Behind the Labor-Share Decline: Worker Power, Market Structure, and Technological Regimes in U.S. Manufacturing

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Abstract

This paper studies the declining labor share in US manufacturing, investigating the underlying mechanisms of worker bargaining power as a key driver. We develop a stylized model showing that an increasing production-to-non-production worker ratio leads to a declining labor share, as production workers have lower structural bargaining power in rent-extraction than non-production workers. We highlight the exposure of heterogeneous within-labor power to sector-specific manufacturing and cyclical dynamic. Leveraging 6-digit NAICS industry data, our empirical strategy builds on a Shift-share granular IV strategy. This allows us to capture shifts in within-industry bargaining power as a key channel. We find a sharp, recession-driven decline in the labor share that only partially reverses during expansions, producing asymmetric distributive effects and marked heterogeneity across technological-sectoral regimes (e.g., ICT-intensive vs. scale-based; tacit-knowledge vs. supplier-dominated). We construct a new industry-level markup measure using an accounting approach, showing that employment composition– rather than rising markups– drives these dynamics. A RIF decomposition of counterfactual kernels confirms that composition effects drive the decline at lower and middle quantiles, while non-negative structure effects support the worker-power channel. Taken together, the findings reveal a novel worker-power channel and offer a new empirical perspective on the cyclical and sector-specific dynamics of the U.S. labor share.

Keywords: Labor Share; Worker Power; Occupational Hierarchies; Technological Regimes; Manufacturing

JEL Codes: E25, J01, J31, J40, J51, L11, L16

1 Introduction

The steady decline of labor share since the 1980s has dominated economic literature in the last decade. This decline is widespread for almost all countries, both developed and developing, but the literature has focused in particular on the US. Specifically, the debate in the literature has focused around the manufacturing sector, especially the US sector, as a case of a school. To shed light on these patterns, we propose a new mechanism behind the dynamics of income distribution in the US manufacturing sector (6-digit) based on the worker power channel. According to the theory we proposed and empirically tested, such power– as granular rent-sharing capacity of workers (voice options proxy)– is exposed to the business cycles dynamics of the labor market (outside options proxy) influencing this workers' ability to appropriate industry' productivity gains. This effect is modulated by sectoral heterogeneity based on microeconomic properties of technological change and industrial dynamics. Our aim is to provide a possible explanation for a complex stylized fact of the US economy.

Why has the decline in labor share attracted so much attention in recent years? What has changed to the dynamics of income distribution compared to the past? Income distribution was, together with the understanding of technological change and its socio-economic spillover effects, one of the main questions on which political economy arose, if not even the main problem as stated by Ricardo (1817). By labor share, we mean the fraction of overall income produced by the economy that is appropriated by workers as wage earners in exchange for the labor offered to produce the final income. By abstracting from the source of rent that produces that final income (Smith, 1776), the other two source- -wages and profits– have attracted numerous analyses. Keynes (1939) pointed out that the labor share for the UK and US from the 1910s to the 1930s was relatively stable, failing to understand this stability he defined it as a 'one of the most surprising, yet best-established, facts in the whole range of economic statistics'. However, this miracle continued even further, to the point that this relativity stability was one of the growth stylized facts of Kaldor (1957). This stylized fact broke down around the 80s especially for the US.

Although the decline of labor share is considered a new stylized fact of our era (Karabarbounis, 2024), at the same time a series of criticisms and methodological considerations have been made. Regardless of any measure considered, the definition of labor share is the ratio between an aggregate compensation measure for the labor factor and a measure of all the aggregate income produced for the economy. Therefore, the labor share is given by the following ratio:

$$\lambda = \frac{W \cdot L}{P \cdot Y}$$

where W is the average compensation per hours worked, L is the total amount of hours worked, P is the price level and Y the total income generated.

The main critical issues concern about the numerator of the labor share: work compensation. Specifically, the literature - trying to answer an apparently simple question such as "What can we actually consider as labor income?" – has identified three main challenges that could bias any measure of distributive share.

The first concerns the treatment of mixed income, self-income proprietors. The scholars wondered how to consider such salary, whether as part of the working salary or as a return on invested capital or a mix between the two. As pointed out by Krueger (1999), correctly pinpointing this component is insidious. Elsby et al. (2013) used different methods to place the income part of self-income proprietors. They attribute about a third of the apparent fall in labor share in the US to the statistical methodology used by the BLS to draw up the headline measure. The second is the increase in depreciation for gross value added associated with a significant increase in the role of intangible capital and investments in Intellectual Property. Following the various reclassifications of the Bureau of Economic Analysis (BEA) on computer software and other IP investments as durable capital goods, Koh et al. (2020) point out that added value is no longer eroded by these types of investments. The third is the increase of housing in value added. For residential housing, mainly used by workers, there is a problem of attributing the income as a return for real estate capital and more generally how to consider such share of the overall income. One way to avoid this may be to focus on the corporate sector (i.e., non-housing) to exclude the portion of labor share that has decreased due to the increase in housing in the value added of the economy (Rognlie, 2016).

Each of these points cast doubt on the fact that the decline in labor share was a global phenomenon (Karabarbounis and Neiman, 2014). In this regard, Gutiérrez and Piton (2020) in their seminal work noticed that when we exclude the housing components and self-employment, there has not been a global decline in labor share, except for Canada and especially US. Given these adjustments, labor share has drastically decreased in US manufacturing, with different trends in Europe. This evidence shows that the decline in labor share is certainly a US fact, with the manufacturing sector as the main contributor to this decline. As they state, the fact that the decline in labor share is not a global phenomenon casts doubt on the set of common explanations, based on technological explanations, for that decline. Based on this methodological evidence, we examine the dynamics of the payroll share– the unambiguous component of the labor share (Gomme and Rupert, 2004)– in U.S. manufacturing at the 6-digit industry level from 1989 to 2016. In this study, we estimate the effect of the technical composition of the labor force on the payroll share across 361 manufacturing industries, focusing on the worker power channel. Our analysis contributes to the literature in four main ways.

First, the literature talking about worker power usually refers to the power of unions, using measures such as density or bargaining coverage (Jäger et al., 2024). Building on the attempt by Stansbury and Summers (2020) to move beyond firm- or industry-level measures of worker representation, our study is the first to exploit within-industry heterogeneity in the labor force based on the hierarchical relationship among workers; that is, their occupational bargaining power. We use the ratio between production and non-production workers, emphasizing the intrinsic power in each category of workers, compared to employers, due to the specific role occupied within production in generating added value for firms .

Second, to grasp factors capable of influencing the power of the two categories of workers within each industry which, if omitted, could bias the estimates, we construct a new indicator of worker power drawing from the shift-share and granular instrumental variable methodology (Gabaix and Koijen, 2024; Goldsmith-Pinkham et al., 2020). We use a 6-digit granular measure of the rent-sharing ability of production vs. to non-production workers as a proxy for voice options: the ability to transfer productivity gains into wages. We make this granular indicator interact with the variation in the national unemployment rate, this as an indicator of workers' outside options.

Third, we study sectoral heterogeneity within the manufacturing sector based on the diversity of innovation patterns in individual 6-digit industries, mapping them into different technological-sectoral regimes (Dosi, 1982; Pavitt, 1984). These regimes, defined according to specific microeconomic properties of technological change in different industries (i.e., sources of knowledge, technological opportunities and appropriability conditions or technological entry barriers). Moreover, such sectoral regimes modulate the effect of industry-specific worker power on income distribution.

Fourth, we show asymmetric cyclical effects of labor market fluctuations (recessions vs expansions) on income distribution. Such effects reveal the inherent asymmetry in the distribution of power not only between firms and workers, but also between different categories of workers: production vs non-production. The former are more exposed to the negative phases of the economic cycle (Hershbein and Stuart, 2024; Yagan, 2019), whose power is weakened further by low aggregate demand, and they do not have the same strength than the latter in transferring productivity gains into wages during the expansionary phases of the cycle. Our work therefore shows dynamics mimicking negative distributive hysteresis.

Our core dataset is the NBER-CES Manufacturing Database, which provides detailed industry-level information on the US manufacturing universe at the 6-digit level from 1958-2016. To this, we have integrated two main datasets: Concentration Subject Series of the U.S. Economic Census for detailed information on industrial concentration ratios from 1997, and level trade flows (exports and imports) data to calculate import-penetration levels for each industry from 1989. Our work originates from a genuine curiosity about whether a positive relationship truly exists between industrial structure and performance—specifically, between concentration dynamics and profitability[1]. In contrast to what can be described as the Kaleckian–Neoclassical nexus (Autor et al., 2020; Kalecki, 1938), we explore whether an inverse relationship exists between the degree of industrial concentration and the dynamics of the labor share. We argue that such a relationship is not ubiquitous but contingent on the specific sectoral regime. To this end, we analyze the sectoral heterogeneity of U.S. manufacturing, shaped by the distinctive technological and learning properties characterizing different regimes (Dosi and Orsenigo, 1988; Pavitt, 1984). Based on specific characteristics, we trace five sectoral regimes in US manufacturing: supplier-dominated (food and textiles), scale-intensive continuous (petroleum and plastic), scale-intensive discontinuous (high-technological routinized sectors, i.e. white and brown manufacturing), specialized suppliers (industrial machinery and instruments), science-based (ICT, pharmaceutical and chemical). This technological-sectoral dimension mediates the relationship between concentration dynamics and profitability dynamics. For the latter, in addition to traditional industrial profitability indices such as ROA and Lerner Index calculated following Grullon et al. (2019), we also estimate a new industrial markup measure inspired by the accounting-approach (Baqaee and Farhi, 2020). The evidence challenges the conventional view that the decline in the labor share is primarily driven by rising corporate power and industry concentration (Barkai, 2020). Instead, it aligns with recent findings on U.S. manufacturing showing that concentration has remained largely constant (Amiti and Heise, 2024) and is not systematically related to either markup dynamics or the decline in business dynamism (Albrecht and Decker, 2025).

Our core question is: *to what extent does worker power offer a more convincing explanation for the decline in the labor share than alternative hypotheses, and how does this explanation strengthen once the technological regimes of U.S. manufacturing industries are taken into account?* To address this, we construct a novel indicator of worker power and introduce a sectoral framing of the concentration–profitability–distribution nexus within U.S. manufacturing.

Rather than using trade union indicators as synonyms of associative power– meant as the ability to join already formed labor market institutions, such as density and bargaining coverage– we use the hierarchical production vs. non-production workers ratio. According to the sociological theory of power resource (Refslund and Arnholtz, 2022), the technical composition of labor can reflect intrinsic dynamics of the labor political power. Over the past decades, U.S. manufacturing has experienced a steady decline in production workers, who have traditionally formed the core of

[1]This positive relationship is a cornerstone of the traditional industrial economics literature (Bain, 1956; Clarke et al., 1984; Schmalensee, 1989)

union membership and for whose representation unions originally were born (Freeman and Medoff, 1984). The manufacturing sector has experienced a downward shift in its labor force composition, declining from nearly 5:1 in the 1960s to about 2.5:1 by 2016. This reduction may partly explain the lack of statistical predictive power of traditional trade union variables (see table 27). This work builds on the idea that production workers hold structurally less power than non-production workers, as their position in the hierarchy leaves the latter in a stronger place from which to bargain with employers.

Among the possible factors influencing this structural power, we consider, on the one hand, the power of workers within-industry (voice options); and on the other hand, the structural conditions of the labor market influencing them differently (outside options). Taking advantage of the granularity of our core dataset, we calculate the ratio of the wage-productivity pass-through between production vs. non-production workers for each of the 361 manufacturing industries. This measures the ability of rent-appropriation within-industry, as an effective sign of the workers' power to transfer higher productivity gains into corresponding wages. Such coupled dynamics have been interrupted since the 1980s and is considered a fact of weakness of the overall workforce (Dosi and Virgillito, 2019; Stansbury and Summers, 2018). The other factor concerns the macroeconomic context determining the outside options. Higher unemployment rates weaken workers' bargaining power to claim higher wages, as unemployment acts a mechanism for containing the conflicting temperature of the labor market (Kalecki, 1943). In fact, higher unemployment is associated with lower wages (Blanchflower and Oswald, 1990, 1995; Gregg et al., 2014). Thus, we make the ratio of pass-through, as the share of granular differential exposure of worker power[2], interact with the change in the national unemployment rate in a granular shift-share IV design.

How much does hierarchical occupational power matter for income distribution? Our baseline IV estimates show a large negative effect of the technical composition of the labor on payroll share: this suggests that a 1% increase in the production vs. non-production workers ratio almost lead to a 1.9% reduction in payroll share. Production workers have less power than non-production workers and are more affected by downturns; a higher share of them reduces income distribution. Our results are robust to the inclusion of an industry-level control variables vector; how the units are weighted in the estimate; to the different and alternative control variables for technological and corporate power factors and to different time windows analyzed. Furthermore, these results are also robust to technological-sectoral differentiation. The worker power channel is strongest and most robust in regimes where production workers play a key role in production process. Finally, these results clearly show a different effect of the phases of the economic cycle: the payroll share appears to be more damaged in periods of increased unemployment than positively influenced by periods of expansion: production workers are more weakened in their ability to extract income at the industry level during recessionary phases.

Finally, we apply the semi-parametric RIF decomposition (Firpo et al., 2009, 2018) to analyze the apparent paradox between changes in the workforce's technical composition and payroll share, disentangling the contribution of each covariates into composition and structure effects across the distribution. The first effect captures how much of the change in payroll share is driven by shifts in the distribution of covariates–that is, how much stems from the population having different characteristics (occupational mix, capital per worker, exposure to foreign competition, markup, sectoral regime, etc.). The second effect captures the portion of the change in payroll share due to shifts in the coefficients (β) linking covariates $\mathbf{X}$ to the outcome Y. In other words, it measures how much of the change comes from differences in the impact (elasticity) of each covariate, holding the dis-

[2]We use worker power as equivalent to bargaining and rent-sharing power.

tribution of covariates fixed. The results confirm the OLS-IV findings: the decline in payroll share is mainly driven by a negative composition effect, which outweighs a generally positive or neutral structure effect. This indicates that, holding characteristics constant, within-industry redistribution hasn't become more "greedy"—industries have not changed how value-added is distributed. The worsening of income distribution is also driven by a strongly negative structure effect for both capital deepening and the production vs. non-production workers ratio, consistent with our hypothesis of declining worker power affecting labor share. In other words, the composition of the labor market limits rent appropriation: production workers have lower worker power than non-production workers, as reflected in the structure effect.

Our work provides new contributions to the literature and important policy evidence. Our analysis disconnects the concentration dynamics from those of profitability, highlighting their specifically technological-sectoral character. Therefore, the decline in labor share is not directly related to dynamics of increase in corporate power. Instead, through a new granular worker power indicator, our estimates highlights that this channel is more compelling than technological and market power explanations. Furthermore, our evidence has important policy implications. If on the one hand antitrust policies are fundamental to mitigate the effects of accumulation of power in the product market, at the same time these are not enough to reverse the declining trend of labor share. As we point out, it is necessary to act simultaneously on strengthening the worker power (of which the unions are only a small part), with direct interventions on production workers. Finally, considering the micro-sectoral nature of manufacturing and the asymmetric cyclical effects, industrial and aggregate demand policies could strengthen workers' bargaining power—particularly for those in structurally weaker sectors and more exposed to adverse economic fluctuations.

Related Literature. The literature attributes four explanations to the decline in labor share[3], especially for the US case. The first is technological change. These works are based on the idea that, following price incentives due to technological improvements, there is an increasingly replacement of the labor factor with capital (Hicks, 1932). The key mechanism is the non-unitary elasticity of substitution, which drives the replacement of production inputs when investment prices—particularly in ICT—fall (Greenwood et al., 1997; Karabarbounis and Neiman, 2014), alongside the adoption of robots and automation at firm-level (Acemoglu and Restrepo, 2018; Hubmer, 2023; Hubmer and Restrepo, 2025). The second is about the role of Chinese imports, especially for US manufacturing (Autor et al., 2013). The mechanism is almost identical to the technological one given the substitution principle underlying it. In fact, the offshoring of US-made production activities in countries with lower labor costs are seen as an attempt to replace tasks carried out by domestic workers with imports of lower-priced final goods (Dorn and Levell, 2024; Elsby et al., 2013). However, this replacement principle can also be activated if materials and labor are complementary factors for production: in this case, a reduction in the detail prices of raw materials imported for production can cause a reduction in labor share due to the replacement with the labor factor (Castro-Vincenzi and Kleinman, 2024).

This work addresses key issues in the literature on the substitution between production factors. We remain skeptical about widespread factor substitution, as suggested by elasticity of substitution estimates (Chirinko et al., 2011; Lawrence, 2015; Oberfield and Raval, 2021). At the same time, we document a strong correlation between labor and capital productivity across sectoral regimes and decades, implying minimal isoquant-driven adjustments: best-practice techniques improve both factors, emphasizing complementarity over substitution (Dosi, 2023; Pasinetti, 1977).

The third explanation is about the increasing corporate power and industrial concentration. Re-

[3]For a thorough review, see Grossman and Oberfield (2022).

cent literature documents a rise in profit shares at the expense of the main factors, capital and labor (Barkai, 2020). This evidence goes hand in hand with a document increase in markup since the 1980s (Loecker and Warzynski, 2012; De Loecker et al., 2020). Indeed, the literature found evidence of increasing industrial concentration for the US (Grullon et al., 2019), negatively associated with labor share (Ganapati, 2021). To explain the link between high markups, high industrial concentration, and low labor share, the literature has drawn on Demsetz's notion of technical efficiency (Demsetz, 1973), which can endogenously increase market power. This is what Autor et al. (2020) refer to as "Superstar Firms": large firms achieve greater productivity gains due to superior technical efficiency, leveraging high fixed costs to adopt the most advanced technologies. This within-industry compositional mechanism drves out less large and efficient industries, increasing in industrial concentration. As a result, superstar firms, with lower labor shares, remain, facing less elastic demand and able to sustain higher markups. This mechanism is highlighted for US manufacturing also by Dinlersoz and Wolf (2024) and Kehrig and Vincent (2021), albeit with different dynamics.

Our work deviates from this univocal and inter-sectoral relationship between industrial outcome and the underlying structure. Drawing on the literature on industrial dynamics and technological change (Dosi, 1982; Nelson and Winter, 2002; Malerba and Orsenigo, 1996; Pavitt, 1984), we trace new evidence that these are mediated by micro-sectoral characteristics. This casts doubt on how much technological-concentration factors are actually behind the dynamics of labor share (i.e., Monopoly Myths: Is Concentration Eroding Labor's Share of National Income?).

The latest explanation provided by the literature concerns labor market power. This includes, on one hand, the effects of employment concentration—particularly in local labor markets—where monopsonistic firm power compresses wages (Azar et al., 2022; Azar and Marinescu, 2024; Gouin-Bonenfant, 2022; Mertens and Schoefer, 2024; Schubert et al., 2025). On the other hand, it emphasizes the role of worker power, shaped either by formal institutions (Ciminelli et al., 2022; Drautzburg et al., 2021) or by a broader decline in overall bargaining strength due to multiple structural factors that have intensified over time (Dosi and Virgillito, 2019; Stansbury and Summers, 2020).

Our work is explicitly linked to this last strand of the literature on worker power. We provide a new power indicator taking into account the loss of rent-sharing power with new estimates on the wage-productivity pass-through. We interact this part of the literature with the literature on sectoral regimes. Our aim is to explore power dynamics behind the distribution of income, which are modulated by the nexus between sectoral regimes and labor market cyclical conditions. This work makes a contribution to both labor and evolutionary industry dynamics literature, providing a new channel through which labor share declines and propagates at a granular-sectoral level.

Roadmap. We organize the paper as follows. Section 2 presents the motivating facts at both macro and industry levels, highlighting why we focus on manufacturing. Section 3 develops the theoretical framework behind the mechanism we test empirically. Section 4 describes the data and empirical specification, including the granular SSIV-based worker power indicator. Section 5 reports baseline results and robustness checks across alternative specifications and estimation strategies. Section 6 presents the semi-parametric RIF decomposition analysis. Finally, Section 7 discusses policy implications and concludes.

2 Motivating Aggregate and Sectoral Facts

We now provide the main empirical evidence motivating our work: we address the reasons of declining labor share in the US and in the manufacturing sector. This section provides an overview of these motivations, starting from the macro context– including a brief discussion of labor share dynamics during recessions– then examining the 2-digit sectoral level, and finally focusing on the US manufacturing sector, which has been central to aggregate labor share changes.

2.1 Aggregate Trends

We analyze the aggregate dynamics of US labor share. The literature wondered what was the best measure to capture the portion of total income produced that actually accrued to labor. Since the aim of this work is not to address such methodological debate, then we use the official labor share released by the Bureau of Labor Statistics. This is the official measure used for the US economy and covers the non-business sector, which is equivalent to approximately 75% of total GDP. The BLS provides official own estimates on the self-owners income component calculated according to the labor-approach of Kravis (1959). This official measure correlates positively with adjustments aimed at including the correct share of self-proprietors' income attributable to the labor factor and not to capital (Karabarbounis, 2024). Furthermore, it uses the gross value added in the denominator (therefore not considering the depreciation of capital), which is useful for highlighting the gap between the dynamics of compensation and labor productivity. That is, how the wealth generated by technological progress is appropriated by workers.

Figure 2 shows the aggregate dynamics of labor share from 1947 to 2024 at a quarterly frequency. Until the 70s the distributive share displayed a stable increasing trend. However, starting from the 70s, there was a slow decline which became more pronounced starting from the 90s, with collapses after 2000 and the Great Recession. Table 1 shows the percentage change in labor share for the different post WWI historical periods. For all the periods examined, labor share has always decreased compared to the previous period. Since the 1980s, the story has been different, with a more significant reduction, even greater than the period characterized by the China Shock. However, the devastating effect of the Great Recession from 2008 onwards stands out, with the Covid-19 period also in between. The recessions, especially the serious and recent ones, have been followed by periods in which labor share has been strongly impacted downwards.

Given these evidences, we investigate the behavior of its cyclical component. Figure 3 shows the cyclical components of labor share with two methods of Hamilton (2018) (HF) and Christiano and Fitzgerald (2003) (CFF). Regardless of the method, labor share clearly shows countercyclical patterns in periods close to recessions. HF shows greater volatility while CF is smoother. However, the countercyclical character is not uniform and depends on specific recessionary episodes. In some of them, it deviates positively from its own trend (1953–54, 1980–82, 2001); in others, however, it deviates negatively (1974–75, 2008–09, 2020).

Table 2 confirms the countercyclical pattern of labor share across business cycle frequencies. Its behavior around recessions and the lagged response relative to GDP dynamics are particularly noteworthy. On average, using both methods, labor share is countercyclical and lags GDP by roughly one quarter—that is, it moves in the opposite direction one quarter after the early expansion phase. Moreover, consistent with the high persistence of the quarterly BLS baseline measure (Mućk et al., 2018), labor share turns procyclical in the following quarters (a rebound effect), as illustrated in figure 3. When output rises above its trend, the labor share moves in the opposite direction, particularly in the period following the onset of expansion. Conversely, when output falls below its trend, the labor share again moves oppositely, anticipating the recessionary phase with a rebound to positive territory. This mean-reverting pattern typically occurs about three quarters after the initial opposite movement of output.

To better characterize the distribution dynamics around recessive phases, we carry out a labor share event study around the eleven post WWII recessive episodes identified by the NBER. Figure 4 displays the dynamics of the labor share during the eight quarters preceding and following the end of each recession. Before each recession, labor share on average tends to increase. After the end of the recession, labor share tends to reduce in the following quarters, with a pronounced persistence. The evidence of countercyclicality is robust to both methods adopted to extract cyclic components.

The countercyclical and specific nature of labor share around the recessive event that emerges from our analysis makes us focus on two factors. First, cyclical phases matter for income distribution. Second, during recoveries, workers' wage compensation does not follow the pace of output. Firms are often reluctant to hire or raise wages (labor hoarding, Okun (1962)), while higher unemployment weakens workers' bargaining power to demand wage increases consistent with the expansionary phase. This leads to a worsening of income distribution. Beyond labor supply effects, we refer to *worker power effects*: downturns weaken workers' ability to negotiate wages in line with the cycle. Can we then speak of distributive hysteresis? This dual interaction—between cyclical phases and the weakening of wage claims—is one of the core theoretical motivations of our analysis.

2.2 Evidence from Sectoral Level

We now investigate the trend of labor share at a sectoral-level, using data from the Bureau of Economic Analysis (BEA) industry accounts. We first examine the 2-digit macro sectors to identify preliminary, though aggregated, signs of sectoral heterogeneity in the dynamics of distributive shares. Solow (1958) noted that what Keynes called "a bit of a miracle" actually concealed compensating sectoral movements beneath aggregate stability. Moreover, examining 2-digit sectoral trends helps clarify why our focus is on the manufacturing sector.

Table 3 shows the labor shares for the 2-digit macro sectors from 1987 to 2023 and the related percentage change. Even though traditional sectors display strong heterogeneity, their labor share has declined sharply, whereas service sectors have experienced an increase. Moreover, among the more traditional sectors, mining (21), manufacturing (31-33) and retail trade (44-45) stand out above all. The same table also reports each 2-digit sector's contribution to total value added and the corresponding percentage change in labor share over the same period. The manufacturing sector's value added share has declined strongly, especially if compared to the other two sectors which saw a significant reduction in labor share such as mining and retail trade. Since the manufacturing sector (31–33) experienced the strongest decline in labor share alongside substantial structural change (Fort et al., 2018; Pierce and Schott, 2016), its fall is particularly significant given the sector's historical importance for the entire US economy (Baily and Bosworth, 2014). This phenomenon is striking for US, even if it is not limited only to it.

Moreover, US manufacturing is a school case because has been the sector most exposed to international competition (Boehm et al., 2020). As a further motivation for the study of income distribution in US manufacturing, it is the sector with the highest decline in unionization (Farber et al., 2021). This draws a line between the decline of union power and the increase in inequality, common not only to the US economy (Jaumotte and Osorio Buitron, 2020).

2.3 Evidence from the US Manufacturing

We now delve into the US manufacturing sector, which has played a key role in the movements of income distribution underlying the aggregate dynamic. We provide empirical evidence for our mechanism and the general hypothesis we want to test in the next sections. To analyze US manufacturing in detail, the core dataset we use is NBER-CES Manufacturing Dataset (Becker et al., 2021). Figure 5 shows the dynamics of the payroll share for the whole manufacturing sector by aggregating the 361 manufacturing industries. As noted by Gutiérrez and Piton (2020), the payroll share in US manufacturing has declined sharply, showing no signs of reversal.

The payroll share is the value-added weighted sum of the payroll shares of each of the 361 industries in the total manufacturing sector:

$$\lambda_{jt} = \sum_j \lambda_{jt}\omega_{jt} \quad \text{with} \quad \omega_{jt} = VA_j/VA, \lambda_{jt} = W_jL_j/VA_j \tag{1}$$

Is this fall a phenomenon within or between industry? The answer helps us understand where to look for the reasons of this collapse. To do this, we apply a shift-share decomposition in order to separate the within from the between component. We decompose changes in the aggregate payroll shares, equation 1, into two components:

$$\Delta\lambda = \underbrace{\sum_j \tilde{\omega_j}\Delta\lambda_j}_{\text{Within}} + \underbrace{\sum_j \tilde{\lambda}\Delta\omega_j}_{\text{Between}} \tag{2}$$

Here, $\tilde{\omega_j}$ is the time average (between two periods) value-added share of each manufacturing industry j in total manufacturing sector value-added; similarly, $\tilde{\lambda}$ is the time average of weighted labor share for each industry j. The within-component indicates how much each 6-digit industry changes its own payroll share. The between-component measures the reallocation of value added towards industries with lower payroll share.

Figure 6 gives the results of equation 2. The two panels show that the fall in payroll share is strongly dominated by a decline within the industry. The panel 6a shows the decomposition of the payroll share by accumulating the variations year after year. The panel 6b shows a decomposition year-by-year. The within component is always dominant in any direction of variation, both positive and negative. Table **??** shows the two components and their share in explaining the change in payroll share for the different periods between 1958 and 2016. It confirms the within-industry decline, even between 2010 and 2016 where there was a slight reversal of trend compared to the past.

The decline in labor share do not depend on a reallocation effect of added value towards industries with a lower labor share (i.e, the value added share of manufacturing industries has shifted towards the pharmaceutical or ICT sectors with a lower labor share). Rather, the steady decline in labor share is a within-industry phenomenon.

2.3.1 Within-Industry-Regime Micro Correlations

2.3.1.1 Technological Variables First, we investigate technological dynamics within-industry manufacturing, according to an input-output relationships. We aim to assess the degree of technological plasticity within industries: that is, how easily technological advances lead to substitution or rebalancing among production inputs (capital and labor). These aspects are crucial for understanding industry-level income distribution dynamics.

We analyze the degree of technical efficiency of each industry, measuring the labor and capital productivity. These two measures capture the level of production efficiency by industries mastering the two main factors of production. Given the heterogeneity in both firm-level and within-industry (Bottazzi et al., 2007; Syverson, 2004), we expect importants differences in how each industry masters the production techniques.

Table 5 shows the two technical efficiency measures are strongly positively correlated at a manufacturing disaggregated-level. This relation holds regardless of any measure of capital used: either total capital or its components, equipment or plant (fixed structures) capital. The sign of this relationship remains unchanged regardless of the estimate made, either pooled OLS or FEs. When controlling for macro time shocks (recessions, price spikes, wars) common to all industries, the relationship turns slightly negative but remains economically negligible.

Has the relationship between technical efficiency measures changed over time? Table 6 also explores possible temporal heterogeneous patterns. Due to the common denominator, industries with a more intense use of capital could have increased the productivity of the capital factor penalizing the labor factor. This may explain why pooled OLS is always strongly negative, reflecting the cross-industry composition. Hence, we include fixed effects to absorb common shocks and industry-invariant characteristics (such as average intensity) that could bias the estimates. Industry FEs provide strongly positive estimates for all the time periods. Time FEs provide negative estimates, even if with a negligible magnitude. When we isolate the idiosyncratic covariance within-industry and over time (Two-Way FEs), the relationship is strongly positive along all the different time periods examined (0.20-0.58). Given the log-log econometric specification, when an industry enjoys technological advancement that increases the productivity of one factor of production, then the productivity of the other factor also increases in turn.

Nonetheless, we explore the within-manufacturing-heterogeneity sector. Therefore, we extend the taxonomy proposed by Pavitt (1984) and apply it to US 6-digit manufacturing. This sectoral classification captures the dynamic evolution within each industry– its innovative sources, technological patterns, firm size, and overall structure– identifying five distinct regimes. The five regimes comprise the following subset of sectors[4]:

1. Supplier-dominated. Industries are characterized by small firms, which cannot perform sufficient R&D activity for technological advances (Acs and Audretsch, 1988). Thus, technological change in these industries is introduced from outside by the acquisition of production inputs and machinery from industries producing them. Industries are textiles, clothing, metal products, etc.

2. Specialized-suppliers. Industries mostly supply intermediate products to produce final products in other downstream sectors, such as supplier-dominated. Average firm size is small: innovations are process-driven and are mainly affected by the requests of their customers (Von Hippel, 2010). R&D activity plays an important role, even if technological change is supported by the tacit nature of knowledge (i.e., we know more than we can tell, Polanyi (1966)) and the degree of embodied skills that workers refine along the assembly line.

