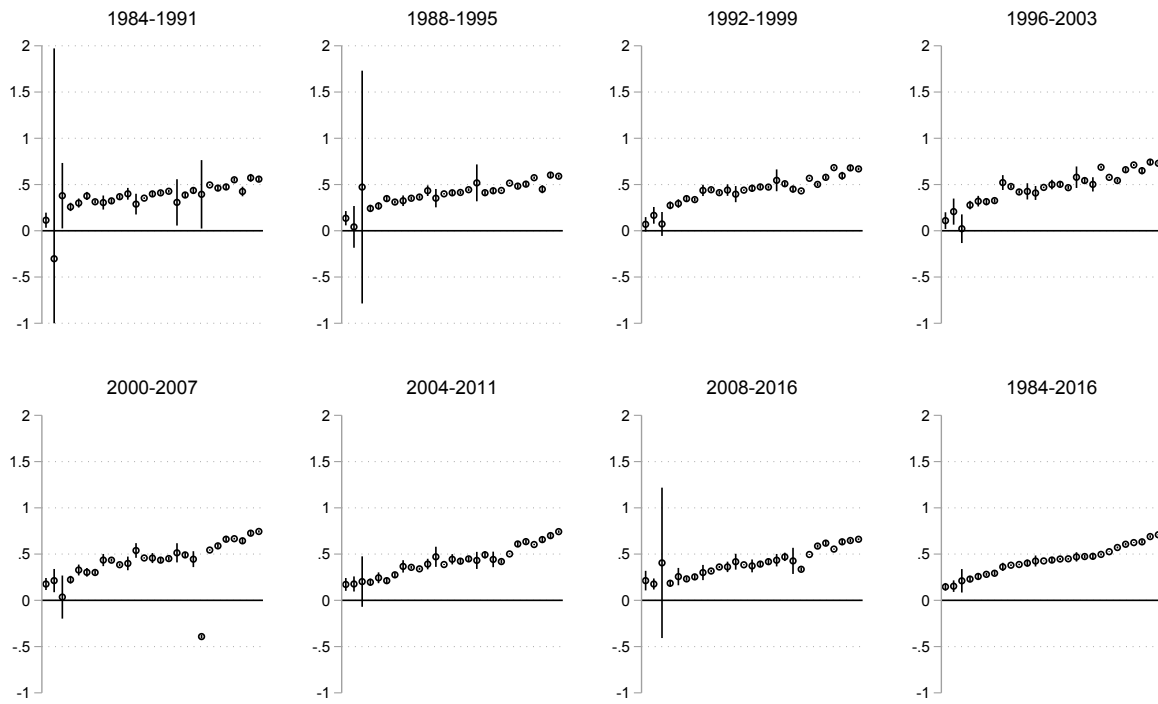
Figure C.4: Output Production Function Rolling Estimation, Intermediary Inputs Elasticity



NAF 38

Note: This figure presents estimates of the intermediary inputs elasticity coefficient β_m from output based rolling estimation in the estimation sample for 1970-2016, by NA38 sector, with 5% confidence intervals.

