THE MICRO-LEVEL ANATOMY OF THE LABOR SHARE DECLINE*

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The labor share in U.S. manufacturing declined from 61% in 1967 to 41% in 2012. The labor share of the typical U.S. manufacturing establishment, in contrast, rose by over 3 percentage points during the same period. Using micro-level data, we document five salient facts: (i) since the 1980s, there has been a dramatic reallocation of value added toward the lower end of the labor share distribution; (ii) this aggregate reallocation is not due to entry/exit, to "superstars" growing faster, or to large establishments lowering their labor shares, but is instead due to units whose labor share fell as they grew in size; (iii) low labor share (*LL*) establishments benefit from high revenue labor productivity, not low wages; (iv) they also enjoy a product price premium relative to their peers; and (v) they have only temporarily lower labor shares that rebound after five to eight years. This transient pattern has become more pronounced over time, and the dynamics of value added and employment are increasingly disconnected. Taken together, we interpret these facts as pointing to a significant role for demand-side forces. *JEL Codes:* E2, L1, L2, L6, O4

I. Introduction

Several recent studies have documented a decline of the aggregate labor share, the portion of GDP paid out in compensation for labor. This finding is important for several reasons. For one, it contradicts one of the stylized facts of Kaldor (1961) that have become foundational for economic growth theories. It is at odds

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with a key building block of standard macroeconomic models, the Cobb-Douglas production function. Last, the finding suggests that an economy's value added gets distributed less to those who produce that value added and more to those who own the means of production.

Numerous explanations have been suggested to explain this aggregate decline, most of which are rooted in firm-level behavior, yet little is known about the dynamics at the micro-level and which structural drivers and shocks are consistent with the empirical picture. This article fills this gap by studying the micro-level anatomy of labor shares and factor reallocation in the manufacturing sector. To help with the interpretation of the empirical results, we first present a conceptual framework that encompasses three of the leading theories that have been proposed in the literature: demand/pricing factors, total factor productivity (TFP)/efficiency channels, and market power in labor markets. We then use confidential data from the U.S. Census of Manufactures (CMF) to study the establishment- and firm-level anatomy of labor shares, with the aim of identifying those theories consistent with the empirical evidence. Based on our empirical work, we argue that only demand factors are capable of explaining the micro-anatomy of labor shares and factor allocations that underlie the manufacturing labor share decline.

We document a number of salient facts. First, we find that the decline in the manufacturing labor share between 1967 and 2012 hides contrasting dynamics at the micro-level: alongside the sectoral decline of almost 5 percentage points per decade, the median establishment saw an increase in its labor share, by about 0.7 percentage points per decade. In other words, the decline of the manufacturing labor share was entirely driven by a strong reallocation of value added toward the low end of the labor share distribution (see Figure I) as the covariance between establishment-level labor shares and value-added shares declined strongly over time. In contrast, the reallocation of labor was much less pronounced over the same period. This evidence is in line with the findings of Autor et al. (2020).

Second, we show that this reallocation was not driven by between-industry or between-region reallocation (see Table V later), by entry and exit, by large establishments lowering their labor shares over time, nor by superstars with initially low labor shares increasing their market share. Instead, we establish that the strong reallocation was driven by units whose labor shares fell at the same time as they grew in size.

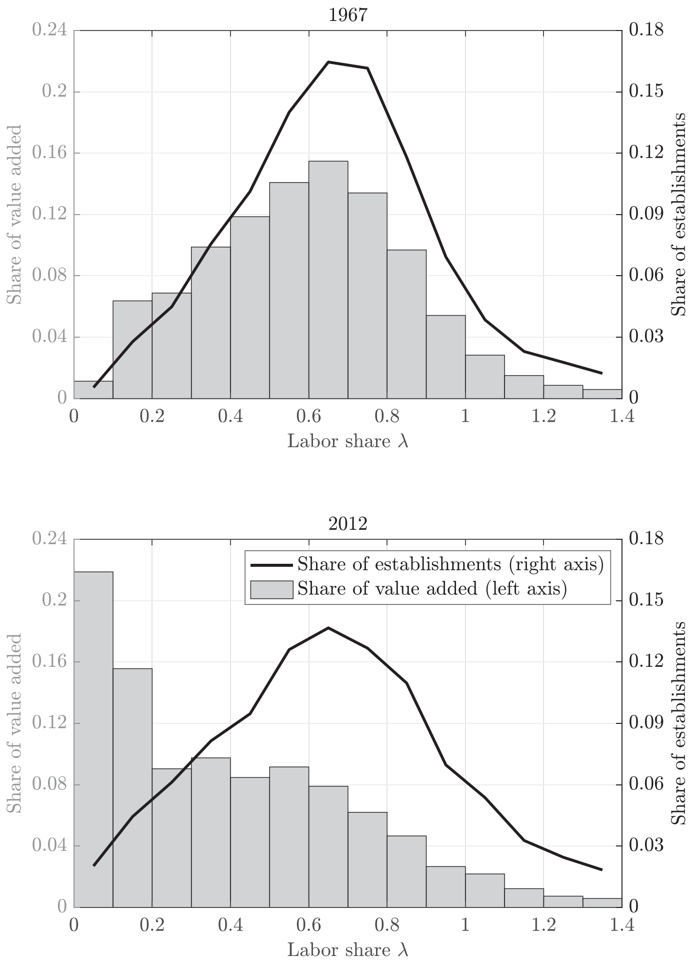


FIGURE I

The Changing Distributions of Labor Shares and Value Added

This figure depicts the raw distribution of labor shares (solid black line) and value added (gray bars) across the full sample, the comprehensive panel of manufacturing establishments in a given census year (details in Online Appendix B). To account for industry-specific differences in the raw and value-added weighted labor share distributions, they are first calculated within each three-digit NAICS industry. Then these distributions are averaged across these 21 manufacturing industries using value-added weights in a given year to obtain an estimate of the typical within-industry distribution of raw and value-added labor shares in that year.

Third, focusing on the components of labor shares, we show that cross-sectional differences are almost entirely driven by value added per worker, not wages. We then focus on establishments in the bottom quintile of the labor share distribution in a specific year and industry, which we define as low labor share (*LL*) establishments. We find that the labor share dynamics of *LL* establishments are shaped by value added, with very little accounted for by employment or wages.

Fourth, we find that *LL* establishments tend to have, on average, significantly higher prices than their peers, thus pointing to a significant role of demand-side forces. Moreover, we show that the sharp increase in the value added of *LL* establishments is associated with a significant rise in prices. We reach these conclusions by using a subsample of the census database that provides information about the value of sales and physical quantity for individual products. Doing so allows us to derive the contribution of the "product price premium" (an establishment's deviation from the average price of its competitors) to differences in sales per worker across establishments and over time.

Fifth, we find that labor share fluctuations at the establishment level are surprisingly transient: the probability that a typical *LL* establishment today loses its *LL* status five years from now is close to 60%. This number would be close to 0% if *LL* establishments had permanently low labor shares. Even more surprisingly, we document that the labor share dynamics of *LL* establishments follow a V-shaped pattern over time: the drop in labor share they experience in the five years preceding *LL* status is almost equal to the rebound in the following five years. In that sense, *LL* establishments are more like "shooting stars" than "superstars."

We complete our empirical analysis by highlighting the evolution of two central features of the micro-level anatomy of the labor share. We first show that the V-shaped labor share pattern described earlier has become more pronounced over time. Moreover, we document that employment has become increasingly disconnected from variations in value added.

These findings, which continue to hold if we use firm-level data, have important implications for our understanding of the drivers of labor share dynamics. In the context of our conceptual framework, they make a strong case for a significant role played by demand factors: technology shocks would counterfactually predict that prices drop with labor shares, whereas monopsony power in labor markets would imply a counterfactual relationship between wages and labor shares. These demand factors could take many forms and may have become more salient as markets became more integrated over this period. For example, they may be driven by strong but ephemeral brand appeal, sudden changes in customer preferences, or the introduction of new, very popular products. With a larger market, firms with high brand appeal would be able to sell their products to a larger customer base. We illustrate these types of forces using several case studies based on Compustat firm-level data and public information from annual reports. Finally, in this type of environment one would reasonably expect successful firms to be those that use advertising more intensively and effectively to spur higher demand for their products. In line with this prediction, we find evidence that *LL* establishments have significantly higher advertising spending than their peers.

The rest of the article is organized as follows. The next section discusses how our article fits in the recent labor share literature. Section III presents a simple conceptual framework to guide the interpretation of the empirical findings from Sections IV to VI. Section VII concludes by presenting a few case studies and evidence on advertising expenditures.

II. Relation to the Literature

A burgeoning literature has documented and offered different explanations for the labor share decline. One set of explanations involves technical change. Karabarbounis and Neiman (2014b) puts forward the notion that technical change embodied in new equipment capital has displaced labor and has lowered the labor share. Eden and Gaggl (2018) and Acemoglu and Restrepo (2018) refine this theory by focusing on information and communication technology capital or robots, respectively. Koh, Santaeulàlia-Llopis, and Zheng (2020) emphasize the rise of intangible capital, such as intellectual property products, research and development, and knowledge capital, in the production function of developed economies. A common ingredient in the arguments of these papers is that the elasticity of substitution between equipment or intangible capital and (routine) labor has to be greater than unity. Some empirical work by Lawrence (2015) and Oberfield and Raval (forthcoming) casts doubt on that, even at high levels of aggregation. But even if capital and labor are complements, Grossman et al. (forthcoming) show that slowing growth in labor- or capital-augmenting technological change can lead to a labor share decline. Alvarez-Cuadrado, Long, and Poschke (2018) show that industry-level specificities in technological change and the elasticity of substitution between capital and labor matter for the dynamics of industry-level factor shares.

Alternatively, Böckerman and Maliranta (2012) present evidence that exposure to international trade is related to the labor share decline in Finland. Elsby, Hobijn, and Şahin (2013) advocate the role of offshoring as an important driver of the labor share decline in the United States. In related work, Boehm, Flaaen, and Pandalai-Nayar (2020) present establishment-level evidence that outsourcing did cut U.S. manufacturing employment while raising the profits per worker of surviving production units. Glover and Short (2020) find the workforce's age composition has shifted toward workers who are less capable of extracting their marginal product of labor as a wage. Kaymak and Schott (2018) document a relationship between cuts in corporate tax rates and labor share declines in Organisation for Economic Co-operation and Development (OECD) countries.

Furman and Orszag (2015) note that the distribution of capital returns—inversely related to the labor share—had shifted up and became more skewed toward high-return firms. Hartman-Glaser, Lustig, and Xiaolan (2019) study Compustat data and find a similar dichotomy between the aggregate and average capital share to what we find in the labor share data. They explain the rise in the aggregate capital share through increasingly risky firm productivity. In their model, more volatile productivity implies that the firm owner can ask for a larger insurance premium, in turn raising the capital share. This is consistent with the finding in Kehrig (2011) that the productivity dispersion across establishments has increased significantly. From the perspective of individual workers, this widening would also pose an increased risk that requires more ex ante insurance.

Next, an emerging strand of the labor share literature emphasizes the role of rising concentration and markups. Autor et al. (2017, 2020), for example, present industry- and firm-level evidence on labor shares and concentration. Grullon, Larkin, and Michaely (2019) use firm-level data from Compustat to document that most U.S. industries became more concentrated over time, with the "winning firm" making large profits and realizing outstanding stock returns as well as engaging in more profitable mergers and acquisitions. Barkai (2020) and De Loecker, Eeckhout, and Unger (2020) show that markups have grown over time, lowering the labor and capital shares. As Edmond, Midrigan, and Xu (2018) show, the rise in markups largely disappears if firm-level markups are aggregated with the proper weights. They nevertheless find large welfare implications of high markups and high-markup dispersion and that reducing markups by taxing large high-markup firms may reduce concentration but also welfare. Like us, they carefully examine the demand-side sources of profitability and labor share dynamics. Baqaee and Farhi (2020) study misallocation in networks and find that high-markup firms have gotten larger over time, which is consistent with our finding that few but large *LL* establishments generate very high revenue labor productivity. This is also corroborated by findings in Neiman and Vavra (2019), who use household scanner data to show that firms are increasingly able to introduce customized products that make up a large share of individual consumer spending.