[4]We consider this granular differentiation a refinement of the sectoral imbalances identified by Acemoglu et al. (2024). Table 7 shows how the 361 NBER-CES manufacturing industries have been classified under the different sectoral-technological regimes.

3. Scale-Intensive. Industries are strongly influenced by the production scale (i.e., the automotive sector). The scale of production and the overall demand affecting the size produced stimulate the innovation activity. Since technological change is incremental, then industries are characterized by a widespread knowledge-base dynamic increasing returns (David, 1985). At the same time, to innovate (both at the product and process levels), these industries adopt science-based production inputs.
   (a) Scale-Intensive Discontinuous. These are complex-product industries such as: automobiles, white goods and other consumer durables.
   (b) Scale-Intensive Continuous. These are flow industries such as oil refining or steel making.
4. Science-based. Industries base their innovative capacity on the co-evolution between internal (R&D) and external (scientific knowledge) knowledge sources (David, 2001; Klevorick et al., 1995; Mokyr, 2011). Innovations are strongly product-oriented. Industries are pharmaceutical, chemical, ICT and semiconductor.

Figure 7 displays a robust positive relationship between labor and capital productivity within each technological–sectoral regime. This holds when we consider equipment-capital and structures (plant) capital separately. At a granular within-industry level, this evidence runs against a standard substitution narrative: rather than trading off along isoquants in response to relative prices, factor efficiencies tend to rise together. In our log–log specification, technological upgrades are associated with a more efficient use of both capital and labor. In fact, the positive co-movement between the two productivity measures is consistent with factor complementarity and with joint technological improvements that raise both labor and capital efficiency[5] . In short, US manufacturing is a world of complementarity rather than substitution. However, our analysis focuses only on physical capital, even when distinguishing between its components: equipment and structures. A promising avenue for future research would be to examine, especially at the firm-level, the role of intangible capital (Crouzet et al., 2022), and assess its potential degrading effects on income distribution (Aum and Shin, 2024).

Finally, the capital deepening process is a structural characteristic of every technological trajectory (Bresnahan, 2010; Dosi, 1982). Any technological improvement within a trajectory makes the entire system (in this case, the manufacturing sector) tend towards a constant mechanization of productivity (see figure 8). This phenomenon has characterized industrial capitalism since its origins (Chandler, 1993), to the point of being considered a natural trajectory (Nelson and Winter, 1977). By natural, we mean a spontaneous process of substituting human effort with inanimate energy embodied in physical capital, independent of relative price movements. Indeed, the lack of alignment between movements in relative prices, capital deepening, and distributional share dynamics was highlighted by Elsby et al. (2013) and Grossman and Oberfield (2022).-

2.3.1.2 Concentration-Profitability Nexus The US industrial structure has been characterized by an increase of industrial concentration, which can be seen as a centuries-old phenomenon (Kwon et al., 2024). The increasing industrial concentration is a stylized fact of the new capitalism stage

[5] We deliberately avoid interpreting this as direct evidence of the elasticity of substitution σ: under constant returns to scale, the sign of $\mathrm{cov}[\ln(Y/L), \ln(Y/K)]$ mainly captures common technological shocks rather than σ itself. Nevertheless, the observed complementarity aligns with numerous empirical estimates of a non-unitary, below-one elasticity of substitution (Chirinko et al., 2011; Chirinko and Mallick, 2017; Knoblach et al., 2020; Gechert et al., 2022; Oberfield and Raval, 2021).

of advanced economies, both in the US (Grullon et al., 2019), and the Europe (Bajgar et al., 2023; Bighelli et al., 2023). Moreover, numerous studies have shown that rising industry concentration and corporate power go hand in hand with declines in investment rates (Gutiérrez and Philippon, 2017; Gutiérrez and Philippon, 2017), firm entry (Decker et al., 2016), and labor share (Autor et al., 2020; Ganapati, 2021).

We therefore analyze the dynamics of industrial concentration for the manufacturing sector, using US industrial concentration data. Since the Census Bureau released the 6-digit NAICS code series starting in 1997 censoring every five years, we use five census time intervals from 1997 to 2012. The advantage of these data is that they cover private industries as well, rather than being limited to publicly traded firms (Compustat), which are not representative of the underlying concentration dynamics—particularly in the manufacturing sector (Ali et al., 2008; Keil, 2017). Our data capture industry-wide concentration dynamics in the product market, without revealing underlying patterns at the local or product-level on the consumer-side, which may diverge from national trends (Rossi-Hansberg et al., 2021). Nonetheless, this level of observation is well fitting for the purposes of our work.

Table 9 shows that increases of concentration are relatively small: the evidence has shown that it is one of the sectors with a limited increase in manufacturing (Amiti and Heise, 2024; Davis and Orhangazi, 2021). The manufacturing sector exerts a compressive force downwards w.r.t. other sectors where industry concentration has increased (Smith and Ocampo, 2025). Overall, we highlight an increase in industrial concentration, for any measure of the largest n firms we use (either they are 4, 8, 20 or 50).

How important is technological-sectoral specificity in trends of increasing concentration? Aggregate sector-wide increases may mask movements and characteristics underlying industrial dynamics. Understanding the role of such features is important for identifying key industries, and their characteristics, underlying increasing concentration. Table 10 reports the percentage change in concentration ratios across technological regimes. Rather than focusing on growth rates, we use levels of industrial concentration, as they better capture the persistence of market power. This persistence perspective is crucial when analyzing the connection between concentration and profitability.

Industrial concentration has increased significantly in three technological–sectoral regimes: supplier-dominated, specialized suppliers, and scale-intensive continuous. By contrast, the scale-intensive discontinuous and science-based regimes experienced a decline in concentration. This sectoral heterogeneity partly challenges the dichotomy between *good* and *bad* concentrations, respectively technological factors and barriers to entry hindering market competition (Covarrubias et al., 2020). While the sources of concentration lie beyond the scope of this study, future research could investigate whether, and to what extent, technological factors (Labini, 1962; Stigler, 1958) (such as increasing returns, the pursuit of greater technical efficiency, and the exit of less efficient firms from the industry) and legal–institutional factors (Khan, 2017) (such as entry barriers, the relaxation of antitrust policies, and patents) have indeed affected rising concentration. It would also be relevant to examine whether differences can be observed within sectoral regimes where firms share similar technological knowledge, yet display heterogeneous outcomes.

One of our aims is to analyze the within-manufacturing concentration-profitability nexus. Understanding how this relation evolves helps to frame the mechanisms shaping within-industry income distribution. Specifically, we aim to characterize how the industry-level ability to extract rents is influenced by the degree of industrial concentration, and how this, in turn, affects the micro-sectoral labor share.

The IO literature continues to debate whether the link between concentration and profitability reflects market power or technological efficiency (Clarke et al., 1984). Both perspectives find an ex-post positive association between concentration and profits. On one hand, evidence shows that rising concentration since the 1980s has corresponded with higher markups and profits, alongside a decline in labor share (Barkai, 2020; De Loecker et al., 2020). Here, higher markups reflect corporate power, not efficiency, allowing firms to sustain large price–cost margins compressing wages (Syverson, 2019). On the other hand, the efficiency view (Demsetz, 1973) argues that more efficient firms expand at the expense of less efficient ones, adopting technologies faster and with lower costs, which increases concentration through within-industry reallocation (Autor et al., 2017; Bessen, 2020; Ganapati, 2021). At the end of this process, the superstar firms will remain, which for technological reasons will have a higher price-cost markups and therefore a lower labor share.

We provide new evidence on the concentration–profitability nexus. We interpret concentration as an indicator of the structural features of a highly heterogeneous industry, rather than a direct measure of market power. Profitability, instead, is examined through newly developed rent-extractivity indices, as industry-level proxies for market power. We employ three profitability measures, including a newly constructed markup indicator.

The first two are the industry-wide equivalents of the ROA and Lerner Index. For their calculation, we follow Grullon et al. (2019) using the NBER-CES dataset. ROA (Return On Assets) is an industry-level profitability measure: profits for each industry are scaled w.r.to the total capital stock used, as an industry-level assets proxy. The Lerner Index rescales profits w.r.to the industry sales value, as an industry-level proxy for profit margins. In Appendix (), we provide a detailed explanation of each variable used in the above equations.

$$ROA_{jt} = \frac{Shipments_{jt} - (Payroll_{jt} + Material_{jt} + Energy_{jt})}{Capital_{jt}} \tag{3}$$

$$Lerner_{jt} = \frac{Shipments_{jt} - (Payroll_{jt} + Material_{jt} + Energy_{jt})}{Shipments_{jt}} \tag{4}$$

We then estimate a new industry-level markup variable using the accounting-profits approach, which requires minimal data manipulation and offers high transparency. As Baqaee and Farhi (2020) note, despite its simplicity, this method provides results comparable to more structural approaches. This suggests that most markup variation aligns with firms' operating accounts (operating income), on which our industry-level accounting measure is also based. The appendix A.3.1.1 shows why and how we estimated the new measure, the time series for the manufacturing sector and for the different sectoral regimes as well as the different methodological issues related to the markup estimation.

$$\mu_{jt} = \frac{Shipments_{jt}}{Material_{jt} + Energy_{jt} + Payroll_{jt}} \tag{5}$$

We use the above measures to test the concentration-profitability nexus. The aim is to understand whether there is a positive relation, i.e., firms in more concentrated industries obtain greater profits and greater market power, or whether it is less obvious than predicted.

Table 11 shows the OLS estimates, using both CR4 and CR8 as independent variables. We estimate the effect of an increase in industry concentration on profitability. Since the concentration-profitability pattern can hide sectoral heterogeneities and can be influenced by time-specific factors, we use the TWFE. A 1% increase in concentration leads to an increase in profitability by almost 0.4%. The results do not change when we check for industry-level characteristics (Gutiérrez and

Philippon, 2017), such as the total value of the shipments and the stock of capital used as an industry-size proxy.

Is there a uniform pattern even when disaggregating by sectoral regimes? We repeat the same exercise differentiating for different regimes. Tables 12 and 13 provide the OLS estimates of the profitability indices on CR4 and CR8, respectively. Contrary the the aggregate results (Table 11), and with the standard relationship predicted by theory– whether grounded in market power or technical efficiency– the relationship appears to be strongly mediated by sectoral technological regimes, and is often weak, absent, or even negative. We always use TWFEs because there are persistent inter-industrial within-regime heterogeneities. The nexus is absent, and in some cases even negative, though statistically insignificant. More concentrated industries actually appear to exhibit higher competitive pressures. The only regime showing a positive and significant link is Supplier-Dominated, which is surprising given its low-tech nature. Science-Based industries also display a positive, though insignificant, relationship, while more traditional regimes show no clear connection[6].

There is no clear link between higher markups and greater concentration. Consistent with recent IO evidence (Albrecht and Decker, 2025), corporate power appears disconnected from industry concentration dynamics, which in turn are unrelated to both market power and technological efficiency explanations, as reflected in our sectoral differentiation. Therefore, this evidence questions the view that the decline in labor share was driven by rising industrial concentration, which is absent in manufacturing (Amiti and Heise, 2024). Moreover, corporate power seems independent of underlying market concentration. Instead, the pattern suggests that corporate power may have expanded as a consequence of weakening worker power, further supporting our argument in light of both the concentration trends and the lack of connection between concentration and profitability.

2.3.1.3 Labor Unions and Declining Worker Power We find evidence of a reduction in workers' ability to extract income for the US economy, as sign of declining worker power in US manufacturing. The first worker-side stylized fact is the decline in unionization. Unions provide workers with greater voice, strengthening their ability to claim higher wages and better conditions, or even to credibly threaten organizing in non-union firms (Farber, 2005; Freeman and Medoff, 1984). In the US economy, unions have been a strong driver of rent-sharing for workers, both for unionized and non-unionized workers as a spillover effect (Farber et al., 2021). Extensive literature has shown the steady decline of the union wage-premia, both at firm and industry-level (Western and Rosenfeld, 2011). In particular, figure 13a shows a steady falling manufacturing union density and coverage rate by 57% and 56% respectively. Figure 13b shows the same differentiated pattern for sectoral regimes.

The main drivers of declining unionization are institutional. Since the 1980s, policies have weakened within-firm bargaining (Western and Rosenfeld, 2011), including the expansion of right-to-work laws (Fortin et al., 2023), while broader shifts in public opinion on unions' role (Levy and Temin, 2007) have further eroded their influence as a social force. Moreover, deunionization is seen as the endogenous product of technological change (Acemoglu et al., 2001), and greater external competition (Ahlquist and Downey, 2023; Baldwin, 2003). However, these technological factors alone do not fully explain the widespread decline in unionization, which affects sectors with very different levels of technological exposure and international competition. Moreover, the United States has experienced a much sharper decline than other countries, even with similar levels

[6] This may reflect non-linearities. Future research could examine if a critical threshold (Dalton and Penn, 1976) shifts the concentration–profitability relationship across sectoral regimes.

of technological change and international competition (Stansbury and Summers, 2020). Among economic factors, the entry of non-union firms into U.S. industries has also played a significant role. Entry and exit dynamics tend to favor these firms, which compete primarily through cost-based strategies rather than productivity improvements. Their main strategy for staying in the market is to offer wages below the average of unionized firms (Dosi et al., 2021). Hence, de-unionization can emerge as an endogenous process driven by the entry of new firms employing non-union workers (Bryson et al., 2018).

Another factor contributing to the weakening of workers' voice is the technical composition of the labor force—the ratio of production to non-production workers. Changes in this ratio shed light on shifts in workplace representation and the distribution of power, revealing workers' potential to extract rents within firms and industries. First, on the associative side, production workers—typically less mobile and less educated—have historically relied on unions to voice their demands; hence, a declining ratio parallels the fall in unionization. Second, on the structural side, it reflects firms' internal employment hierarchies, shaping the relative power of workers within industries. The position each group occupies within the job hierarchy reflects both their contribution to value-added creation and their ability to negotiate wage increases consistent with that contribution. Generally, non-production have a greater extractive-capacity than production workers, for many reasons going beyond the technological explanations. In section 3 we will provide the theoretical channel underlying the division of labor-worker power nexus for US manufacturing income distribution dynamics.

Panel 14a displays the evolution of the production-to-non-production worker ratio in manufacturing. In the 1960s, production workers dominated, almost five-to-one non-production worker. Since the 1970s, the ratio has steadily declined, reaching about two-to-one by 2009. As discussed later, this shift has had major implications for both worker power and income distribution. Panel 14b shows this trend across technological regimes. Traditional regimes remained relatively stable, with a slight rise in the Scale-Intensive Discontinuous regime. Within this regime, the sharp drop during the Great Recession stands out, though unsurprising given the prominence of the automotive sector (NAICS 336). By contrast, other regimes saw substantial declines in their technical labor composition.

Finally, as a further rent-sharing ability factor in US manufacturing we analyze the wage dispersion for the two categories of workers across all the granular manufacturing industries. The wage differences between industries can reflect rent-sharing with workers (Abowd et al., 2012; Dickens and Katz, 1987; Krueger and Summers, 1988), which are an industry-wage premia. We therefore estimate the dispersion of the fixed-effects of wages per employee, for production and non-production workers, as a within-industry-manufacturing rent-sharing proxy.

Figure 15 reports the standard deviation of our estimates for the two worker categories. Controlling for industry-level characteristics, we interpret wage differences captured by fixed effects as a proxy for workers' ability to extract rents within industries. A clear divergence emerges: production workers experience a marked decline in wage dispersion—indicating shrinking residual rent-sharing—while non-production workers show the opposite pattern, with dispersion rising substantially. Although we cannot directly test for sorting effects, we include labor productivity as a control. Our results align with recent evidence on the decline in inter-industry wage variance (Kim and Sakamoto, 2008; Stansbury and Summers, 2020). Further details on the estimation of fixed effects are provided in appendix A.3.1.2.

As a robustness check, we replicated the estimation without distinguishing worker categories. For total compensation per worker, we find an increasing trend, consistent with Haltiwanger and

Spletzer (2020). This further supports our evidence that the production-to-non-production worker ratio has significant implications for income distribution, whose effects are often masked when labor heterogeneity is ignored.

3 Theoretical Mechanism, Worker Power and Sectoral Regimes

We now propose the rational for a new theoretical framework that emphasizes the worker power channel as a key driver underlying the income distribution dynamics. In particular, we introduce hierarchical occupational power: we introduce asymmetry not only between employers and employees' power, but also within the workforce. Power is not uniformly distributed between production and non-production workers. We define worker power as the capacity to convert productivity gains into higher wages, enabling workers to claim a greater share of rents at the expense of other factors. Within the workforce, the power differs according to the position along the internal division of labor. As previously mentioned, a worker's position within the internal division of labor confers structural power (Refslund and Arnholtz, 2022), which, for various reasons, alters their interactions with the employer and affects their ability to extract income.

The division of labor, while distributing tasks to secure productivity gains and control for the employer (Smith, 1776), also generates an asymmetric distribution of knowledge and power among workers (Braverman, 1974; Cetrulo et al., 2020). Consequently, this power asymmetry manifests within the labor force itself. The role of production and non-production workers not only expresses a spontaneous distribution of tasks (Autor, 2015; Goldin and Katz, 1999), but rather provides an indication of the underlying power structures. Managerial and supervisory roles, positioned at the top of the hierarchy, are closer to the employer and thus hold significantly more power than manual productive roles. A distributive conflict within labor arises because both groups contribute to the income appropriated by the firm. The resulting power dynamic is fundamentally zero-sum: gains for one group imply losses for the other.

3.1 A Stylized Model of Worker Power and Labor Share

We characterize the compositional channel of the workforce in a stylized model, where heterogeneous worker power is a key driver for labor share dynamics. To stress the complementarity of the input factors, we assume a fixed-proportions production function. We assume the existence of only physical capital stock, K, and heterogeneous labor factor, distinguishing between production, L_B, and non-production workers, L_W[7].

We assume homogeneous output. Moreover, since there no intermediate inputs in this model, final output coincides with value added. This makes compatible it with our empirical design and the variables we use.

$$Y = \min\{\, a_B L_B,\ a_W L_W,\ a_K K \,\} \tag{6}$$

where a_B, a_W are the labor productivity of production and non-production workers; a_K is the capital productivity. By deriving the labor demands, we get the technical composition of labor force:

$$\vartheta_L \equiv \frac{L_B}{L_W} = \frac{a_W}{a_B}, \qquad \text{convention: keep } a_B \text{ fixed and set } a_W = \vartheta_L\, a_B \tag{7}$$

[7] We use B and W as subscripts to distinguish the two components of the work factor by referring to blue and white collars respectively.

We now introduce the key behavioral assumption underlying our theory and empirical design we built on it. Wages, shaped by relative power relations, follow the total productivity contributed by all workers, both production and non-production. As a result, wages are directly proportional to the capacity to appropriate those productivity gains.

$$W_B = \rho^B A, \qquad W_W = \rho^W A, \qquad \rho^W > \rho^B > 0 \tag{8}$$

where A is the total labor productivity (i.e., $A = a_B + a_W$). Given the markup-pricing rule, the unit cost of production is given by the sum of unit labor costs (for both production and non-production workers) and unit cost of capital[8].

$$p = (1+\mu)\big(ULC_B + ULC_W + UMC\big) \tag{9}$$

where $\quad ULC_B = \dfrac{W_B}{a_B} = \dfrac{\rho^B A}{a_B}, \quad ULC_W = \dfrac{W_W}{a_W} = \dfrac{\rho^W A}{a_W} \qquad UMC \equiv \frac{\varphi}{a_K} > 0.$

where φ is the cost of capital.

By writing unit labor cost as a function of the compositional ratio 7, the labor share is defined as follows:

$$\lambda_{\vartheta_L} = \frac{c_L(\vartheta_L)}{(1+\mu)\,[\,c_L(\vartheta_L) + UMC\,]} \tag{10}$$

***Proposition* 1.** *The elasticity of the labor share to the labor composition (Production vs. Non-Production workers) is given by:*

$$\frac{d\lambda_{\vartheta_L}}{d\vartheta_L} = \underbrace{\frac{\varphi}{(c_L+\varphi)^2(1+\mu)]}}_{>0} \cdot \left(\frac{-A\rho^W}{\vartheta_L^2 a_b}\right) < 0 \tag{11}$$

where $c_{\vartheta_L} = \frac{\rho^B A}{a_B} + \frac{\rho^W A}{\vartheta_L a_B} = \frac{A}{a_B}\left(\rho^B + \frac{\rho^W}{\vartheta_L}\right).$

According to proposition 1, an increase in production vs non-production workers leads to a reduction in labor share, given the complementarity of the factors (i.e., a necessary condition is that the capital is positive). An increase in this composition makes the workforce more unbalanced towards workers with lower power, therefore a lower extraction capacity which lowers the entire distributive share that the workforce can grab. The full mathematical derivations of the above equations and proposition 1 are provided in Appendix B.

3.2 Intuition

We now outline the intuition for Proposition 1: an increase in the share of low-power workers (e.g., production or blue-collar) reduces the average bargaining power of the workforce. This weakens the wage-productivity nexus and, consequently, the labor share—particularly when capital costs are non-zero.

Imagine that the value added is divided between the production factor: labor and capital. Given the labor heterogeneity, production and non-production workers hold different power, due to the

[8]For simplicity, and to maintain consistency with the empirical analysis, we conventionally assume that the capital factor encompasses all material factors of production. Accordingly, we denote its unit cost by UMC.

role along the corporate hierarchy vis-à-vis to the others. Thus, non-production have a greater ability to appropriate productivity gains than production workers. An increase in the share of production workers relative to non-production workers has a double reinforcing effect. First, a compositional effect makes the workforce more blue-collar-intensive, thereby lowering its average bargaining power. Second, because production workers' wages decouple from productivity growth and they represent the majority, overall labor costs are reduced for firms. Given the labor-capital complementarity, an increase in production vs. non-production workers reduces the labor share[9]. Indeed, when unit labor costs fall due to weaker bargaining power, such fixed cost ensures an increasing of profit share at the expense of the labor share (Barkai, 2020).

This theoretical result motivates our empirical test of a negative relationship between the production vs. non-production workers ratio and the labor share. Moreover, sectoral-technological trajectories can affect the division of labor and then the skewness of power between production and non-production workers. Contrary to the skill-biased technological change narrative (Acemoglu and Autor, 2011; Goldin and Katz, 1998; Katz and Murphy, 1992), we argue that worker power is rooted primarily in job characteristics, not in ex-ante educational attainment. In our framework, hierarchical position is built upon firm-specific skills acquired on the job. Through a process of osmosis with their work, workers assume roles whose value is intrinsically linked to their tasks and organizational environment (Cohen et al., 1996). It is the broader techno-sectoral regime, therefore, that modulates the expression of this power. We provide a framework for understanding the heterogeneity we expect to find across different technological-sectoral regimes (e.g., ICT-intensive vs. supplier-dominated), which systematically alter the power gap, $\rho^B - \rho^W$, and thus the sensitivity of the labor share to changes in workforce composition.

Technological-sectoral regimes are characterized by distinct forms of technological knowledge and labor requirements. Because the demand for their output exhibits varying degrees of elasticity, these regimes face differential exposure to cyclical fluctuations in aggregate demand. Through this co-evolution of a sector regime's productive structure with the demand elasticity for its products, the cyclical macroeconomic conditions of labor market affect the within-industry workers' power. Recessive periods, characterized by rising unemployment, weaken aggregate worker power by diminishing their outside options (Kalecki, 1943; Blanchflower and Oswald, 1995). This occurs because higher unemployment reduces wage resistance and strengthens corporate power by improving their outside options. Therefore, rising unemployment enable firms to impose lower wages on the employed workforce given a rise in labor supply. Sectoral regimes modulate the interaction between general macroeconomic conditions of the labor market and worker power (see 1), amplifying or not the final effect on income distribution given the technical composition of the workforce.

Such adverse macroeconomic labor market conditions not only weaken worker power overall but also exert an asymmetric effect due to the pre-existing within-labor power differentials. The effects of these conditions on production and non-production workers will differ substantially. In particular, a worker's position in the corporate hierarchy determines how macroeconomic fluctuations influence their ability to extract productivity gains. During recessions, the pass-through parameter for production workers (ρ^B) erodes more significantly than that for non-production workers (ρ^W). This asymmetric erosion of bargaining power exacerbates the decline in the labor share outlined in Proposition 1 and underlyies the distributive asymmetries we observe empirically.

[9]This effect occurs because a portion of the value added must always be allocated to cover the non-zero cost of capital (equation 11, where $UMC \equiv \varphi/a_K > 0$).

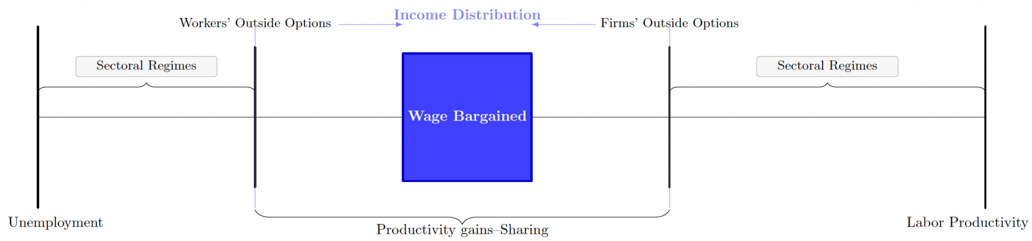

Figure 1: Distribution of Rents and Bargaining Conflict

4 Data and Empirical Strategy

We now test our underlying hypothesis stated in Proposition 1. Our aim is to explore the theoretical mechanism across the narrowly defined manufacturing industries, and testing it also for the different sectoral regimes. We are therefore interested in estimating the elasticity of the labor share with respect to the technical composition of labor. Hence, we specify the following baseline regression equation over the period 1989–2016:

$$\log\lambda_{jt} = \alpha + \beta \times \log\left(\frac{BC_{jt}}{WC_{jt}}\right) + \gamma \times \log\mathbf{X_{jt}} + \delta_j + \delta_t + \epsilon_{jt} \tag{12}$$

where j denotes an industry, t denotes time, λ_{jt} is the industry-level payroll share– defined as the ratio of total payroll to total value added: the *unambiguous* part of labor share (Gomme and Rupert, 2004). Our regressor of interest is $\frac{BC}{WC}_j t$: the production vs. non-production workers ratio. We include a vector of industry-level controls $\mathbf{X_{jt}}$, industry (δ_j) and time effects-fixed (δ_t), an d the error term ϵ_{jt}. The error term may capture factors not accounted for by sectoral and time dummies, including those related to technological change, international competition, or industrial structures altering the elasticity we estimate. To address this, we control for a set of industry-specific characteristics such as capital intensity, price variables (i.e., energy, materials, investments), import penetration, profitability, and industry concentration.

While our empirical specification accounts for key observables, the error term may still capture unobserved factors influencing how the technical composition of labor shapes income distribution. Among these potential confounding channels, we focus on the role of worker power, as the interaction between within-industry bargaining power and macroeconomic labor market conditions. This channel operates through two main mechanisms: i) industry-level rent-sharing power, ii) and the broader macroeconomic context where unemployment affects workers' outside options and thus their ability to translate productivity gains into wages[10]. To disentangle this specific mechanism, we construct a new indicator of worker power using a granular Shift-Share IV design. This approach allows us to open up the black box of confounding factors and isolate this channel through which worker power transmits compositional changes into distributional outcomes.

[10]We acknowledge but exclude geographical-institutional factors such as right-to-work laws, which have been shown to weaken workers' structural power (Brady et al., 2013; Farber, 1984; Feigenbaum et al., 2018). While relevant, these dynamics lie beyond the scope of our current identification strategy.

4.1 Data Sources

To estimate the baseline equation 12, we mainly use three data sources. The core dataset is the NBER-CES Manufacturing Industry Database (Becker et al., 2021), which provides a panel of detailed industry-level information. Appendix C.1.1 documents our core dataset and the procedures for constructing the additional variables used in this study.

To check for international competition trends, we calculate the import penetration for each manufacturing industry using industry-level trade flows (exports and imports) from Peter Schott. Appendix C.1.2 details the use of this data and the calculation of import penetration.

We incorporate concentration dynamics using the U.S. Economic Census Concentration Subject Series (1997, 2002, 2007, 2012), which narrows the sample that includes this control. Appendix C.1.3 provides details on the data handling.

Finally, we use unionization data (Density and Coverage) constructed by Barry Hirsch and David Macpherson. Appendix C.1.4 provides details on how we mapped industry-level data on unionization from 4 to 6-digit.

4.2 Constructing a Worker Power Indicator

We construct our within-industry measure of workers' bargaining power. Our aim is to capture the ability to bargain and rent-sharing patterns within each manufacturing industry at the 6-digit level. Given the structural worker power specific to the occupational-hierarchical structure of each industry, our structural measure of worker power is the wage-productivity pass-through between production and non-production workers for each industry j.

Our granular indicator directly measures worker power as the intrinsic ability to translate productivity gains into wages, a capacity shaped by the hierarchical employment structure. Following the approach of Stansbury and Summers (2020), we interpret the wage-productivity pass-through as a direct measure of worker power[11]. We construct a 6-digit measure of rent-gaining power in US manufacturing using labor productivity (Bell et al., 2024; Stansbury and Summers, 2020), following the established approach in the literature on rent-sharing (Card et al., 2014, 2018; Dosi et al., 2020; Guiso et al., 2005). We estimate distinct measures for production and non-production workers based on the following econometric specification across 1958-1985.

$$\begin{cases} log\left(w^{B}_{jt}/L_{jt}\right) & = \alpha^{B} + \rho^{B} log(LP_{j,t-1}) + \chi_{t1} + \chi_{t2} + \nu^{B}_{jt} \\ log\left(w^{W}_{jt}/L_{jt}\right) & = \alpha^{W} + \rho^{W} log(LP_{j,t-1}) + \chi_{t1} + \chi_{t2} + \nu^{W}_{jt} \end{cases} \tag{13}$$

We now provide the econometric details of our methodological choices. First, we estimate the pass-through in a log–log specification. This is useful for capturing the widening gap between labor productivity and wage levels (Greenspon et al., 2021; Stansbury and Summers, 2018), modeling a structural relationship, such as worker power, that is also industry-specific. Moreover, we can interpret the results directly in terms of the elasticity of wages with respect to labor productivity.

To address the problem of simultaneity (i.e., that wages at the same time can influence labor productivity) and to mitigate any endogeneity problems about the measurement of rents such as labor productivity, we use its lagged version. Following the literature, we use the lagged value

[11] The monopsony literature considers rent-sharing patterns as function of primitives of firms' labor demand curves (Kline et al., 2019; Lamadon et al., 2022), rather than an expression of worker bargaining power. We instead adopt this last perspective, which originates from wage-bargaining literature. Alan (2011) makes a consistent review of the different approaches taken to estimate such rent-sharing effects

of the rents variable—whether defined as labor productivity, firm profits, or industrial profits per worker (Blanchflower et al., 1996; Hildreth and Oswald, 1997). This is a standard econometric practice to address endogeneity concerns, often by employing the lag as an instrument (Bell et al., 2024; Christofides and Oswald, 1992; Mengano, 2022). Our baseline OLS estimates with two-way fixed effects (industry and year), presented in table 14, are robust to this approach. Specifically, IV estimates using lagged productivity as an instrument yield very similar results (available upon request), indicating that residual time-varying endogeneity after controlling for fixed effects is limited. On the one hand, we capture the bargaining dimension where workers try to obtain wage adjustments to the past firm or industry performance. On the other hand, we try to mitigate any estimation bias due to the simultaneous effect of wages on productivity.