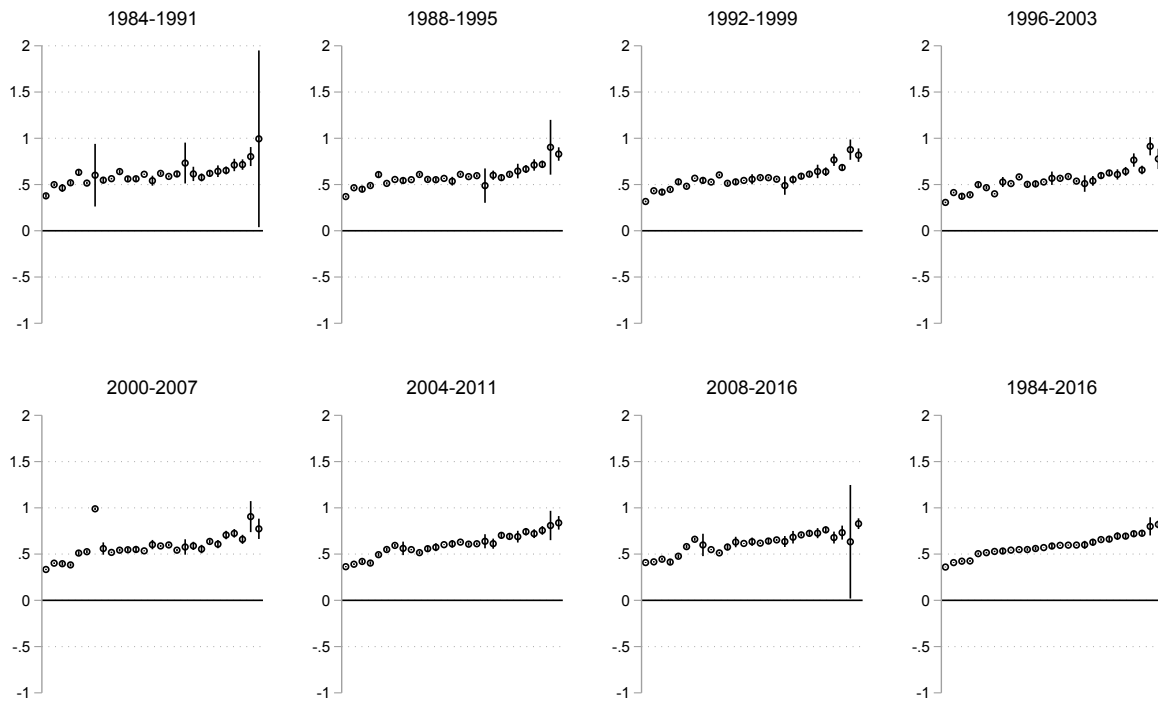
Figure C.5: Output Production Function Rolling Estimation, Labor Elasticity



NAF 38

Note: This figure presents estimates of the labor elasticity coefficient β_l from output based rolling estimation in the estimation sample for 1984-2016, by NA38 sector, with 5% confidence intervals.

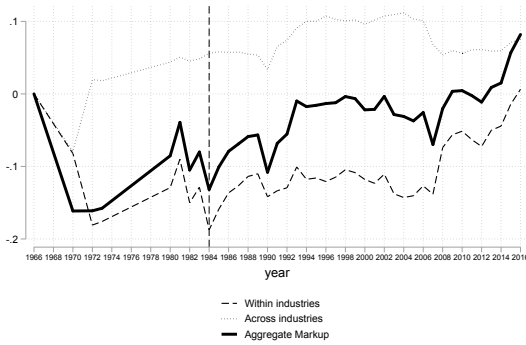
Figure C.6: Output Production Function Rolling Estimation, Intermediary Inputs Elasticity



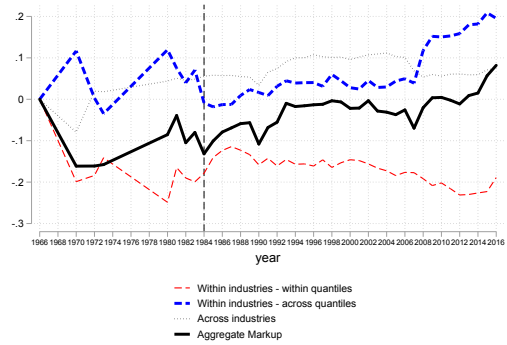
NAF 38

Note: This figure presents estimates of the intermediary inputs elasticity coefficient β_m from output based rolling estimation in the estimation sample for 1984-2016, by NA38 sector, with 5% confidence intervals.