Our finding of lots of turnover among highly productive *LL* units is consistent with the findings in Brynjolfsson et al. (2008). They establish that IT investment enables better scalability, thus making it possible for individual firms to quickly generate the large sales we observe in the data. They also find that those IT-intensive industries are typically more concentrated and exhibit higher turnover. In a calibrated model with nonhomothetic production functions and information technology as an input, Lashkari, Bauer, and Boussard (2020) show that larger firms are more IT intensive and display lower labor shares. As the relative price of IT falls over time, market activity is reallocated toward *LL* firms, generating a decline in the aggregate labor share.

Issues related to the measurement of the labor share abound. Elsby, Hobijn, and Şahin (2013) refine the imputation of the labor portion of noncorporate income, an adjustment that only moderately mitigates the labor share decline. Bridgman (2018) claims that the rise of less durable capital such as computers and software means that a larger share of value added is spent on replacing depreciated capital. Karabarbounis and Neiman (2014a) explore that issue using worldwide data and show that the potential of higher depreciation to explain the labor share decline is limited: broad trends in the gross and net labor shares are in fact quite similar.

III. Conceptual Framework

The main objective of this article is to study the micro-level anatomy of the aggregate labor share decline. Many different causes—patterns of reallocation across micro units, or different types of shocks—may lead to that outcome. Knowing which causes hold empirical ground will help us understand those structural features of the U.S. economy that matter for the labor share decline. In this section, we lay out a succinct conceptual framework to guide our analysis, built around a simple production function. Its purpose is not to undertake a formal quantitative assessment of different causes but to identify the qualitative relevance of a variety of shocks and reallocation dynamics that could be behind the aggregate labor share decline. Throughout the empirical analysis, we refer back to this conceptual framework to interpret our findings.

III.A. Micro-Level Forces behind the Aggregate Labor Share Decline

To frame our analysis, consider a specific production unit i (firm, plant, etc.) at time t that employs L_{it} workers at wage rate W_{it} to produce Y_{it} units of a good sold at price P_{it}. The labor share of that unit is then the ratio of its labor cost to the nominal value added: $\lambda_{it} \equiv \frac{W_{it}L_{it}}{P_{it}Y_{it}}$. Summing up across units, one can express the aggregate labor share, λ_t, as the weighted sum of the individual labor shares:

$$\lambda_t = \frac{W_t L_t}{P_t Y_t} = \frac{\sum_i W_{it} L_{it}}{\sum_i P_{it} Y_{it}} = \sum_i \omega_{it}\lambda_{it} \tag{1}$$

$$= \overline{\lambda}_{it} + Cov(\omega_{it}, \lambda_{it}), \tag{2}$$

where λ_{it} corresponds to the labor share of production unit i at time t and $\omega_{it} \equiv \frac{P_{it}Y_{it}}{\sum_i P_{it}Y_{it}}$ denotes the value-added weight of unit i. The second line in the expression derives from Olley and Pakes (1996) and is useful to illustrate how the aggregate labor share depends on the common unweighted average, $\overline{\lambda}_{it}$, as well as the joint distribution of labor shares and value added, $Cov(\omega_{it}, \lambda_{it})$. We turn our attention to two broad types of distributional changes that are compatible with an aggregate labor share decline. In the next section, we present a set of candidate economic shocks at the micro level that can rationalize these changes.

1. Common Effect / Trend. First, a fall in the aggregate labor share can be the result of a decline in the unweighted average of the distribution of labor shares. That is, any change that affects all or most units symmetrically will alter $\overline{\lambda}_{it}$.

2. Composition Effects. Second, equation (2) indicates that the aggregate labor share can decline if the joint distribution of labor shares and value-added shares evolves in a way that reduces the covariance between these two objects. Abstracting from entry and exit for the moment, this change in the joint distribution can be decomposed into three readily interpretable terms:[1]

$$\Delta Cov(\omega_{it}, \lambda_{it}) = Cov(\omega_{it-1}, \Delta\lambda_{it}) + Cov(\Delta\omega_{it}, \lambda_{it-1}) + Cov(\Delta\omega_{it}, \Delta\lambda_{it}). \quad (3)$$

i. $Cov(\omega_{it-1}, \Delta\lambda_{it}) < 0$: the "Big Player" scenario. Changes in unit-level labor shares, $\Delta\lambda_{it}$, may be correlated with initial size ω_{it-1}. For example, large units could be more successful in lowering their wage bill while keeping output constant, in turn depressing their individual labor shares. The covariance term, $Cov(\omega_{it}, \lambda_{it})$, would fall because $Cov(\omega_{it-1}, \Delta\lambda_{it}) < 0$.
ii. $Cov(\Delta\omega_{it}, \lambda_{it-1}) < 0$: the "Superstar" scenario. Conversely, market share changes, $\Delta\omega_{it}$, may be negatively correlated with the initial level of labor shares λ_{it-1}. For example, superstar units with constant but lower-than-average labor shares may be growing faster over time. As a result, the covariance term in equation (2), $Cov(\omega_{it}, \lambda_{it})$, would decline because $Cov(\Delta\omega_{it}, \lambda_{it-1}) < 0$.
iii. $Cov(\Delta\omega_{it}, \Delta\lambda_{it}) < 0$: the "Rising Star" scenario. Last, labor share changes, $\Delta\lambda_{it}$, and relative growth, $\Delta\omega_{it}$, may be negatively correlated. For example, some units may experience shocks or take actions that lead them to simultaneously gain market share and lower their labor share.

1. The detailed decomposition can be found in Online Appendix A.

The covariance term, $Cov(\omega_{it}, \lambda_{it})$, would decline because $Cov(\Delta\omega_{it}, \Delta\lambda_{it}) < 0$.

It is worth pointing out that these three covariance-based scenarios can be mapped into a familiar shift-share decomposition:

$$\Delta\lambda_t = \underbrace{\sum_i \omega_{it-5}\Delta\lambda_{it}}_{\text{Shift}} + \underbrace{\sum_i \Delta\omega_{it}\lambda_{it-5}}_{\text{Share}} + \underbrace{\sum_i \Delta\omega_{it}\Delta\lambda_{it}}_{\text{Interaction}}. \tag{4}$$

The Big Player, Superstar, and Rising Star scenarios, respectively, correspond in equation (4) to the Share, Shift, and Interaction terms.

The discussion in this section makes it clear that the micro-level dynamics of labor shares and market shares can affect the aggregate labor share through many channels. Next, we identify a number of micro-level shocks that may shape these dynamics through their impact on the components of labor and market shares: wages, employment, prices, and real output.

III.B. Micro-Level Effects of Demand, Supply, and Monopsony Shocks

From deunionization to automation to rising market power, different forces may affect labor shares at the micro level through distinct components, such as wages or markups. In the empirical section, we study those components, with the aim of identifying explanations that are less likely to be relevant and theories that merit attention in further research. To frame our analysis, consider that the production unit i takes factor prices as given when hiring labor L_{it} and renting capital K_{it}. To ease the exposition, we assume that output Y_{it} is produced using a Cobb-Douglas production function: $Y_{it} = A_{it}K_{it}^{\alpha_i}L_{it}^{1-\alpha_i}$, where $\alpha_i \in (0, 1)$. The insights in this section, however, hold without constant returns to scale and under more general homothetic production functions without biased technical change.

Under these assumptions, unit i's labor share can be written as

$$\lambda_{it} = \frac{W_{it}L_{it}}{P_{it}Y_{it}} = \frac{W_{it}}{ARPL_{it}} = \frac{W_{it}}{P_{it}APL_{it}}, \tag{5}$$

where W_{it} denotes the market wage, and $ARPL_{it} = \frac{P_{it}Y_{it}}{L_{it}}$ and $APL_{it} = \frac{Y_{it}}{L_{it}}$ are the average revenue and physical products of labor, respectively. Next, through the lens of this simple framework, we analyze three broad classes of theories that have been proposed in the literature to explain the decline in the labor share.

1. Demand Shocks and Markups. Let us decompose λ_{it} and ω_{it}:

$$\lambda_{it} = \frac{W_{it}}{P_{it}APL_{it}} = \frac{W_{it}}{\mu_{it}MC_{it}APL_{it}} = \frac{1-\alpha_i}{\mu_{it}} \tag{6}$$

$$\omega_{it} = \frac{P_{it}Y_{it}}{\sum_i P_{it}Y_{it}} = \frac{\mu_{it}MC_{it}Y_{it}}{\sum_i P_{it}Y_{it}}, \tag{7}$$

where μ_{it} corresponds to the price markup, P_{it}, over the marginal cost, MC_{it}. The last expression for the labor share follows from the Cobb-Douglas production function, where $1 - \alpha_i$ corresponds to the labor elasticity of output.

Consider that, for some reason, customers value unit i's products or brand image more than that of the competition. With an isoelastic demand schedule, markups are fixed and the only effect of this preference shock would be to raise the unit's market share, ω_{it}. The aggregate labor share could in turn be affected by a composition effect: for example, the concentration of preference shocks on low labor share units would imply that $Cov(\Delta\omega_{it}, \lambda_{it-1})$ is negative.

Alternatively, unit-level labor shares may be affected if markups are endogenous. For example, a demand shock may bring unit i into a less elastic part of its demand curve as in Kimball (1995) or Melitz and Ottaviano (2008), leading it to increase its markup. From the two equations, we can clearly see how an idiosyncratic demand shock that raises unit i's markup μ_{it} leads to a fall in its labor share λ_{it} and a rise in its market share ω_{it}. Hence, labor shares and market shares would be negatively correlated: $Cov(\Delta\omega_{it}, \Delta\lambda_{it}) < 0$. The sources and consequences of rising markups have been extensively studied recently; see Grullon, Larkin, and Michaely (2019); Barkai (2020); Baqaee and Farhi (2020); Gutiérrez and Philippon (2017); Edmond, Midrigan, and Xu (2018); De Loecker, Eeckhout, and Unger (2020); and Neiman and Vavra (2019).

2. Supply-Side Shocks. Technology is another channel that has been suggested by the literature as a potential driver of the downward labor share trend. With a Cobb-Douglas production function, a positive technology shock lowers the unit's marginal cost, MC_{it}, and increases its average labor productivity, APL_{it}, in such a way that these changes exactly cancel each other; under our assumptions, the only factors specific to unit i's labor share are its production elasticity α_i and its markup μ_{it}. Therefore, higher TFP on its own does not have a direct effect on the unit's labor share λ_{it}, but it will increase its market share ω_{it}.[2] Standard TFP shocks could lower the aggregate labor share if they are correlated with labor share levels, that is, $Cov(\Delta\omega_{it}, \lambda_{it-1}) < 0$, as described in the "composition" paragraph. Examples of these type of shocks include Kaymak and Schott (2018), Alvarez-Cuadrado, Long, and Poschke (2018), Grossman et al. (forthcoming), and Lashkari, Bauer, and Boussard (2020).

TFP shocks may have a different effect if producers do not pass through all the cost savings of a technology shock through lower prices. Instead, producers may choose to raise markups μ_{it} because, for example, producing on a larger scale brings them to a less elastic portion of their demand schedule, as in Kimball (1995) and Melitz and Ottaviano (2008). This would be in line with the explanation of Autor et al. (2017, 2020). Under this scenario, equations (6) and (7) imply that an idiosyncratic TFP shock will move unit i's labor share and market share in opposite directions. Examples of these shocks are featured in Grossman et al. (forthcoming), Leblebicioğlu and Weinberger (2020), and Karabarbounis and Neiman (2014b).

Notice that these dynamics are similar to those under the scenario of a demand shock with nonisoelastic demand schedules, except for one important difference: prices will decline after supply-side TFP shocks, whereas they will increase under demand shocks.

3. Monopsony Power. Last, we turn to the role of market power in labor markets. If labor market concentration allows businesses to extract rents from workers, we need to relax our assumption that units take factor prices as given. Instead, we follow

2. This assumes a price elasticity of demand larger than unity, as is standard in the literature. These points generalize to Cobb-Douglas production functions with nonconstant returns to scale and constant elasticity of substitution production functions with constant returns to scale and Hicks-neutral technology.