Moreover, we include macro-period fixed effects that capture the two dominant phases of the post-WWII U.S. economy: the Golden Age (1958–1972) and the Oil Crisis (1973–1985). These effects absorb economy-wide shocks– such as the inflationary periods and oil shocks of 1973 and 1979– that influence wages and productivity across all industries. From an econometric standpoint, this strategy also prevents the over-parameterization that would result from using annual fixed effects. Overall, the combination of lagged labor productivity and macro-time fixed effects captures industry-specific characteristics without requiring further instrumentation for the unobserved productivity.

Using the estimated industry-specific wage-productivity pass-through, we construct a worker power vector defined as the ratio of rent-sharing power between the two worker categories within each industry. We then analyze the statistical properties and distribution of this vector across the 361 US manufacturing industries.

$$\rho = \underbrace{\left(\frac{\rho_j^B}{\rho_j^W} \right)}_{361\times 1} \quad \forall\, j = \{31111, 311119, ..., 339999\}, \qquad \begin{cases} \rho > 1 \text{ if } \rho_j^B > \rho_j^W \\ \rho = 1 \text{ if } \rho_j^B \approx \rho_j^W \\ \rho < 1 \text{ if } \rho_j^B < \rho_j^W \end{cases} \tag{14}$$

Table 15 provides descriptive statistics of the pass-through their ratio estimates. Consistent with theoretical expectations, the power to convert productivity gains into wages is significantly higher among non-production workers compared to production workers. Figure 17 shows the kernel distribution of both worker power estimates, equation, $\{\rho_j^B, \rho_j^W\}$, and their ratio, ρ. The analysis of the two worker power measures reveals that the distribution for non-production workers is shifted to the right relative to that of production workers, reflecting their higher power values across industries, figure 17a. This pattern is also evident in the distribution of their ratio, figure 17b. The average ratio of less than one reflects the power asymmetry between worker categories: production workers exhibit a wage-productivity pass-through that is, on average, only 88.3% as strong as that of non-production workers.

We analyze how production and non-production workers power is distributed across all the 361 U.S. manufacturing industries. Figure 18 presents a scatter plot of the pass-through estimates for both worker categories, showing the distribution of industries by their relative power balance. This confirms our theoretical hypothesis: non-production workers have greater power than production workers in most industries. We also report industries where worker bargaining power is substantially similar between the two categories. The full list of these industries is provided in Table 16. Table 17 lists the outlier industries at both tails of the ratio distribution. These correspond, respectively, to the bottom-left and top-right clusters in panel 17b, identifying industries where non-production workers exhibit the highest absolute levels of power, and conversely, those where production workers do. We identify two extreme groups of industries in rent-sharing dynamics. On the one hand, industries where production workers appropriate productivity gains at a rate more than 30% higher than non-production workers. On the other hand, industries where production workers appropriate only 40% of what non-production workers capture. The first group represents traditional manufacturing industries, in contrast to the second group, which is composed of ICT-intensive industries.

We account for key distributional characteristics– such as skewness, kurtosis, and modality– in the worker power of both worker categories. The distribution of production workers' power exhibits a bimodal structure, which reflects two subgroup patterns within U.S. manufacturing. In one subgroup of industries, production workers have weaker bargaining power, leading productivity gains to be captured primarily by profits or non-production workers. In the other subgroup, they have stronger bargaining power, resulting in a robust wage-productivity link, even if it remains below the average for non-production workers. This stands in contrast to the unimodal distribution for non-production workers, whose tasks, knowledge, and managerial status are consistently rewarded in line with productivity dynamics. Moreover, production workers display greater variance in bargaining power than non-production workers.

To delve deeper into the bimodal nature of the production workers power distribution and the greater variance of non-production workers, we explore the dynamics of worker power along different technological-sectoral regimes. Analyzing separately the distribution of worker power for the two categories of workers, panel 19a, a sectoral differentiation does not alter the power balance between production and non-production workers, with the latter having greater power than the former and therefore a distribution more shifted further to the right.

Table 18 presents the statistical moments of the two distributions. Regimes such as Science-Based and Specialized Suppliers exhibit the largest power gap, with production workers having significantly lower power than their non-production counterparts. This pattern is consistent with the broader trend wherein high-tech and ICT-intensive sectors display the most pronounced intra-labor power asymmetry, to the direct detriment of production workers, who capture only a minimal share of industry-level rents. The Science-Based regime shows negative skewness for production workers: the fat left tail reflects a concentration of industries where their bargaining power is extremely low, thereby pulling down the average. Similarly, the Supplier Dominated regime exhibits comparable, though less severe, patterns of asymmetry, characterized by low variance and a strong concentration around the mean. Here, production workers are systematically disadvantaged but uniformly distributed across the regime's industries.

By contrast, Scale-Intensive regimes display a more symmetrical distribution of worker power, generally favoring production workers relative to other regimes. Within such regimes, the Scale-Intensive Continuous shows the highest modal worker power for production workers across all regimes. However, non-production workers also achieve high levels, which widens the inter-category power gap and allows them to capture a substantial share of productivity gains. Conversely, the Scale-Intensive Discontinuous regime is the most favorable to production workers, as evidenced by a markedly smaller power gap. Here, the distribution of non-production workers displays strong positive skewness, indicating a niche of industries where their pass-through values are exceptionally high. Nevertheless, the overall regime average remains relatively balanced, due to the comparatively strong position of production workers.

Figure 19b presents the distribution of the worker power gap, ρ, across different technological-sectoral regimes. Notably, the Scale-Intensive regime exhibits a trimodal structure: while certain industry niches confer substantial bargaining power to both worker categories, a significant share of industries demonstrate near parity between production and non-production workers. This latter group is predominantly concentrated in the automotive sector (NAICS 336), where production workers have maintained a strong historical bargaining position. In contrast, other regimes exhibit distinct distributional patterns: the Science-Based and Supplier-Dominated regimes display slight bimodality, while the Specialized Supplier regime follows a unimodal distribution. In high-tech and ICT-intensive sectors, where power is strongly skewed toward non-production workers, rents are disproportionately appropriated by this group.

Figure 20 shows the distribution of worker power across the 361 manufacturing industries, disaggregated by sectoral regime. Industries around parity between worker categories are concentrated exclusively within the Scale-Intensive and Supplier-Dominated regimes, table 19. The outliers listed in table 16 reveals that those in the left tail of the distribution, where worker power is weakest, are predominantly located within Science-Based and Specialized Supplier regimes. Conversely, the right tail, characterized by strong bargaining power among production workers, is concentrated almost entirely in the Scale-Intensive Discontinuous regime (including not only automotive sectors, NAICS 336, but also white goods and household appliance manufacturing, NAICS 3352) along with several industries in the Supplier-Dominated regime. Overall, this evidence reinforces the distributional patterns identified in the preceding analysis.

4.3 Shift-Share IV

We integrate our granular, industry-level measure of worker power (ρ) with a macroeconomic indicator of changing outside options in the labor market, using the change in the unemployment rate. An increase in the unemployment rate weakens workers' bargaining power by deteriorating their outside options, while simultaneously expanding the pool of workers firms can hire at lower cost[12]. Furthermore, given how we construct worker power, business cycle phases can differentially impact production and non-production workers. Therefore, by interacting our granular measure of worker power with business cycle fluctuations that shift workers' outside options, we construct the following shift-share instrument:

$$Z_{jt} = \sum_j \rho_j^{1958-85} \times \Delta \text{ unemployment}_t \tag{15}$$

Our instrument is motivated by the interaction between two dimensions of worker power. Its core is a granular industry-level index that captures the pass-through of productivity gains to production and non-production workers, reflecting both the heterogeneous exposure of industries to macroeconomic fluctuations and the differential pass-through between the two worker categories. To this, we add a shift component based on the national unemployment rate, which proxies the macroeconomic status of the labor market. This choice aligns with the wage-curve hypothesis (Blanchflower and Oswald, 1995), wherein higher unemployment pressures workers to accept lower wages due to the threat of replacement by the unemployed. Moreover, it is in line with theories of unemployment as a disciplinary device (Shapiro and Stiglitz, 1984; Yellen, 1995) and the Marxian concept of industry reserve army of labor (Kalecki, 1943; Rebitzer, 1988). From our perspective, unemployment affects workers asymmetrically based on their hierarchical position, thereby altering their bargaining power and capacity to appropriate productivity gains.

[12] Figure 21 presents the annual percentage change in the national unemployment rate.

5 Empirical Results

Our results show that a higher share of production workers relative to non-production workers reduces the industry-level labor share, as the differential exposure of worker power to macroeconomic fluctuations is the key driver. These findings are robust across alternative econometric specifications and different sets of control variables. We provide the results of the baseline regression, the IV estimates, as well as economic and econometric robustness checks following Goldsmith-Pinkham et al. (2020). We then present the results disaggregated by sectoral regime, concluding with an analysis of the asymmetric effects of business cycle phases on income distribution.

5.1 Baseline Results

Table 20 provides baseline unweighted OLS estimates for the period 1989-2016, adding industry-level controls to capture the industry-level market power, capital deepening, energy price and import penetration dynamics. The workforce technical composition coefficient is negative and statistically significant for all specifications, also when we add all the controls. This validates our theoretical hypothesis: an increase of production vs. non-production workers worsens the distribution of overall income in favor of wage earners. These estimates, calculated with TWFE, imply that a 1% increase of production vs. non-production workers ratio leads to a reduction of the manufacturing labor share by 0.18%. This coefficient remains absolutely stable with all the various industry-level controls added (from column 2 to 5).

We estimate the same baseline specification without two-way fixed effects to examine the importance of idiosyncratic sectoral heterogeneity in mediating how workforce technical composition affects income distribution. Table 21 presents the results from three specifications: pooled OLS, time fixed effects, and industry fixed effects. The pooled OLS and time fixed effects estimates show no statistically significant relationship between our key regressor and the labor share. In contrast, controlling for time-invariant industry characteristics reveals a strong, statistically significant effect of workforce composition on income distribution, consistent in both magnitude and direction with our main findings. This exercise confirms the critical role of industrial heterogeneity: an increase in the share of production workers—who possess weaker bargaining power—reduces the workforce's overall capacity to appropriate productivity gains, as hypothesized. This power dimension is embedded in the structural features of each sector, captured by our granular worker power metric 14. The results in Table 21 validate this mechanism, showing the negative effect emerges precisely when accounting for time-invariant industrial characteristics—where the institutional and technological foundations of worker power reside.

The results disaggregated by technological-sectoral regimes (Tables 22–26) show coefficients that are consistently signed in line with our theoretical predictions, although their statistical significance varies across regimes. This sectoral heterogeneity further corroborates the mechanism outlined in Proposition 1.

$$\hat{\beta}^{OLS} < 0$$

The consistent sign and statistical significance of the relationship after controlling for time-invariant industrial characteristics suggest potential omitted variable bias in simpler specifications. This pattern persists even after accounting for conventional factors like technology, energy prices, capital intensity, market power, and import penetration. The small and insignificant coefficients in pooled OLS and time fixed effects models indicate that omitted industrial characteristics are crucial in explaining the effect of workforce composition. When we isolate within-industry variation over time, the coefficient becomes negative and significant, indicating that a rise in the share of production workers relative to non-production workers within industries is associated with a reduction in the labor share. Given the importance of these idiosyncratic features, we employ an industry-specific worker power index to capture the relative rent-sharing capacity of production and non-production workers.

Another industry-specific dimension concerns labor market institutions and union tradition. Table 27 presents OLS estimates substituting unionization measures (density and bargaining coverage) for our production/non-production worker ratio. The statistical insignificance of these associative power proxies reinforces the superiority of our structural power variable in granular 6-digit manufacturing analysis. The consistent negative sign across specifications underscores the importance of industry-specific characteristics, which our worker power measure effectively captures.

5.2 Main IV Results

Our analysis now turns to the worker power mechanism underlying the established relationship between workforce composition and labor share. We implement our granular worker power measure in specification 12 to examine how industry-specific power differentials interact with labor market fluctuations. All specifications cluster standard errors at the industry level. The baseline IV estimates include industry fixed effects to avoid absorbing the macroeconomic shocks captured by our shift component, while robustness checks incorporate year fixed effects to account for specific aggregate shocks. The analysis covers the period 1990–2016, ensuring complete data availability across all variables.

Table 28 shows the results. Column (1) reports the unweighted OLS estimate for our regressor of interest, while columns (2) and (3) present unweighted OLS estimates with full controls. Column (4) shows the 2SLS unweighted estimate for the regressor of interest alone. The coefficient is strongly negative, and economically and statistically significant, also including all the controls. The estimates show that a 1% increase in the production vs. non-production workers ratio leads to a significant reduction in the labor share of 2.33% at the industry level, rising to 2.71% when all controls are included. In all specifications, the first-stage KP Wald statistic is sufficiently high to confirm the strength of our instrument.

To account for heterogeneous industry size, we weight each observation by 1990 industry-level total employment, the first year in our sample, to prevent smaller industries from disproportionately influencing the IV estimates. This approach ensures that the 361 manufacturing industries are weighted according to their economic size, recognizing that large and small industries cannot be treated equally in the analysis. Column (5) reports the 2SLS estimate for our coefficient of interest, while columns (6) to (8) present the 2SLS estimates with the sequential addition of controls. Compared to the unweighed version, the 2SLS estimate is greater with a lower standard errors[13]. The coefficient remains statistically and economically significant with a consistent negative sign across both OLS and unweighted 2SLS estimates, supported by strong first-stage diagnostics. The weighted estimates show particular stability, ranging from -1.86 to -2 across specifications. This

[13] We have corrected the t-ratios of the second stage of the 2SLS estimate, applying the correction criteria for the standard errors proposed by Lee et al. (2022). These correction factors depend on first-stage F-statistics. However, the applications of these corrective factors, both for weighted and unweighted estimates, provide t-ratios that are abundantly higher than 1.96. This indicates that the coefficient of interest is always statistically significant different from zero at the 5% level.

indicates that a 1% increase in the production-to-non-production worker ratio reduces the manufacturing payroll share by approximately 1.9%, ceteris paribus.

From the overall IV estimates, both for the unweighted and weighted versions, the workforce technical composition is always statistically significant and negative, coherent with the economic theory we propose. For both unweighted and weighted IV estimates, we notice that:

$$|\hat{\beta}^{IV}| > |\beta^{OLS}|$$

This supports our empirical strategy of combining variables that capture distinct aspects influencing how the production/non-production worker ratio affects the payroll share. The Wu-Hausman test—significant for both weighted and unweighted versions—confirms that the OLS estimates in table 20 might suffer from omitted variable bias. The direction of this bias, as evidenced by the coefficient sign, indicates that OLS underestimates the true negative effect, which is more accurately captured by our 2SLS estimates.

Our estimates identify a Local Average Treatment Effect (LATE) for manufacturing industries where worker power is particularly sensitive to macroeconomic conditions. For these "complier" industries, a 1% increase in the production-to-non-production workers ratio reduces the labor share by approximately 1.6%, showing how workforce composition affects income distribution precisely where bargaining power is most elastic to labor market fluctuations. This confirms that bargaining power plays a crucial role in shaping distributional outcomes within this responsive subset of industries. We will return to this crucial point when discussing the asymmetric effects of the business cycle.

Figure 22 demonstrates the strong predictive power of our instrument, which captures the interaction between worker power and macroeconomic conditions. The first-stage relationship clearly identifies the large group of industries where bargaining power is highly sensitive to labor market macroeconomic fluctuations, confirming our theoretical prediction that the workforce technical composition becomes negatively dependent on these cyclical dynamics.

5.2.1 Sectoral Regimes IV Results

Having demonstrated how workforce composition transmits instrumental variation to income distribution, we now examine how technological-sectoral regimes mediate this worker power channel. This sectoral framework allows us to map the coevolution of technological paradigms, organizational structures, internal power relations, and cyclical demand patterns—ultimately revealing how these interrelated dimensions shape distributional outcomes across industrial contexts. The socio-technological-sectoral regimes are characterized by the coevolution between:

1. A specific basic knowledge (scientific, tacit and cumulative, process or product-oriented or both).

2. A specific industrial structure and organization (relative size of innovating firms, intensity and direction of technological change, relationship with suppliers and customers).

3. The internal power structure reflects the specific role of production and non-production workers within the production process. These roles depend on the type of knowledge embodied in workers and on whether such knowledge can be used collectively or individually for the production activities.

4. The type of the goods produced by firms and the demand elasticity to cyclical fluctuations.

This coevolution shapes income distribution, with workers' power playing an active role that is fundamentally mediated by their sectoral regime. In what follows, we analyze the results for each regime and conclude with a summary table characterizing the distinct types of coevolution and their ultimate effect on distribution.

- **Supplier Dominated** (Food, Textile, Clothing, Non-complex Metals). Table 30 shows a weak association between workforce composition and income distribution through our identified worker power channel. In this regime, technological opportunities are limited and largely embedded in intermediate inputs introduced from other sectors, while small firms dominate a fragmented industrial structure. The power structure is sharply divided: non-production workers show wide variation in rent-sharing ability, while production workers are more homogeneous and concentrated around a lower mean (figures 19a and 20). Production workers' role remains marginal due to their embodied knowledge type and hierarchical subordination, making their already fragile bargaining power particularly vulnerable to labor market fluctuations.

  Simultaneously, the inelastic demand for non-durable goods shifts macroeconomic effects toward firm dynamics– specifically, cost competition among small firms through market entry and exit. This fragmented setting, characterized by weak power structures and potential invasion by non-union firms competing on costs (Dosi et al., 2021), explains the difficulty in identifying a clear power channel, as reflected in the weak first stage and low statistical significance.

- **Scale Intensive Continuous** (Steel, Cements, Refining, Complex metals). Table 31 shows that a 1% increase in the workforce technical composition reduces the labor share by approximately 2.5%. This regime's technological trajectory, dependent on specialized suppliers' inputs and driven by process innovation, embeds crucial knowledge in complex plant operations sustained by production workers' experiential learning. Therefore, their role grants them relatively high power, yet hierarchically subordinate.

  Two features makes the worker power channel central here: the inherent fragility of workers' bargaining power within the hierarchical division of labor; and the high elasticity of demand, which connects the regime to investment cycles. During downturns, collapsing demand and rising unemployment strongly undermine production workers' capacity to convert productivity into wages. Such erosion of their collective bargaining power directly worsens income distribution, confirming the worker channel's central role as reflected in the statistically and economically significant results.

- **Scale Intensive Discontinuous** (Transport Equipments, i.e., cars; Brown and White Durable Goods, i.e., TVs, washing machines, etc.). Table 32 shows that a 1% increase in the technical composition of work reduces the labor share by about 1% in this regime. Here, basic knowledge is integrated through internal R&D and product design, with large firms operating at high economies of scale dominating the industrial structure. The power structure is hybrid: historically strong labor market institutions, such as trade unions, have granted production workers substantial bargaining power, while economies of scale and learning processes have afforded them significant task-based power due to their central role in production. This results in an almost symmetrical distribution of occupational power across the hierarchy.

  Given the durable nature of the goods produced, demand elasticity is very high. Negative phases of the business cycle thus lead to postponed purchases and sharp production contractions. Production workers' crucial role in the process makes them particularly vulnerable during downturns, reducing their ability to translate productivity gains into wages. The presence of consolidated—though increasingly eroded—labor market institutions explains why the effect is less pronounced than in the Scale-Intensive Continuous regime. Nevertheless, the power channel remains evident: production workers' sensitivity to unemployment fluctuations erodes their bargaining power and worsens income distribution.

- **Specialized Suppliers** (Machine tools, Industrial machinery, Measurement and control instruments). Table 33 shows that a 1% increase in production workers reduces the labor share by approximately 1.7% in the Specialized Suppliers regime. This regime builds on highly cumulative, tacit knowledge developed through close customer relationships, with production focused on specialized machinery and inputs for other industrial sectors.

  Production workers here possess fundamental craft-task power derived from their practical knowledge and essential skills in understanding "what is needed for whom." This grants them important collective power, though they remain hierarchically subordinate to non-production workers. The regime's dependence on investment cycles creates high, albeit delayed, demand elasticity. During economic downturns, production contractions systematically weaken production workers' bargaining position, confirming the presence of a distinct power channel as reflected in the statistically significant results.

- **Science Based** (Pharmaceutical, Fine chemicals, Semiconductors and ICT). Table 34 shows that the worker power channel is nearly irrelevant in the Science-Based regime, as evidenced by a very weak first stage and low statistical significance. This regime relies primarily on scientific advances and strong science-innovation linkages, with innovation driven by internal R&D and dominated by large firms that appropriate returns through patents and technical know-how.

  The power structure is strongly skewed toward capital and non-production workers, while production workers play only a marginal role in the production process, resulting in very low relative power. Furthermore, the high technological content of output makes demand inelastic to business cycles, insulating workers' bargaining positions from labor market fluctuations.

Our sectoral analysis reveals a clearer picture than aggregate manufacturing results. Each technological-sectoral regime constitutes a distinct ecosystem with unique knowledge bases, organizational structures, and internal hierarchies that shape employment power dynamics. Within these systems, labor market fluctuations– proxying workers' outside options– interact differently, generating heterogeneous distributional outcomes.

In regimes where production workers play central roles, power hierarchies are pronounced, and demand is elastic (Scale-Intensive and Specialized Suppliers), business cycles strongly affect income distribution through the power channel. Conversely, where production workers are marginal (Supplier Dominated) or non-production workers dominate innovation (Science Based) with inelastic demand, cyclical impacts are muted or bypass the power channel entirely. This framework coherently explains the heterogeneity in our results, demonstrating how structural and cyclical factors jointly determine distributional outcomes.

5.2.2 Asymmetric Effects: Unemployment Increases and Reductions

Our main mechanism operates predominantly during periods of rising unemployment (see Figure 21). Therefore, our results are primarily driven by recessionary phases that deteriorate economic conditions and reduce workers' outside options, especially for production workers, weakening their capacity of passing productivity-gains into wages. This power reduction channel thus constitutes the main driver of our findings.

We validate this hypothesis by testing for a deeper type of asymmetric effects of cyclical labor market conditions on the worker power channel: is the erosion of worker power during downturns more severe and statistically robust than its recovery during upturns? This further investigation provides a stringent validation of our theoretical mechanism and makes a novel empirical contribution to the literature on asymmetric business cycle effects on income distribution.

Our theory of hierarchical employment power implies an inherently asymmetric response to business cycle fluctuations. Due to their subordinate position and higher substitutability with the unemployed, production workers face greater exposure to labor market conditions. Consequently, we predict their bargaining power erodes sharply during recessions, while recovery in expansions remains partial and uncertain. This asymmetry– where power losses in downturns are more pronounced and statistically robust than gains in upturns—suggests a micro–foundation for distributive hysteresis. Ours is among the few contributions demonstrating such asymmetric rent-sharing, where workers' capacity to claim wage increases responds differentially to the direction of cyclical variation.

Few works have explored potential rent-sharing asymmetries in response to the type of shock. Acemoglu et al. (2022) find rent-sharing only for positive variations, in line with Arai and Heyman (2009) and Cho and Krueger (2022). Consistent with our thesis that workers are more adversely affected by negative fluctuations than they are advantaged by positive ones, Mertens et al. (2025) document that rent-sharing capacity deteriorates under rising input prices but remains unresponsive to price reductions[14]. Conversely, there are works that show substantial symmetry in worker rent-sharing (Garin and Silvério, 2024).

We focus on potential asymmetric effects of labor market fluctuations on workers' rent-sharing bargaining power. Our contribution shifts attention to the macroeconomic context and its implications for worker power, and consequently for income distribution. While asymmetric rent-sharing has often been analyzed in relation to downward nominal wage rigidities (Adamopoulou et al., 2025; Olivei and Tenreyro, 2010), our approach instead seeks to microfound such asymmetries through the worker power channel. This aligns with recent macroeconomic research on asymmetric effects of cyclical fluctuations through labor markets (see Section 3.9 of Cerra et al. (2023)), particularly regarding the asymmetric impact of unemployment rate fluctuations (Dupraz et al., 2025).

Our analysis especially highlights that such asymmetries in the worker power channel work mainly for production workers, who are most affected by rising unemployment. This finding is consistent with evidence documenting scarring effects through the labor market channel, especially among the most disadvantaged workers (Hershbein and Stuart, 2024; Yagan, 2019). Recent contributions, such as Carnevale and Di Francesco (2025), further support this view, showing significant asymmetric effects linked to heterogeneity within the labor force.

To test our hypothesis of asymmetric effects, we divide our sample into periods of rising versus

[14]For a complementary analysis of asymmetric distributional effects from energy price shocks during the post-COVID inflationary period, see Fierro and Martinoli (2025).

falling unemployment rates. We decompose the shift component of our instrument 15 into positive and negative variations. Based on this sign decomposition, we therefore estimate the effects of equation 12.

$$\Delta\ u_t = \begin{cases} \Delta\ u_t^+ \text{ Recessionary Phase} \\ \Delta\ u_t^- \text{ Expansionary Phase} \end{cases}$$

The results, in table 35, provide clear evidence of asymmetry. Starting with the reduced form evidences, columns (1) and (2) show the results of the labor share regression on our instrument for the recessive and expansive phases respectively. We find statistically and economically significant asymmetric effects in worker power over the business cycle: rising unemployment rates significantly erode worker power, reducing the labor share, while declining unemployment during expansions enables a recovery of worker power—particularly for production workers—allowing them to benefit from economic improvement. This result aligns with the literature on labor market hysteresis (Aaronson et al., 2019; Carnevale and Di Francesco, 2025), which builds on Okun (1973)'s premise that sustained economic expansion disproportionately benefits certain worker categories. To capture this relationship, figure 23 presents binned scatter plots from our reduced-form regressions, showing that changes in the national unemployment rate affect income distribution through the worker power channel asymmetrically, whose effects are both statistically and economically significant.

Columns (3) and (4) show our IV results, where the worker power and its interaction with the labor market cyclical phases are the key transmission channel for the distribution of income through the workforce technical composition. The results confirm the direction of the relationship previously observed in the reduced-form analysis, while revealing a substantively important finding.

- **Recessionary Phase**. We find robust and systematic losses. As unemployment increases, a 1% increase of production vs. non-production workers ratio reduces the labor share by approximately 0.87% (Column 3), a large magnitude and highly significant negative effect (p-value<0.001). The validity of this mechanism is confirmed by a very strong first-stage, consistently with a dramatic and systematic collapse of the production workers' bargaining power as their outside options worsen.

- **Expansionary Phase**. We find a rebound effect that is statistically fragile: as unemployment falls, a 1% increase in the production vs. non-production workers ratio corresponds to a 1.37% rise in the labor share (Column 4). However, this positive effect, while comparable in magnitude, is statistically weaker ($p < 0.05$) than the corresponding negative effect observed during recessions. The weak first-stage relationship during economic upswings underscores the inherent fragility of worker power recovery in expansionary periods. Therefore, the recovery of bargaining power, particularly for production workers, is a more volatile and less systematic process compared to the robust, predictable erosion observed during recessions.

To further confirm the robustness of the asymmetric effects results, we formally test the equality of the respective coefficients. The equality test, shown in table 36, rejects the null hypothesis (p-value<0.001) that the two coefficients are equal across all business cycle phases. This confirms that the relationship between workforce technical composition and income distribution– mediated by the exposure of worker power channel to unemployment fluctuations– is structurally asymmetric, both in magnitude and in the statistical strength of the effect.

We document asymmetric state dependence: downturns reduce the labor share more than upturns increase it. This observed asymmetry can be consistent with potential distributive hysteresis (Figure **??**)– where economic downturns inflict deeper scars than subsequent expansions can heal– although we cannot support a definitive long-run persistence. Nevertheless, this represents a compelling avenue for future investigation, particularly regarding how negative cyclical fluctuations persistently affect income distribution and firm-level dynamics through the worker power channel.

We imagine a metaphor capturing the hierarchy in the division of labor and the relative power. U.S. manufacturing can be imagined as a ship with two decks: an upper one (non-production workers) and a lower one (production workers). During storms (economic recessions) the waves hit the lower deck first and most violently, flooding it quickly. The sailors below are therefore the first to get wet. Yet when the weather is good (during expansions) the sun reaches the upper deck first and most fully. The lower deck, darker and damp, remains wet for much longer, and its sailors cannot fully enjoy the sunlight, just as they are the most exposed when storms strike.

Overall, we identify a worker power channel that exhibits asymmetry not only in direction (sign) but also in magnitude (size) and statistical robustness. Recessions systematically erode worker power, while expansions restore it only partially and with statistical fragility. This creates a *ratchet-like* dynamic where a downturn diminishes bargaining power, even if subsequent recoveries fail to fully restore it. Our results are consistent with Kalecki (1943)'s insight about unemployment as a disciplinary device that structurally weakens labor's position (Lindbeck and Snower, 1986; Shapiro and Stiglitz, 1984).

5.3 Robustness Checks

We now address potential objections about the validity of our empirical design. To this end, we first provide methodological validity checks for our instrument, and then show that our results remain robust under alternative econometric specifications relative to the baseline model in equation 12.

5.3.1 Evaluating the SSIV Design

Our empirical setup involves the heterogeneous and differential exposure of the worker power for each manufacturing industry to cyclical fluctuations in the national unemployment rate. Therefore, we carry out an anatomical dissection of the instrument 15 to fully understand the role of each industry. As Goldsmith-Pinkham et al. (2020) show, the shift-share design's combination of heterogeneous industry-level instruments with a weight matrix obscures which specific industries drive the statistical variation. Consequently, we cannot precisely identify which specific manufacturing industry disproportionately drives our results.

Our instrument is built upon the combination of the industry-level worker power share of production vs. non-production workers ratio, with the national unemployment rate change. Therefore, high-weight instruments have a quantitatively important role in driving the results. Hence, GPSS propose a decomposition to identify which industries drive the results and in what proportion. Following Rotemberg (1983), they decompose the SSIV estimator into a weighted combination of the just-identified estimates for each individual instrument. The purpose of this decomposition is to identify the variation in specific industries that drive the main results for our mechanism. Furthermore, as already noted by Andrews et al. (2017), these weights can be interpreted as an elasticity to sensitivity-misspecification.

Using a common shift g_t (change in national unemployment rate) combined with sectoral shares ρ_j, we differ from the canonical setup by GPSS employing differentiated sectoral shifts g_{kt}. Our choice is motivated by the underlying research question about the effects of heterogeneous worker power exposure to cyclical macroeconomic fluctuations (proxying outside options) on income distribution. Since Rotemberg weights of our setup capture heterogeneity in the exposure of industries to the common shift, the identification comes from cross-sectional variation in shares ρ_j rather than variation in sectoral shifts. Key assumptions– exclusion, quasi-exogeneity of shares, and stability– are tested through our robustness analyses.