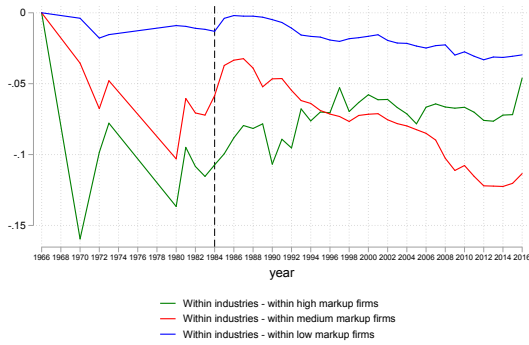
Figure C.7: Decomposition of Aggregate Non Rolling Markup on Output Variations, 1966-2016



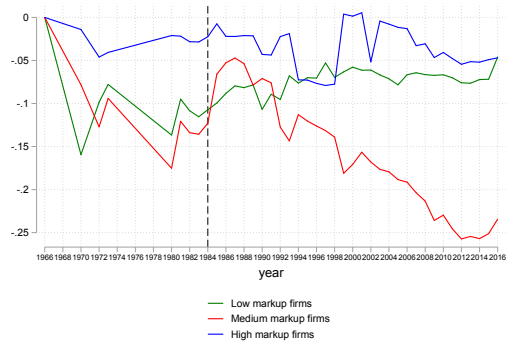
(a) Within/Cross Industries



(b) Within/Cross Quantiles



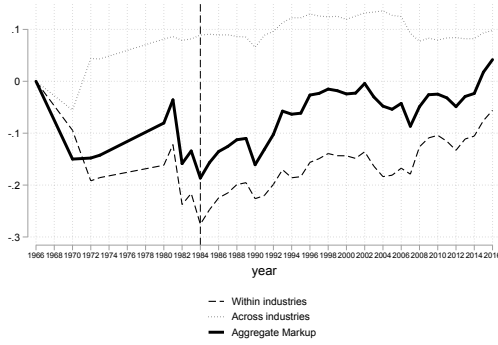
(c) Contributions by Quantiles



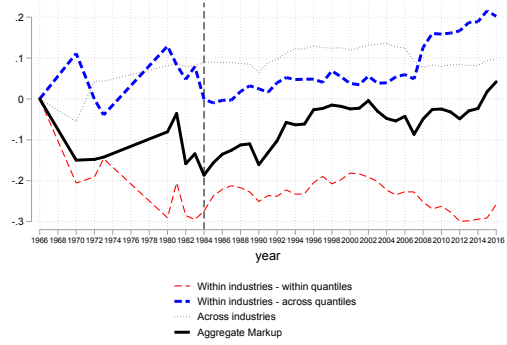
(d) Average Variations by Quantiles

Note: This figures reports the decomposition of the aggregate non rolling markup on output. Decomposition is described in section A.5. Quantiles of markups are calculated each year within 2-digit industries. Sample is firms in the market sectors, excluding agriculture, finance and real estate. Before 1984, it includes all non-individual firms with positive value-added, sales, and labor costs, and markup is based on estimates of the sum of labor elasticity coefficient β_l and intermediary input coefficient β_m from output non rolling estimation in the estimation sample for 1970-2016. From 1984, it includes all firms with positive value-added, employment, and labor costs, and markup is based on estimates of the sum of labor elasticity coefficient β_l and intermediary input coefficient β_m from output based non rolling estimation in the estimation sample for 1984-2016.

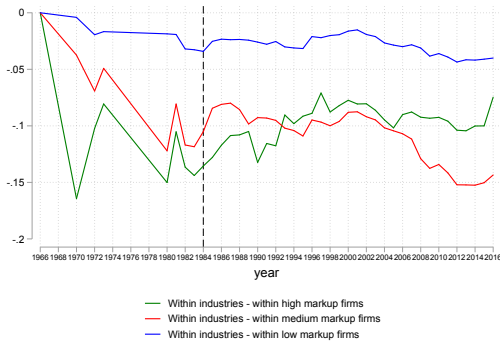
Figure C.8: Decomposition of Aggregate Rolling Markup on Output, 1966-2016