Berger, Herkenhoff, and Mongey (2019) and rewrite the wage of production unit i, W_{it}, as its marginal revenue product of labor, $MRPL_{it}$, times a generic wage markdown, denoted $\nu_{it} \leqslant 1$. The more market power a firm has, the more it can depress the wage beneath the marginal revenue product, which is captured by a lower value of ν_{it}.

$$(8) \qquad \lambda_{it} = \frac{W_{it}L_{it}}{P_{it}Y_{it}} = \frac{W_{it}}{ARPL_{it}} = \frac{\nu_{it}MRPL_{it}}{ARPL_{it}} = \nu_{it}(1-\alpha_i)$$

$$(9) \qquad \omega_{it} = \frac{P_{it}Y_{it}}{\sum_i P_{it}Y_{it}}.$$

Note that a lower ν_{it} alone decreases the unit's labor share but does not increase its value-added weight unless it is profitable to expand scale or adjust its price relative to its peers. A stronger wage markdown may result from increasing labor market concentration (Berger, Herkenhoff, and Mongey 2019; Jarosch, Nimczik, and Sorkin 2019; Azar, Marinescu, and Steinbaum forthcoming, Hershbein, Macaluso, and Yeh 2020), labor market deregulation, such as deunionization (Fichtenbaum 2011), "right-to-work" laws (Blanchard and Giavazzi 2003), demographic factors (Glover and Short 2020), or search-and-matching frictions (Gouin-Bonenfant 2018). Although the empirical evidence on the link between business concentration trends and labor shares is ambiguous (see Berger, Herkenhoff, and Mongey 2019; Hershbein, Macaluso, and Yeh 2020), the use of micro-level data allows us to assess its role for the labor share decline.

This conceptual framework, though simple, provides a lens through which we can interpret the micro-level evidence on labor shares, value added, employment, wages, and prices. We turn to documenting a series of empirical findings that inform us of the forces behind the decline in the aggregate labor share.

IV. Labor Share: Macro Trends and Micro Reallocation

In this section, we discuss our data sources and describe how we compute the labor share at the manufacturing establishment level. We produce a number of findings that highlight the micro-level dynamics at play behind the fluctuations of the manufacturing labor share.

IV.A. Data Sources and Measurement

Our focus is on the labor share dynamics in the U.S. manufacturing sector. This choice was driven by a number of reasons. First, as highlighted by Elsby, Hobijn, and Şahin (2013), manufacturing is one of the sectors where the labor share decline has been most pronounced, making it a natural starting point to study the macro and micro dynamics of the labor share decline. Second, many of the explanations commonly put forward to explain the fall in the labor share (such as automation, competitive pressures by globalization, offshoring, and the eroding power of labor unions) are particularly relevant in the context of goods-producing activities. Third, data at the level of individual manufacturing establishments from the U.S. Census Bureau have been heavily studied and are considered to be of higher quality than for other sectors. For example, the information on intermediate inputs and energy use contained in the CMF database allows us to construct reliable measures of value added instead of having to rely on alternative variables, such as sales or revenue to generate establishment-level labor shares.

Fourth, the longer time coverage for the manufacturing sector allows us to contrast the dynamics of the labor share before and after the start of its secular decline, around the early 1980s. While our analysis starts in 1967, the U.S. Census Bureau began to sample establishments in other sectors only in the 1980s or 1990s. Fifth, the higher degree of homogeneity for some manufacturing goods will allow us to disentangle the respective roles of prices and quantities in driving the phenomena we document in the following sections. Sixth, because we consider data from the producer side and focus on the manufacturing sector, our analysis is unlikely to be affected by the measurement problems present in household-level income data. For example, Elsby, Hobijn, and Şahin (2013) argue that self-employment income matters significantly for these trends. In addition, our results are unlikely to be biased by the evolution of housing prices that affect the measurement of real estate income: Rognlie (2015) documents that income from housing alone was responsible for the labor share dynamics computed from household-side surveys, and Eden and Gaggl (2018) document a similar pattern for residential capital income in more aggregate income and product accounts. Finally, computations by Koh, Santaeulàlia-Llopis, and Zheng (2020) show that manufacturing is one of the few sectors where the measured labor share decline is not overturned by the rise in intellectual property products.

The results derived throughout the article come from the establishment-level CMF database. The U.S. Census Bureau collects data on all manufacturing establishments in the Economic Census, which is taken every five years from 1967 until 2012.[3] We drop all observations that are administrative records or are not part of the "tabbed sample," which makes up the official tabulations published by the Census Bureau. We verify that the labor share dynamics in our data coincide with those documented in the Multifactor Productivity Tables published by the Bureau of Labor Statistics (BLS). The aggregate manufacturing labor share λ_t in a given industry and year t is defined as

$$\lambda_t = \frac{W_t L_t}{P_t Y_t}, \tag{10}$$

where $W_t L_t$ denotes manufacturing labor costs and $P_t Y_t$ is nominal value added produced in the manufacturing sector at time t, gross of depreciation and taxes. Focusing on the raw nominal data provides us the advantage of avoiding measurement issues related to inflation.

We define the following items as labor costs: salaries and wages for permanent and leased workers, involuntary labor costs (such as unemployment insurance or social security contributions) netted out from wages, and voluntary labor costs (such as health, retirement, and other benefits paid to employees).[4] Value added is measured as sales plus inventory investment for final and work-in-progress goods less resales, material inputs, contract work, and energy expenditures. We drop all observations with a negative labor share and those in the top percentiles to avoid outliers driving our results. After the truncation, our baseline sample contains about 1.7 million establishment-year observations throughout all

3. The 1963 census lacks a substantial portion of labor compensation, so we ignore it in this article.

4. The Census Bureau does not collect information on nonmonetary compensation or ownership rights, which have monetary value to an employee. Stock options, for example, are counted as labor income for tax purposes once a manager exercises the option but not at the point the manager acquires the option. Ongoing research in finance is interested in the rising share of deferred compensation in total labor compensation (Eisfeldt, Falato, and Xiaolan 2021). Such an increase in unmeasured compensation could potentially mitigate the manufacturing labor share decline.

census years 1967–2012. For more details on the construction of the sample and the variables of interest, see Online Appendix B.

Next we study the anatomy of the decline in the manufacturing labor share by exploiting the establishment-level data described already. We present and analyze five main findings on the micro-level dynamics of the labor share. Our view is that any theory of manufacturing labor share dynamics should be compatible with these salient facts. Although our analysis is at the establishment level, all subsequent results also hold if we aggregate to the firm level. We present those firm-level results in Online Appendix C.

IV.B. The Labor Share: Aggregate Decline, Micro-Level Increase

We start by exploiting the decomposition of the manufacturing labor share λ_t introduced in equations (1) and (2).

From the decomposition, we can readily identify two broad ways a decline in the manufacturing labor share may come about. First, it could follow from a general decline of the unit-level labor shares λ_{it}, which would be reflected in a lower (unweighted average) $\overline{\lambda}_{it}$. For example, this may come from a rise in markups or monopsony power common to all units. Second, the fall in the manufacturing labor share λ_t could be the result of a decline in the covariance between λ_{it} and ω_{it}. For instance, this would happen if low labor share establishments experience an increase in their economic weight over time.

1. The Labor Share of the Median Establishment Increases. We now aim to disentangle these various scenarios with the help of micro-level data. As a first exercise, Figure II plots several quantiles of the raw distribution of establishment-level labor shares λ_{it} in each census year since 1967, alongside the manufacturing labor share.

Figure II highlights diverging trends in the labor shares at the sectoral and establishment level, particularly since the mid-1980s: while the manufacturing labor share declines by 4.5 percentage points per decade, on average, the median labor share increases by 0.7 percentage points per decade. The unweighted average labor share, $\overline{\lambda}_{it}$, and the top and bottom quartiles strongly co-move with the median. This finding already makes it clear that the manufacturing labor share decline is not mainly driven by a shift of the distribution of labor shares in individual

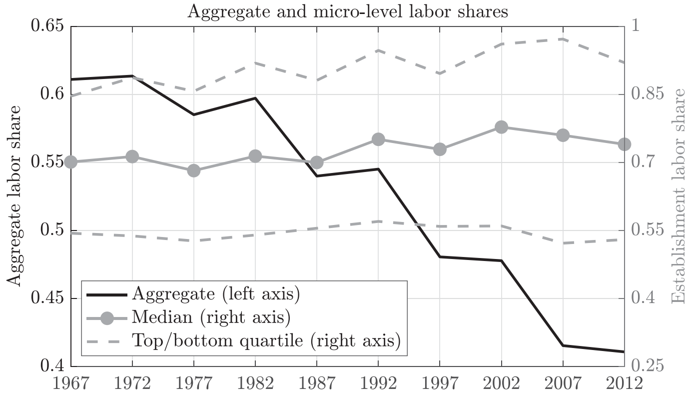


FIGURE II

Sectoral and Establishment-Level Labor Shares in U.S. Manufacturing

The figure plots the sectoral manufacturing labor share (black line, left axis) against the year-by-year quantiles of the cross-establishment labor share distribution (gray lines, right axis): the solid gray line with circles reflects the median, per U.S. Census disclosure rules, defined as the average of the sample of observations between the 49th and 51st percentile; the dashed gray lines reflect the first and third quartile, defined analogously to the median. Although the manufacturing labor share declines strongly, the median and top quartile labor share increase over time. For details on the full sample, see the notes to Figure I and Online Appendix B.

establishments (corresponding to the λ_{it} terms in equation (1)). Instead, our evidence points to the importance of reallocation (corresponding to the ω_{it} terms in equation (1)) as the main driver of the manufacturing labor share dynamics.[5] We turn our attention to this next.

2. Reallocation: Dramatic for Value Added, Anemic for Labor. The diverging trends between macro- and micro-level labor shares imply that the ω_{it} terms in equation (1) must play a central role in driving down the manufacturing labor share through a reallocation of value added toward the left tail of the labor share distribution. To quantify this reallocation, we divide the distribution of labor shares λ into 10 percentage point–wide bins, from 0% to 140% in each year. For each labor share bin, we compute its share of total manufacturing value added, employment, and

5. In Online Appendix B, we show that the decline in the manufacturing labor share is present for both production and nonproduction workers.

number of establishments. To control for industry-specific differences, we compute these shares for each three-digit NAICS industry and then aggregate them up in each bin using the industry's value-added weight at the annual level. The subsequent analysis therefore refers to reallocation of value added within a typical industry.[6] As we show in Online Appendix E, reallocation between industries, regions, or legal forms of organization plays essentially no role in the decline of the manufacturing labor share.

The light gray bars in the left column of panels in Figure III display the distributions of the number of establishments (top), labor input (middle), and value added (bottom) against the labor share in 1967; the dark gray bars in the right column show the analog distributions in 2012. There are three main takeaways. First, the unweighted distribution of establishments against the labor share did not see any significant change, besides a slight fattening of the tails, also visible in Figure II. Second, the distribution of employment suggests only a very limited reallocation of labor input to low-labor-share establishments. On the other hand, other panels paint a picture consistent with a dramatic reallocation of output. Most of value added in 1967 is produced by establishments in the middle of the labor share distribution (between 50% and 80%). The value-added weighted median labor share is 62%. Over the following decades, however, the economic activity shifts gradually and persistently toward the low labor share spectrum: by 2012, half of manufacturing value added is accounted for by establishments with a labor share less than 32%. The presence of only a few establishments that account for the lion's share of value added implies that the output-based size distribution has become very right-skewed: by 2012, a few establishments are very large in terms of output without accounting for a proportional employment share. The disconnect between value added and labor reallocation is a key feature of the labor share decline. Similar evidence at the firm level has been found for other sectors in the United States by Autor et al. (2020), for Canada by Gouin-Bonenfant (2018), and for China by Berkowitz, May, and Nishioka (2017).

Referring back to our discussion surrounding equation (2) in the conceptual framework, the findings make it clear that common trends (e.g., a generalized increase in markups or monop-

6. Repeating this exercise at other aggregation levels, we find almost no difference between three- and four-digit NAICS levels, whereas the reallocation of value added to low labor shares within six-digit NAICS industries is even stronger.