Table 37 provides the top-10 highest weights industries. The symmetrical distribution of these influential industries across sectoral regimes confirms that our results reflect broad-based heterogeneity rather than being driven by outliers in any particular regime. To further validate this finding, we conducted two additional robustness checks. First, we measured the weight concentration of these industries to assess how much instrumental variation is driven by the most influential sectors. Second, we quantified the specific contribution of the top-10 industries to the instrument's total variation, thereby evaluating their precise role in generating our results. Although the top 10 industries account for 22% of the total instrumental weight (as measured by Rotemberg weights), their collective contribution to the final estimate amounts to only 7.1% in absolute terms. This low concentration of absolute contributions indicates that our results are not driven by extreme sectoral outliers, but rather reflect a broad-based economic relationship distributed throughout the manufacturing sector. Figure 24 shows the weight distribution for all the individual instruments: the pattern is almost symmetrical with few industries having significant weights along the two tails. Such a relatively symmetric distribution supports the interpretation that our results are not driven by sectoral outliers, but reflect a general and robust economic effect.

To assess whether the exclusion of the top 10 industries affects our previous results, we re-estimate the baseline specification, equation 12, after removing the 10 industries (table 37). Table 38 shows that our main coefficient of interest remains between –2.641 and –2.697, maintaining both its negative sign and statistical significance across all specifications even after excluding the top 10 industries and including various controls. The KP Wald F-statistics, ranging from 28.9 to 34.2, confirm the instrument's continued strength after this exclusion. Together with the low Rotemberg weight concentration noted earlier, these results demonstrate that our findings reflect a generalized economic mechanism rather than being driven by sector-specific outliers, as we show in table 38. Our coefficient of interest becomes progressively more negative, reaching -2.64, when the top 10 industries are excluded. This pattern suggests that industries with higher instrumental weights exhibit less negative effects, likely due to structural features such as stronger labor market institutions, accumulated tacit knowledge, or more resilient worker-firm relationships that cushion them against unemployment fluctuations. This finding reinforces the evidence from sectoral regimes analysis. Moreover, it robustly confirms the core relationship: the coefficient remains negative and highly significant, while the instrument maintains strong explanatory power, underscoring the reliability of our identified worker power channel.

Table 39 examines the structural characteristics of industries with high Rotemberg weights. These influential industries are predominantly low-capital-intensive (70%) and low-markup (70%), indicating our instrument gives greater weight on labor-intensive sectors with moderate market power. Additionally, 60% exhibit high union density (mirrored in coverage rates), highlighting how labor institutions buffer cyclical fluctuations through worker power. Nevertheless, even strong unions– particularly in Scale-Intensive Discontinuous regime– do not neutralize the hierarchical occupational power channel underlying our results. The concentration of high-value-added industries among those receiving greatest instrumental weight confirms that our identification strategy primarily captures sectors with significant scale economies and substantively involved production workers, aligning with our cross-regime findings. Furthermore, the relatively balanced exposure to import penetration (40% high vs. 60% low) indicates that instrumental variation is not concentrated in industries particularly exposed to international competition.

Following GPSS, we report the Rotemberg weights for the just-identified β_k relationship with the first-stage KP Wald statistic. Given the structure of our instrument with a common shift g_t, the heterogeneity analysis is conducted at the sectoral $regime \times\ year$ level. This specification captures both time (through variation in g_t) and cross-sectional variation (through regime-specific shares $\rho_{r,t}$). We cannot perform this analysis at the single industry-level, as the common shift prevents the instrument from being defined separately for each industry. The coefficients $\beta_{r,t}$ is the just-identified effects for each technological-sectoral regime and year, while the weights $\alpha_{r,t}$ capture their contribution to the overall estimate. This level of aggregation is methodologically appropriate: it reflects the time-varying but common nature of the national shift, preserves cross-regime variation, and maintains statistical power by avoiding noisy industry-level estimates.

Figure 25 shows the distribution of Rotemberg weights across technological regimes, corroborating the sectoral IV estimates (Tables 30–34). Regimes with the strongest first-stage relevance–Scale-Intensive Continuous (KP = 29.9) and Specialized Suppliers (KP = 24.9)– also exhibit the largest labor share effects ($\beta = -2.55$ and -1.85, respectively). Their elevated weights underscore the centrality of workers in production, amplifying the transmission of shifting outside options through the worker power channel. Meanwhile, the Scale-Intensive Discontinuous regime, while exhibiting a more moderate labor share effect ($\beta = -0.787$), contributes substantially to overall instrumental variation ($\alpha_r = 0.314$), reflecting its structural importance in U.S. manufacturing. Despite its smaller effect magnitude, the statistically and economically significant result (Table 32) confirms that workers' collective role in specialized processes exposes their bargaining power to cyclical fluctuations, with clear distributional consequences. In contrast, the Science-Based regime shows both weak first-stage strength (KP = 6.10) and a limited labor share effect ($\beta = -0.961$), consistent with its R&D-intensive structure. The Supplier Dominated regime also demonstrates a below-average effect. This convergence of quantitative evidence—Rotemberg weights, first-stage strength, and regime-specific estimates—with qualitative institutional features substantiates our core argument: the worker power channel operates most strongly where high basic knowledge, essential worker roles, hierarchical organization, and cyclical demand elasticity co-evolve.

To further test the robustness of our results, we conducted a leave-one-industry-out analysis, estimating baseline regression 361 times, each excluding a different industry at a time. Figure 26 demonstrates strong coefficient stability across all leave-one-out iterations, with estimates clustered between -1.775 and -1.988 (SD = 0.05). The persistent negative sign and statistical significance across all specifications confirm the robustness of our findings against influential observations. Kleibergen-Paap Wald statistics remain robust across all specifications– ranging between 31.88 and 41.35– confirming that the our instrument does not depend on any specific industry. We provide further evidence that our findings are not sensitive to the exclusion of any individual industry, supporting the interpretation of a general economic effect rather than driven by industrial outliers at the 6-digit level.

As suggested by GPSS, we test whether pre-period worker power shares predict pre-existing industry-level characteristics. This balancing test examines if our instrument's heterogeneous exposure to unemployment changes correlates with observables at the industry-level. A lack of significant correlation would support the instrument's (quasi-)exogeneity. To do this, we regress granular power share workers to a set of pre-1989 industrial characteristics, using the 1985 as pre-period year. This choice is methodologically coherent, as we are testing characteristics contemporary to the construction of the share component. Furthermore, 1985 represents the 'initial state' of the industrial structure immediately before our study period, capturing the structure that existed before the unemployment fluctuations that we consider. Table 40 provides the results of this identification robustness check. Controlling for technological-sectoral regimes, a pre-1989 cross-section shows limited explanatory power for worker-power shares (within $R^2 = 0.091$). Capital intensity shows a weak positive association (0.6% elasticity per 10% increase), while total inventories are weakly negative (0.3% elasticity). Markups and energy prices remain unrelated. These minimal correlations, robust to alternative specifications and inference methods, confirm that industrial shares are largely orthogonal to confounding structural characteristics, with any associations being economically small and theoretically coherent.

Because our SSIV uses a common national shift (the change in the unemployment rate, Δu_t) interacted with pre-period granular shares ρ_j, conventional pre-trend/event-study graphs are uninformative, as there is no pre-treatment period where $\Delta u_t = 0$. Following the logic of common-shock designs, we implement *placebo-lead-instruments* built from future values of the national unemployment change:

$$Z_{j,t}^{(+h)} = \rho_j \times \Delta u_{t+h},\ h = \{1, 2\} \tag{16}$$

We conduct a test by replacing our baseline instrument $Z_{j,t} = \rho_j \times \Delta u_t$ with placebo-leads $Z_{j,t}^{(+h)} = \rho_j \times \Delta u_{t+h}$, while maintaining the original regressor, fixed effects, and controls from specification 12. Under the non-anticipation assumption, future unemployment changes should not affect current workforce composition through worker power. Accordingly, we expect a weak first-stage relationship and statistically insignificant second-stage effects. Table 41 shows the results. Consistent with non-anticipation effects, the KP Wald first-stage F collapses (e.g.,<5 across specifications) and the second-stage coefficient is small and statistically insignificant when using $Z_{j,t+1}$ or $Z_{j,t+2}$ as instruments[15]. Conversely, the baseline contemporaneous instrument delivers strong first-stage (KP Wald > 35 for all specifications) and a stable, negative effect on the payroll share (in line with the main results in table 29). These patterns support the timing restriction inherent in our common-shift SSIV and corroborate the interpretation of our main estimates

Our instrument passes a series of diagnostic checks, supporting the validity of our research design. In summary, we show that 1) A few industries drive the instrument's variation, but their exclusion does not alter the core results; 2) the highest weights regimes are those where workers, especially production, play a crucial role, and they coevolve with basic knowledge for the functioning of the production activity; 3) our estimates are not driven by any single industry, demonstrating strong stability and a remarkably robust first-stage relationship; 4) there are no anticipatory effects of changes in the unemployment rate, confirming that the identified worker power channel responds to contemporaneous labor market conditions.

5.3.2 Alternative Specifications and Economic Channels

While our empirical design is theoretically grounded, we further strengthen identification by testing the exclusion restriction. This requires our instrument 15 to affect the labor share only through the production vs. non-production worker ratio, by altering how workforce composition affects income distribution through industry-level worker power exposed to labor market fluctuations.

[15] There is an exception for a slight significance for $t + 1$ when we include all control variables. Nonetheless, KP Wald is still weak even though it is on the threshold of 5.

We have established that future unemployment changes ($\Delta u_{t+1}, \Delta u_{t+2}$) neither predict labor share nor correlate with our main regressor. This supports the theoretical premise that current labor market conditions affect income distribution specifically through workforce composition's interaction with worker power, rather than through alternative channels. However, since unemployment fluctuations behave as a common macroeconomic event that could simultaneously affect industries through multiple channels, we address potential confounding– such as demand shocks hitting production-worker-intensive industries– through industry-level controls and technological-sectoral regime differentiation. This approach helps isolate the worker power channel from other concurrent transmission mechanisms while maintaining the exclusion restriction.

To ensure our instrument captures labor market dynamics rather than other macroeconomic shocks, we augment the specification with specific year fixed effects for 2000, 2001, and 2008, characterized by the China Shock, Dot-com bubble, and Global Financial Crisis. These dummies absorb common level shifts in the payroll share during these years. As Table 42 shows, our coefficient of interest remains negative, stable, and highly significant across specifications, while first-stage statistics (KP Wald 29.1–41.4) confirm the instrument strength. The event-year coefficients are positive in 2000–2001 and negative in 2008, but they do not attenuate the worker power effect of composition on the payroll share. This pattern supports our exclusion restriction: the identifying variation comes from the cross-industry worker-power exposure ρ_j to labor market conditions, not from contemporaneous macro shocks affecting all industries alike.

We have shown that our mechanism works only through the workforce technical composition, remaining unaffected by other macroeconomic shocks that might influence labor market conditions. However, we further verify that the mechanism affecting worker power reflects general macroeconomic conditions in the labor market– where unemployment is the best proxy for capturing variations in workers' external options– rather than representing an idiosyncratic factor of unemployment fluctuations. To grasp labor market dynamics altering workers' rent-sharing abilities. We therefore test common indicators of the degree of functioning of the labor market as alternative shifts.

We theoretically argue that worker power, when exposed to workers' outside options alterations due to a change in labor market conditions, affects the income distribution given the workforce technical composition. If this channel has been correctly identified empirically, then using different proxies of the labor market state only needs to change the way the factor moves the composition (i.e., the first stage), not the overall effect of the composition, log (BC/WC), on labor share. An invariance of β to the proxy change would highlight that we are grasping the right mechanism (hierarchical worker power), not an idiosyncratic property of any macro variable in the labor market.

We test two alternative measures of labor market conditions. First, we employ the vacancy-unemployment (V-U) ratio as a standard measure of labor market tightness. When job openings increase relative to the number of unemployed workers, firms face greater difficulty in filling positions while workers find it easier (Diamond, 2011; Elsby et al., 2013). This tightening of the labor market consequently strengthens workers' wage bargaining position. We use it as an alternative shift to the usual unemployment slack measure. Second, we use the employment-to-population (E-P) ratio as an additional indicator of labor market tightness (Abraham et al., 2020). A rising employment rate relative to the total working-age population signals stronger labor force utilization and typically generates upward pressure on wages. Table 43 shows both first-stage and second-stage results using these alternative labor market indicators.

The estimates are unchanged and the sign is consistent with our baseline in table 29. During expansionary phases, the labor market tightens and these shift industry labor composition. Panel A

(V–U) captures the labor demand side: when vacancies rise, firms hire relatively more production workers, so the first stage on log (BC/WC) is positive. Rising participation increases the share of production workers, lowering aggregate bargaining power and reducing the labor share, as shown in Table 43. The IV coefficient on $\log(BC/WC)$ remains negative and significant across all labor market proxies: unemployment, vacancies, and the E-P ratio. This result supports our theoretical mechanism: a higher proportion of production workers reduces average bargaining power, concentrating rent-sharing among non-production workers and lowering the labor share. The coherence of these findings across distinct labor market macroeconomic channels reinforces the exclusion restriction, confirming that our instrument affects the payroll share primarily through shifts in workforce composition.

Excluding Great Recession Years. The Great Recession years included in our analysis may raise doubts that the results are primarily driven by the strong variations of those years. After the outbreak of financial crisis, unemployment increased significantly between 2008 and 2009 (figure 21). This trend might bias estimates, especially if the results can be driven by those industries whose worker power is most exposed to fluctuations in unemployment. This concern is more than legitimate if we take into account the role of manufacturing for the US economy and specifically the role of the automotive sector during the Financial Crisis. Table 44 shows the results excluding these years (Panel A), including all industry-level controls. Although this reduces the sample size, the results are robust ($\beta = -2.24\%$), closely aligning to the baseline estimate ($\beta = -2.03\%$). Moreover, given the important role of the automotive sector, we repeat by also excluding the Scale Intensive Discontinuous regime (Panel B), which includes the automotive sector (336 NAICS). The results are robust and are not driven by the role the automotive industry played during the Great Recession.

Alternative Market Power Measure. We test an alternative measure of market power, replacing our accounting-based markup. To ensure that this alternative specification does not alter our findings, we re-estimate the baseline model using the Lerner Index, constructed as Grullon et al. (2019)[16]. Table 45 shows the results for both specification with our markup measure and the Lerner Index. The results are robust: the coefficient maintains its negative sign and statistical significance across specifications. When controlling for the Lerner Index, a 1% increase in the production worker share reduces the labor share by approximately 1.82%, closely aligning with the 2.03% reduction observed when using markup controls. This stability confirms the persistent effect of workforce composition on income distribution regardless of the market power measure employed.

Alternative Technological Variables. To assess the sensitivity of our results to capital measurement, we disaggregate total capital intensity into equipment and structures. Table 46 shows remarkably stable estimates across specifications: a 1% increase in production workers reduces the labor share by approximately 2.05%, confirming our findings are robust to alternative capital intensity measures.

Moreover, we test one of the findings of Hubmer (2023): higher equipment-intensive to structure-intensive industries experience a sharper decline in the labor share. Table 47 confirms the stability of our core results: the coefficient on workforce composition remains consistent with previous estimates, showing that a 1% increase in production workers reduces the labor share by approximately 2.18%. While the relationship appears slightly negative, it aligns with our established pattern. Furthermore, as illustrated in Figure 27, equipment intensity relative to structures shows only a weak

[16] The correlation between our Markup accounting measurement and the Lerner Index is 79%.

association with labor share changes, reinforcing our identified worker power channel.

Alternative Price Variables. We test alternative measures of price variables. To assess the stability and consistency of our estimates, we replace the energy price with the materials and investment goods' price. Table 48 shows the results. Compared to the baseline estimates, the coefficients show only minimal variation while maintaining consistent negative signs, statistical significance, and economic magnitude. A 1% increase in the production worker share continues to reduce the labor share by approximately 1.95%, regardless of whether energy, materials, or investment prices are controlled for. This stability confirms that our core finding– linking workforce composition to income distribution through the worker power channel– is not sensitive to the specific input price measures used.

6 RIF Decomposition Analysis

While aggregate studies have established the decline of the labor share in advanced economies (Karabarbounis, 2024), and U.S. manufacturing (Gutiérrez and Piton, 2020), the distributional mechanisms behind this trend remain inadequately explained. The manufacturing sector presents a particular puzzle: as figures 5 and 14 show, the payroll share has fallen despite a declining ratio of production to non-production workers. This is a pattern that seems to contradict conventional compositional explanations. This paradox motivates our investigation: why has the manufacturing labor share continued to decrease even as the workforce composition shifted toward fewer production workers with lower bargaining power?

Traditional decomposition methods, particularly Oaxaca-Blinder approaches, have focused exclusively on mean effects, yet manufacturing payroll shares exhibit substantial heterogeneity across the distribution. The observed polarization pattern, with sharp declines at lower quantiles but stability or even growth at higher quantiles, suggests different economic mechanisms may be operating across the distribution. We therefore adopt unconditional quantile regression (UQR) with a recentered influence function (RIF) (Firpo et al., 2018), to decompose labor share changes across the entire distribution, allowing us to distinguish between composition effects (changes in workforce and industrial structure) and wage structure effects (changes in remuneration patterns) at different quantiles.

This two-stage procedure enables us to: i) decompose changes in the payroll share distribution into composition effects (shifts in industrial characteristics) and structure effects (changes in the compensation premiums associated with those characteristics); ii) attribute each component to specific covariates, including the technical composition of the labor force and the production-to-non-production worker ratio. The method's principal advantage lies in its capacity to perform detailed decompositions for any distributional statistic—such as quantiles—while preserving the intuitive interpretation of traditional Oaxaca-Blinder decompositions.

We employ this methodology to test our central hypothesis: the decline in manufacturing payroll shares reflects not merely compositional shifts in workforce structure, but more fundamentally, the erosion of production workers' bargaining power. The RIF decomposition framework enables precise quantification of how observed distributional changes stem from:

- **Composition effects**: Changes in the distribution of the production/non-production worker ratio across manufacturing industries

- **Structure effects**: Changes in the relative wage premiums associated with these worker categories, capturing shifts in rent-sharing dynamics

We first employ a counterfactual kernel density approach (DiNardo et al., 1996), to compare actual payroll share distributions with either initial-year characteristics vs final-year wage structures scenarios or vice versa. This preliminary analysis quantifies how compositional shifts and structural changes separately contribute to the observed distributional transformation. Figure 28 displays Epanechnikov kernel density estimates comparing manufacturing payroll share distributions between 1988–89 (blue line) and 2015–16 (black line). The distribution shows a pronounced leftward shift with increased variance in the later period, indicating both declining labor shares and growing sectoral heterogeneity within U.S. manufacturing. The fatter left tail in 2015–16 reveals an expansion of industries with particularly low labor shares. The counterfactual analysis provides crucial insights into underlying mechanisms. When we reweight the 1988–89 distribution using 2015–16 industrial composition while holding structural coefficients constant (green dotted line), the distribution shifts further left, demonstrating that compositional changes alone– particularly sectoral reallocation– would have substantially reduced labor shares. Conversely, applying 2015–16 structural coefficients to the 1988–89 industrial composition (black dotted line) produces a distribution that nearly returns to the initial period's levels, suggesting that structural changes in wage-setting mechanisms partially counteracted the downward pressure from compositional shifts. This divergence between compositional and structural effects highlights the complex dynamics driving labor share evolution, setting the stage for the detailed RIF decomposition that follows.

Building on this distributional evidence, we now implement a Recentered Influence Function (RIF) decomposition to disentangle the evolution of manufacturing payroll shares between the initial and final periods. Figure 29 displays the total change in log payroll share across percentiles, decomposed into composition effects (changes in industrial characteristics) and structure effects (changes in wage-setting patterns and distributive premiums) using the methodology of Firpo et al. (2018) and Firpo et al. (2009). The decomposition reveals a striking pattern of distributional divergence. At the 10th percentile, nearly the entire decline stems from structural effects– primarily eroding worker power– while compositional factors would have partially offset this decline. This suggests a pronounced weakening of production workers' bargaining position at the lower tail. By the 25th percentile, both composition and structure contribute to the decline, though structural forces remain dominant. From the median upward, this pattern reverses: compositional changes drive most of the reduction, while structural effects turn positive and attenuate the fall (Table 49). Overall, compositional shifts explain most of the payroll share reduction across the distribution, with substantial structural pressure concentrated at the bottom, consistent with disproportionately eroded bargaining power among production workers in vulnerable industries.

We now examine how specific covariates, particularly the production vs. non-production workers ratio, contribute to such distributional changes through their respective composition and structure effects, thereby identifying where workforce composition most critically shaped manufacturing's evolving income distribution. Figure 30 presents the detailed RIF decomposition, attributing payroll share changes to specific covariates through composition and structure effects. Beginning with our central variable– the production vs. non-production workers ratio– we observe a markedly negative structure effect (red) from the 10th to 75th percentiles, minimal around the median and attenuating only at the 90th percentile. Even holding composition constant, the relationship between production workers and payroll shares has become progressively more negative, consistently with eroding worker bargaining power. The composition effect (blue) remains modest and slightly negative throughout, confirming that workforce composition changes alone cannot explain the decline. Rather, the structural deterioration in worker power drives the downward shift across the lower and middle distribution. Capital intensity emerges as the primary compositional driver, exerting strong negative pressure particularly at lower quantiles, while its structure effect remains negative but moderates at higher percentiles. Together, these effects indicate capital deepening has systematically shifted the payroll distribution leftward, especially impacting vulnerable industries. Markup variations show limited compositional influence but provide structural cushioning in the upper distribution, transitioning from slightly negative at the 10th percentile to positive at the 75th-90th percentiles. Import penetration demonstrates negligible compositional impact while structurally mitigating decline at lower quantiles. This covariate-specific analysis confirms that declining worker power– particularly the structural deterioration in production workers' bargaining position– constitutes the dominant force reshaping manufacturing's income distribution.

This semi-parametric analysis reveals worker power as the fundamental mechanism driving distributional change, especially at the bottom tail. The structural erosion of production workers' bargaining power, concentrated in lower quantiles, emerges as the key factor explaining the manufacturing paradox. While capital deepening shifts the entire distribution leftward through compositional effects, it is the deterioration in worker power that reverses the expected relationship between workforce composition and labor share. The declining production vs. non-production workers ratio, which should rise payroll shares, is overwhelmed by this structural deterioration in bargaining power. Therefore, the manufacturing sector exhibits both a general leftward shift from capital intensity and a selectively depressed lower tail from eroded worker power, creating an environment where production workers face compounded disadvantages through both compositional and structural channels.

7 Conclusions

The decades-long decline of the labor share in U.S. manufacturing has generate a vibrant debate in the literature over the last decade, centering primarily on technological substitution and the rising market power of "superstar firms." This paper has argued that these explanations, while valuable, offer an incomplete picture. By introducing and empirically testing a novel worker power channel, rooted in the hierarchical division between production and non-production workers, we provide a fresh lens through which to view the income distribution trends.

Our core finding is that the technical composition of the labor force– i.e., the production to non-production workers ratio– is an important determinant of the payroll share. This relationship is not only compositional but is fundamentally underlying power structures. Production workers, occupying a structurally weaker position along the corporate hierarchy, have a diminished capacity to translate productivity gains into wages. An increase in their share relative to non-production workers therefore reduces the average bargaining power of the workforce, leading to a decline in the labor share. This mechanism is powerfully validated by our granular shift-share IV design, which interacts an industry-specific measure of occupational bargaining power with fluctuations of the national unemployment rate.

The narrative deepens when viewed through the perspective of technological-sectoral regimes. The effect of worker power is not uniform, but is mediated by the specific knowledge bases, organizational structures, and demand elasticities that characterize different sectors. The channel is strongest in regimes like Scale-Intensive and Specialized Suppliers, where production workers play a central, collective role in the production process and where demand is highly cyclical. Conversely, it is muted in Science-Based industries, where non-production workers dominate innovation, and in Supplier-Dominated sectors, where the fragmented industrial structure and marginal role of production workers dampens their power. This sectoral heterogeneity challenges *one-size-fits-all* theories of the labor share decline and underscores the importance of micro-founded, sector-regimes power analyses.

Furthermore, we uncover a critical asymmetry in the business cycle's impact. Recessions, by sharply increasing unemployment, act as a brutal disciplining device, swiftly eroding the bargaining power of production workers and inflicting deep scars on the labor share. Expansions, however, provide only a fragile and statistically weaker recovery. This asymmetric pattern implies that each downturn pushes income distribution downward in a way not fully offset by subsequent recoveries, producing a plucking effect that gradually and persistently erodes labor's position.

Our findings carry significant implications that extend beyond academic debate. They suggest that antitrust policy, while crucial for product market competition, is likely insufficient to reverse the decline in labor's share. If rising industrial concentration is not the primary driver in manufacturing, and if markups are disconnected from concentration dynamics, then policies focused only on corporate power will miss the mark. Instead, our analysis calls for a renewed focus on institutions and policies that directly bolster worker power (Hafiz and Marinescu, 2023). This includes, but is not limited to, strengthening collective bargaining, especially for production workers in vulnerable sectors. It also points to the importance of aggregate demand management: running a "high-pressure" economy with tight labor markets can be a powerful tool for rebuilding workers' bargaining power and mitigating the distributive scars of recessions.

In conclusion, the story of the falling labor share in U.S. manufacturing is, to a significant extent, a story of *shifting-power-within-workplace*. It is a story of a hierarchical divide between categories of labor force, of how this divide is amplified by sector-specific technological trajectories, and of how the business cycle asymmetrically weakens the already vulnerable. By refocusing on the granular dynamics of worker power, we move closer to a more human—centered understanding of where the fruits of technological progress have gone.

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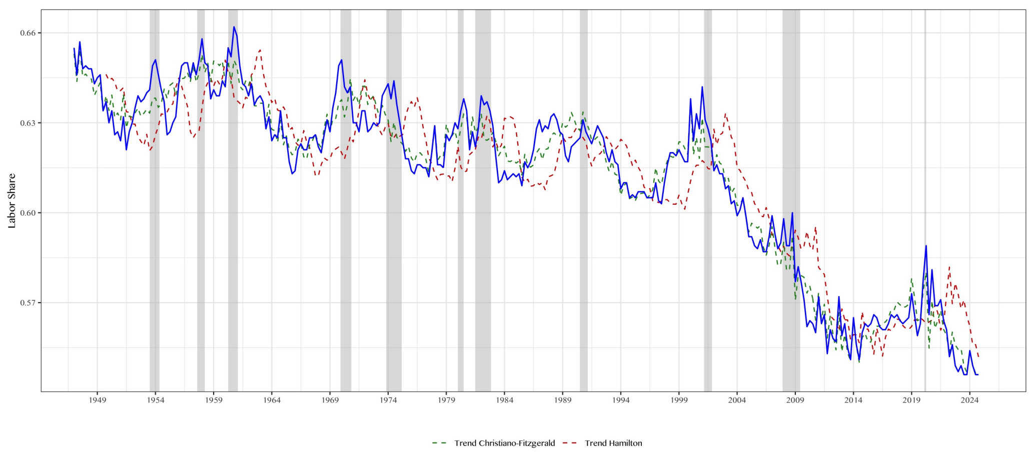
A Motivating Aggregate and Sectoral Facts

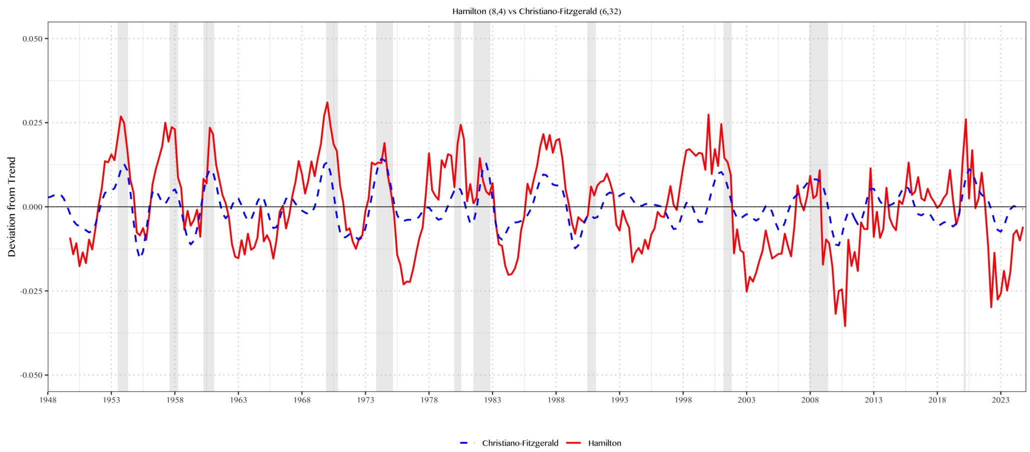
A.1 Aggregate Trends

Figure 2: US Labor Share, 1947:Q1-2024:Q4



Notes: This figure shows the Bureau of Labor Statistics Headline Series at quarterly frequency. It measures labor compensation and an official estimates of self-proprietors' income components of Nonfarm Business Sector. Green and red lines show the estimated trend respectively by Christiano and Fitzgerald (2003) and Hamilton (2018) filter.

Figure 3: US Labor Share, Cyclical Decomposition



Notes: This figure shows the cyclical component of the BLS labor share headline compared to its trend. By applying the Hamilton and Christiano-Fitzgerald Filter methods, we use the defaults settings for quarterly time series.

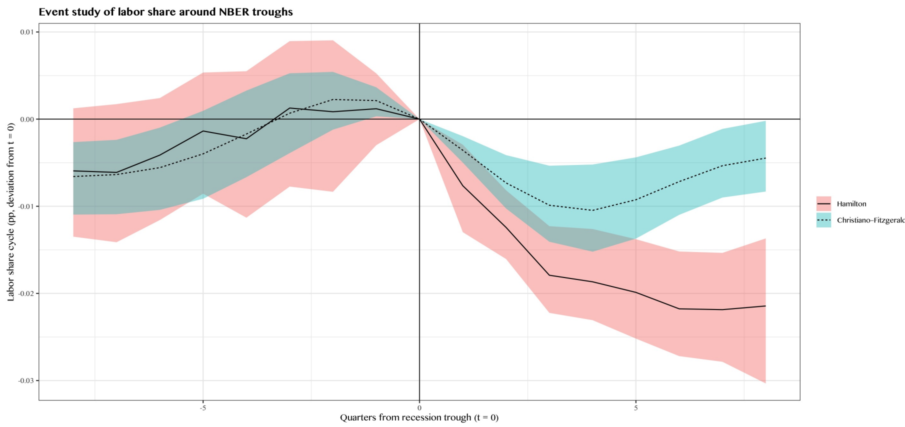
Period	Labor Share at time 0	Labor Share at time 1	Δ (%)
1947–1963	0.655	0.639	-2.4
1963–1979	0.639	0.626	-2.0
1980–1995	0.628	0.606	-3.5
1995–2007	0.606	0.599	-1.2
2008–2024	0.598	0.554	-7.4

Table 1: % Variation of Labor Share by Period

Lag	Hamilton Filter	Christiano-Fitzgerald Filter
-6	0.007	0.055
-5	-0.041	0.017
-4	-0.048	-0.035
-3	-0.060	-0.096
-2	-0.076	-0.151
-1	-0.111	-0.179
0	-0.140	-0.163
1	-0.056	-0.105
2	-0.037	-0.025
3	0.023	0.049
4	0.065	0.094
5	0.085	0.109
6	0.122	0.108

Table 2: Cross-correlation matrix w.r.t. GDP and standard deviation of Hamilton (0.077) and Chrstiano-Fitzgerald (0.11) filter.