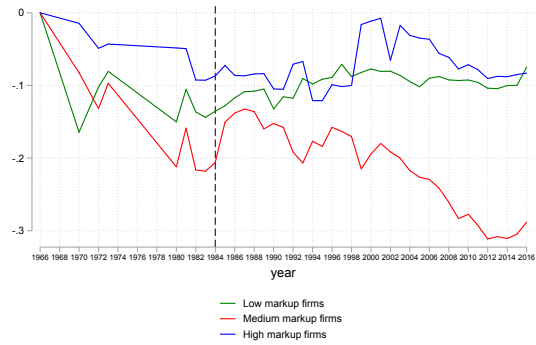
(a) Within/Cross Industries



(b) Within/Cross Quantiles



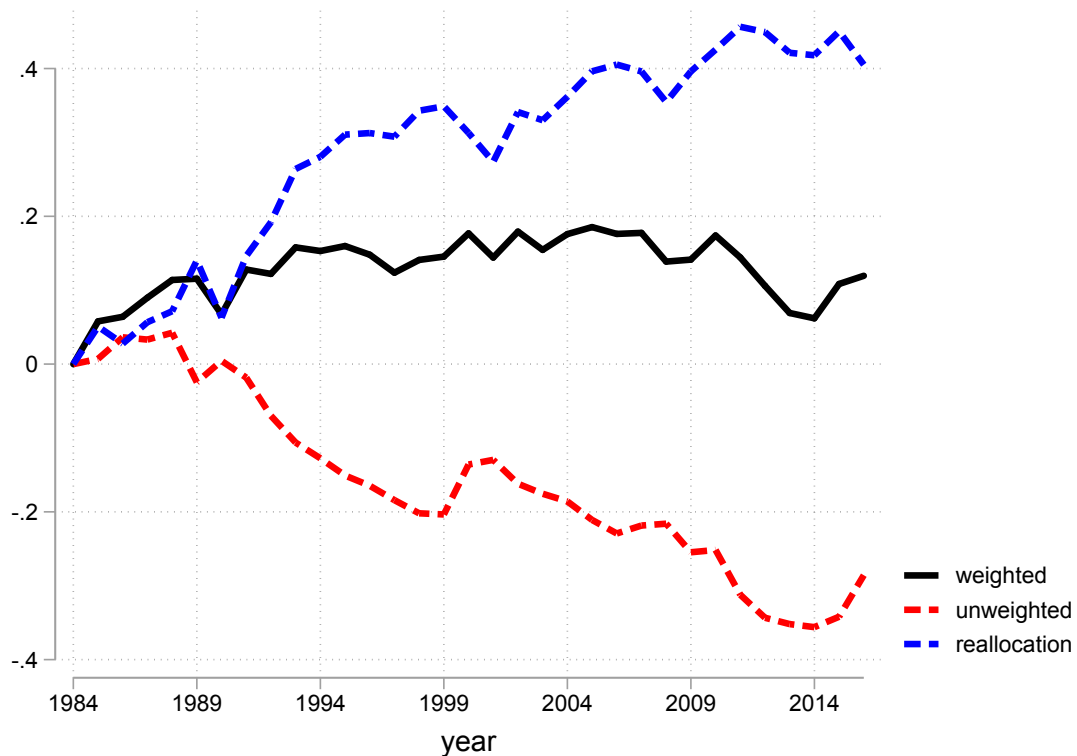
(c) Contributions by Quantiles



(d) Average Variations by Quantiles

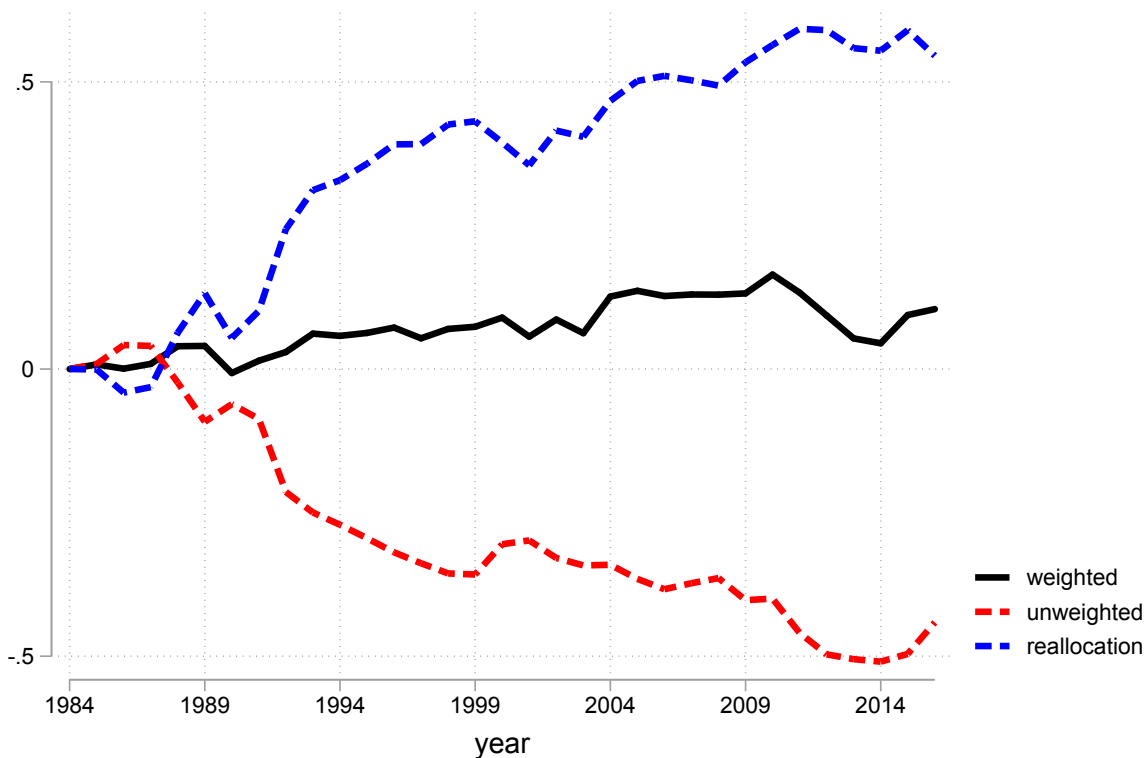
Note: This figure reports the decomposition of the aggregate rolling markup on output. Decomposition is described in section A.5. Quantiles of markups are calculated each year within 2-digit industries. Sample is firms in the market sectors, excluding agriculture, finance and real estate. Before 1984, it includes all non-individual firms with positive value-added, sales, and labor costs, and markup is based on estimates of the sum of labor elasticity coefficient β_l and intermediary input coefficient β_m from output rolling estimation in the estimation sample for 1970-2016. From 1984, it includes all firms with positive value-added, employment, and labor costs, and markup is based on estimates of the sum of labor elasticity coefficient β_l and intermediary input coefficient β_m from output based rolling estimation in the estimation sample for 1984-2016.

Figure C.9: Weighted and Unweighted Mean Markup, Non Rolling Value-Added Estimation, Proxy Variable Method