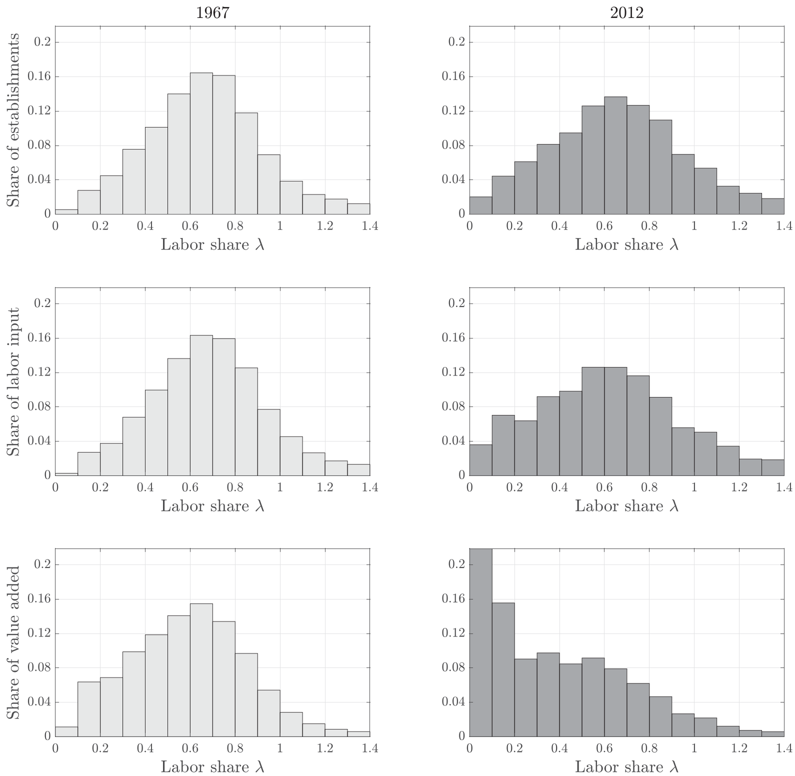


FIGURE III

Distribution of Establishments, Labor Input, and Value Added Conditional on Labor Share

The bars in the two panels in the first row reflect the raw cross-establishment distribution of labor shares in 1967 (light gray on the left) and 2012 (dark gray on the right). The panels in the middle row display the allocation of labor, and those in the bottom row display that of value added. For details on the full sample, see the notes to Figure I and Online Appendix B.

sony power) are unlikely to be behind the decline in the manufacturing labor share. Such a general development would have manifested itself through a leftward shift of the unweighted distribution by 20 percentage points, on average, yet it has remained centered around $\lambda = 0.65$ (top row of Figure III). Hence, the manufacturing labor share decline must be driven by a strong decline in the covariance between establishment-level labor shares and market shares, $Cov(\omega_{it}, \lambda_{it})$: since the 1980s, low labor share establishments (though small in number) have also happened to be much larger producers than their high labor share peers, as is visible in Figure III. In contrast, the middle row indicates that the distribution of the labor input did not follow the same dramatic pattern: this concentration of value added did not come with a similar shift in the distribution of employment. In the next section, we investigate what could be behind this development and argue that the joint dynamics of value added and the labor share is central to this phenomenon.

IV.C. Labor Share and Size: The Importance of Joint Dynamics

Although the evidence on reallocation in Figure III is stark, it does not reveal how the reallocation of value added came about. In the conceptual framework in Section III.A, we illustrated three distinct patterns that can lead to this phenomenon. Recall that $Cov(\omega_{it}, \lambda_{it})$ can decline due to:

i. $Cov(\omega_{it-1}, \Delta\lambda_{it}) < 0$: the Big Player scenario. Large establishments may see their labor shares drop (e.g., because of an increase in their markups or monopsony power), while smaller ones experience the opposite trend. In the last row of Figure III, this would correspond to the bulk of value added shifting leftward as the largest establishments in the middle of the distribution lower their labor shares over time.
ii. $Cov(\Delta\omega_{it}, \lambda_{it-1}) < 0$: the Superstar scenario. Superstars are commonly defined as units with high productivity and low labor shares (all else equal), an advantage that enables them to take over their market. In the context of the distribution of value added in Figure III, this would correspond to establishments initially at the left end of the labor share distribution outgrowing their peers and accounting for most of production by 2012. A variant would be the entry of low-labor-share and exit of high-labor-share establishments.
iii. $Cov(\Delta\omega_{it}, \Delta\lambda_{it}) < 0$: the Rising Star scenario. Under the third scenario, some establishments raise their labor productivity without increasing wages or hiring additional employees. As a result, they experience a simultaneous rise in their market shares and a fall in their labor shares. In Figure III, this would correspond to units initially in the middle of the labor share distribution moving leftward

and growing over time, while others move rightward in the labor share distribution and shrink.

All three scenarios would be compatible with the negative covariance between labor shares and market shares that we document in the previous section, as well as (i) the relatively stable median labor share and (ii) the larger portion of manufacturing output produced at the bottom of the labor share distribution. In this section, we put them to the test with the help of our detailed data.

1. Did Initially Large Establishments Depress the Labor Share? First, we study if large establishments systematically lowered their labor shares while their smaller peers saw their labor shares rise. Such labor share dynamics conditional on initial size may stem from increasing monopsony power of large establishments in input markets or the ability to innovate at a higher rate than small establishments. To test this hypothesis, we compare the actual labor share to a counterfactual in which we keep an establishment's market share equal to its initial value, while allowing its labor share λ_{it} to evolve over time as it does in the data. For this exercise, we focus on a strongly balanced panel between 1967 and 2012 since the initial market share and labor share changes of establishments entering or exiting are not well defined.[7] Despite its more limited coverage, we are reassured by the fact that the aggregate labor share trend in this strongly balanced sample looks very similar to the one in the full sample: between 1982 and 2012, the manufacturing labor share falls by 22 percentage points in the former versus 19 percentage points in the latter. This suggests that most of the reallocation we documented earlier is occurring among long-lived incumbent establishments, rather than being driven by entry and exit.[8]

7. The strongly balanced sample accounts for roughly 30,000 establishment-year observations, which corresponds to about one-twelfth of manufacturing value added in a given census year.

8. Though our evidence on entry and exit is largely consistent with the findings of Autor et al. (2020), this is somewhat in contrast to the role of the extensive margin for employment dynamics as documented by Fort, Pierce, and Schott (2018): although entry and exit (of establishments within firms or firms altogether) may account for 88% of employment changes in U.S. manufacturing, labor shares of entrants and exiting establishments are not different enough from that of incumbents, and the value added they account for is not large enough for them to impact the manufacturing labor share decline.

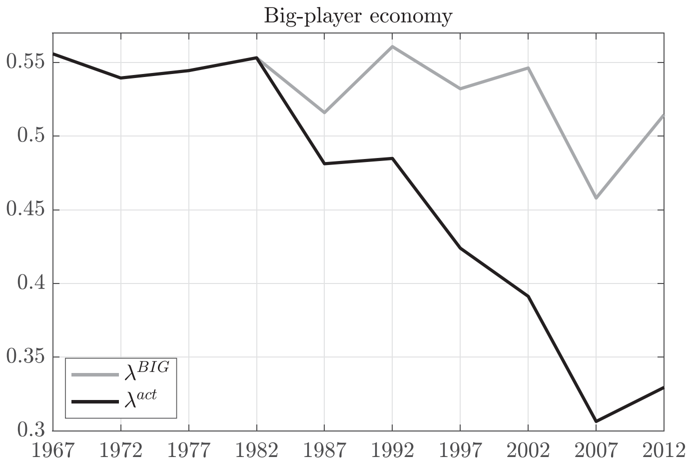


FIGURE IV

The Limited Role of Initially Large Establishments

The figure plots the actual manufacturing labor share, $\lambda_t^{act} = \sum_i \omega_{it}\lambda_{it}$, against the counterfactual labor shares in the Big-Player Scenario, $\lambda_t^{BIG} = \sum_i \omega_{i1982}\lambda_{it}$. It shows that establishments that were initially relatively large did not experience a particularly strong labor share decline. Underlying this analysis is the strongly balanced sample of manufacturing establishments 1967–2012; details are in the text.

The counterfactual labor share in this Big Player scenario is constructed as:

$$\lambda_t^{BIG} = \sum_i \lambda_{it}\omega_{i1982}.$$

We choose 1982 as the base year of this counterfactual because it coincides with the start of the manufacturing labor share decline.[9] If the manufacturing labor share decline was predominantly driven by large establishments lowering their labor shares over time, we would expect λ_t^{BIG} to exhibit a decline similar to that of the actual manufacturing labor share in the strongly balanced panel, λ_t^{act}. Figure IV shows this is not the case: the Big Player counterfactual labor share, λ_t^{BIG}, falls by only 4 percentage points between 1982 and 2012, compared to a 22 percentage point drop

9. As a robustness check, we also consider 1977 as a starting point or as defining the "initial values" as the average around the 1982 census: $\overline{\omega}_{i1982} = E_i[\omega_{i\tau}]$, $\tau =$ 1977, 1982, and 1987.

in the actual labor share over the same period. In other words, the fall in the manufacturing labor share does not appear to be driven by a divergence in the relative labor shares of initially large versus small establishments. We therefore conclude that $Cov(\omega_{it}, \lambda_{it})$ in equation (2) did not decline because $Cov(\Delta\lambda_{it}, \omega_{i1982})$ was negative.

2. Did Initial "Superstars" Depress the Labor Share? Next we test the Superstar hypothesis. Under this scenario, one should observe a reallocation of market share toward superstar establishments, units that are highly productive and feature low labor shares. If those superstars outgrow their peers, this would naturally depress the aggregate labor share. In this case, the decreasing covariance between labor shares and market shares in equation (2) would instead be driven by the fact that market share growth over the 1982–2012 period is negatively correlated with labor shares in 1982 (i.e., $Cov(\lambda_{i1982}, \Delta\omega_{it}) < 0$). As we saw in Section III.B, this could have happened, for example, if they had been more prone to experience positive TFP shocks over this period.

To assess this scenario, we compute the following counterfactual:

$$\lambda_t^{STAR} = \sum_i \lambda_{i1982}\omega_{it}.$$

As in the previous counterfactual, we focus first on the strongly balanced sample of manufacturing establishments, an assumption we relax later.

The top panel of Figure V plots the evolution of the superstar economy counterfactual (λ_t^{STAR}). We find a noticeable rise in the counterfactual labor share: from 55% in 1982, it increases to 60% by 2012, while the actual labor share falls to 33%. The takeaway is that manufacturing establishments with an initially low labor share (the superstars) did not seem to experience, on average, higher growth in value added between 1982 and 2012.[10]

Recall that the analysis was conducted using a strongly balanced panel. Although the evolution of the manufacturing labor

10. We find a similar pattern within almost all of the 21 manufacturing industries, indicating that the superstar economy hypothesis is not responsible for within-industry dynamics either.