Figure 4: Event-study of Labor Share around Recession Episodes



Notes: This figure shows an event-study of labor share behavior around each recession episodes. We use $t = 0$ the NBER trough: offical end of recession, when output reverts and recovery starts. For each event (i.e., recession), we build a window of $[-8, +8]$ quarters, excluding events closest to the end of the sample. We normalize each episode by subtracting at $t = 0$ as each curve starts from the trough. We then compute the cross-events average, building 95% confidence bands by bootstraping by-event. The 95% bands are constructed as follows: for each h horizon, we take the percentiles at the tails (2.5 and 97.5) of the distribution of bootstrap means over 2000 replicates. For each recession, quarterly observations are strongly correlated. By resampling individual quarters, they would inevitably become independent of each other. Instead, by resampling for each event (from the beginning to the end of the recessionary period), we preserve the characteristics of each recession (amplitude, duration, asymmetry). The bands therefore reflect the variability between recessions and say how precise each point estimation curve is.

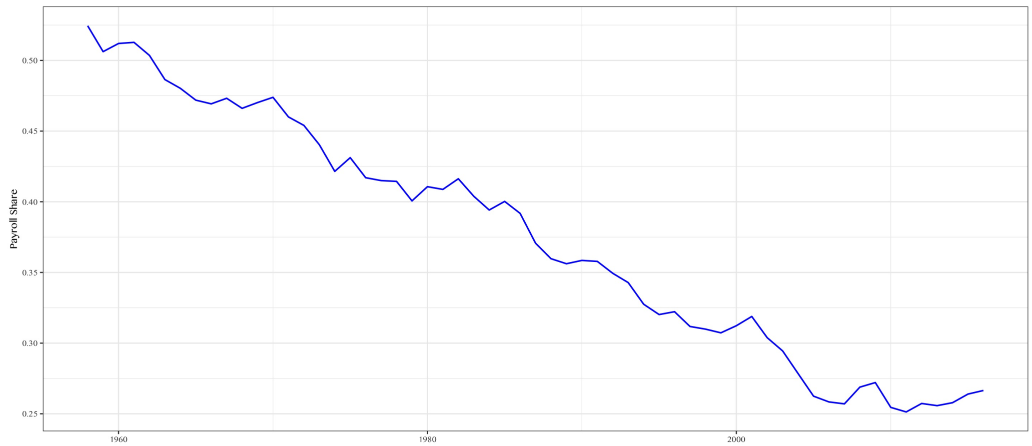
A.2 Evidence from Sectoral Level

Sector	LS 1987	VA 1987	LS 2023	VA 2023	Δ LS (%)	Δ VA (%)
Private industries	52.6	85.7	47.9	88.8	-8.9	3.6
Agriculture, forestry, fishing, and hunting (11)	20.1	1.6	26.1	1.0	29.9	-37.5
Mining (21)	40.6	1.5	21.2	1.5	-47.8	0.0
Utilities (22)	24.7	2.6	21.8	1.6	-11.7	-38.5
Construction (23)	69.0	4.3	61.0	4.4	-11.6	2.3
Manufacturing (31-33)	63.8	18.1	46.6	10.2	-26.9	-43.6
Wholesale trade (42)	54.1	5.9	42.8	6.0	-20.9	1.7
Retail trade (44-45)	60.6	7.1	45.4	6.4	-25.1	-9.9
Transportation and warehousing (48-49)	68.9	3.2	57.6	3.4	-16.4	6.2
Information (51)	40.1	4.6	36.6	5.3	-8.7	15.2
Finance and insurance (52)	23.3	5.7	22.0	7.3	-5.6	28.1
Real estate and rental and leasing (53)	6.5	11.6	14.4	13.7	121.5	18.1
Professional and business services (54)	66.2	8.0	71.7	13.0	8.3	62.5
Management of companies and enterprises (55)	77.5	1.6	67.3	1.8	-13.2	12.5
Administrative and waste management services (56)	69.3	1.8	71.1	3.2	2.6	77.8
Educational services, health care, and social assistance (61-62)	79.8	5.7	81.0	8.5	1.5	49.1
Arts, entertainment, recreation, accommodation, and food services (71)	61.5	3.2	57.6	4.4	-6.3	37.5
Other services, except government (81)	61.0	2.5	69.8	2.1	14.4	-16.0

Table 3: Labor Share and Value Added Share by Sector (2-digit NAICS), 1987-2023. Data are from BEA Value Added by Industry.

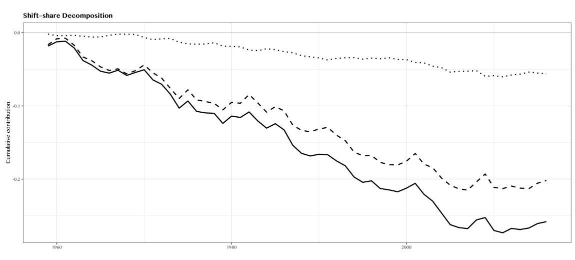
A.3 Evidence from US Manufacturing

Figure 5: 6-digit US Manufacturing Payroll Share

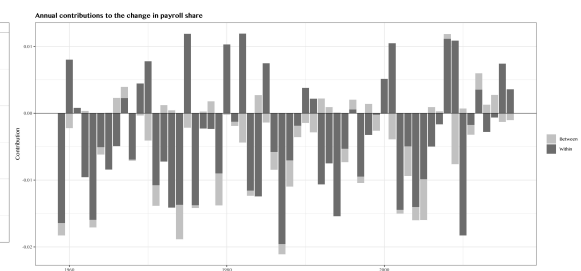


Notes: This figure shows the payroll Share at the 6-digit level along the entire time span covered by the NBER-CES core dataset (1958-2016). The manufacturing labor share measure is the ratio between the total payroll of all employees and the total added value of each manufacturing industry.

Figure 6: Shift–Share Decomposition of 6-digit US Manufacturing Payroll Share



(a) Total variation, within- and between-industry contributions to changes in aggregate payroll share. $\Delta\lambda = -0.258$, Within $= -0.223$ ($\sim 86\%$), Between $= -0.035$ ($\sim 14\%$).



(b) Within and between year-by-year contributions. The sum over years equals the full-span change (1958–2016).

Table 4: Shift-Share Decomposition Across Time Periods

Period	$\Delta\lambda$	Within	Between	Within (%)	Between (%)
1958–1970	-0.051	-0.046	-0.004	91.8	8.2
1971–1982	-0.044	-0.036	-0.007	82.9	17.1
1982–1995	-0.096	-0.088	-0.008	91.3	8.7
1995–2009	-0.048	-0.026	-0.022	54.9	45.1
2010–2016	0.012	0.009	0.003	71.9	28.1

Notes: This table reports the results of shift-share decomposition by subperiods (levels). Within and between shares are percentages of $\Delta\lambda$ within each subperiod.

A.3.1 Within-Sector Micro Correlations

Table 5: Labor vs. Capital Productivity OLS Regression

	(1)	(2)	(3)	(4)
$\log$(Capital Productivity)	0.7443***	1.494***	-0.1162***	0.2545***
	(0.0428)	(0.0217)	(0.0429)	(0.0232)
Observations	21,299	21,299	21,299	21,299
R^2	0.26877	0.79166	0.80072	0.97644

Notes: This table shows the OLS estimates of labor vs. capital productivity (log–log) regressions. Observations correspond to industry-year pairs for the 361 NAICS industries in the NBER-CES dataset, from 1958-2016. columns are: (1) Pooled OLS; (2) Industry FE; (3) Time FE; (4) Two-way FE (industry + year). Standard errors clustered at the industry-level are in parentheses. *p$<$0.1; **p$<$0.05; ***p$<$0.01.

Table 6: Input Factors Productivities Correlation

	1958–1970			
	(1)	(2)	(3)	(4)
log(Capital Productivity)	-0.125	0.592	-0.163	0.197
	(0.418)	(0.165)	(0.373)	(0.064)
Observations	4,693	4,693	4,693	4,693
R^2	0.036	0.862	0.235	0.979
Adjusted R^2	0.035	0.850	0.233	0.978
	1971–1982			
	(1)	(2)	(3)	(4)
log(Capital Productivity)	-0.001	1.073	-0.176	0.438
	(0.526)	(0.154)	(0.423)	(0.075)
Observations	4,332	4,332	4,332	4,332
R^2	0.00000	0.921	0.352	0.981
Adjusted R^2	-0.0002	0.914	0.350	0.979
	1982–1995			
	(1)	(2)	(3)	(4)
log(Capital Productivity)	-0.070	0.887	-0.150	0.412
	(0.536)	(0.138)	(0.496)	(0.087)
Observations	4,693	4,693	4,693	4,693
R^2	0.006	0.939	0.151	0.976
Adjusted R^2	0.006	0.934	0.149	0.974
	1995–2009			
	(1)	(2)	(3)	(4)
log(Capital Productivity)	-0.074	0.437	-0.079	0.456
	(0.582)	(0.215)	(0.554)	(0.106)
Observations	5,054	5,054	5,054	5,054
R^2	0.005	0.874	0.101	0.969
Adjusted R^2	0.005	0.864	0.099	0.967
	2010–2016			
	(1)	(2)	(3)	(4)
log(Capital Productivity)	0.120	0.608	0.115	0.575
	(0.584)	(0.071)	(0.583)	(0.068)
Observations	2,527	2,527	2,527	2,527
R^2	0.012	0.987	0.016	0.989
Adjusted R^2	0.012	0.985	0.014	0.987

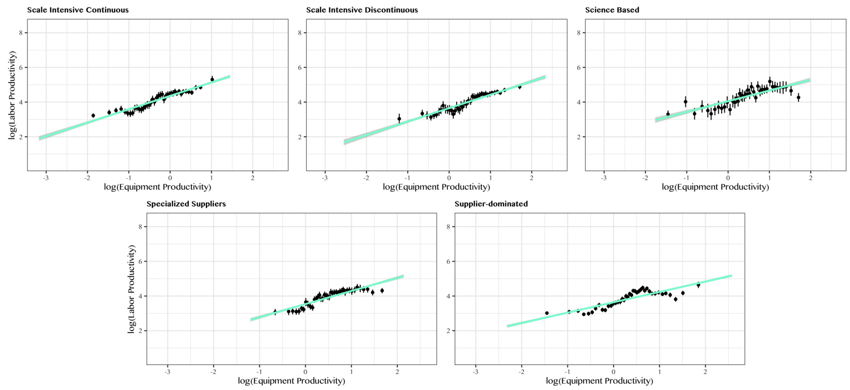
Notes: This table report the results of labor vs. capital productivity (log–log) regression. Period panels in vertical format. Observations correspond to industry-year pairs for the 361 NAICS industries in the NBER-CES dataset. Columns are: (1) Pooled OLS; (2) Industry FE; (3) Time FE; (4) Two-way FE (industry + year). Standard errors clustered at the industry level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 7: NAICS Codes by Industry Regime

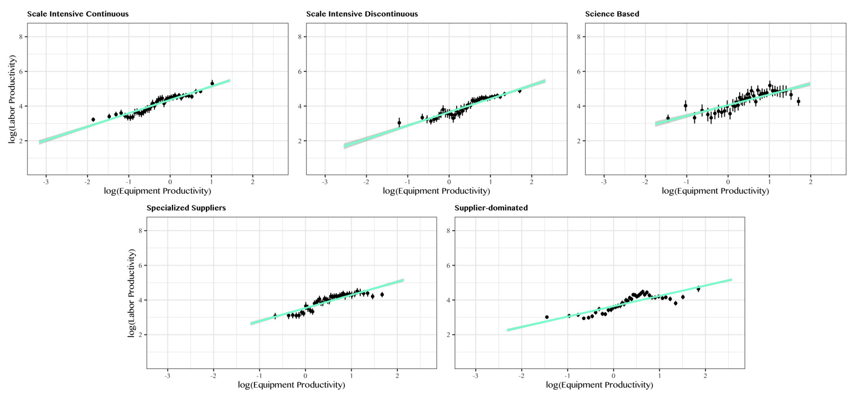
Panel A: Supplier Dominated	
311	Food Manufacturing
312	Beverage and Tobacco Product Manufacturing
313	Textile Mills
314	Textile Product Mills
315	Apparel Manufacturing
316	Leather and Allied Product Manufacturing
321	Wood Product Manufacturing
3222	Converted Paper Product Manufacturing
323	Printing and Related Support Activities
327999	All Other Miscellaneous Nonmetallic Mineral Product Manufacturing
332 (Except 3321)	Fabricated Metal Product Manufacturing
337	Furniture and Related Product Manufacturing
3399	Other Miscellaneous Manufacturing
Panel B: Scale Intensive Continuous	
3221	Pulp, Paper, and Paperboard Mills
3241	Petroleum and Coal Products Manufacturing
3251	Basic Chemical Manufacturing
3252	Resin, Synthetic Rubber, and Artificial and Synthetic Fibres and Filaments Manufacturing
326	Plastics and Rubber Products Manufacturing
327	Nonmetallic Mineral Product Manufacturing
331	Primary Metal Manufacturing
3321	Forging and Stamping
Panel C: Scale Intensive Discontinuous	
3331	Agricultural, construction and mining machinery manufacturing
33431	Audio and video equipment manufacturing
3346	Manufacturing and Reproducing Magnetic and Optical Media
335 (Except 3359)	Electrical Equipment, Appliance, and Component Manufacturing
336	Transportation Equipment Manufacturing
Panel D: Specialized Suppliers	
333	Machinery Manufacturing
3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
3359	Other Electrical Equipment and Component Manufacturing
3391	Medical Equipment and Supplies Manufacturing
Panel E: Science Based	
3253	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing
3254	Pharmaceutical and Medicine Manufacturing
3255	Paint, Coating, and Adhesive Manufacturing
3256	Soap, Cleaning Compound, and Toilet Preparation Manufacturing
3259	Other Chemical Product and Preparation Manufacturing
3341	Computer and Peripheral Equipment Manufacturing
3342	Communications Equipment Manufacturing
3344	Semiconductor and Other Electronic Component Manufacturing

Notes: This table shows the classification of US manufacturing industries in the different technological-sectoral regimes. The list of industries and related data comes from the NBER-CES Manufacturing Database.

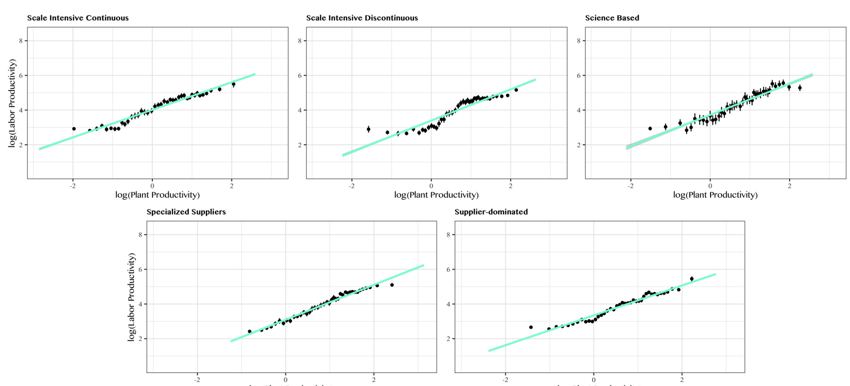
Figure 7: Micro-Sectoral Input Factors Productivities Correlation



(a) Labor productivity vs. capital productivity (binscatter by regime).



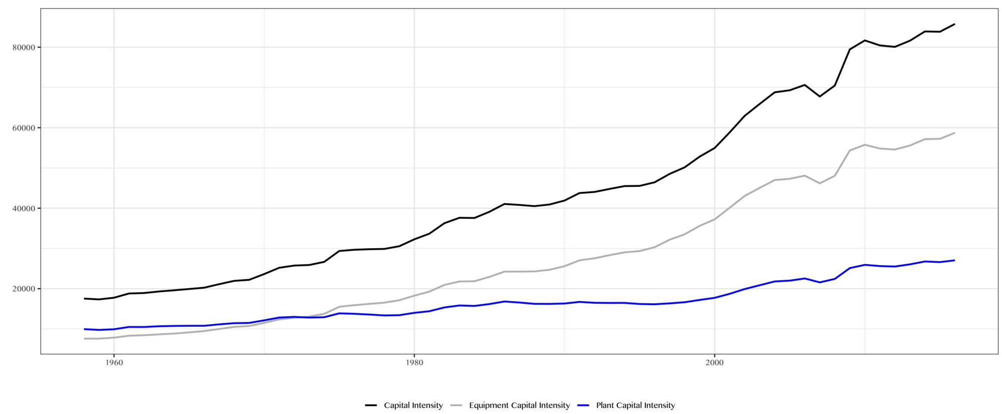
(b) Equipment (real equipment capital) vs. labor productivity.



(c) Plant (real structures capital) vs. labor productivity.

Notes: This figure shows the micro–sectoral regime correlations. Observations within each regime are grouped into quantile bins ($n \approx 40$). The line is OLS on micro data with 95% CIs.

Figure 8: Capital Intensities



Notes: This figure shows the different measures of capital intensity. The black line measures total capital intensity, as the ratio of total capital stock to total employment. Total capital stock is the sum of: equipment and plant capital. The gray and blue lines represent the intensity for these two capital components. Data on capital and employment come from NBER-CES Manufacturing Data.

A.3.1.1 Concentration-Profitability Nexus

We provide the results of industry concentration analysis.

Table 8: Concentration Ratios Change

	1997	**2012**	**Δ (%)**
CR4	41	42.7	4.1
CR8	53.3	55.9	4.9
CR20	68	70.4	3.5
CR50	80	81.8	2.3

Table 9: Notes: This table shows the percentage variation of Concentration Ratios from 1997 to 2012. Data are from Concentration Subject Series of the U.S. Economic Census for 6-digit Manufacturing industries.

Table 10: Concentration Ratios Change by Regime (1997–2012)

	1997	2012	Δ (%)
		Supplier-dominated	
CR4	35.3	39.3	11.4
CR8	46.2	49.8	7.6
CR20	60.7	63.1	3.8
CR50	73.3	74.7	1.9
		Specialized Suppliers	
CR4	36.3	37.7	3.8
CR8	48.7	51.3	5.3
CR20	64	66.4	3.8
CR50	77	79.3	3
		Scale Intensive Continuous	
CR4	30.7	39.4	28
CR8	44.7	55	23.2
CR20	63.4	72	13.6
CR50	78.5	84.2	7.3
		Scale Intensive Discontinuous	
CR4	65.5	59.8	-8.7
CR8	76.2	73.6	-3.4
CR20	84.7	83.7	-1.1
CR50	91.2	91.3	0.1
		Science Based	
CR4	45.6	43.3	-5
CR8	59.9	58.2	-2.8
CR20	75.5	75.3	-0.3
CR50	86.7	87.5	0.9

Markup Estimation. In line with an accounting framework, we compute markup as the simple ratio between industry-level sales (i.e., how much each industry sells both as a final product and as an intermediate product to another industry) and an industry-level equivalent of cost-goods-sold.

$$\mu_{jt} = \frac{Shipments_{jt}}{Material_{jt} + Energy_{jt} + Payroll_{jt}}$$

As industry-level sales variable, we use the value of shipments, expressed in millions of dollars and based on the net value of sales. Because it also includes sales made by each industry as work contracts and services provided to others, we can consider this measure a good measure of gross revenues from normal industry-wide business operations. As industry-level cost variable, we use the sum of the variable cost sources by each industry: materials, energy and labor. Therefore, equation 5 is an average cost markup.

Our markup measure captures the price–cost margin, offering a simple calculation while remaining robust to uncertainties in available input data (Basu, 2019; Syverson, 2019). We do not assume any underlying production function connecting profit margin to the returns-to-scale. This point raised a number of doubts and critical issues about the different methods to estimate the output elasticity w.r.to production inputs. Moreover, our measure—essentially net operating margins (Gutiérrez and Philippon, 2017)—does not rely on estimates of the return on capital. It is among the few in the literature to provide a long-run, 6-digit level measure of extractivity or market power for US manufacturing. Importantly, it allows comparability with ROA and the Lerner Index, which is crucial for analyzing the concentration–profitability nexus.

We depart from the dominant markup literature, which typically uses a production-based approach following Hall (1988) and Loecker and Warzynski (2012), recently refined by De Loecker et al. (2020) (DEU). The key difference is not the formula itself, but the underlying assumption of cost minimization used to derive output elasticities with respect to productive inputs.

$$\mu_{jt} = \underbrace{\vartheta_{jt}}_{\text{output-elasticity of the variable input}} \cdot \underbrace{\frac{P_{jt}Q_{jt}}{P^V_{jt}V_{jt}}}_{\text{revenue share of the variable input}}$$

DEU multiply our ratio (equation 5) by a time- and sector-specific term capturing how the underlying technology links price-setting power above marginal cost to the primitive demand conditions (Raval, 2023). In contrast, we assume constant returns to scale for all industries. While simplistic, this avoids several concerns and criticisms regarding the reliability of estimates from the DEU method (Basu, 2019)[17].

[17]Final markup estimates are highly sensitive to the chosen method (Davis, 2024; Edmond et al., 2023; Traina, 2018).

Our sectoral differentiation on specific microeconomic properties of technological knowledge help us to provide a markup estimate approximating a sector-specific heterogeneity. This partially attenuates the assumption of CRTS. Moreover, DEU note that, regardless of the method used—including our simpler approach—the long-run trend and growth rate of markups are unaffected by the assumed returns-to-scale or sector- and time-specific elasticities. In other words, long-term markup dynamics do not depend on technological-change factors. Our long-run analysis aligns with this perspective: figure 9 shows that our markup estimates closely follow the trends reported by DEU, both for manufacturing (Census data) and the overall economy (Compustat data). We calculate the average aggregate-manufacturing markup as follows:

$$\mu_t = \sum_j \varpi_{jt}\mu_{jt}$$

where ϖ_{jt} is the industry-weight. By industry-weight, we use the share of industry-level sales (i.e., value of shipments). As a robustness check, we multiply our markup measure by a constant, time-invariant factor—calibrated at 0.85 by DEU—to account for returns-to-scale, while we assume it to be unitary. Figure 10 shows that the trend remains identical, just scaled downward, confirming that long-term increases in the price–cost markup are not driven by technological factors.

Panel 11a shows the markup evolution across sectoral regimes, while panel 11b displays their distribution. Unsurprisingly, Science-Based industries exhibit the strongest markup growth, especially since the 1980s. Supplier-Dominated industries, despite low technological content and reliance on external inputs, show a similar upward trend, though less pronounced. In contrast, traditional regimes– Scale-Intensive and Specialized Suppliers– characterized by tacit knowledge and economies of scale, display almost constant price–cost markups over time.

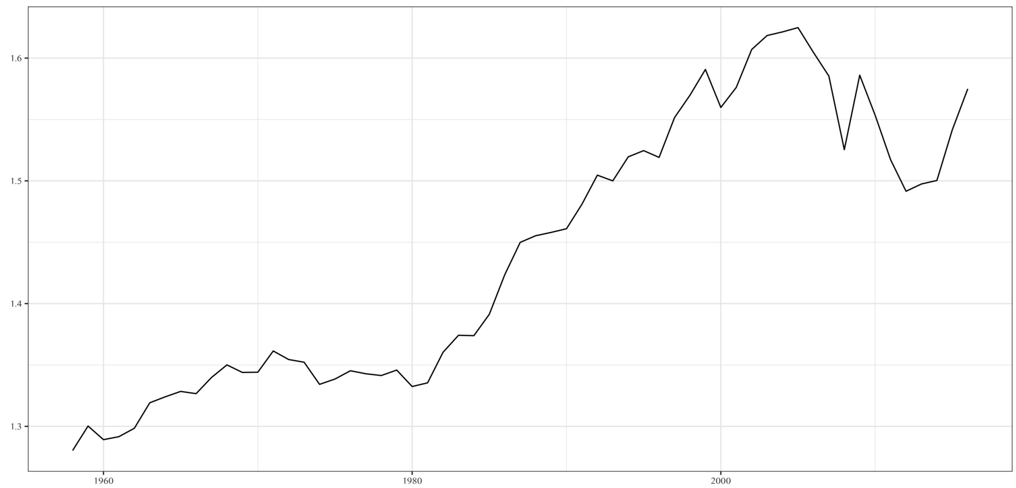
These trends reveal the distributional shifts in markups across the entire manufacturing sector. Figure **??** shows the kernel density of unweighted markup for all 361 six-digit manufacturing industries in 1958 and 2016. The distribution has not only widened, but the right tail has thickened, indicating that a few industries—mainly within Science-Based and Supplier-Dominated regimes—drive the increase. Panel **??** reports the moments of the weighted aggregate markup distribution. Most industries exhibit only modest growth in markup over time, but the pronounced rise in the 75th and 90th percentiles since the 1980s reflects the strong upward pull of a limited set of high-markup industries, largely in the Science-Based regime.

Understanding the across and within-regime dynamics behind the increase in price-cost markup (because two regimes characterized by such different industrial and technological dynamics exhibit the same growing trend as markup) goes beyond the scope of this work, but remains an interesting future line of research. Nonetheless, the analysis of the distributional properties of our markup measure and the conclusions drawn from it are in line with the stylized facts found by the reference literature (De Loecker et al., 2020; Díez et al., 2021). Therefore, despite not having adopted a production approach for estimation and having opted for a simple accounting method, we can conclude that our estimate is robust from different angles.

In all estimates, including ours, labor costs are included in the cost component. By default, we consider labor costs as part of variable costs in the denominator of equation **??**. However, when testing the worker power hypothesis via payroll share dynamics, we use a labor-cleaned version. This is because a decline in worker power reduces workers' ability to extract rents, lowering labor costs and mechanically increasing markup. Such an increase would not reflect genuine corporate power (Stansbury and Summers, 2020). To isolate the worker power channel, section 4 uses the markup measure excluding labor costs.

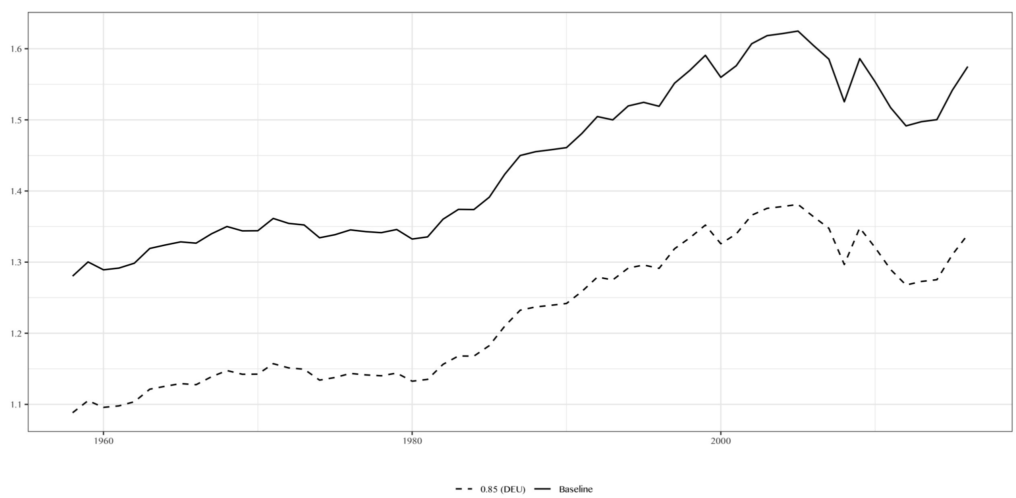
For a recent and thorough review, both economic and methodological, see Syverson (2024).

Figure 9: Aggregate Manufacturing Markup



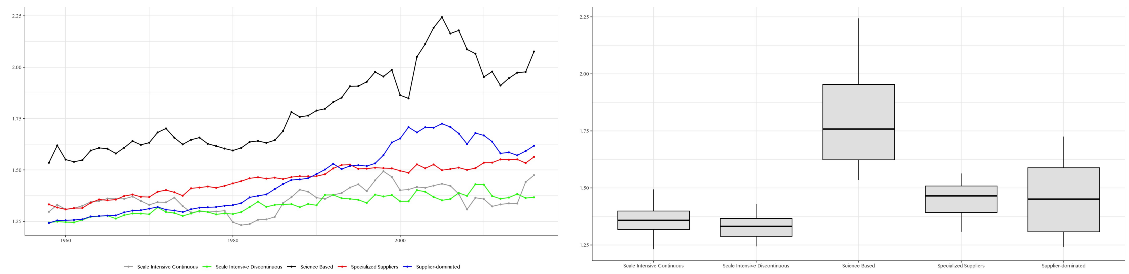
Notes: This figure shows the average aggregate markup for manufacturing (6-digit). Data comes from NBER-CES Manufacturing Data. The average is revenue-weighted. The figure shows the dynamics of markup from 1958 to 2016.

Figure 10: Aggregate and Time-Invariante Shift Manufacturing Markup



Notes: This figure shows the average aggregate markup for manufacturing (6-digit). Data comes from NBER-CES Manufacturing Data, from 1958-2016. The average is revenue-weighted. The figure shows the dynamics of a time-invariant constant elasticity markup ($\vartheta = 0.85$), as done by Konczal and Lusiani (2022).

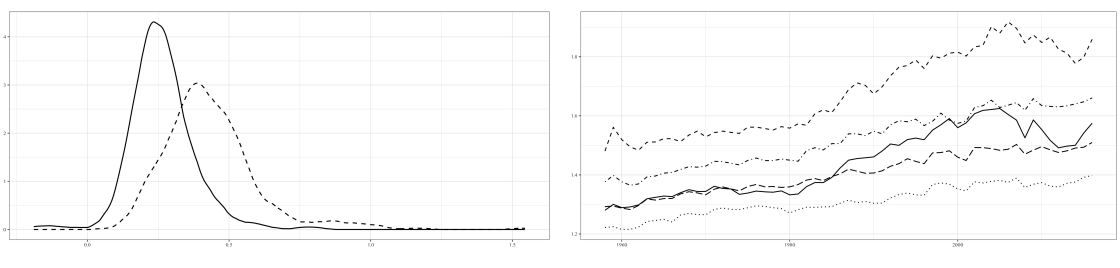
Figure 11: Markup Trends by Regime



(a) Evolution of markup for different sectoral regimes. Data comes from NBER-CES Manufacturing Data, from 1958-2016. The average amrkup is revenue-weighted.

(b) Distribution (min., 25° percentile, mean, median, 75° percentile, max.) of average markup across sectoral regimes. Data comes from NBER-CES Manufacturing Data, from 1958-2016.

Figure 12: The Distribution of Markup



(a) Kernel density for all 361 6-digit manufacturing industries. Kernel is Epanechnikov.

(b) Percentile distribution of weighted average markup.