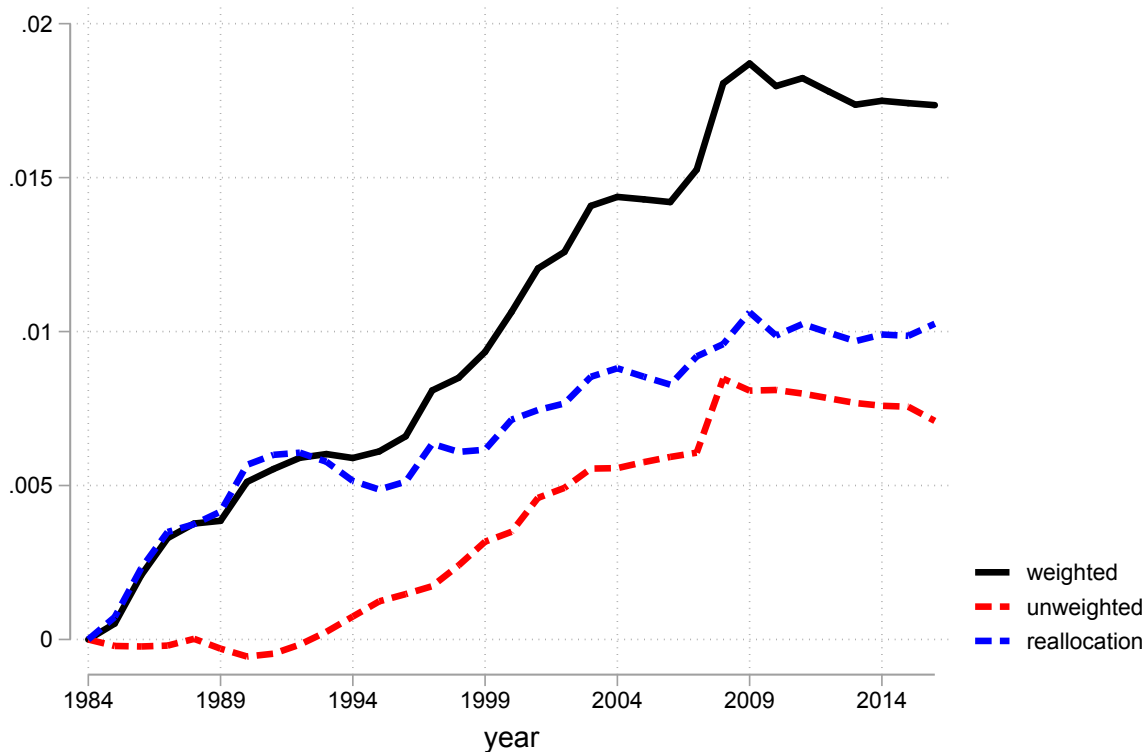
Note: This figure reports the cumulative variations of the weighted and unweighted mean markup on value-added based on non-rolling estimation of a value-added production function on the 1984-2016 sample, using the proxy variable method in [Akerberg et al. \(2015\)](#). Reallocation is defined as the difference between the variations in unweighted and weighted mean.

Figure C.10: Weighted and Unweighted Mean Markup, Rolling Value-Added Estimation, Proxy Variable Method



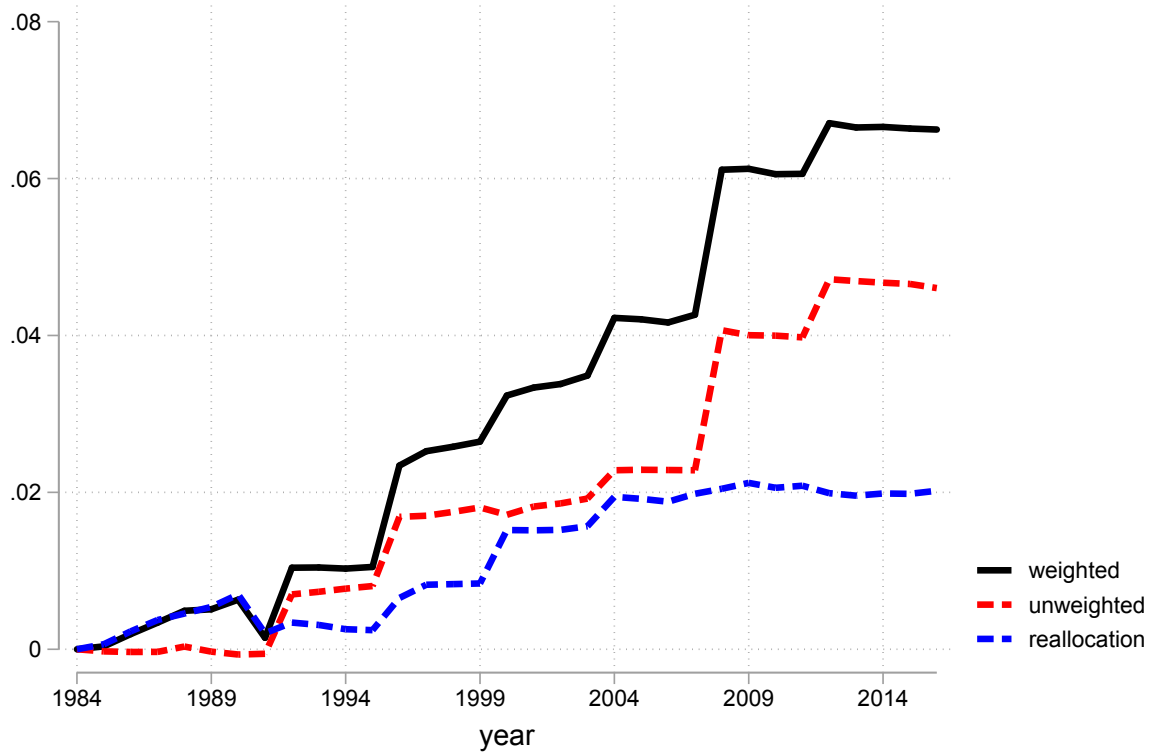
Note: This figures reports the cumulative variations of the weighted and unweighted mean markup on value-added based on rolling estimation of a value-added production function on the 1984-2016 sample, using the proxy variable method in [Akerberg et al. \(2015\)](#). Reallocation is defined as the difference between the variations in unweighted and weighted mean.