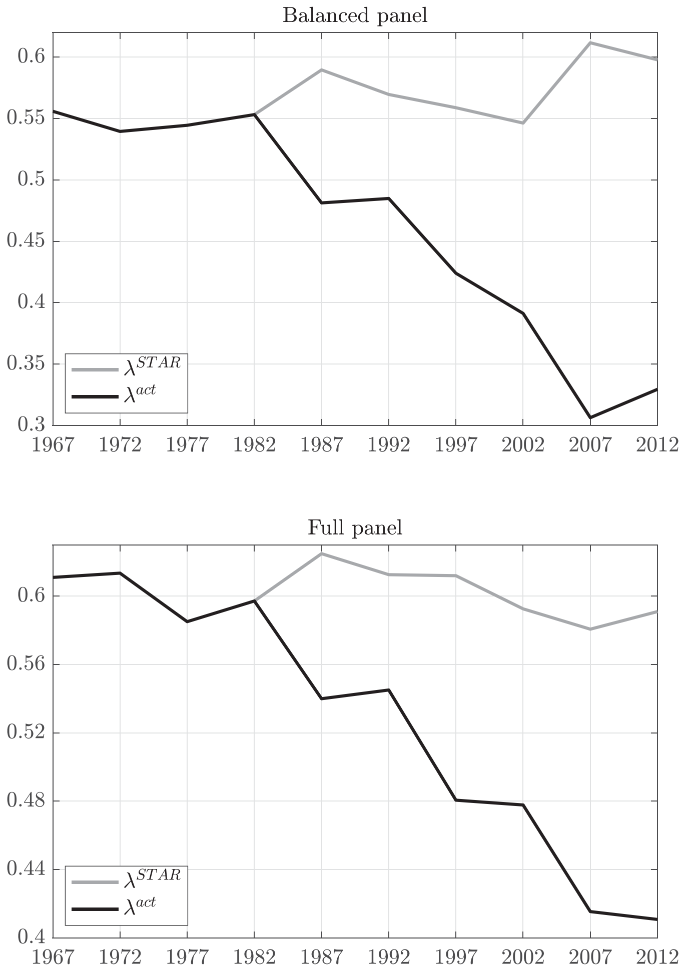


FIGURE V

The Limited Role of Initial Superstar Establishments

The figure plots the actual manufacturing labor share, $\lambda_t^{act} = \sum_i \omega_{it}\lambda_{it}$, against the counterfactual labor share in the superstar economy, $\lambda_t^{STAR} = \sum_i \omega_{it}\lambda_{i1982}$. In the top panel, we only sum over establishments that are continually active between 1967 and 2012 (details in Section IV.C.1); in the bottom panel we sum over all establishments ever active between 1967–2012 (the full sample). If an establishment has not entered by 1982, we assign it the labor share in its entry year as λ_{i1982} and a market share of zero until it enters; for exiting establishments we assign a market share of zero after they exit. The analogue counterfactual for "superstar firms" is displayed in Figure XIX in the Online Appendix.

share in this sample mirrors that of the full sample, one could still argue that entry and exit may be important forces over longer horizons. For example, one could imagine that a low-labor-share entrant in 1992 may turn out to account for a large share of value added by the 2000s. In addition, high labor share establishments may have been driven out of business by 2012. Yet entering and exiting establishments have been excluded from our analysis so far. We now relax this assumption.

Specifically, we repeat our superstar counterfactual including all establishments that are at some point part of the sample between 1967 and 2012, including those that exit or enter along the way. Note that by definition, we now cover 100% of establishments in every census year. If an establishment enters after 1982, we assign it a market share of zero until entry; this allows entrants to influence the counterfactual labor share during their existence, for example, by eventually growing their market shares. For exiters, we assign them a market share of zero in the years after their exits. Finally, in the spirit of our initial superstar counterfactual, we keep an establishment's labor share in all years equal to its initial labor share (either in 1982 or at entry).[11]

We then recompute the aggregate labor share using the establishment's actual time-varying value-added weights (based on an aggregate value added for year t that includes all establishments active at the time). The actual and counterfactual labor shares are plotted in the bottom panel of Figure V. The takeaway is similar to that from the balanced panel: the counterfactual falls by 1 percentage point between 1982 and 2012, a small fraction of the actual decrease of 19 percentage points. This finding hints at the limited role played by entry and exit in driving the decline of the manufacturing labor share.[12] This evidence is in line with the insight in Section IV.C.1 that the aggregate labor share trends in the strongly balanced sample and the full sample are virtually the same.

In Online Appendix C, we reproduce this alternative counterfactual at the firm level and find similar results.

3. The Importance of "Rising Stars." The takeaway from the two exercises in the previous section is that neither market share

11. Results are similar if we use an average of the labor share in the first two census years of existence as the initial labor share.

12. Separate counterfactuals allowing only for entrants or exiters yield similar conclusions.

dynamics nor labor share dynamics at the establishment level can, on their own and separately, explain the historical drop in the labor share of the U.S. manufacturing sector, λ_t^{act}. Instead, the joint dynamics of labor shares and size at the micro level, $Cov(\Delta\omega_{it}, \Delta\lambda_{it})$, must be key to our understanding of the nature of reallocation behind the downward trends in $Cov(\omega_{it}, \lambda_{it})$ and the manufacturing labor share λ_t.[13] They are also consistent with a polarization of labor shares across establishments, rationalizing the fattening of the tails of the (unweighted) labor share distribution that we describe in Section IV.B (see plots in the middle row of Figure III).

What could be behind these joint dynamics? The conceptual framework of Section III.B provides a few candidates. For example, establishments facing nonisoelastic demand schedules may have experienced strong positive demand or TFP shocks. As discussed, we would expect higher markups as a result, leading to a fall in those establishments' labor shares λ_{it} and a rise in their economic weights ω_{it}, turning them into rising stars. The same negative empirical relationship between λ_{it} and ω_{it} would follow from some establishments gaining monopsonistic power in labor markets.

Distinguishing between the various scenarios that we identified in Section III ultimately requires a deeper analysis of the micro-level dynamics of labor shares and value-added shares, which we turn our attention to for the rest of this article. In the next section, we identify the respective roles of value added, employment, and wages in driving fluctuations in establishments' labor shares.

V. Lessons from Micro-Level Labor Share Components

V.A. *Labor Shares Are Driven by Value Added, Not Wages or Employment*

The first two findings imply that the factors behind the decline in the manufacturing labor share must (i) catalyze a reallocation of economic activity toward low labor share establishments

13. This conclusion follows directly from the fact that the three covariance-based scenarios we presented can be mapped into a familiar shift-share decomposition as shown in equation (4). When we compute the three terms of the shift-share decomposition, we confirm empirically that the interaction term dominates the shift-share decomposition.

and (ii) generate a negative correlation between labor share and value-added dynamics at the establishment level. As we saw in the context of the conceptual framework of Section III.B, all three types of shocks we discussed—demand, technology, or monopsony—are, under some assumptions, consistent with this evidence. To discriminate between them, we turn our attention to the cross-sectional and time-series properties of the components of the labor share: wages, value added, employment, product prices, and quantities.

1. Wages and Labor Productivity across Establishments. As a first step, we study the role of wages. We rewrite the log of the labor share of establishment i at time t as

$$\log \lambda_{it} = \log W_{it} - \log ARPL_{it}, \tag{11}$$

where W_{it} is the average employee's wage and $ARPL_{it} = \frac{P_{it}Y_{it}}{L_{it}}$ denotes the average revenue product of labor.[14] As we saw in the conceptual framework, monopsony power in labor markets would predominantly affect wages W_{it}, whereas theories of efficiency or demand factors would affect $ARPL_{it}$.

To ensure that our results are not driven by systematic differences across industries, regions, or time, as well as to make them more readily interpretable (wages and value added per worker are nominal variables), we study an establishment's wage and value added per worker relative to that of its peer group. We define peers to be establishments that are active in the same state and three-digit NAICS industry.[15] The relative wage, $\widetilde{w}_{it}$, and revenue labor productivity, $\frac{\widetilde{p_{it}y_{it}}}{l_{it}}$, are then defined in logs as

14. It is important to notice that both W_{it} and $ARPL_{it}$ are nominal variables, the latter compounding both physical labor productivity and prices. In the language of the recent productivity literature, we study revenue labor productivity. In the next section, we differentiate between revenue labor productivity and physical labor productivity, the analog of physical total factor productivity (TFPQ) in Foster, Haltiwanger, and Syverson (2008) and Hsieh and Klenow (2009).

15. We find that this definition of peer group strikes the right balance between making establishments comparable while keeping enough observations in a peer group to obtain sufficiently precise results. Choosing finer industry or region definitions do not significantly change the conclusions.

follows:

$$\widetilde{x}_{it} \equiv \log X_{it} - \overline{\log X_{-i,t}} \quad \text{where } \overline{\log X_{-i,t}} \equiv \sum_{j \neq i} \frac{P_{jt} Y_{jt}}{\sum_{j \neq i} P_{jt} Y_{jt}} \log X_{jt}$$

$$\text{and } X_{it} = W_{it}, \ \frac{P_{it} Y_{it}}{L_{it}}, \tag{12}$$

where we omit the industry and region subscripts for expositional purposes. The measure $\widetilde{x}_{it}$ is, by definition, centered around zero and denotes an establishment's percentage deviation from the value-added weighted average of its peers. The advantage is that the metric of both relative measures are log point differences, which can be compared across markets, years, and industries.

Our first exercise is to study the relationship between the labor share λ and its two components ($\widetilde{w}$ and $\widetilde{\frac{py}{l}}$) in the cross-section. To do so, we run the following nonparametric regressions:

$$\widetilde{x}_{it} = f(\lambda_{it}) + \varepsilon_{it}, \qquad \widetilde{x}_{it} = \widetilde{w}_{it}, \ \frac{\widetilde{p_{it} y_{it}}}{l_{it}}, \tag{13}$$

where $\widetilde{x}_{it}$ is either establishment i's relative wage, $\widetilde{w}_{it}$, or labor productivity, $\widetilde{\frac{p_{it} y_{it}}{l_{it}}}$. The function $f(\cdot)$ is the object of interest: it indicates whether low labor share establishments pay lower wages than their peers and/or experience higher labor productivity. To ensure that we measure economically relevant relationships, each observation is weighted by the establishment's value-added share (the findings below are even stronger for unweighted regressions). Notice that we cannot include multiple right-hand-side variables in this local polynomial regression. Because $\widetilde{w}$ and $\widetilde{\frac{py}{l}}$ are defined in each industry, year, and region, we ensure that our findings are not driven by systematic differences along those dimensions.

The results of the two nonparametric regressions are displayed in Figure VI. They paint a clear picture. First, relative wages are nearly orthogonal to the labor share: establishments with a low labor share do not, on average, pay their workers more or less than their peers.[16] By definition, differences in the labor share therefore have to be explained by differences in relative

16. Note that our estimate's error bands denote the noise across establishments, not workers. Weighting observations (establishments) by their number of employees would reflect the more dispersed wage distribution observed in

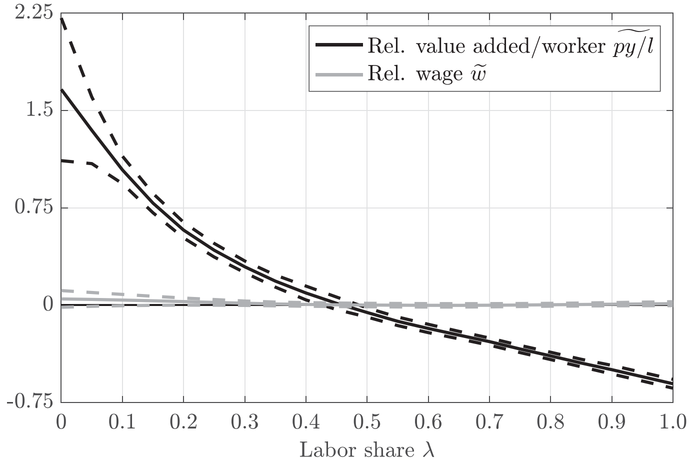


FIGURE VI

Labor Productivity Dominates Cross-Sectional Differences of Labor Shares

The figure displays the cross-sectional differences in relative value added per worker $\widetilde{\frac{py}{l}}$ and the relative wage $\widetilde{w}$ against the labor share, λ_{it} in the full sample pooled across all census years. All relative measures denote log-point differences vis-à-vis their peers as defined in equation (12). Dashed lines denote 95% error bands.

labor productivity. Indeed, the relationship between these two variables is strongly negative: $\widetilde{\frac{py}{l}}$ starts at about 1.6 for establishments with a near-zero labor share and then gradually declines through the labor share spectrum, hitting the average labor productivity ($\widetilde{\frac{py}{l}} = 0$) at a labor share of $\lambda = 0.46$. These differences are large. For example, establishments at the bottom decile have a labor share of about $\lambda = 0.27$. They experience a relative labor productivity of $\widetilde{\frac{py}{l}} = 0.35$, meaning that they produce $\exp(0.35) \approx 1.42$ times more value added per worker than the average establishment in the same industry, region, and year.

At the other end of the spectrum, establishments with a labor share of unity exhibit $\widetilde{\frac{py}{l}} = -0.61$, which means that they produce only a bit above half the value added per worker ($\exp(-0.61) \approx 0.54$) of their peers. The takeaway from this analysis is that low labor share establishments do not pay lower wages than their peers, as would be expected under theories of the labor share

worker- or household-level data. Even though we choose the more conservative establishment-level relative wage, the 95% error bands always include zero.

decline that rely on labor market power. Instead, they generate high value added per worker, which is consistent with theories of superior efficiency or consumer preferences.