Table 11: Concentration-Profitability Regression

Panel A: CR4

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR4)	0.189*	0.141***	0.096***	0.101***	0.097***	0.096***	0.062***	0.060***	0.059***
	(0.084)	(0.038)	(0.028)	(0.030)	(0.028)	(0.028)	(0.014)	(0.013)	(0.013)
log(vship)		0.835***	1.076***		0.070***	0.076**		0.047***	0.051***
		(0.031)	(0.024)		(0.021)	(0.024)		(0.010)	(0.012)
log(cap)			−1.024***			−0.024			−0.016
			(0.041)			(0.041)			(0.022)
Num. Obs.	1440	1440	1440	1440	1440	1440	1440	1440	1440
R^2	0.750	0.904	0.950	0.833	0.837	0.837	0.869	0.874	0.874
Adj. R^2	0.666	0.872	0.933	0.777	0.781	0.781	0.824	0.831	0.831

Panel B: CR8

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR8)	0.189	0.171***	0.126***	0.129***	0.127***	0.126***	0.085***	0.084***	0.084***
	(0.117)	(0.049)	(0.037)	(0.039)	(0.037)	(0.037)	(0.017)	(0.016)	(0.016)
log(vship)		0.838***	1.078***		0.072***	0.078**		0.048***	0.052***
		(0.032)	(0.024)		(0.021)	(0.024)		(0.011)	(0.012)
log(cap)			−1.027***			−0.027			−0.017
			(0.041)			(0.041)			(0.022)
Num. Obs.	1440	1440	1440	1440	1440	1440	1440	1440	1440
R^2	0.749	0.904	0.950	0.833	0.836	0.837	0.869	0.874	0.874
Adj. R^2	0.664	0.871	0.933	0.776	0.781	0.781	0.825	0.832	0.832

Notes: This table reports coefficients from regressions of different profitability measures (ROA, Lerner Index and Markup) on industry concentration. Data are from NBER-CES Manufacturing Data to compute the profit measures. Concentration measures are from the U.S. Economic Census Concentration Subject Series for years 1997, 2002, 2007, 2012. Due to missing concentration data for industry 325110 (Petrochemical Manufacturing) in 1997–2007, that industry is excluded. OLS with two-way fixed effects (industry & year). Standard errors clustered at the industry level in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 12: CR4-Profitability Regression Across Sectoral Regimes

Panel A: Scale Intensive Continuous

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR4)	0.029	0.062	0.048	0.047	0.048	0.048	0.057^{*}	0.058^{*}	0.058^{*}
	(0.239)	(0.078)	(0.070)	(0.072)	(0.069)	(0.070)	(0.031)	(0.028)	(0.028)
log(vship)		0.716^{***}	1.038^{***}		0.024	0.038		0.025^{*}	0.036^{*}
		(0.059)	(0.044)		(0.026)	(0.044)		(0.013)	(0.019)
log(cap)			-1.046^{***}			-0.046			-0.036
			(0.107)			(0.107)			(0.039)
Num. Obs.	292	292	292	292	292	292	292	292	292
R^2	0.773	0.893	0.948	0.839	0.839	0.839	0.845	0.847	0.848
Adj. R^2	0.693	0.854	0.929	0.782	0.781	0.781	0.790	0.792	0.792

Panel B: Scale Intensive Discontinuous

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR4)	-0.065	-0.008	-0.006	-0.004	-0.006	-0.006	0.051	0.051	0.051
	(0.295)	(0.211)	(0.208)	(0.201)	(0.208)	(0.208)	(0.040)	(0.042)	(0.041)
log(vship)		0.863^{***}	0.967^{***}		-0.020	-0.033		0.001	-0.006
		(0.107)	(0.088)		(0.078)	(0.088)		(0.032)	(0.034)
log(cap)			-0.892^{***}			0.108			0.062
			(0.167)			(0.167)			(0.075)
Num. Obs.	172	172	172	172	172	172	172	172	172
R^2	0.733	0.878	0.900	0.627	0.628	0.629	0.710	0.710	0.713
Adj. R^2	0.634	0.831	0.861	0.490	0.487	0.484	0.603	0.600	0.601

Panel C: Science Based

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR4)	0.541^{*}	0.233	0.028	0.093	0.043	0.028	0.063	0.029	0.029
	(0.299)	(0.157)	(0.128)	(0.150)	(0.129)	(0.128)	(0.083)	(0.071)	(0.069)
log(vship)		0.933^{***}	1.168^{***}		0.151^{*}	0.168^{*}		0.104^{*}	0.105^{*}
		(0.122)	(0.085)		(0.082)	(0.085)		(0.049)	(0.050)
log(cap)			-1.080^{***}			-0.080			-0.002
			(0.140)			(0.140)			(0.102)
Num. Obs.	128	128	128	128	128	128	128	128	128
R^2	0.701	0.889	0.943	0.741	0.762	0.763	0.799	0.819	0.819
Adj. R^2	0.587	0.845	0.919	0.643	0.667	0.665	0.723	0.747	0.745

Panel D: Specialized Suppliers

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR4)	0.564^{**}	0.153	0.063	0.134^{*}	0.065	0.063	0.073^{*}	0.038	0.037
	(0.206)	(0.105)	(0.052)	(0.063)	(0.050)	(0.052)	(0.034)	(0.026)	(0.027)
log(vship)		1.000^{***}	1.173^{***}		0.170^{***}	0.173^{***}		0.085^{**}	0.086^{**}
		(0.086)	(0.049)		(0.045)	(0.049)		(0.025)	(0.027)
log(cap)			-1.022^{***}			-0.022			-0.010
			(0.054)			(0.054)			(0.027)
Num. Obs.	224	224	224	224	224	224	224	224	224
R^2	0.721	0.888	0.956	0.678	0.710	0.710	0.682	0.714	0.714
Adj. R^2	0.621	0.847	0.940	0.563	0.603	0.601	0.568	0.608	0.606

Panel E: Supplier-dominated

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR4)	0.151	0.169^{**}	0.134^{***}	0.134^{***}	0.136^{***}	0.134^{***}	0.063^{**}	0.064^{**}	0.063^{**}
	(0.109)	(0.052)	(0.030)	(0.030)	(0.030)	(0.030)	(0.021)	(0.021)	(0.021)
log(vship)		0.787^{***}	1.092^{***}		0.077^{***}	0.092^{***}		0.047^{***}	0.058^{***}
		(0.036)	(0.021)		(0.020)	(0.021)		(0.011)	(0.013)
log(cap)			-1.053^{***}			-0.053			-0.037
			(0.050)			(0.050)			(0.030)
Num. Obs.	624	624	624	624	624	624	624	624	624
R^2	0.760	0.920	0.966	0.911	0.915	0.915	0.913	0.917	0.917
Adj. R^2	0.678	0.892	0.954	0.881	0.885	0.886	0.883	0.888	0.889

Notes: Coefficients from OLS regressions of profitability measures (ROA, Lerner Index, Markup) on industry concentration (CR4), by sectoral regime. Two-way fixed effects (industry & year). Standard errors clustered at the industry level in parentheses.*p<0.1; **p<0.05; ***p<0.01.

Table 13: CR8-Profitability Regression Across Sectoral Regimes

Panel A: Scale Intensive Continuous

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR8)	−0.054	0.038	0.073	0.068	0.071	0.073	0.067	0.070^{+}	0.072^{+}
	(0.366)	(0.097)	(0.093)	(0.101)	(0.094)	(0.093)	(0.041)	(0.035)	(0.036)
log(vship)		0.716^{***}	1.041^{***}		0.025	0.041		0.026^{+}	0.039^{*}
		(0.062)	(0.045)		(0.026)	(0.045)		(0.013)	(0.019)
log(cap)			-1.050^{***}			−0.050			−0.040
			(0.104)			(0.104)			(0.038)
Num. Obs.	292	292	292	292	292	292	292	292	292
R^2	0.773	0.893	0.948	0.839	0.839	0.840	0.844	0.846	0.847
Adj. R^2	0.693	0.854	0.929	0.782	0.781	0.781	0.789	0.791	0.792

Panel B: Scale Intensive Discontinuous

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR8)	0.009	0.000	−0.019	−0.022	−0.022	−0.019	0.068	0.068	0.069
	(0.390)	(0.288)	(0.282)	(0.281)	(0.283)	(0.282)	(0.058)	(0.058)	(0.057)
log(vship)		0.863^{***}	0.968^{***}		−0.020	−0.032		0.000	−0.007
		(0.105)	(0.085)		(0.075)	(0.085)		(0.031)	(0.033)
log(cap)			-0.893^{***}			0.107			0.063
			(0.166)			(0.166)			(0.076)
Num. Obs.	172	172	172	172	172	172	172	172	172
R^2	0.733	0.878	0.900	0.627	0.628	0.629	0.709	0.709	0.712
Adj. R^2	0.634	0.831	0.861	0.490	0.487	0.484	0.602	0.599	0.600

Panel C: Science Based

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR8)	0.557	0.141	−0.100	−0.009	−0.079	−0.100	0.036	−0.011	−0.013
	(0.396)	(0.234)	(0.198)	(0.209)	(0.194)	(0.198)	(0.103)	(0.096)	(0.095)
log(vship)		0.944^{***}	1.178^{***}		0.158^{+}	0.178^{*}		0.107^{*}	0.109^{*}
		(0.123)	(0.082)		(0.080)	(0.082)		(0.049)	(0.050)
log(cap)			-1.096^{***}			−0.096			−0.009
			(0.140)			(0.140)			(0.102)
Num. Obs.	128	128	128	128	128	128	128	128	128
R^2	0.694	0.887	0.943	0.740	0.762	0.764	0.798	0.819	0.819
Adj. R^2	0.577	0.842	0.919	0.641	0.668	0.666	0.721	0.747	0.744

Panel D: Specialized Suppliers

	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR8)	0.801^{*}	0.237^{+}	0.131^{+}	0.226^{*}	0.134^{+}	0.131^{+}	0.118^{*}	0.071^{+}	0.070^{+}
	(0.311)	(0.125)	(0.079)	(0.098)	(0.076)	(0.079)	(0.050)	(0.037)	(0.038)
log(vship)		0.999^{***}	1.168^{***}		0.164^{***}	0.168^{**}		0.083^{**}	0.084^{**}
		(0.085)	(0.048)		(0.045)	(0.048)		(0.025)	(0.027)
log(cap)			-1.020^{***}			−0.020			−0.010
			(0.053)			(0.053)			(0.027)
Num. Obs.	224	224	224	224	224	224	224	224	224
R^2	0.722	0.888	0.957	0.683	0.712	0.713	0.686	0.716	0.716
Adj. R^2	0.621	0.847	0.940	0.568	0.606	0.604	0.573	0.611	0.609

Panel E: Supplier-dominated

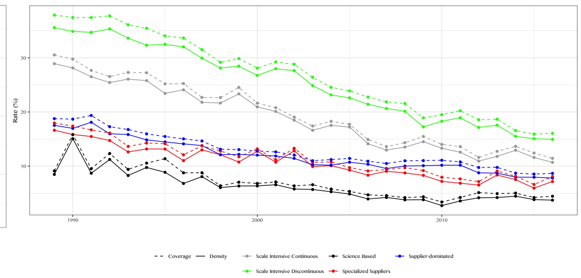
	ROA			Lerner Index			Markup		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
log(CR8)	0.118	0.203^{**}	0.172^{***}	0.165^{***}	0.174^{***}	0.172^{***}	0.093^{***}	0.098^{***}	0.097^{***}
	(0.131)	(0.070)	(0.043)	(0.041)	(0.043)	(0.043)	(0.024)	(0.024)	(0.024)
log(vship)		0.790^{***}	1.096^{***}		0.080^{***}	0.096^{***}		0.049^{***}	0.060^{***}
		(0.036)	(0.021)		(0.020)	(0.021)		(0.011)	(0.013)
log(cap)			-1.056^{***}			−0.056			−0.038
			(0.050)			(0.050)			(0.029)
Num. Obs.	624	624	624	624	624	624	624	624	624
R^2	0.759	0.920	0.966	0.911	0.915	0.915	0.914	0.918	0.919
Adj. R^2	0.676	0.892	0.954	0.880	0.885	0.885	0.884	0.890	0.890

Notes: Coefficients from OLS regressions of profitability measures (ROA, Lerner Index, Markup) on industry concentration (CR8), by sectoral regime. Two-way fixed effects (industry & year). Standard errors clustered at the industry level in parentheses.$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

A.3.1.2 Labor Unions and Declining Worker Power

We provide the results for unionization manufacturing time series.

(a) Union Density and Coverage Database constructed by Barry Hirsch and David Macpherson, from 1989-2016. We mapped the 4-digit data (original version) to 6-digit.

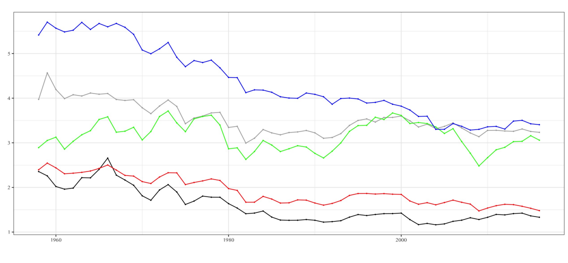


(b) Union Density and Coverage Database constructed by Barry Hirsch and David Macpherson, from 1989-2016. We mapped the 4-digit data (original version) to 6-digit. We differ along sectoral regimes: density (solide) and coverage (dashed).

Figure 13: Unionization Data

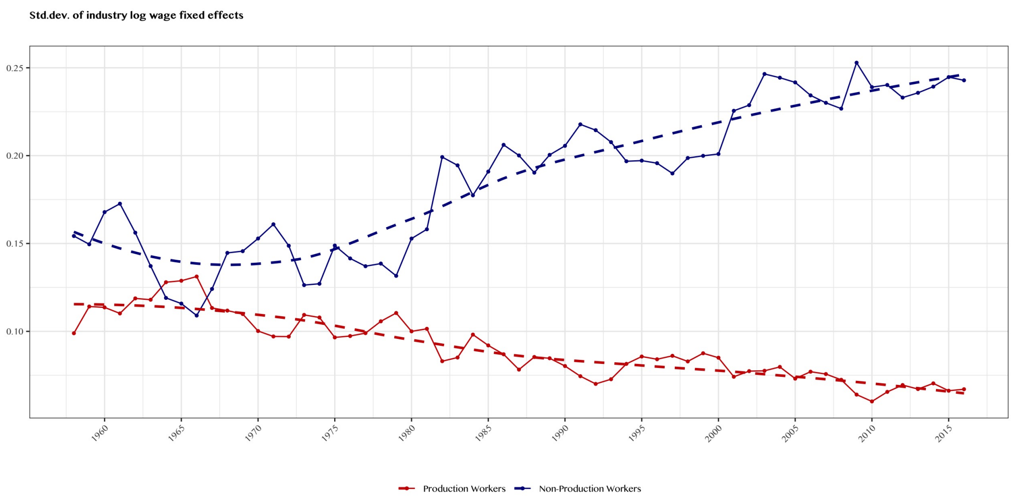
Figure 14: Production vs. Non-Production Workers Ratio

(a) Production vs. Non-Productive Workers Ratio. Data are from NBER-CES Manufacturing Data, 1958-2016. The data was aggregated to the whole manufacturing sector using the employment share for each industry as weights.



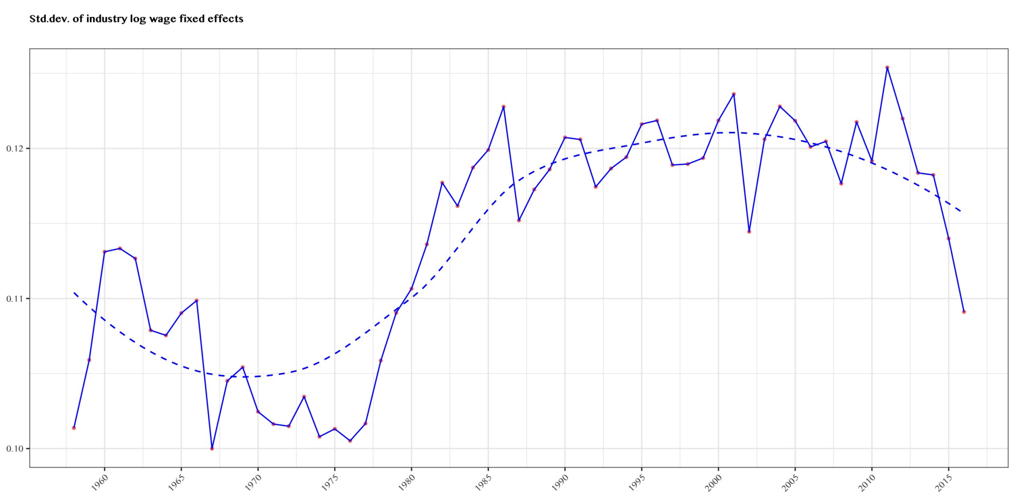
(b) Production vs. Non-Productive Workers Ratio across sectoral regimes. Data are from NBER-CES Manufacturing Data, 1958-2016. The data was aggregated to the whole manufacturing sector using the employment share for each industry as weights. Change between 1958 and 2016: SID (+5.77%); SIC (-18.6%); SD (-37.1%); SS (-38.2%); SB (-43.5%).

Figure 15: Standard Deviation of Production and Non-Production Workers' Industry Wage Effects



Notes: This figure shows industry (6-digit) log wage fixed effects standard deviation for production and non-production workers. Data are from NBER-CES Manufacturing Data. Industry fixed effects are estimated as industry dummies in annual log wage regressions over 1958–2016, for production and non-production workers.

Figure 16: Standard Deviation of Industry Wage Effects



Notes: This figure shows industry (6-digit) log wage fixed effects standard deviation. Data are from NBER-CES Manufacturing Data. Industry fixed effects are estimated as industry dummies in annual log wage regressions over 1958–2016, for all the workers.

Industry wage premia (conditional), by worker group. For each group $g \in \{\text{Production}, \text{Non-Production}\}$ and each year

t, we estimate across industries i:

$$\underbrace{\log w_{it}^{(g)}}_{\text{log wage per worker}} = \underbrace{\beta_t^{(g)}}_{\text{coefficients}}{}^{\top} \underbrace{X_{it}}_{\left(\log \text{Markup}_{it},\, \log(K/L)_{it},\, \log \text{Labor Productivity}_{it},\, \log \text{Total Shipments}_{it}\right)} + \underbrace{\alpha_{it}^{(g)}}_{\text{industry wage premium (conditional)}} + \varepsilon_{it}^{(g)}. \tag{17}$$

Group-specific dependent variables:

$$\log w_{it}^{(P)} = \log(\texttt{Blue\_Wage\_Per\_Worker}_{it}) \qquad \text{(Production workers)},$$
$$\log w_{it}^{(NP)} = \log(\texttt{White\_Wage\_Per\_Worker}_{it}) \qquad \text{(Non-Production workers)}.$$

Notes. $\alpha_{it}^{(g)}$ denotes the (year-t) industry fixed effect, interpreted as the *conditional* industry wage premium; it is normalized to sum to zero within year t. All controls enter in logs as indicated in X_{it}.

B Supplementary Derivations

From efficiency conditions of fixed-proportions production function, equation 6, we derive the demand for labor to obtain the compositional ratio (7):

$$L_B = \frac{Y}{a_B}, \quad L_W = \frac{Y}{a_W}$$

Given the markup-pricing rule, equation 9, we write it in terms of unit production costs.

$$p = (1+\mu)\left(\frac{\rho^B A}{a_B} + \frac{\rho^W A}{a_W} + \frac{\varphi}{a_K}\right)$$

Given the compositional ratio 7, we write the unit labor costs in terms of ϑ_L:

$$c_L(\vartheta_L) = ULC(\vartheta_L)_B + ULC(\vartheta_L)_W = \frac{\rho^B A}{a_B} + \frac{\rho^W A}{\vartheta_L a_B} = \frac{A}{a_B}\left(\rho^B + \frac{\rho^W}{\vartheta_L}\right)$$

We derive the elasticity of unit labor costs with respect to the technical composition of labor:

$$\frac{dc_L}{d\vartheta_L} = \frac{a_B \rho^W A}{(\vartheta_L a_B)^2} = \frac{A\rho^W}{\vartheta_L^2 a_B} < 0$$

By definition from the markup-pricing rule and wage-bargaining, equations 8 and 9, labor share is defined as follows:

$$\lambda = \frac{WL}{PY} = \frac{(W_B L_B + W_W L_W)Y}{PY} = \frac{\overbrace{\frac{\rho^B A}{a_B} + \frac{\rho^W A}{a_W}}^{c_L}}{(1+\mu)\left(\underbrace{\frac{\rho^B A}{a_B} + \frac{\rho^W A}{a_W}}_{c_L} + \frac{\varphi}{a_k}\right)}$$

where for simplicity and without losing generality we rename the unit cost of the material as a constant $UMC = \frac{\varphi}{a_K}$.

We can rewrite the labor share according to the composition of the work, so by calculating its relative elasticity with respect to it, we obtain the result of proposition 1.

$$\lambda_{\vartheta_L} = \frac{\frac{A}{a_B}(\rho^B + \frac{\rho^W}{\vartheta_L})}{(1+\mu)\left(\frac{A}{a_B}(\rho^B + \frac{\rho^W}{\vartheta_L}) + UMC\right)}$$

$$\frac{d\lambda_{\vartheta_L}}{d\vartheta_L} = \underbrace{\frac{\varphi}{(c_L+\varphi)^2(1+\mu)]}}_{>0} \cdot \left(\frac{-A\rho^W}{\vartheta_L^2 a_b}\right) < 0$$

C Data and Empirical Strategy

C.1 Sample Construction and Data Processing

C.1.1 NBER-CES Manufacturing Industry Database

Our main dataset is the NBER-CES Manufacturing Database (Becker et al., 2021). This is a joint effort between the National Bureau of Economic Research (NBER) and U.S. Census Bureau's Center for Economic Studies (CES), containing annual industry-level data from 1958-2018 on output, employment, payroll and other input costs, investment, capital stocks, TFP, and various industry-specific price indexes. We use the 2012 NAICS version of 364 six-digit industries.

To balance the panel, we exclude the final two years (2017-18), as capital variables (total stock, equipment, plant) are missing for all industries. Furthermore, due to a lack of observations between 1958 and 1996, we exclude the following industries from the main dataset: 311811 (Retail Bakeries), 326212 (Tire Retreading), and 339116 (Dental Laboratories). Consequently, our core dataset spans the period from 1958 to 2016 and comprises 361 industries, resulting in a total of 21,299 observations. To the initial dataset of 20 variables, we construct and append several new variables, many of which are subsequently used for robustness checks..

We compute the industry-level labor share as the ratio between total payroll and total added value[18]. Capital intensity is measured as the ratio of total capital stock to total employment. For robustness checks, we calculate equipment and plant intensity as the ratio of each to total employment. We measure labor productivity as the ratio of total value added to total employment. Similarly, capital productivity as the ratio of total value added to total capital stock. As a robustness check, we calculate the productivity of capital components—equipment and plants—as the ratio of total value added to each.

We calculate non-production workers as the difference between total employment and production workers, identifying the supervisors above the line-supervisor level, clerical, sales, office, professionals, and technical workers.

Profitability variables (ROA, Lerner Index and Markup) are calculated as described above in section 2.3.1.2.

C.1.2 Industry-level Trade Flows Data

We use trade flows (exports and imports) from Peter Schott to calculate import penetration at the 6-digit industry level for US manufacturing. We calculated the import penetration as follows:

$$IP_{jt} = \frac{Industry\,Imports_{jt}}{Domestic\,Absorption_{jt}} = \frac{Industry\,Imports_{jt}}{Shipments_{jt} - Net\,Exports_{jt}}$$

where $Net\,Exports_{jt} = Industry\,Exports_{jt} - Industry\,Imports_{jt}$.

Our benchmark trade data comes from the US HS-level Imports and Exports dataset (1989-2023) by Schott (2008). We use data through 2016 to maintain compatibility with the NBER-CES Manufacturing Database. This dataset involves the use of the HS (Harmonized-System) classification. The Harmonized System (HS) is an international classification system administered by the World Customs Organization. The 2-, 4-, and 6-digit HS headings and subheadings are the basis for the 10-digit statistical classification systems used in the United States. This classification allows us to use 15-digit granular data.

For the imports, we use a general variable measuresing the total physical arrivals of merchandise from foreign countries, whether such merchandise enters consumption channels immediately or is entered into bonded warehouses or Foreign Trade Zones under CBP custody. Exports measure the total physical movement of merchandise out of the United States to foreign countries, whether such merchandise is exported from within the U.S. Customs territory or from a CBP bonded warehouse or a U.S. Foreign Trade Zone. For both of these variables, we use the Year-to-Date (YTD) version.

Finally, we apply the concordance codes referring to the NAICS 2012 classification.

C.1.3 Industry Concentration Data

Data on industrial concentration are drawn from the U.S. Economic Census (1997, 2002, 2007, 2012) and converted using standard concordances. Since 6-digit concentration values (CR4, CR8, CR20, CR50) are only reported every five years from 1997 onward, the sample is consequently restricted to these census years.

[18]The labor share calculated using this method shows a persistent decline since the 1960s, a trend consistent with the findings of Castro-Vincenzi and Kleinman (2024), who have identified the underlying reasons.

C.1.4 Unionization Data

The Union Membership and Coverage Database– constructed by Hirsch, Macpherson and Even, and available at www.unionstats.com– is an Internet data resource providing private and public sector labor union membership, coverage, and density estimates compiled from the monthly household Current Population Survey (CPS) using BLS methods. Detailed industry series begin in 1983.

We map the unionization data from the provided SIC 4-digit level to our 6-digit industry classification. This mapping assumes that the unionization rate is uniform across all product-level (6-digit) industries within a broader 4-digit group.

For example, SIC code 1070 (Animal Food, Grain and Oilseed Milling) corresponds to NAICS classifications 3111 (Animal Food Manufacturing) and 31112 (Grain and Oilseed Milling). These are further mapped to all their underlying 6-digit industries, including 311111 (Dog and Cat Food Manufacturing), 311119 (Other Animal Food Manufacturing), 311211 (Flour Milling), 311212 (Rice Milling), 311213 (Malt Manufacturing), 311221 (Wet Corn Manufacturing), 311224 (Soybean and Other Oilseed Processing), 311225 (Fats and Oils Refining and Blending), and 311230 (Breakfast Cereal Manufacturing). The same procedure is applied to all remaining industries.

C.2 Constructing a Worker Power Indicator

Table 14: Industry-Level Regression of Wage-Productivity Pass-Through, Manufacturing

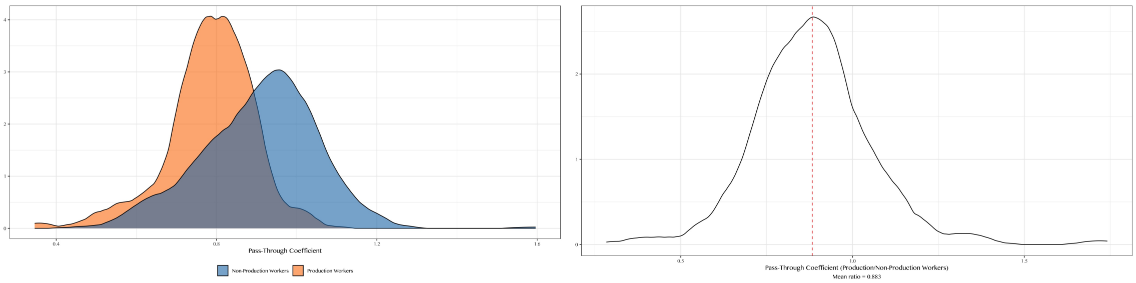
	Production Workers	**Non-Production Workers**
Lagged Labor Productivity	0.245***	0.224***
	(0.023)	(0.032)
Num. Obs.	10,108	10,108
R^2 Adj.	0.982	0.978

Notes: This table reports results from the regression of industry-level compensation per worker on the labor productivity lagged by one period. The regression is for both the production and non-production workers. Observations are for industry-year for all the pooled 361 industries, covering the period 1958-1985. We control for both industry and year fixed effects. Data are from NBER-CES Manufacturing Database. Standard errors clustered at the industry-level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 15: Summary Statistics of Pass-Through Estimates

Statistic	ρ^B	ρ^B_{se}	ρ^B_{pval}	ρ^W	ρ^W_{se}	ρ^W_{pval}	ρ
Min.	0.3462	0.0103	0.0000e+00	0.4661	0.0155	0.0000e+00	0.2835
1st Qu.	0.7339	0.0248	0.0000e+00	0.8154	0.0446	0.0000e+00	0.7758
Median	0.7930	0.0352	0.0000e+00	0.9208	0.0596	0.0000e+00	0.8831
Mean	0.7842	0.0418	2.12e-06	0.9083	0.0680	3.58e-05	0.8826
3rd Qu.	0.8590	0.0507	0.0000e+00	1.0009	0.0833	0.0000e+00	0.9677
Max.	1.0874	0.1928	1.84e-04	1.5962	0.2673	7.19e-03	1.7418

Notes: This table reports the main summary statistics of our pass-through estimates for production (ρ^B) and non-production workers (ρ^W), as well its ratio (ρ). The table also gives the standard errors and the relative p-value of the workers' power estimates. Data are from the NBER-CES Manufacturing Database, for 1958-1985.

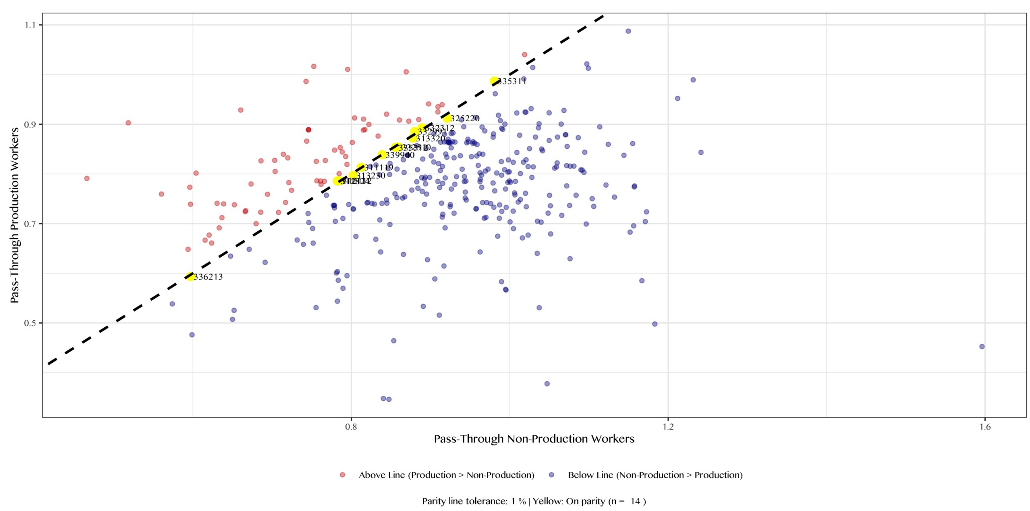


(a) Kernel Density Estimation of Production and Non-Productive Workers Pass-Through. Kernel is Epanechnikov. Data are from NBER-CES Manufacturing Data, 1958-1985.

(b) Kernel Density Estimation of Production vs. Non-Productive Workers Ratio Pass-Through. Kernel is Epanechnikov. Data are from NBER-CES Manufacturing Data, 1958-1985.