Figure C.11: Weighted and Unweighted Mean Automation, Non Rolling Value-Added Estimation



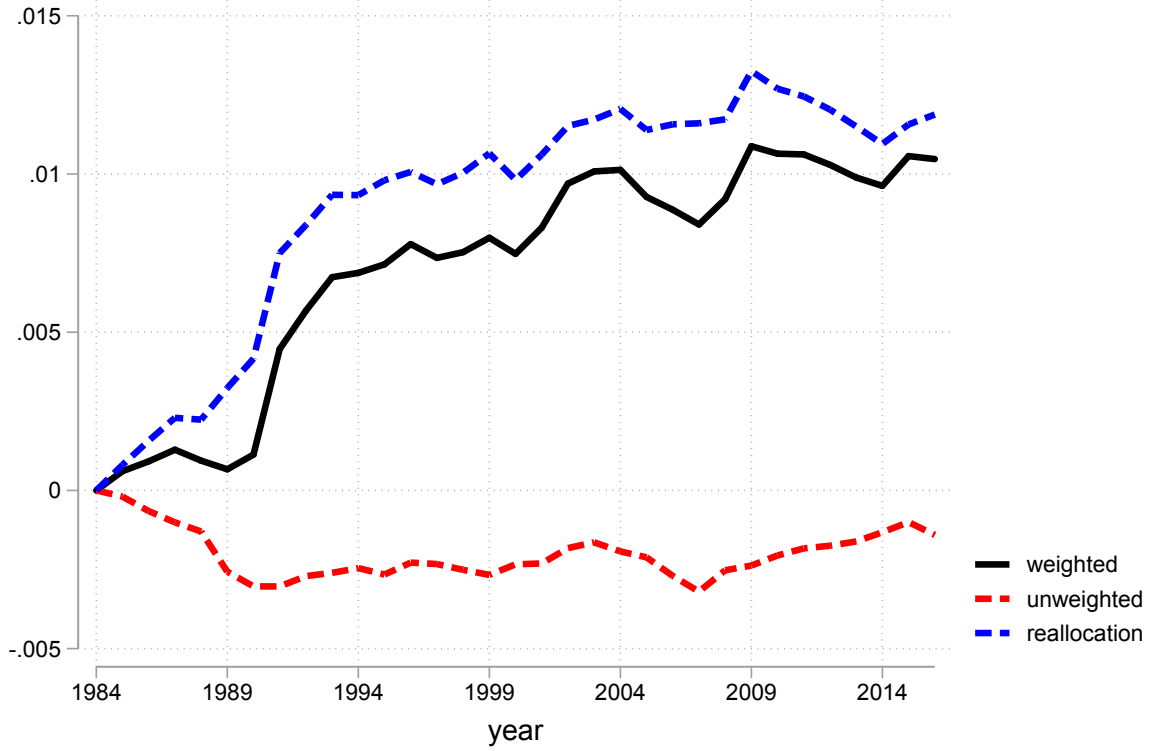
Note: This figures reports the cumulative variations of the weighted and unweighted mean automation parameter α on value-added based on non rolling estimation of a value-added production function on the 1984-2016 sample. Reallocation is defined as the difference between the variations in unweighted and weighted mean.