2. Dynamic Evidence. In Section IV.C, we show that the joint dynamics of the labor share and value added at the establishment level are central to the aggregate behavior of the labor share. Next we delve deeper into these dynamics by focusing on establishments at the bottom of the labor share distribution. This group, as we show in Section IV.B, experienced a dramatic rise of its economic importance between 1967 and 2012. We start by defining and characterizing this subsample before studying its dynamics.

Defining low labor share establishments. We define low-labor share (*LL*) establishments as those in the lowest quintile of the labor share distribution, in a given year and three-digit NAICS industry. The quintiles are industry specific due to the wide range of average labor shares across industries.

To highlight the role of *LL* establishments in shaping aggregate dynamics, we start by recomputing the manufacturing labor share without them. If reallocation toward lower labor shares was pervasive throughout the distribution in general, we would expect to also observe a labor share decline in the subsample without *LL* establishments, albeit from a higher starting point. The labor shares including and excluding *LL* establishments are shown in Figure VII. Two aspects stand out: first and unsurprisingly, the level of the manufacturing labor share without the bottom quintile of the distribution is much higher, at about 0.75. Second, and more important, the level does not exhibit any decline: while the actual manufacturing labor share starts to fall in the 1980s, the counterfactual manufacturing labor share without *LL* establishments fluctuates around its time-series mean, with no discernible downward trend in the second half of the sample. In other words, although reallocation among non-*LL* establishments may be taking place, it does not contribute meaningfully to the empirically observed manufacturing labor share decline. This indicates that analyzing the nature of *LL* establishments is key to understanding the forces behind the labor share decline. For more details on defining *LL* establishments, see Online Appendix D.

Going back to the cross-sectional analysis of Section V.A.1, we find that *LL* establishments have an average relative labor productivity, $\widehat{\frac{py}{l}}$, of 0.596 compared with −0.428 for non-*LL* establishments; the average *LL* establishment thus produces about

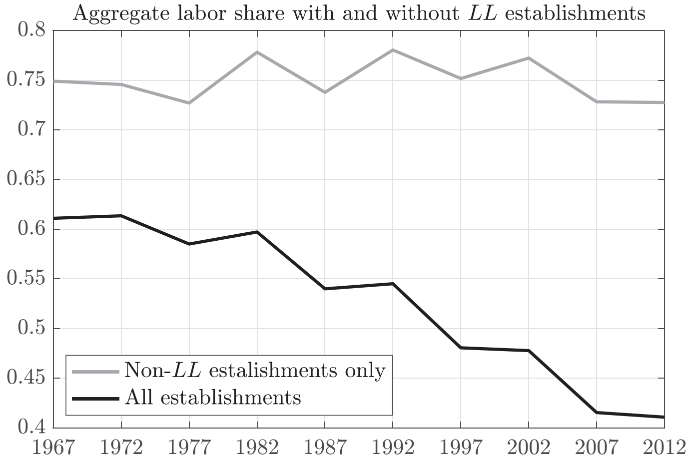


FIGURE VII

The Importance of LL Establishments for the Manufacturing Labor Share Decline

The figure plots the manufacturing labor shares computed on the full sample (black line) against that computed for the panel after dropping the set of LL establishments (gray line) defined as the set of establishments in the bottom quintile of the labor share distribution in a given industry and year. It shows that non-LL establishments do not contribute to the decline of the manufacturing labor share.

2.8 times more value added per worker than the typical non-LL establishment. Yet in terms of relative wages, they are not significantly different than their peers.

The dynamics of the labor share components. Next we investigate how the dynamics of the typical LL establishment's labor share, and that of its components, differ from those of non-LL establishments. Using the data, our objective is to decompose the growth rate of micro-level labor shares ($\Delta \log \lambda_{it}$) into the contributions from wages ($\Delta \log W_{it}$), employment ($\Delta \log L_{it}$), and value added ($\Delta \log(P_{it} Y_{it})$):

$$\Delta \log \lambda_{it} = \Delta \log W_{it} + \Delta \log L_{it} - \Delta \log(P_{it} Y_{it}).$$

Our strategy is to use a regression approach to quantify the change of a specific variable for LL establishments relative to their peers. In particular, we first construct the growth rates in the labor share, employment, wage bill, and value added between two census years (from years $t - 5$ to t) for each establishment in the panel. We regress these changes on a dummy variable that equals

TABLE I
DYNAMICS OF LL ESTABLISHMENTS

	$\Delta \log \lambda_{it}$ (1)	$\Delta \log W_{it}$ (2)	$\Delta \log L_{it}$ (3)	$\Delta \log(P_{it}Y_{it})$ (4)
β	-0.4632^{***}	-0.0099	0.0001	0.4532^{***}
	(0.0154)	(0.0100)	(0.0284)	(0.0442)
Change in percentage points	-18.04	-0.4	0.0	-17.7
R^2	0.186	0.135	0.021	0.114

Notes. This table shows the pooled OLS regression of equation (14) on the full sample. Observations are weighted using the share of establishment *i*'s value added in overall manufacturing value added. Standard errors are clustered at the four-digit NAICS industry level. Significance levels are denoted by * (10% level), ** (5% level), and *** (1% level).

1 if an establishment is among the LL establishments in the current census year:

$$\Delta \log x_{it} = c + \beta \mathbb{I}\{LL_{it}\} + \gamma X_{it} + \varepsilon_{it} \qquad \text{where}$$
$$x_t = \lambda_{it}, W_{it}, L_{it}, \text{ or } P_{it}Y_{it}. \tag{14}$$

While the level of the labor share of LL establishments is below that of their peers by definition—they consist of LL establishments in the lowest quintile in a given year and industry—our aim here is to uncover their relative dynamics from the estimates of the coefficient β in equation (14). That is, we study how the dynamics of the labor share and its components for the typical LL establishments differ from those of non-LL establishments over the previous five-year window. Note that we do not require that LL establishments in period t also be LL establishments in $t-5$. The vector X_{it} contains industry, region, and year dummies as controls. We estimate equation (14) with and without value-added weights to account for the fact that larger establishments are likely to have less volatile labor shares. The procedure is similar for the wage bill, employment, and value-added regressions.[17] Results from the weighted regressions are displayed in Table I.

The first column of Table I implies that relative to the previous census year, an establishment that has LL status at time t saw its labor share fall by 46%. This strongly significant estimate translates into a labor share drop of 18 percentage points, which corresponds to an annual drop of 3.6 percentage points.

17. We also study the dynamics of capital intensity and intermediates and find little evidence that they are different for LL establishments relative to their peers.

Table I, columns (2)–(4) present the results from a similar value-weighted regression but with the relative wage, employment, or value added on the left side of the equation. They indicate that out of the 18 percentage point drop in the labor share for the typical *LL* establishment, a full 17.7 percentage points come from increasing value added relative to non-*LL* establishments. In contrast, the relative dynamics of wages and employment do not contribute to the differential labor share dynamics of *LL* establishments in a meaningful way. Note that when we estimate the relative dynamics in an unweighted fashion, the results are even stronger, suggesting a relative labor share decline of 29 percentage points, on average, for *LL* establishments. Again, an overwhelming proportion of this change is driven by value added.

Going back to the framework of Section III.B, recall that we could write the labor share as $\lambda_{it} = \frac{\nu_{it} MRPL_{it}}{ARPL_{it}}$. Because we find no evidence that wages are important for explaining labor share differences across establishments or over time, we can conclude that the "exploitation parameter," ν_{it}, is not a quantitatively important factor driving labor shares in our sample. In sum, it appears unlikely that increased monopsony power in the labor market is behind the fall in the manufacturing labor share.

V.B. Low Labor Shares Stem Mostly from a Product Price Premium

The previous section highlights the key role played by value added: cross-sectional and dynamic differences between *LL* and non-*LL* establishments appear to be driven by nominal value added per worker. This leaves two candidate forces driving the manufacturing labor share decline: nominal price dynamics and real labor productivity. Next we provide evidence that demand-side factors, rather than technology, appear to be a key driver of micro-level labor share patterns.

1. Measuring Prices. To identify the relative contributions of these two distinct forces, we turn to another data source provided by the U.S. Census Bureau: the product trailer to the CMF. For each establishment, the product trailer records the value of sales generated by individual products (variable `PV`). In addition, it collects information on the physical quantity of products shipped (variable `PQS`) for a sample of establishments whenever a meaningful metric can be used. In those cases, we can compute the average product-level price charged by an individual establishment. We use this subset of the database to disentangle the contribution of prices from that of physical productivity.

Our analysis is inspired by the approach pioneered in Foster, Haltiwanger, and Syverson (2008), though we deviate from their methodology in that we consider products at the 10-digit NAICS level, a finer definition of product than most of the literature.[18] This is a product-coding system devised by the Census Bureau and is based on the NAICS industry code. Second, because our aim is to study an establishment's prices and real productivities relative to that of its peers, we only use observations that are not imputed to ensure that values are directly comparable (for details, see Online Appendix B).[19]

The price data have some drawbacks, however. For one, the imputation flags for prices and quantities are only available starting with the 1992 census, and coverage is very limited in the 1992 and 2012 census. Most important, only a few industries have well-defined quantity measures for (a subset of) their products. In addition to the products studied by Foster, Haltiwanger, and Syverson (2008), examples of manufacturing goods we consider are certain homogeneous chemicals (measured in metric tons) or metals such as aluminum sheets (measured in thousand pounds), for example, but not vehicles or clothing, which are measured in the generic unit "number." All these limitations imply that we are left with a panel of 130,000 year-establishment-product observations whose quality is high enough to study prices and quantities separately. We refer to the resulting panel as the "matched price sample" to distinguish it from the full sample, our default panel. In terms of coverage, the matched price sample captures 4% of product-year observations, and we note that establishments with at least one product in the matched price sample account for about a tenth of employment and a sixth of sales in the full sample. We also verify that the aggregate labor share of establishments in the matched price sample exhibits the same decline as in the full sample.

18. Foster, Haltiwanger, and Syverson (2008) define products at the seven-digit SIC code level, while Bernard, Redding, and Schott (2010, 2011) aggregate product sales to the five-digit SIC level of products; both definitions are coarser than ours.

19. White, Reiter, and Petrin (2018) show that the product trailer data set is seriously contaminated by imputations based on industry averages or regression models.

The matched price sample allows us to link an establishment's product-level prices and its revenue labor productivity, which we earlier find to be the key driver of labor shares in the cross-section and time series. Because all price data are sales based, we switch to studying sales per worker, rather than value added per worker, when analyzing the price versus physical productivity difference. We define relative sales per worker analogous to that of relative value added per worker in equation (12):

$$\widetilde{\frac{p_{it}q_{it}}{l_{it}}} \equiv \log\left(\frac{P_{it}Q_{it}}{L_{it}}\right) - \overline{\log\left(\frac{P_{-i,t}Q_{-i,t}}{L_{-i,t}}\right)} \quad \text{where} \tag{15}$$

$$\overline{\log\left(\frac{P_{-i,t}Q_{-i,t}}{L_{-i,t}}\right)} \equiv \sum_{j\neq i} \frac{P_{jt}Q_{jt}}{\sum_{j\neq i} P_{jt}Q_{jt}} \log\left(\frac{P_{jt}Q_{jt}}{L_{jt}}\right).$$

Naturally, the products in the matched price sample are more homogeneous than those in the full census sample. The distribution of $\widetilde{\frac{p_{it}q_{it}}{l_{it}}}$ can thus be expected to be more compressed in the Matched Price Sample than in the full census sample. Yet, our analysis in Online Appendix B reveals that differences in sales per worker remain the main driver of both cross-sectional and dynamic moments of the labor shares in the matched price sample.

2. Product Prices across Establishments and over Time. To make prices comparable across establishments, we adopt the treatment of nominal wages and labor productivity in Section V.A by comparing establishment-level prices to a peer group. This time, we have to start at the product level. First, we normalize prices at the level of the 10-digit NAICS product ℓ:

$$\widetilde{p}_{i\ell t} \equiv \log P_{i\ell t} - \overline{\log P_{-i,\ell t}} \quad \text{where}$$

$$\overline{\log P_{-i,\ell t}} \equiv \sum_{j\neq i} \frac{P_{j\ell t}Q_{j\ell t}}{\sum_{j\neq i} P_{j\ell t}Q_{j\ell t}} \log P_{j\ell t}. \tag{16}$$

That is, we compare the price of product ℓ sold by establishment i at time t to the weighted average of the prices charged for the same product by all other establishments $j \neq i$ in the same year. $\widetilde{p}_{i\ell t}$ denotes the log-point difference that establishment i charges for product ℓ compared with the average price charged by its peers for the same product.