Figure 17: Density Kernel Estimation of Worker Power Estimates

Figure 18: Worker Power Distribution along 6-Digit Manufacturing Industries



Notes: Scatterplot of the production and non-production workers' pass-through. The diagonal dotted line represents the unit threshold of ρ. Observations above report industries where production has greater power than non-production workers, and vice versa. Data are from NBER-CES Manufacturing Database, 1958-1985. Along the dotted line, we report the specific industries whose pass ratio is essentially close to one: they are industries where production and non-production workers have almost identical power. The total industries on the parity line are 14 and are listed in table 16.

Table 16: List of Industries with Symmetrical Power Distribution

Industry	ρ^B	ρ^W	ρ
311119 (Other Animal Food Manufacturing)	0.8132	0.8123	1.0010
311824 (Dry Pasta, Dough, and Flour Mixes Manufacturing from Purchased Flour)	0.7858	0.7823	1.0045
312111 (Soft Drink Manufacturing)	0.7857	0.7829	1.0036
312112 (Bottled Water Manufacturing)	0.7863	0.7850	1.0017
313230 (Nonwoven Fabric Mills)	0.7969	0.8022	0.9934
313320 (Fabric Coating Mills)	0.8721	0.8775	0.9938
325220 (Artificial and Synthetic Fibers and Filaments Manufacturing)	0.9122	0.9210	0.9904
332312 (Fabricated Structural Metal Manufacturing)	0.8926	0.8894	1.0036
332510 (Hardware Manufacturing)	0.8541	0.8596	0.9936
332991 (Ball and Roller Bearing Manufacturing)	0.8853	0.8800	1.0060
335311 (Power, Distribution, and Specialty Transformer Manufacturing)	0.9869	0.9805	1.0065
335312 (Motor and Generator Manufacturing)	0.8535	0.8557	0.9974
336213 (Motor Home Manufacturing)	0.5933	0.5970	0.9938
339940 (Office Supplies (except Paper) Manufacturing)	0.8387	0.8390	0.9996

Notes: Industries on the parity line: cases where the pass-through coefficient for production and non-production workers is statistically indistinguishable (ratio $\rho \approx 1$).

Table 17: Industry Outliers along the Worker Power Distribution

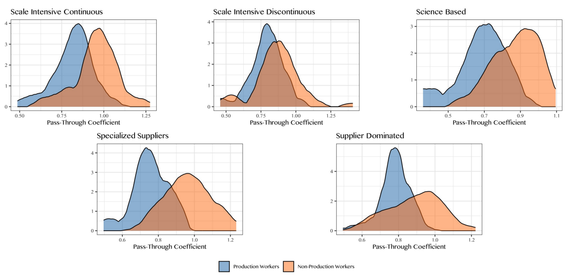
Panel A: Left Tail ($\rho < 0.4$)

Industry	ρ
334111 (Electronic Computer Manufacturing)	0.4139
334112 (Computer Storage Device Manufacturing)	0.4085
334118 (Computer Terminal and Other Computer Peripheral Equipment Manufacturing)	0.3607
334517 (Irradiation Apparatus Manufacturing)	0.4208
334613 (Blank Magnetic and Optical Recording Media Manufacturing)	0.2835

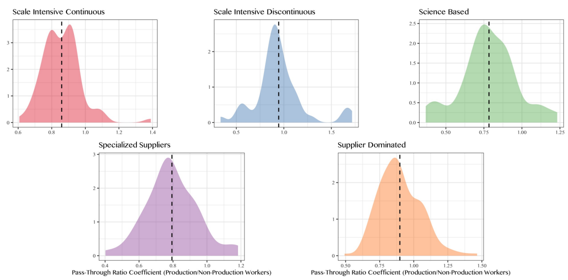
Panel B: Right Tail ($\rho > 1.3$)

Industry	ρ
311511 (Fluid Milk Manufacturing)	1.4062
311512 (Creamery Butter Manufacturing)	1.3273
311615 (Poultry Processing)	1.3275
335224 (Household Laundry Equipment Manufacturing)	1.7418
335228 (Other Major Household Appliance Manufacturing)	1.6969
336370 (Motor Vehicle Metal Stamping)	1.3506
336419 (Other Guided Missile and Space Vehicle Parts and Auxiliary Equipment Manufacturing)	1.3555

Notes: Industries with extreme values of the pass-through ratio (ρ). Panel A reports industries with $\rho < 0.4$, Panel B those with $\rho > 1.3$.



(a) Kernel Density Estimation of Production and Non-Productive Workers Pass-Through. Kernel is Epanechnikov. Data are from NBER-CES Manufacturing Data, 1958-1985.



(b) Kernel Density Estimation of Production vs. Non-Productive Workers Ratio Pass-Through. Kernel is Epanechnikov. Vertical dotted line represents the average. Data are from NBER-CES Manufacturing Data, 1958-1985.

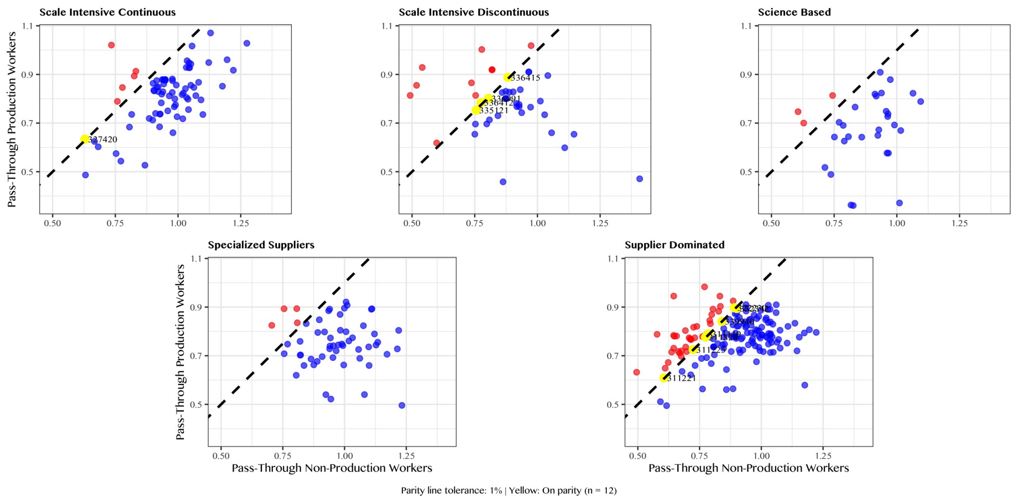
Figure 19: Density Kernel Estimation of Worker Power Estimates across Sectoral Regimes

Table 18: Worker Power Moments of Distribution

Panel A: Production Workers (ρ^B)				
Regime	**Mean**	**Variance**	**Skewness**	**Kurtosis**
Scale Intensive Continuous	0.815	0.0134	-0.576	3.53
Scale Intensive Discontinuous	0.787	0.0140	-0.681	3.86
Science Based	0.677	0.0204	-0.763	3.09
Specialized Suppliers	0.753	0.00987	-0.460	3.14
Supplier Dominated	0.779	0.00697	-0.647	4.14
Panel B: Non-Production Workers (ρ^W)				
Regime	**Mean**	**Variance**	**Skewness**	**Kurtosis**
Scale Intensive Continuous	0.955	0.0165	-0.387	3.53
Scale Intensive Discontinuous	0.870	0.0268	0.256	4.98
Science Based	0.877	0.0150	-0.405	2.45
Specialized Suppliers	0.967	0.0157	0.119	2.45
Supplier Dominated	0.887	0.0216	-0.241	2.49

Notes: This table reports the moments of the distribution of pass-through coefficients for production (Panel A) and non-production (Panel B) workers, by Pavitt technological-sector class.

Figure 20: Worker Power Distribution across Technological-Sectoral Regimes



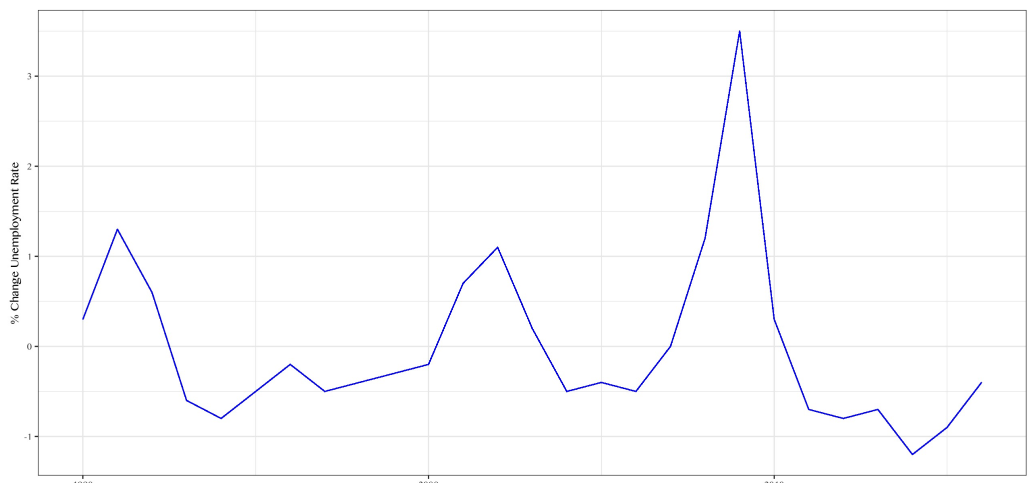
Notes: Scatterplot of the production and non-production workers' pass-through across sectoral regimes. The diagonal dotted line represents the unit threshold of ρ. Observations above report industries where production has greater power than non-production workers, and vice versa. Data are from NBER-CES Manufacturing Database, 1958-1985. Along the dotted line, we report the specific industries whose pass ratio is essentially close to one: they are industries where production and non-production workers have almost identical power. The total industries on the parity line are 12 and are listed in table 19.

Table 19: List of Industries with Symmetrical Power Distribution by Technological-Sectoral Regime'

Industry	ρ^B	ρ^W	ρ	**Regime**
311119 (Other Animal Food Manufacturing)	0.7903	0.7867	1.0046	Supplier Dominated
311221 (Wet Corn Milling and Starch Manufacturing)	0.6094	0.6059	1.0057	Supplier Dominated
311225 (Fats and Oils Refining and Blending)	0.7256	0.7244	1.0016	Supplier Dominated
311824 (Dry Pasta, Dough, and Flour Mixes Manufacturing from Purchased Flour)	0.7767	0.7740	1.0035	Supplier Dominated
322230 (Stationery Product Manufacturing)	0.8974	0.8909	1.0073	Supplier Dominated
327420 (Gypsum Product Manufacturing)	0.6339	0.6287	1.0084	Scale Intensive Continuous
332312 (Fabricated Structural Metal Manufacturing)	0.8943	0.9002	0.9935	Supplier Dominated
335121 (Residential Electric Lighting Fixture Manufacturing)	0.7532	0.7560	0.9962	Scale Intensive Discontinuous
336412 (Aircraft Engine and Engine Parts Manufacturing)	0.7840	0.7753	1.0113	Scale Intensive Discontinuous
336415 (Guided Missile and Space Vehicle Propulsion Unit and Propulsion Unit Parts Manufacturing)	0.8881	0.8821	1.0068	Scale Intensive Discontinuous
336991 (Motorcycle, Bicycle, and Parts Manufacturing)	0.8015	0.8049	0.9958	Scale Intensive Discontinuous
339940 (Office Supplies (except Paper) Manufacturing)	0.8413	0.8403	1.0012	Supplier Dominated

Notes: This table shows the industries on (or very near) the parity line: pass-through coefficients for production and non-production workers are statistically indistinguishable; the ratio $\rho \approx 1$.

Figure 21: Unemployment Rate Change



Notes: Δ YoY Unemployment Rate, 1989-2016. Data are from FRED Series UNRATE.

D Results

D.1 Baseline Results

Table 20: Baseline OLS Estimation Results for Manufacturing Industries

	(1)	(2)	(3)	(4)	(5)
log(BC/WC)	-0.180^{***}	-0.187^{***}	-0.177^{***}	-0.177^{***}	-0.172^{***}
	(0.027)	(0.028)	(0.026)	(0.026)	(0.026)
log(Markup)		-0.866^{***}	-0.866^{***}	-0.866^{***}	-0.867^{***}
		(0.059)	(0.058)	(0.058)	(0.058)
log(Capital Intensity)			0.045^{+}	0.044^{+}	0.041
			(0.026)	(0.026)	(0.026)
Import Penetration				0.002	0.002
				(0.002)	(0.002)
log(Energy Price)					-0.110^{*}
					(0.046)
Num.Obs.	10108	10108	10108	10108	10108
R^2 Adj.	0.876	0.910	0.910	0.910	0.911
R^2 Within	0.039	0.300	0.304	0.304	0.307
Industry and Year FE	X	X	X	X	X

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report OLS estimation results and include industry and year fixed effects. All the observations are unweighted. Standard errors are clustered at the industry-level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 21: Baseline OLS Estimation Robustness Checks for Manufacturing Industries

	Panel A: Pooled OLS	**Panel B: Time FE**	**Panel C: Industry FE**
Intercept	0.700^{***}		
	(0.178)		
log(BC/WC)	-0.013	-0.010	-0.168^{***}
	(0.029)	(0.028)	(0.026)
log(Markup)	-0.306^{**}	-0.313^{**}	-0.831^{***}
	(0.112)	(0.111)	(0.057)
log(Capital Intensity)	-0.336^{***}	-0.338^{***}	-0.027
	(0.024)	(0.026)	(0.022)
Import Penetration	0.020	0.020	0.002
	(0.015)	(0.015)	(0.002)
log(Energy Price)		-0.021	-0.418^{***}
		(0.082)	(0.034)
Num.Obs.	10108	10108	10108
R^2 Adj.	0.419	0.425	0.899
R^2 Within	–	0.399	0.427

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. Panel A reports pooled OLS, with the estimates of intercepts as well. Panel B reports the estimates when we include only year fixed effects. Panel C reports the estimates when we include only industry fixed effects. All the observations are unweighted. Standard errors are clustered at the industry-level. *p<0.1; **p<0.05; ***p<0.01.

Table 22: OLS Estimation Results for Supplier-Dominated Regime

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
log(BC/WC)	-0.145^{***}	-0.117^{***}	-0.119^{***}	-0.119^{***}	-0.121^{***}
	(0.036)	(0.033)	(0.035)	(0.035)	(0.035)
log(Markup)		-0.876^{***}	-0.876^{***}	-0.876^{***}	-0.877^{***}
		(0.110)	(0.109)	(0.109)	(0.109)
log(Capital Intensity)			-0.008	-0.008	-0.005
			(0.032)	(0.032)	(0.032)
Import Penetration				0.000	0.000
				(0.001)	(0.001)
log(Energy Price)					0.066
					(0.085)
Num.Obs.	4368	4368	4368	4368	4368
R^2 Adj.	0.913	0.938	0.938	0.938	0.938
R^2 Within	0.034	0.309	0.309	0.309	0.310
Industry and Year FE	X	X	X	X	X

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report OLS estimation results and include industry and year fixed effects. All the observations are unweighted. Standard errors are clustered at the industry-level. *p<0.1; **p<0.05; ***p<0.01.

Table 23: OLS Estimation Results for Scale Intensive Continuous Regime

	(1)	(2)	(3)	(4)	(5)
log(BC/WC)	-0.203^{**}	-0.202^{***}	-0.198^{***}	-0.198^{***}	-0.177^{**}
	(0.073)	(0.056)	(0.057)	(0.056)	(0.055)
log(Markup)		-1.158^{***}	-1.150^{***}	-1.150^{***}	-1.159^{***}
		(0.107)	(0.106)	(0.104)	(0.107)
log(Capital Intensity)			0.089	0.089	0.095
			(0.072)	(0.072)	(0.070)
Import Penetration				-0.001	0.015
				(0.076)	(0.075)
log(Energy Price)					-0.236^{***}
					(0.062)
Num.Obs.	2072	2072	2072	2072	2072
R^2 Adj.	0.861	0.912	0.913	0.913	0.916
R^2 Within	0.026	0.385	0.393	0.393	0.415
Industry and Year FE	X	X	X	X	X

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report OLS estimation results and include industry and year fixed effects. All the observations are unweighted. Standard errors are clustered at the industry-level. *p<0.1; **p<0.05; ***p<0.01.

Table 24: OLS Estimation Results for Scale Intensive Discontinuous Regime

	(1)	(2)	(3)	(4)	(5)
log(BC/WC)	-0.231^{*}	-0.266^{*}	-0.234^{**}	-0.231^{**}	-0.226^{**}
	(0.097)	(0.103)	(0.074)	(0.072)	(0.070)
log(Markup)		-0.654^{***}	-0.730^{***}	-0.715^{***}	-0.722^{***}
		(0.144)	(0.093)	(0.084)	(0.082)
log(Capital Intensity)			0.120	0.095	0.094
			(0.077)	(0.074)	(0.073)
Import Penetration				0.124	0.127
				(0.087)	(0.089)
log(Energy Price)					-0.087
					(0.134)
Num.Obs.	1204	1204	1204	1204	1204
R^2 Adj.	0.719	0.770	0.778	0.781	0.782
R^2 Within	0.083	0.247	0.277	0.287	0.289
Industry and Year FE	X	X	X	X	X

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report OLS estimation results and include industry and year fixed effects. All the observations are unweighted. Standard errors are clustered at the industry-level. *p<0.1; **p<0.05; ***p<0.01.

Table 25: OLS Estimation Results for Specialized Suppliers Regime

	(1)	(2)	(3)	(4)	(5)
log(BC/WC)	-0.185^{***}	-0.193^{***}	-0.156^{***}	-0.159^{***}	-0.161^{***}
	(0.038)	(0.032)	(0.035)	(0.036)	(0.038)
log(Markup)		-0.916^{***}	-0.918^{***}	-0.919^{***}	-0.923^{***}
		(0.117)	(0.112)	(0.114)	(0.116)
log(Capital Intensity)			0.097^{*}	0.094^{+}	0.094^{+}
			(0.047)	(0.049)	(0.048)
Import Penetration				0.014	0.017
				(0.012)	(0.013)
log(Energy Price)					-0.159
					(0.115)
Num.Obs.	1568	1568	1568	1568	1568
R^2 Adj.	0.725	0.805	0.810	0.811	0.812
R^2 Within	0.045	0.322	0.342	0.344	0.350
Industry and Year FE	X	X	X	X	X

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report OLS estimation results and include industry and year fixed effects. All the observations are unweighted. Standard errors are clustered at the industry-level. *p<0.1; **p<0.05; ***p<0.01.

Table 26: OLS Estimation Results for Science Based Regime

	(1)	(2)	(3)	(4)	(5)
log(BC/WC)	-0.093	-0.237^{*}	-0.237^{*}	-0.237^{*}	-0.232^{*}
	(0.087)	(0.090)	(0.089)	(0.089)	(0.091)
log(Markup)		-0.900^{***}	-0.902^{***}	-0.906^{***}	-0.906^{***}
		(0.136)	(0.128)	(0.128)	(0.131)
log(Capital Intensity)			-0.008	-0.013	-0.021
			(0.088)	(0.091)	(0.089)
Import Penetration				0.007	0.008
				(0.006)	(0.006)
log(Energy Price)					-0.134
					(0.115)
Num.Obs.	896	896	896	896	896
R^2 Adj.	0.817	0.875	0.875	0.875	0.875
R^2 Within	0.006	0.320	0.321	0.322	0.325
Industry and Year FE	X	X	X	X	X

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report OLS estimation results and include industry and year fixed effects. All the observations are unweighted. Standard errors are clustered at the industry-level. *p<0.1; **p<0.05; ***p<0.01.

Table 27: OLS Estimation for Unionization Measures on Labor Share

	(1)	(2)	(3)	(4)	(5)
Panel A: Union Density					
log(Union Density)	-0.014^{*}	-0.013^{*}	-0.009^{+}	-0.009^{+}	-0.009^{+}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
log(Markup)		-0.860^{***}	-0.861^{***}	-0.861^{***}	-0.862^{***}
		(0.064)	(0.062)	(0.062)	(0.063)
log(Capital Intensity)			0.069^{*}	0.069^{*}	0.064^{*}
			(0.029)	(0.029)	(0.028)
Import Penetration				0.002	0.002
				(0.002)	(0.002)
log(Energy Price)					-0.143^{**}
					(0.049)
Num.Obs.	10108	10108	10108	10108	10108
R^2 Adj.	0.871	0.904	0.906	0.906	0.906
R^2 Within	0.001	0.258	0.267	0.267	0.273
Industry and Year FE	X	X	X	X	X
Panel B: Union Coverage					
log(Union Coverage)	-0.011^{+}	-0.009	-0.006	-0.006	-0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
log(Markup)		-0.860^{***}	-0.861^{***}	-0.861^{***}	-0.863^{***}
		(0.064)	(0.063)	(0.063)	(0.063)
log(Capital Intensity)			0.070^{*}	0.069^{*}	0.064^{*}
			(0.029)	(0.029)	(0.028)
Import Penetration				0.002	0.002
				(0.002)	(0.002)
log(Energy Price)					-0.143^{**}
					(0.049)
Num.Obs.	10108	10108	10108	10108	10108
R^2 Adj.	0.871	0.904	0.906	0.906	0.906
R^2 Within	0.001	0.258	0.267	0.267	0.273
Industry and Year FE	X	X	X	X	X

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of unionization measures, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Panel A reports results for union density that measures the percentage of a workers that belongs to an union for each industry. Panel B reports results for union coverage, that measures the proportion of workers whose wages, benefits, and working conditions are determined by a collective agreement for each industry. Data are from NBER-CES Manufacturing Database for the period 1989-2016. Unions data are from www.unionstats.com, from Hirsch, Macpherson and Even. All the specification columns report OLS estimation results and include industry and year fixed effects. All the observations are unweighted. Standard errors are clustered at the industry-level. *p<0.1; **p<0.05; ***p<0.01.

D.2 Main IV Results

Table 28: The Effect of Technical Composition on the Labor Share: OLS and 2SLS Estimates

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
log(BC/WC)	-0.180***	-0.187***	-0.172***	-2.327***	-2.644***	-2.715***
	(0.027)	(0.028)	(0.026)	(0.442)	(0.493)	(0.491)
Controls:						
log(Markup)		-0.866***	-0.878***		-0.839***	-0.87***
		(0.059)	(0.059)		(0.148)	(0.151)
log(Capital Intensity)			0.041		-0.516***	-0.44***
			(0.026)		(0.079)	(0.098)
Import Penetration			0.001		0.0028	0.003
			(0.001)		(0.004)	(0.004)
log(Energy Price)			-0.11*			-0.211*
			(0.045)			(0.096)
Observations	10.108	10.108	10.108	9.747	9.747	9.747
First-Stage and Diagnostic Statistics						
KP Wald F-stat				26.7	26.6	27.7
Wu–Hausman test				135.6***	224.9***	318.2***

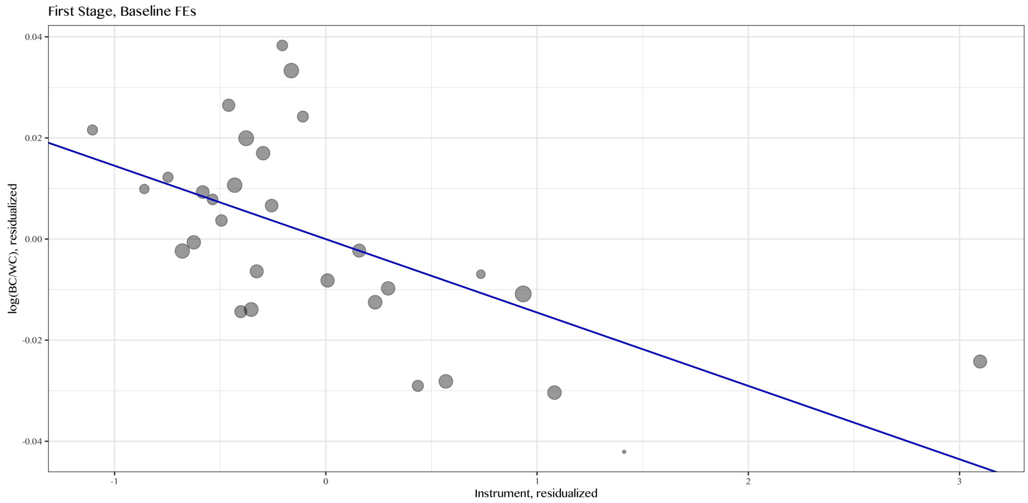
Notes: This table presents OLS and 2SLS results from the regression of the log payroll share on the log of production vs non-production workers at the industry-level. Observations correspond to industry-year pairs for the 361 NAICS industries in the NBER-CES dataset for the period between 1990 and 2016. Columns (4) to (6) report 2SLS estimates, using Z_{jt} as an instrument for log(BC/WC). The Wu–Hausman test rejects the null hypothesis that the OLS estimator is consistent. The Kleibergen-Paap F-statistic exceeds the critical value for weak instruments. All the observations are unweighted. The columns of the 2SLS estimates only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 29: The Effect of Technical Composition on the Labor Share: Weighted OLS and 2SLS Estimates

	OLS			2SLS				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(BC/WC)	-0.180***	-0.187***	-0.172***	-2.327***	-1.864***	-1.988***	-1.991***	-2.033***
	(0.027)	(0.028)	(0.026)	(0.442)	(0.34)	(0.335)	(0.336)	(0.329)
Controls:								
log(Markup)		-0.866***	-0.878***			-0.687**	-0.687**	-0.713**
		(0.059)	(0.059)			(0.226)	(0.226)	(0.226)
log(Capital Intensity)			0.041			-0.431***	-0.432***	-0.372***
			(0.026)			(0.069)	(0.069)	(0.10)
Import Penetration			0.001				0.002	0.002
			(0.001)				(0.003)	(0.003)
log(Energy Price)			-0.110*					-0.191
			(0.045)					(0.126)
Observations	10.108	10.108	10.108	9.747	9.747	9.747	9.747	9.747
Weights	No	No	No	No	Yes	Yes	Yes	Yes
First-Stage and Diagnostic Statistics								
KP Wald F-stat				26.7	34.6	39.6	39.6	41.2
Wu–Hausman test				135.6***	155.7***	224.1***	224.4***	315.4***

Notes: This table presents OLS and 2SLS results from the regression of the log payroll share on the log of production vs non-production workers at the industry-level. Columns (4) to (8) report 2SLS estimates, using Z_{jt} as an instrument for log(BC/WC). Observations correspond to industry-year pairs for the 361 NAICS industries in the NBER-CES dataset for the period between 1990 and 2016. The Wu-Hausman test rejects the null hypothesis that the OLS estimator is consistent. The Kleibergen-Paap F-statistic exceeds the critical value for weak instruments. Columns (5) to (8) are weighted by the total employment of the industry in year 1990. The columns of the 2SLS estimates only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Figure 22: First-Stage Binned Scatter Plots



Notes: The figure is a binned scatter plot about the first-stage relationship between the instrumented (BC/WC) and the instrumental variable Z_{jt}. Both are residualized on the fixed effects on all industry-level controls. Residuals are calculated on the basis of column (6) of table 29. Residualizing, we control for fixed effects and industry-level covariates. Therefore, we are able to visualize the net relationship between Z and X, cleaned of possible confounding factors. Given the first stage regression equation, $\log Z_{jt} = \pi \log(BC/WC)_{jt} + \text{controls} + \epsilon_{jt}$, the figure therefore represents the coefficient π.