Figure C.12: Weighted and Unweighted Mean Automation, Rolling Value-Added Estimation



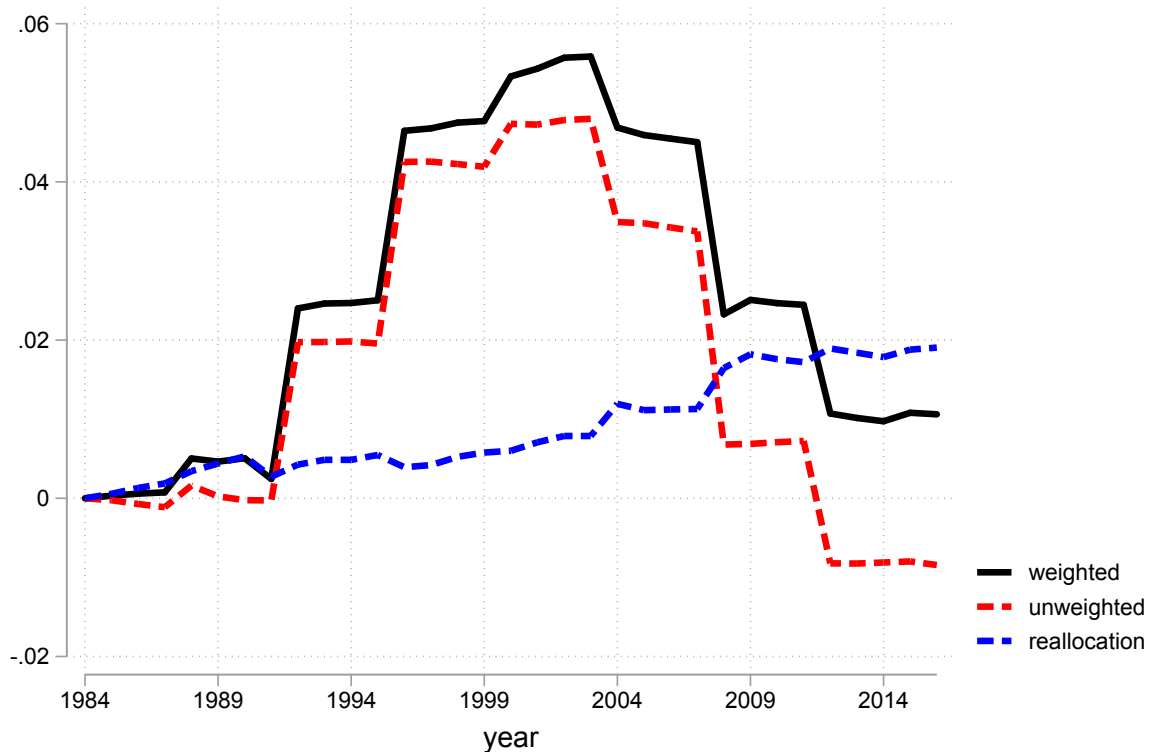
Note: This figure reports the cumulative variations of the weighted and unweighted mean automation parameter α on value-added based on rolling estimation of a value-added production function on the 1984-2016 sample. Reallocation is defined as the difference between the variations in unweighted and weighted mean.

Figure C.13: Weighted and Unweighted Mean Returns to Scale, Non Rolling Value-Added Estimation



Note: This figures reports the cumulative variations of the weighted and unweighted mean returns to scale γ on value-added based on non rolling estimation of a value-added production function on the 1984-2016 sample. Reallocation is defined as the difference between the variations in unweighted and weighted mean.

Figure C.14: Weighted and Unweighted Mean Returns to Scale, Rolling Value-Added Estimation



Note: This figure reports the cumulative variations of the weighted and unweighted mean returns to scale γ on value-added based on rolling estimation of a value-added production function on the 1984-2016 sample. Reallocation is defined as the difference between the variations in unweighted and weighted mean.