We aggregate these relative prices across all products offered by establishment i and year t to obtain the establishment-level sales-weighted average relative product price $\widetilde{p}_{it}$:

$$\widetilde{p}_{it} \equiv \sum_{\ell \in i} \widetilde{p}_{i\ell t} \frac{P_{i\ell t} Q_{i\ell t}}{\sum_{\ell \in i} P_{i\ell t} Q_{i\ell t}}.$$

We refer to $\widetilde{p}_{it}$ as the average product price premium that establishment i charges relative to its peers across its product lines. This measure represents the mean log-point difference between an establishment's output prices and those of its peers.[20] We use this new variable to study its behavior in the cross-section and the time series.

Cross-Sectional Evidence. Similar to our earlier approach, we nonparametrically estimate the cross-sectional relationship between the product price premium and the labor share. Because sales are multiplicative in prices and quantities, we can interpret the magnitude of the product price premium as the share of relative sales per worker explained by prices; the remainder is the portion explained by physical labor productivity $\frac{\widetilde{q}}{l}$. If establishments with a low labor share operated superior technologies and produced the same goods ℓ more efficiently, we would expect them to post lower prices in those categories and sweep up the market at the expense of their peers. Such technology-driven growth would show up as a generally negative $\widetilde{p}$ for establishments with a low labor share and vice versa for high labor share establishments. If, on the other hand, low labor share establishments faced favorable demand conditions that allowed them to post a higher price and generate higher revenues as a result, we would anticipate an opposite pattern: positive $\widetilde{p}$ for low labor share and negative $\widetilde{p}$ for high labor share establishments.

The contributions of the two components (relative prices and relative physical productivity) to differences in relative sales are

20. A word of caution is warranted here: as argued by Edmond, Midrigan, and Xu (2018), the theoretically correct approach would be to use a cost-weighted average. In our case, unfortunately, the lack of cost information at the product level means that we have no choice but to rely on a sales-weighted average. This creates a (most likely) upward bias that depends, among other things, on the variation of relative product prices $\tilde{p}_{ilt}$ in an establishment. But we find that relative product prices in establishments are not very dispersed; in particular, establishments overwhelmingly focus on either high-price products ($\tilde{p}_{ilt} > 0\ \forall l \in i$) or low-price products ($\tilde{p}_{ilt} < 0\ \forall l \in i$), thus making the bias likely small.

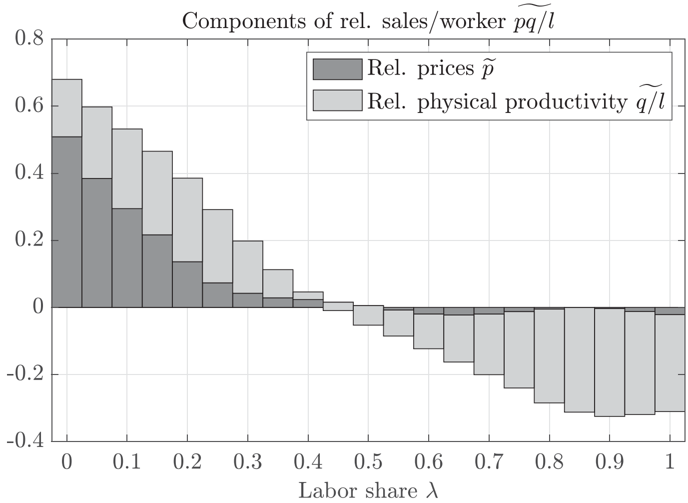


FIGURE VIII

The Contributions of Physical Productivity and Prices to Relative Sales per Worker

The figure displays the cross-sectional differences in relative prices $\widetilde{p}$ (dark gray bars) and relative physical labor productivity $\frac{\widetilde{q}}{l}$ (light gray bars) against the labor share λ_{it} in the matched price sample; $\widetilde{p}$ is defined in equation (16) and $\frac{\widetilde{q}}{l}$ is defined as the difference between $\frac{\widetilde{pq}}{l}$ (defined in equation (15)) and $\widetilde{p}$.

depicted in Figure VIII. First, we can see that *LL* establishments charge, on average, higher prices than their peers for the same 10-digit products. Our estimates from the matched price sample indicate that the average relative price of *LL* establishments is 0.15 compared to -0.041 for non-*LL* establishments, translating into a product price premium of $\exp(0.15 + 0.041) \approx 21\%$. This contributes a fair amount to the $\exp(0.430 + 0.096) \approx 69\%$ higher relative sales per worker of *LL* establishments. Second, the contribution of prices to relative sales are crucial in characterizing those establishments with the lowest labor share. For example, for establishments with a labor share below 25%, relative prices explain about half of the differences in sales per worker ($\frac{\widetilde{pq}}{l}$). However, relative prices play only a little role in explaining differences in establishments' sales/workers with a labor share of 50% and more.

Dynamic Evidence. Analogous to the dynamic analysis of wages, employment, and value added in the previous section, we repeat the estimation of equation (14) for relative prices, $\Delta\widetilde{p}_{it}$. We find strong evidence of a rise in prices concomitant to the drop in labor share for low labor share units: compared to their non-*LL* peers, the relative prices of *LL* establishments increase by a statistically significant 16.8% on average from the previous census year (from $t-5$ to t), or 3.2% per year.

Overall, the findings in this section provide important insights that help us discriminate between the potential theories behind the dramatic decline in the manufacturing labor share. From the framework of Section III.B, we know demand- and technology-based theories could be compatible with findings (i) to (iv): preference or TFP shocks, combined with nonisoelastic demand schedules, can explain the joint dynamics of labor and market shares at the establishment level because both of them would increase markups. This process leads to a reallocation of economic activity toward units that lower their labor share and become *LL* establishments. Yet the fact that relative prices and labor shares comove negatively represents strong evidence that demand shocks are key to rationalizing the labor share dynamics of *LL* establishments: under technology shocks, we would expect relative prices to fall alongside labor shares. Furthermore, we provide additional evidence on the nonimportance of supply factors in Online Appendix E.

VI. Shooting Stars and the Labor Share Decline

Seen through the lens of the conceptual framework of Section III.B, our evidence indicates that demand factors must be playing a central role: they can rationalize both the joint dynamics of labor share and value added and the importance of prices in driving the high nominal labor productivity of low labor share establishments. The analysis of *LL* establishments also shows that this status is the product of an economically large rise in value added, driven mainly by higher prices. But what is the dynamic nature of these underlying demand drivers? Is their impact on the labor shares of establishments highly persistent or transient? The answer is relevant at many levels. For one, it can instruct policy makers on the nature of concentration: transient labor and market shares would have different implications for competition policy than if the economy was characterized by *LL* establishments that are progressively taking over their market and are lowering their labor shares. Moreover, it can help us have

TABLE II

TRANSITION PROBABILITIES OF *LL* STATUS

	Non-LL_{t+5}	LL_{t+5}
Panel A: Unweighted transitional dynamics		
Non-LL_t	0.854	0.146
LL_t	0.583	0.417
Panel B: Weighted transitional dynamics		
Non-LL_t	0.922	0.078
LL_t	0.536	0.464

Notes. The table shows the Markov matrix of labor shares from census to census in the full sample. Panel A considers the share of establishments that remain/leave/enter *LL* status when quintiles are unweighted, and Panel B displays the share of manufacturing value added accounted for by the *LL* establishments when defined by *VA*-weighted quintiles.

a better sense of the nature of demand factors and their effect on firms' actions. With these objectives in mind, we turn to an analysis of the labor share persistence at the micro level.

VI.A. The Transience of Low Labor Shares

In this section, we document that micro-level labor shares exhibit significant transience using both a Markov transition matrix and dynamic regression approach. We also address the potential issue of measurement error.

1. Markov Transitional Dynamics. We start by analyzing the transition dynamics of *LL* and non-*LL* establishments. Our objective is to assess whether the demand drivers identified in findings (iii) and (iv) are important enough to perturb the rankings of establishments along the labor share dimension. We do so with the help of a Markov transition matrix, displayed in Table II. More specifically, we ask a simple question: conditional on an establishment's labor share at time t, what is the probability that it has *LL* status at time $t + 5$? If *LL* status was highly persistent, this probability should be equal to 100%. At the polar opposite, if labor shares are so volatile that they perturb the ranking every period, we should expect the identity of *LL* establishments to be random and the transition probability to be close to 20%.

Table II shows that over the sample period, the probability that an establishment retains *LL* status from census year to census year (a five-year window) is only 41.7%. Although this is higher than if *LL* status were perfectly random (20%), the transition probability indicates that labor share at the establishment level is surprisingly transient, even for the most productive establishments.

One may be concerned that the results in Table II are mostly driven by small, economically insignificant establishments. For this reason, we also consider Markov transition matrices of quintiles weighted by economic activity and confirm the transient dynamics of *LL* establishments. These results are displayed in Table II, Panel B; although they indicate slightly more persistence, the overall impression remains unchanged.

2. V-Shaped Labor Share Dynamics of LL Establishments. In light of their surprisingly temporary nature, we aim next to quantify the labor share dynamics that occur in the years following *LL* status. To do so, we adopt the same type of regression framework as in Sections V.A.2 and V.B.2, which captures the dynamics of *LL* establishments relative to their peers. Specifically, we regress both backward-looking (from years $t-5$ to t) and forward-looking (from t to $t+5$) percentage point changes in establishment-level labor shares on a dummy variable that equals 1 if an establishment is among the *LL* establishments in the current census year:

$$\Delta \log \lambda_{it} = c_1 + \beta_{-5}\mathbb{I}\{LL_{it}\} + \gamma X_{it} + \varepsilon_{1it} \tag{17}$$

$$\Delta \log \lambda_{it+5} = c_2 + \beta_{+5}\mathbb{I}\{LL_{it}\} + \gamma X_{it} + \varepsilon_{2it}. \tag{18}$$

Our objective is to rely on the estimates of the coefficients β_{-5} and β_{+5} in equations (17) and (18) to characterize how the labor share dynamics of *LL* establishments differ from those of non-*LL* establishments over a 10-year window around the reference period. Note that we do not require that *LL* establishments in period t also be *LL* establishments in $t-5$ and in $t+5$; an establishment could well have *LL* status for a single year. The vector X_{it} contains controls that have been described earlier, and estimation is done with and without value-added weights. Results are displayed in Table III. Because equations (14) for λ_{it} and (17) are equivalent here, the weighted results in the first row here are exactly the dynamics shown in Table I, column (1).

If the labor shares of *LL* establishments were to permanently reach a lower level relative to their non-*LL* peers, the coefficient β_{+5} would be close to zero. The estimation indicates, however, that this is clearly not the case: β_{+5} is statistically different than zero. In fact, it shows again that *LL* status is highly transient. While a typical establishment with *LL* status at time t saw its labor share

TABLE III
BEFORE-AFTER DYNAMICS OF *LL* ESTABLISHMENTS

Variable	$\Delta \log \lambda_t$ (1)	$\Delta \log \lambda_{t+5}$ (2)	$\Delta\lambda_t$ (3)	$\Delta\lambda_{t+5}$ (4)	$\Delta\lambda_t$ (5)	$\Delta\lambda_{t+5}$ (6)
β_{-5}	-0.4632^{***}		-0.1804^{***}		-0.2896^{***}	
	(0.0154)		(0.0100)		(0.0076)	
β_{+5}		$+0.3844^{***}$		$+0.1542^{***}$		$+0.2710^{***}$
		(0.0177)		(0.0102)		(0.0071)
R^2	0.186	0.108	0.102	0.070	0.111	0.096
VA weights	yes	yes	yes	yes	no	no

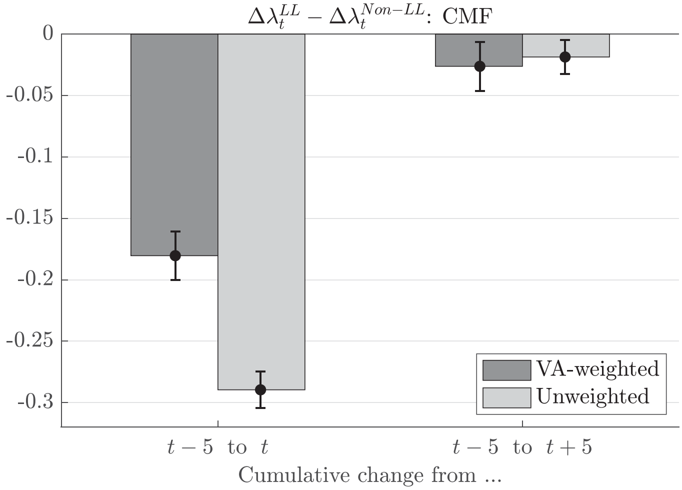
Note. The table shows the pooled OLS regression of equations (17) and (18) on the full sample. For more details, see the notes to Table I.

since $t - 5$ shrink by 46.3% (column (1)), it rises by 38.4% in the subsequent five years (column (2)).