D.2.1 Sectoral Regimes IV Results

Table 30: 2SLS Estimation Results for Supplier-Dominated Regime

	(1)	(2)	(3)	(4)	(5)
log(BC/WC)	-3.843	-3.685*	-3.037*	-3.034*	-2.914*
	(2.645)	(1.765)	(1.323)	(1.319)	(1.190)
log(Markup)		0.121	0.087	0.086	0.047
		(0.723)	(0.634)	(0.633)	(0.597)
log(Capital Intensity)			-0.701*	-0.700*	-0.755*
			(0.301)	(0.300)	(0.345)
Import Penetration				-0.001	-0.001
				(0.002)	(0.001)
log(Energy Price)					0.244
					(0.312)
Observations	4212	4212	4212	4212	4212
Weights	Yes	Yes	Yes	Yes	Yes
First-Stage and Diagnostic Statistics					
KP Wald F-stat	1.98	3.98	5.08	5.10	5.70
Wu–Hausman test	40.1***	85.5***	84.4***	85.5***	108.1***

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report 2SLS estimation results and include industry and year fixed effects. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 31: 2SLS Estimation Results for Scale Intensive Continuous Regime

	(1)	(2)	(3)	(4)	(5)
log(BC/WC)	-2.547***	-2.495***	-2.665***	-2.551***	-2.532***
	(0.728)	(0.683)	(0.634)	(0.606)	(0.621)
log(Markup)		-0.282	-0.624*	-0.653**	-0.697**
		(0.267)	(0.243)	(0.227)	(0.249)
log(Capital Intensity)			-0.421***	-0.369**	-0.309*
			(0.118)	(0.108)	(0.135)
Import Penetration				-0.297+	-0.255
				(0.177)	(0.208)
log(Energy Price)					-0.111
					(0.158)
Observations	1998	1998	1998	1998	1998
Weights	Yes	Yes	Yes	Yes	Yes
First-Stage and Diagnostic Statistics					
KP Wald F-stat	29.6	28.1	28	30.3	30.4
Wu–Hausman test	76.6***	74.4***	130.3***	120.0***	173.8***

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report 2SLS estimation results and include industry and year fixed effects. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Table 32: 2SLS Estimation Results for Scale Intensive Discontinuous Regime

	(1)	(2)	(3)	(4)	(5)
log(BC/WC)	-0.787**	-0.975**	-1.153***	-1.145***	-1.304***
	(0.260)	(0.287)	(0.312)	(0.290)	(0.289)
log(Markup)		-0.507+	-0.648**	-0.661**	-0.861***
		(0.257)	(0.225)	(0.229)	(0.211)
log(Capital Intensity)			-0.426***	-0.402***	-0.239***
			(0.096)	(0.077)	(0.052)
Import Penetration				-0.101	-0.076
				(0.188)	(0.176)
log(Energy Price)					-0.495*
					(0.197)
Observations	1188	1188	1188	1188	1188
Weights	Yes	Yes	Yes	Yes	Yes
First-Stage and Diagnostic Statistics					
KP Wald F-stat	13.3	12.5	14.6	14.6	14.1
Wu–Hausman test	9.15***	13.9***	16.8***	17.6***	28***

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report 2SLS estimation results and include industry fixed effects. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Table 33: 2SLS Estimation Results for Specialized Suppliers Regime

	(1)	(2)	(3)	(4)	(5)
log(BC/WC)	-1.852***	-1.923***	-1.687**	-1.705**	-1.718**
	(0.367)	(0.369)	(0.522)	(0.531)	(0.541)
log(Markup)		0.552	-0.304	-0.305	-0.460
		(0.528)	(0.314)	(0.322)	(0.323)
log(Capital Intensity)			-0.560***	-0.571***	-0.396**
			(0.086)	(0.092)	(0.136)
Import Penetration				0.031	0.048
				(0.042)	(0.044)
log(Energy Price)					-0.469**
					(0.159)
Observations	1512	1512	1512	1512	1512
Weights	Yes	Yes	Yes	Yes	Yes
First-Stage and Diagnostic Statistics					
KP Wald F-stat	24.5	14.7	23.1	22.7	22.5
Wu–Hausman test	78.2***	79.1***	67.2***	66.9***	97.6***

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report 2SLS estimation results and include industry and year fixed effects. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Table 34: 2SLS Estimation Results for Science Based Regime

	(1)	(2)	(3)	(4)	(5)
log(BC/WC)	-0.961	-1.195+	-1.030+	-1.056+	-1.084+
	(0.716)	(0.630)	(0.588)	(0.600)	(0.587)
log(Markup)		-1.212***	-1.287***	-1.31***	-1.311***
		(0.274)	(0.275)	(0.282)	(0.279)
log(Capital Intensity)			-0.1257***	-0.136***	-0.086+
			(0.029)	(0.031)	(0.046)
Import Penetration				0.018**	0.019**
				(0.006)	(0.006)
log(Energy Price)					-0.200
					(0.119)
Observations	837	837	837	837	837
Weights	Yes	Yes	Yes	Yes	Yes
First-Stage and Diagnostic Statistics					
KP Wald F-stat	5.9	6.71	6.7	6.5	6.7
Wu–Hausman test	4.16**	6.82***	5.27**	5.47**	6.46**

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report 2SLS estimation results and include industry and year fixed effects. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

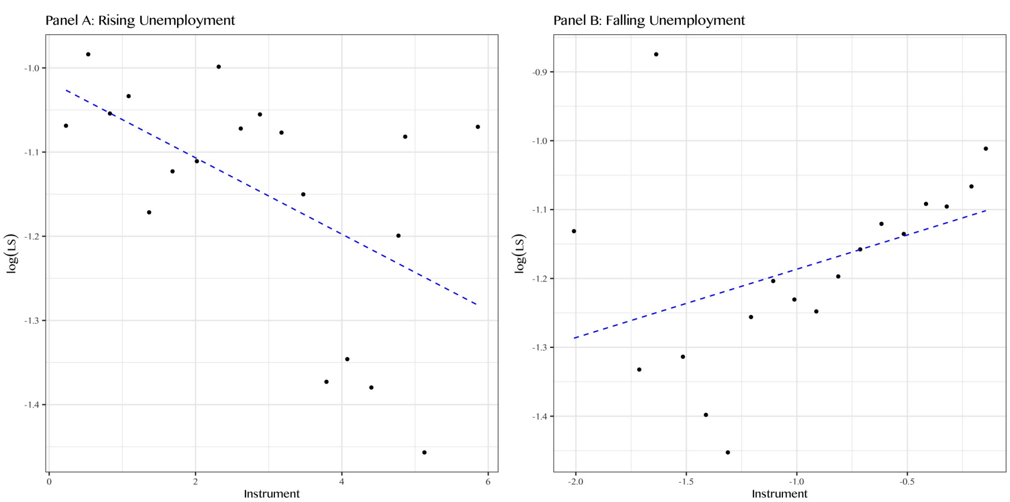
D.2.2 Asymmetric Effects: Unemployment Increases and Reductions

Table 35: Asymmetric Effects of Unemployment Variation

	Reduced form		**2SLS**	
	Rising Unemployment **(1)**	Falling Unemployment **(2)**	Rising Unemployment **(3)**	Falling Unemployment **(4)**
Instrument Z_{jt}	-0.0228***	0.1676***		
	(0.0033)	(0.0150)		
log(BC/WC)			-0.869***	1.367*
			(0.189)	(0.545)
Observations	3,249	6,137	3,249	6,137
Estimator	OLS	OLS	2SLS	2SLS
Adj. R^2	0.821	0.0511	0.828	0.546
First-Stage and Diagnostic Statistics				
KP Wald F-stat			35.5	8.067
Wu–Hausman test			9.654**	45.7***

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing. Columns 1 and 2 report reduced form results from OLS regressions of log labor share on our instrument, where we split the sample into industries experiencing an increase (decrease) in unemployment rate. In columns 3 and 4, we instrument log of labor force technical composition with our instrument, including all the controls and industry fixed effects. The 3 and 4 columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Figure 23: Income Distribution and Unemployment Changes



Notes: Binned scatter plots, NBER-CES Manufacturing Dataset 1990–2016. Panel A (B) plots log labor share against our industry-level instrument for rising (falling) unemployment rate.

Table 36: Equality test of coefficients: downturn vs upturn

Hypothesis	z-statistic	p-value
H_0: $\beta^- = \beta^+$	3.876	0.000106^{***}

Notes: Two-sample test comparing 2SLS estimates obtained on disjoint subsamples (upturns and downturns). The variance of the difference is computed as the sum of the two variances. Standard errors are clustered at the industry level.

D.3 Robustness Checks

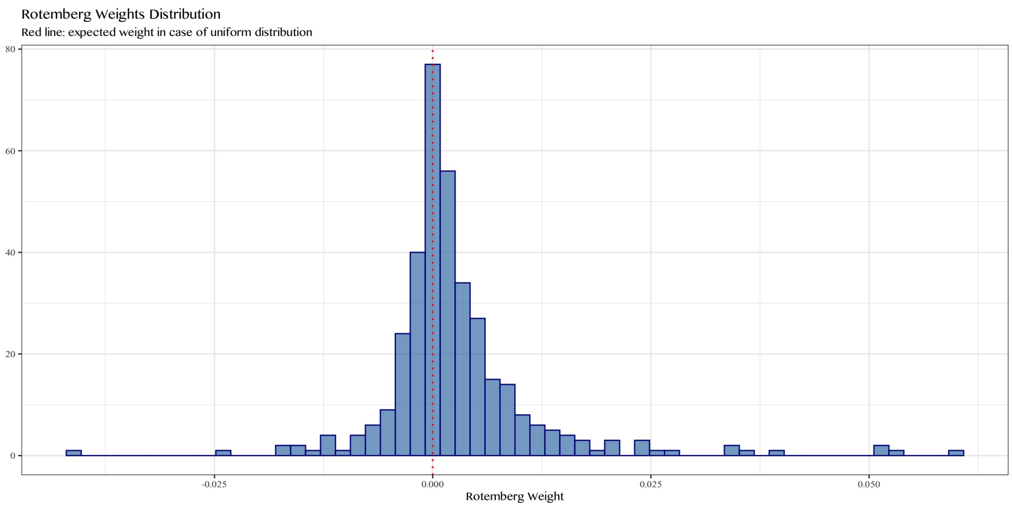
D.3.1 Evaluating the SSIV Design

Table 37: Influential Industries

Industry	**Industry Description**	ρ_j	**Rotemberg Weight**
336112	Light Truck and Utility Vehicle Manufacturing	1.12	0.0608
325412	Pharmaceutical Preparation Manufacturing	0.89	0.0532
311812	Commercial Bakeries	0.93	0.0522
326199	All Other Plastics Product Manufacturing	0.90	0.0517
315240	Women's, Girls', and Infants' Cut and Sew Apparel Manufacturing	0.82	-0.0403
336390	Other Motor Vehicle Parts Manufacturing	0.93	0.0401
336413	Other Aircraft Parts and Auxiliary Equipment Manufacturing	0.71	0.0353
336320	Motor Vehicle Electrical and Electronic Equipment Manufacturing	0.85	0.0343
336370	Motor Vehicle Metal Stamping	1.29	0.0339
333415	Air-Conditioning and Warm Air Heating Equipment and Commercial and Industrial Refrigeration Equipment Manufacturing	1.11	0.0274

Notes: We report the Rotemberg weights for the top 10 industries that contribute the most to the total variation of the instrument. The table shows pronounced heterogeneity across industries, with contributions spanning all sectoral regimes of the manufacturing sector: 331812, 315240 (Supplier Dominated); 326199 (Scale-Intensive Continuous); 336112, 336390, 336413, 336320 (Scale-Intensive Discontinuous); 333415 (Specialized Suppliers); and 325412 (Science-Based). We also compute the share of the top 10 industries' weights relative to the total contribution of all industries, $\frac{\sum_{j\in \text{Top 10}} |\alpha_j|}{\sum_{j=1}^{K} |\alpha_j|} = 7.1\%$, as well as their concentration in explaining the overall variation of our instrument 15, $\frac{\sum_{j\in \text{Top 10}} |\alpha_j \cdot \beta_j|}{\sum_{j=1}^{K} |\alpha_j \cdot \beta_j|} = 22\%$.

Figure 24: Rotemberg Weights Distribution



Notes: This figure represents the distribution of Rotemberg weights. Distribution represents the weight for each industry. The dotted red line ideally represents the average around which the mass of the weights should be distributed.

Table 38: 2SLS Estimation Results without 20 Top Rotemberg Weights Industries

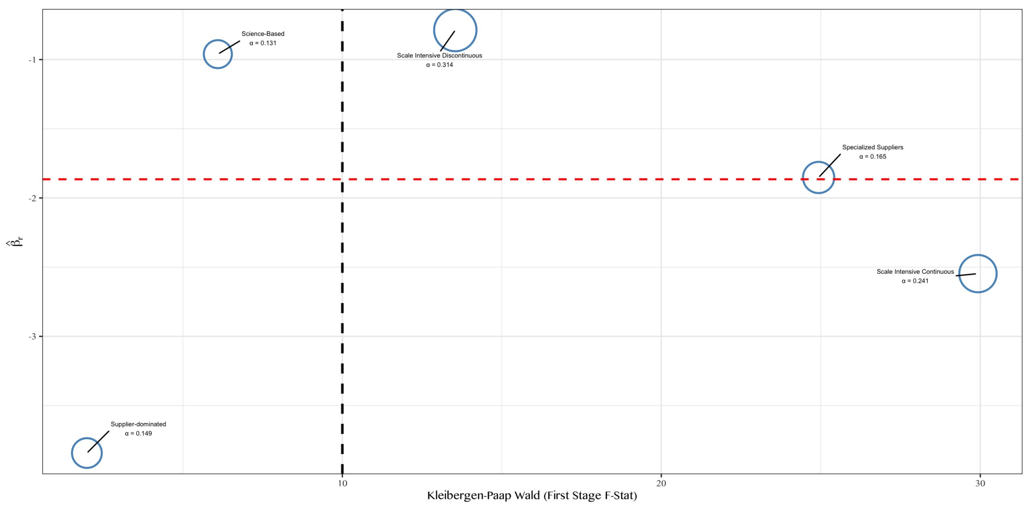
	(1)	(2)	(3)	(4)	(5)
log(Blue/White Ratio)	-2.641***	-2.779***	-2.604***	-2.608***	-2.697***
	(0.506)	(0.514)	(0.483)	(0.483)	(0.484)
log(Markup)		-0.579*	-0.735*	-0.735*	-0.763**
		(0.233)	(0.285)	(0.285)	(0.284)
log(Capital Intensity)			-0.475***	-0.476***	-0.404***
			(0.075)	(0.075)	(0.093)
Import Penetration				0.003	0.003
				(0.004)	(0.004)
log(Energy Price)					-0.233*
					(0.110)
Observations	9477	9477	9477	9477	9477
Weights	Yes	Yes	Yes	Yes	Yes
First-Stage and Diagnostic Statistics					
KP Wald F-stat	28.9	29.9	33.7	33.7	34.2
Wu–Hausman test	155.9***	213.7***	218.1***	218.4***	305.4***

Notes: The table reports regressions for rent-sharing IV regressions excluding the top-10 Rotemberg weights industries. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing, 1990-2016. All the specification columns report 2SLS estimation results and include industry fixed effects. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). The Wu-Hausman test rejects the null hypothesis that the OLS estimator is consistent. The Kleibergen-Paap F-statistic exceeds the critical value for weak instruments. Standard errors clustered at the industry-level are in parenthesis. $^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

Table 39: Structural Characteristics of Top 10 Industries by Rotemberg Weight

Industry	Capital Intensity	Union Density	Markup	Value Added	Import Penetration
311812	Low	High	High	High	Low
315240	Low	Low	Low	High	High
325412	High	Low	High	High	Low
326199	Low	Low	Low	High	Low
333415	Low	Low	Low	High	Low
336112	High	High	Low	High	High
336320	Low	High	Low	High	High
336370	High	High	Low	High	Low
336390	Low	High	Low	High	Low
336413	Low	High	High	High	High

Figure 25: Heterogeneity of β_k Across Technological-Sector Regimes



Notes: The y-axis depicts the estimated interest coefficient of the second stage IV regression for the technical composition of labor force, where the instrument is the product of the shifts and shares of a single instrument $r \in R = \{\text{Supplier Dominated}, \text{Scale Intensive Continuous}, \text{Scale Intensive Discontinuous}, \text{Specialized Suppliers}, \text{Science Based}\}$. The x-axis depicts the corresponding first stage KP Wald of this regression. The size of the points are scaled by the size of the Rotemberg weight. The red dashed line is the estimated coefficient of our baseline IV regression, table 29. Data are from NBER-CES Manufacturing Database, 1990-2016.

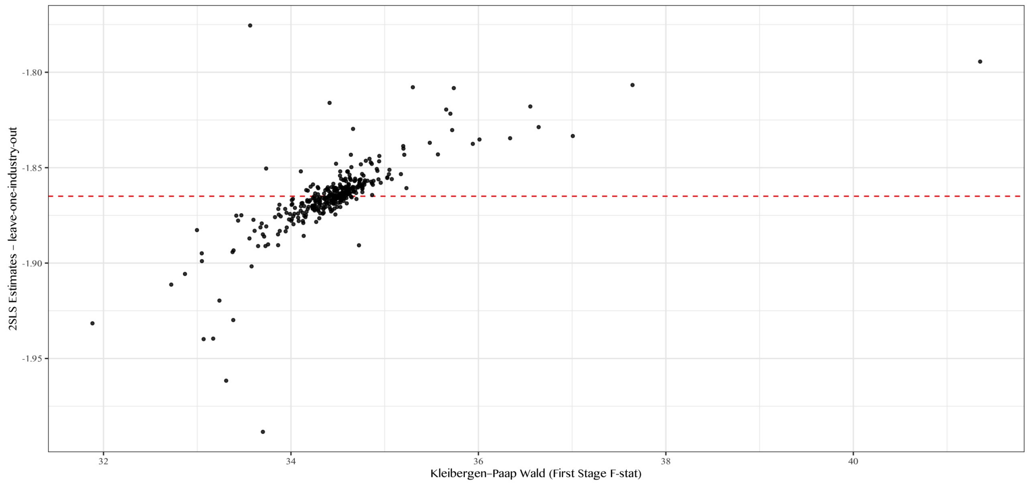


Figure 26

Table 40: OLS Estimation Results for Granular Worker Power Index, ρ

	Worker Power Shares
log(Markup)	-0.069
	(0.053)
log(Capital Intensity)	0.060^{***}
	(0.015)
log(Total Inventories)	-0.032^{**}
	(0.011)
log(Energy Price)	-0.063
	(0.077)
Observations	361
Fixed Effects	Sectoral Regimes
R^2 Adj.	0.147
R^2 Within	0.091

Notes: OLS estimation with regime fixed effects (5 categories). Dependent variable: log(ρ). Robust standard errors are reported in parentheses. ***p<0.001; **p<0.01; *p<0.05.

Table 41: TSLS Estimation for alternative instruments with future changes $\Delta u_{t+1,t+2}$

	(1)	(2)	(3)	(4)	(5)
Panel A: Instrument = $Z_{j,t+1}$					
log(BC/WC)	-0.839	-0.678	-0.475	-0.475	-1.707**
	(0.720)	(0.673)	(0.528)	(0.528)	(0.807)
log(Markup)		-0.584***	-0.695***	-0.695***	-0.719***
		(0.096)	(0.095)	(0.095)	(0.193)
log(Capital Intensity)			-0.208**	-0.208**	-0.314***
			(0.087)	(0.087)	(0.118)
Import Penetration				0.001	0.001
				(0.001)	(0.001)
log(Energy Price)					-0.227***
					(0.076)
Observations	9,025	9,025	9,025	9,025	9,025
KP Wald (1st stage)	3.01	2.96	3.80	3.80	5.52
Wu–Hausman p-value	0.079	0.135	0.396	0.396	< 0.001
Panel B: Instrument = $Z_{j,t+2}$					
log(BC/WC)	-3.828	-3.593	-4.038	-4.038	-5.031
	(2.519)	(2.710)	(3.224)	(3.224)	(10.467)
log(Markup)		-0.309	-0.598	-0.598	-0.531
		(0.509)	(0.481)	(0.482)	(0.904)
log(Capital Intensity)			-0.764	-0.764	-1.003
			(0.556)	(0.556)	(2.269)
Import Penetration				0.000	-0.000
				(0.002)	(0.003)
log(Energy Price)					0.246
					(1.662)
Observations	8,664	8,664	8,664	8,664	8,664
KP Wald (1st stage)	2.68	2.16	1.83	1.83	0.26
Wu–Hausman p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Panel C: Instrument = $Z_{j,t}$					
log(BC/WC)	-1.473***	-1.610***	-1.976***	-1.977***	-2.051***
	(0.254)	(0.256)	(0.349)	(0.349)	(0.335)
log(Markup)		-0.510**	-0.678**	-0.678**	-0.708**
		(0.157)	(0.231)	(0.231)	(0.235)
log(Capital Intensity)			-0.433***	-0.433***	-0.381***
			(0.074)	(0.074)	(0.106)
Import Penetration				0.001	0.001
				(0.001)	(0.002)
log(Energy Price)					-0.184
					(0.130)
Observations	9,025	9,025	9,025	9,025	9,025
KP Wald (1st stage)	45.7	48.5	36.7	36.8	41.6
Wu–Hausman p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Notes: The table reports regressions for different instruments $Z_{j,t+(1,2)}$ constructed using the future changes in unemployment rate. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing. All the specification columns report 2SLS estimation results and include industry fixed effects and are weighted for the employment industry-level in 1990. Panel A reports the results for the one-year ahead changes in unemployment rate. Panel B reports the results for the two-years ahead changes in unemployment rate. Panel C reports the results for our baseline instrument 15, using the observations corresponding to the Panel A. Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

D.3.2 Alternative Specifications and Economic Channels

Table 42: 2SLS Estimation Results with Specific Year Dummies for Macro Shocks

	(1)	(2)	(3)	(4)
log(BC/WC)	-2.034***	-2.091***	-1.890***	-2.100***
	(0.329)	(0.344)	(0.306)	(0.397)
year2000		0.096***	0.091***	0.098***
		(0.023)	(0.020)	(0.021)
year2001			0.087***	0.087***
			(0.022)	(0.024)
year2008				-0.053
				(0.037)
Observations	9,747	9,747	9,747	9,747
Controls	Yes	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes
First-Stage and Diagnostic Statistics				
KP Wald (1st stage)	41.2	39.7	41.4	29.1
Wu–Hausman test	315.4***	318.5***	276.3***	264.6***

Notes: The table reports regressions adding the dummies year which represent particular macro shocks for the economy and manufacturing US. 2000 and 2001 (China Shock and Dot-com Bubble) and 2008 (Financial Crisis). All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing, 1990-2016. All the specification columns include industry fixed effects and are weighted for the employment industry-level in 1990. The Wu–Hausman test rejects the null hypothesis that the OLS estimator is consistent. The Kleibergen-Paap F-statistic exceeds the critical value for weak instruments. Standard errors clustered at the industry level are reported in parentheses. $^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

Table 43: Alternative Shifts of the Labor Market

	First Stage (OLS)	Second Stage (2SLS)
Panel A. Vacancy-to-Unemployment Ratio		
	0.097^{***}	-2.315^{***}
	(0.016)	(0.363)
Observations	9,747	9,747
Controls	Yes	Yes
Weights	Yes	Yes
KP Wald (1st stage)		39.2
Panel B. Employment-Population Ratio		
	0.011^{***}	-2.051^{***}
	(0.002)	(0.383)
Observations	9,747	9,747
Controls	Yes	Yes
Weights	Yes	Yes
KP Wald (1st stage)		29.6

Notes: The table reports regressions with alternative shift components of labor market. We report both first stage coefficient on the instrument Z_{jt} and second stage coefficient on the interest variable log (BC/WC). All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing, 1990-2016. All the specification columns include industry fixed effects and are weighted for the employment industry-level in 1990. We add all the following baseline industry-level controls: $\log$(Markup), $\log$(Capital Intensity), Import Penetration, $\log$(Energy Price). The Kleibergen-Paap F-statistic exceeds the critical value for weak instruments. Standard errors clustered at the industry level are reported in parentheses. $^{+}$p$<$0.1; *p$<$0.05; **p$<$0.01; ***p$<$0.001.

Table 44: Baseline vs. No Financial Crisis Years (Panel A) and Excluding Scale Intensive Discontinuous Regime (Panel B)

Panel A: Baseline vs. No Financial Crisis Years				
	Baseline		**No Financial Crisis Years**	
	OLS **(1)**	2SLS **(2)**	OLS **(3)**	2SLS **(4)**
log(BC/WC)	-0.131***	-2.034***	-0.135***	-2.244***
	(0.036)	(0.329)	(0.035)	(0.438)
Controls	Yes	Yes	Yes	Yes
Observations	9,747	9,747	9,025	9,025
Estimator	OLS	2SLS	OLS	2SLS
Adj. R^2	0.902	0.331	0.903	0.199
First-Stage and Diagnostic Statistics (2SLS only)				
KP Wald F-stat		41.2		27.0
Wu–Hausman test		315.4***		272.3***

Panel B: Excluding Scale Intensive Discontinuous (SID) Regime				
	Baseline		**No SID**	
	OLS **(5)**	2SLS **(6)**	OLS **(7)**	2SLS **(8)**
log(BC/WC)	-0.131***	-2.034***	-0.111**	-2.364***
	(0.036)	(0.329)	(0.040)	(0.469)
Controls	Yes	Yes	Yes	Yes
Observations	9,747	9,747	8,559	8,559
Estimator	OLS	2SLS	OLS	2SLS
Adj. R^2	0.902	0.331	0.911	0.207
First-Stage and Diagnostic Statistics (2SLS only)				
KP Wald F-stat		41.2		27.7
Wu–Hausman test		315.4***		297.2***

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. The table provides a comparison between our baseline regressions with an alternative specification that excludes the years of the Great Recession (2008-2009). All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report 2SLS estimation results and include industry and year fixed effects. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Table 45: Different Market Power Measures: Baseline (Markup) vs. Lerner Index

	Baseline (Markup) (1)	**Lerner Index** (2)
log(BC/WC)	-2.034***	-1.817***
	(0.329)	(0.333)
Controls	Yes	Yes
Main control	Markup	Lerner Index
Observations	9,747	9,747
Weights	Yes	Yes
First-Stage and Diagnostic Statistics		
KP Wald (1st stage)	41.2	33.5
Wu–Hausman test	315.4***	196.1***

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. Column (1) reports baseline results with our accounting markup variable. Column (2) reports the result using the Lerner index following Grullon et al. (2019). All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report 2SLS estimation results and include industry and year fixed effects. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Table 46: Different Capital Intensities: Baseline (K/L) vs. E^k/L vs. P^k/L

	Baseline (Capital Intensity) (1)	**Equipment Intensity** (2)	**Plant Intensity**
log(BC/WC)	-2.034 ***	-2.09***	-2.02***
	(0.329)	(0.356)	(0.321)
Controls	Yes	Yes	Yes
Observations	9.747	9.747	9.747
Weights	Yes	Yes	Yes
First-Stage and Diagnostic Statistics			
KP Wald (1st stage)	41.2	35.8	45.1
Wu–Hausman test	315.4***	312.2***	326***

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. Column (1) reports baseline results with capital intensity. Column (2) reports the result using the equipment capital intensity. Column (3) reports the result using the plant capital intensity. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report 2SLS estimation results and include industry and year fixed effects. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Table 47: Test with Equipment Intensity/Plant Intensity

	2SLS
log(BC/WC)	-2.181***
	(0.376)
Controls	Yes
Observations	9,747
Weights	Yes
First-Stage and Diagnostic Statistics	
KP Wald F-stat	35.5
Wu–Hausman test	347.4***

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. We use the equipment vs. plant intensity as a control-variable. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

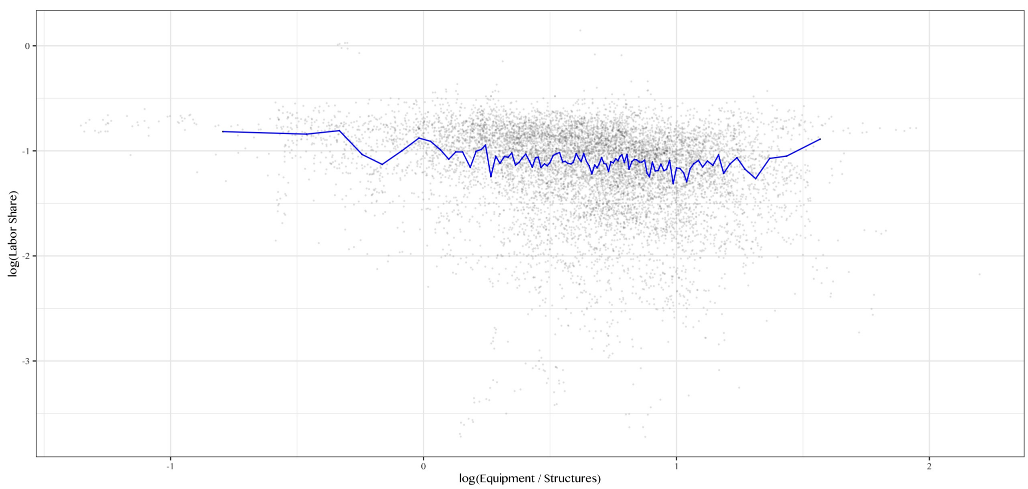


Figure 27: This figure shows the binned scatterplot between log(Equipment/Structures) and log(Labor Share). Points are averages (1990 employment weights) per bin of log(Equipment/Structures). The line connects the averages to visualize the trend. The transparent dots show the individual data points. Data comes from NBER-CES Manufacturing Database. Estimates of OLS regression with TWFE are the following: log $EI/PI = -0.144^{*}$. That is, a 1% increase in equipment intensity compared to plant is weakly associated with a 0.14% reduction in labor share for each industry.

Table 48: 2SLS Results — Baseline vs. Alternative Price Measures

	(1)	(2)	(3)
log(BC/WC)	-2.034***	-1.888***	-1.917***
	(0.329)	(0.417)	(0.342)
Controls	Yes	Yes	Yes
Price variable	Energy Price	Investment Price	Material Price
Observations	9,747	9,747	9,747
Estimator	2SLS	2SLS	2SLS
Weights	Yes	Yes	Yes
First-Stage and Diagnostic Statistics			
KP Wald F-stat	41.2	18.8	38.5
Wu–Hausman test	315.4***	138.5***	271.5***

Notes: We report results from the regression of industry-level log labor share (i.e., payroll share) on the log of labor force technical composition, as well as a vector of industry-level control variables. Column (1) reports baseline results with energy price. Column (2) reports the result using the investment price. Column (3) reports the result using the material price. All the observations are industry-year couple for the 361 industries in US manufacturing. Data are from NBER-CES Manufacturing Database for the period 1989-2016. All the specification columns report 2SLS estimation results and include industry and year fixed effects. All the industry-year observations are weighted for the employment industry-level in 1990. The columns only report industry FE due to the time component of the shift in the SSIV (15). Standard errors clustered at the industry-level are in parenthesis. $^{+}$p<0.1; *p<0.05; **p<0.01; ***p<0.001.

E RIF Decomposition Analysis

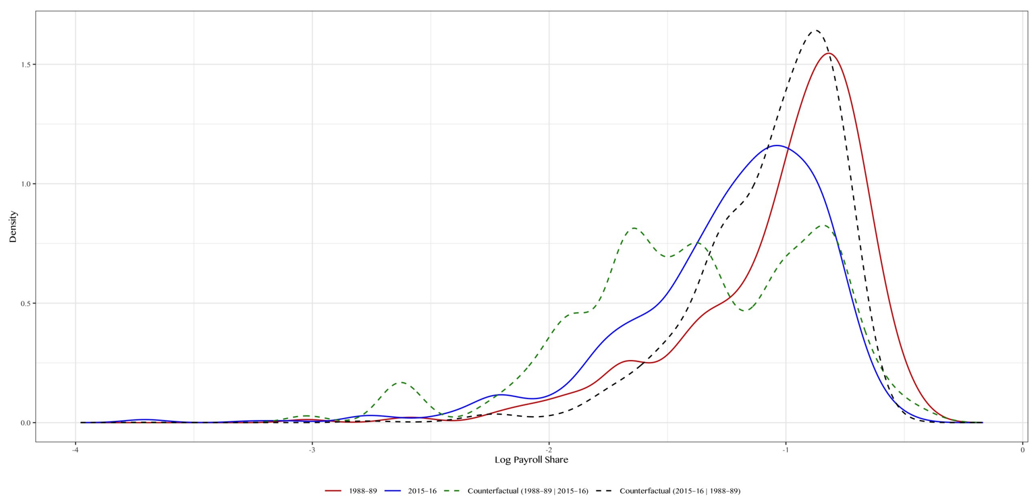


Figure 28: Kernel Density Estimation of payroll share. Kernel is Epanechnikov.

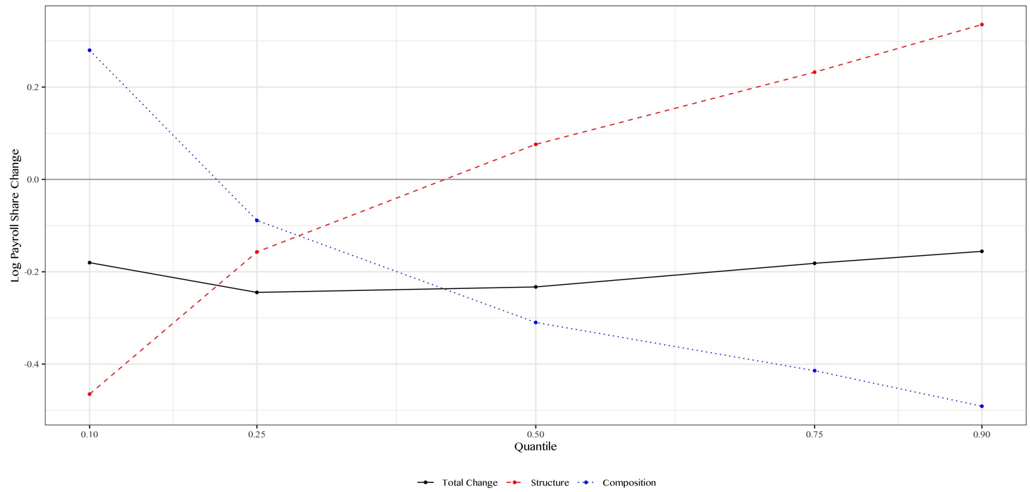


Figure 29: Decomposition of Total Change into Composition and Wage Structure Effects.

Table 49: Decomposition of log Payroll Share into Composition and Structure Effect

Quantile	Total Change	Structure	Composition	Error Approximation
10%	-0.180	-0.465	0.280	0.098
25%	-0.245	-0.157	-0.089	0.065
50%	-0.233	0.076	-0.310	0.013
75%	-0.182	0.232	-0.414	-0.037
90%	-0.156	0.335	-0.491	-0.066

Figure 30: Decomposition of Total Change into Composition and Wage Structure Effects