To ease interpretation, we repeat regressions (17) and (18) with the percentage point change of labor shares, $\Delta\lambda_{it} = \lambda_{it} - \lambda_{it-5}$, on the left side instead of the growth rate. As column (3) shows, *LL* establishments experience a relative labor share decline of 18 percentage points. Yet, in the five-year period thereafter (from t to $t + 5$), the coefficient estimates of β_{+5} in columns (3) and (4) indicate that the change in the labor share of establishments that are *LL* in year t will expand by 38.4% (corresponding to 15.4 percentage points) more than that of non-*LL* establishments.

Finally, we report the results for β_{-5} and β_{+5} as cumulative growth rates in the top panel of Figure IX. The figure confirms that compared to $t - 5$, time-t *LL* establishments appear to be barely different than their non-*LL* peers by $t + 5$. The unweighted estimates in columns (5) and (6) are stronger, indicating that small *LL* establishments see even more extreme labor share dynamics in absolute value. All in all, our analysis appears to show that the average *LL* establishment experiences a rather temporary drop and rebound in its labor share. This finding is in line with the earlier evidence from the Markov transition matrices and confirms the low persistence of *LL* status.

3. Labor Share Dynamics and Measurement Error. One potential concern is that the low persistence of the labor share is driven by widespread measurement error. Under this scenario, LL_t establishments would simply be establishments that experienced large (negative) mismeasurement at time t yet whose fundamentals were not any different than the typical establishment in the



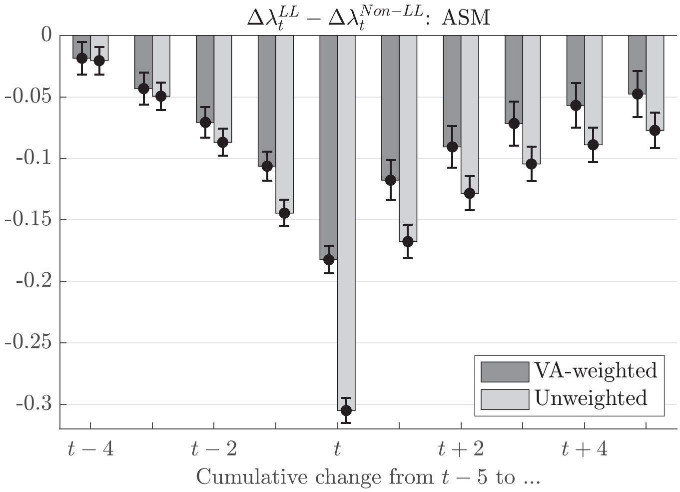


FIGURE IX

The Temporary Fall and Rise of Labor Shares of *LL* Establishments

The top panel shows the cumulative evolution of the labor share of the average *LL* establishment relative to their peers in the full sample before (t − 5 to t) and after (t to t + 5) the year it is in *LL* status. Unweighted dynamics are in dark gray, value-added weighted dynamics are in light gray, and whiskers denote 95% error bands. The y-axis represents labor share changes, where the labor share is expressed as a decimal. The bottom panel shows analogous labor share dynamics of *LL* establishments in the Annual Survey of Manufactures data.

population. This would mechanically give rise to the temporary change shown in the top panel of Figure IX. Using only data every five years would make our analysis vulnerable to measurement errors in that single year. Although this may be a concern, especially for small *LL* establishments, measurement error for large establishments whose labor share is low is much less likely, as the Census Bureau pays a lot of attention to large producers that matter greatly for their aggregate tabulations.

To alleviate this concern, we turn our attention to the Annual Survey of Manufactures (ASM) sample. While this yearly data set merely captures about 55,000 establishments in a given census year on average, its macro-level labor share dynamics are very similar to those of the census. Crucially, its yearly frequency allows us to more easily disentangle signal from noise: if *LL* status were merely driven by idiosyncratic measurement error, we would expect establishments that have *LL* status to look, on average, like their non-*LL* peers five years before and after (census frequency) and in the years directly following and preceding year t (ASM frequency).

For this robustness check, we adapt the estimation in equations (17) and (18) to an annual frequency and run 10 regressions, one for each of the preceding 5 and subsequent 5 years. The results are reported in the bottom panel of Figure IX. They confirm the transient nature of the labor share that we found using census years. Although the trough at t is unmistakable, notice that the relative change in the labor share is not taking place entirely between $t - 1$ and t but instead occurs regularly over the preceding years. Also, notice that it does not recover fully even after five years, when the labor share is estimated to still be 5–8 percentage points below the level of non-*LL* establishments. All in all, our evidence appears to indicate that the transient nature of *LL* status is not merely an artifact of transient measurement error.[21]

VI.B. The Drivers of the V-shaped Labor Share Dynamics

In Section IV.C, we documented that the drop in the labor share of the typical *LL* establishment is due to a strong increase

21. Because both labor share and value-added share dynamics are driven by sales growth, we consider a robustness check where we aggregate sales from individual products from the product trailer of the CMF and find similar results to those presented in Figure IX.

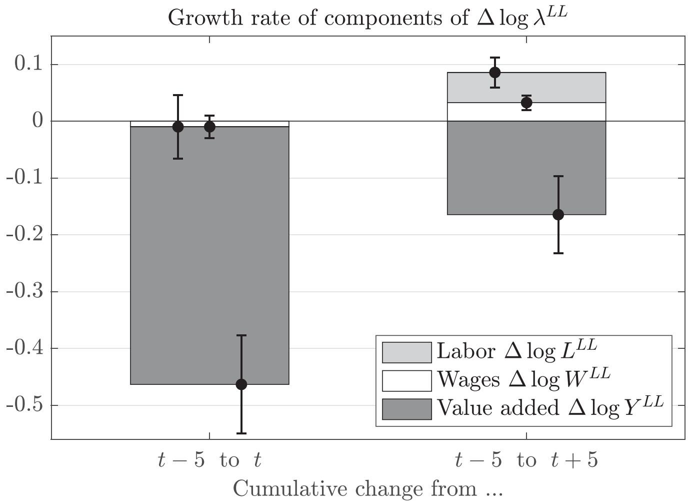


FIGURE X

Value-Added Dynamics Dominate the Labor Share Dynamics of *LL* Establishments

This figure displays the dynamic contributions of the changes in wages, employment, and value added for labor share dynamics of the average *LL* establishment relative to its peers in the full sample. The first bars display their contributions before ($t-5$ to t) and the second bars their cumulative contributions until after ($t-5$ to $t+5$) the year an establishment is in *LL* status. Whiskers denote 95% error bands.

in value added. In the context of the V-shaped dynamics discussed earlier, this naturally leads to another question: is the rebound of the *LL* labor share in the following five years driven by employment or wages catching up with revenue labor productivity? The former would suggest that demand shocks, although a dominant driver of micro-level labor shares, are rather transient; the latter, on the other hand, could result from labor adjustment costs or rigid wages. To quantify the relative contributions of wages, employment, and value added to the t to $t+5$ labor share dynamics of *LL* establishments, we estimate equations (17) and (18) for these three variables separately. The results are displayed in Figure X.

The leftmost bar in Figure X depicts graphically the results from Table I: between $t-5$ and t, the average *LL* establishment saw its labor share shrink by 18 percentage points (or 46%) relatively to the typical non-*LL* establishment, and this drop is entirely due to the differential in value-added growth. The rightmost bar incorporates the five following years. We see that the V-shaped pattern of the labor share between $t - 5$ and $t + 5$ is mainly a result of the reversal of the initial jump in value added of *LL* establishments. This retreat of value-added growth accounts for 11.5 of the 15.5 percentage point rebound in the average *LL* labor share, whereas wages and employment contribute only 2 percentage points each to the labor share rebound. In other words, there is little contribution coming from a delayed response of employment and wage growth.

Turning our attention to the factors behind the retreat of value added, we do find some evidence that it is partly driven by a delayed response of materials. When estimating equations (17) and (18) for this component, we obtain an initial $t - 5$-to-t relative response of time-t *LL* establishments of only 2.7% over five years, yet the response increases by another 7.8% between t and $t + 5$. Using the matched price sample, we also find evidence that in the subsequent five years most (but not all), of the initial jump in the product price premium of *LL* establishments is reversed. Specifically, we find that the cumulative change in the average product price premium from $t - 5$ to $t + 5$ is only 7.8% (less than 1% on an annual basis), compared with the 16.8% (3.2% annual) between $t - 5$ and t that we found earlier. We see this as evidence that the transitory nature of demand factors lends low labor share establishments only temporary market power.

VI.C. Did Demand Shocks Become More Important over Time?

The previous section identified a number of empirical findings that characterized the key drivers of the manufacturing labor share decline. First, the increasingly negative comovement of labor shares and value-added shares at the establishment level was crucial for the decline from the 1980s onward (findings (i) and (ii)). Second, using our conceptual framework from Section III, we provided additional empirical facts pointing to demand factors as the engine of these aforementioned micro-level dynamics (findings (iii)–(v)). In this section, we provide evidence of significant changes in the micro-level anatomy of labor shares and their components over our sample period. In the context of the conceptual framework of Section III.B, we contend that these findings are consistent with a rise in the volatility of demand-side factors.

1. The V-Shaped Labor Share Pattern Gets Deeper over Time. We start by investigating the evolution over time of the V-shaped labor share pattern of *LL* establishments that we documented earlier. We repeat the dynamic analysis described by equations (17) and (18) separately for the 1972 and 1977 censuses, denoted as 1970s, and the 2007 and 2012 censuses, denoted as 2000s. Both unweighted and value-added weighted estimates for these equations are shown in Figure XI.

Focusing first on the $t-5$ to t dynamics, we find that the labor share dynamics of *LL* and non-*LL* establishments get increasingly different over time. In the weighted case, comparing the left and right panels indicates that the differential increased by 50%, from a relative 14 percentage points in the 1970s to a relative 21 percentage points by the 2000s. Our earlier finding that labor share dynamics are very transient, on the other hand, appears to hold over time: between $t-5$ and $t+5$, the (weighted) cumulative differential is about -2 percentage points in the 1970s versus -3 percentage points in the 2000s, with neither estimate being statistically different from zero. In the unweighted case, the $t-5$ to t differential is on average 24 percentage points in the 1970s and increases to 33 percentage points by the 2000s. Again, most of this difference disappears once we consider a 10-year window centered around year t. Taken together, the evidence indicates a clear deepening over time of the labor share V-shaped pattern.

2. Industry-Level Evidence. What is the relationship between the V-shaped labor share pattern at the micro level and the decline in the manufacturing labor share? Although a full structural analysis is beyond the scope of this article, we provide some tentative evidence by investigating the relationship between the deepening of the V-shape and the evolution of the labor share across the 21 three-digit NAICS manufacturing industries. For each, we run the regression in equation (17) from 1987 onward accounting for a trend in the deepening of the labor share V-shape of *LL* establishments. We also compute the change in the industry's labor share using the same BLS industry data underlying Figure XVI in the Online Appendix.

Finally, we study the relationship between these two variables by plotting an industry's V-shape deepening against the change in its labor share. Figure XII paints a clear picture: those

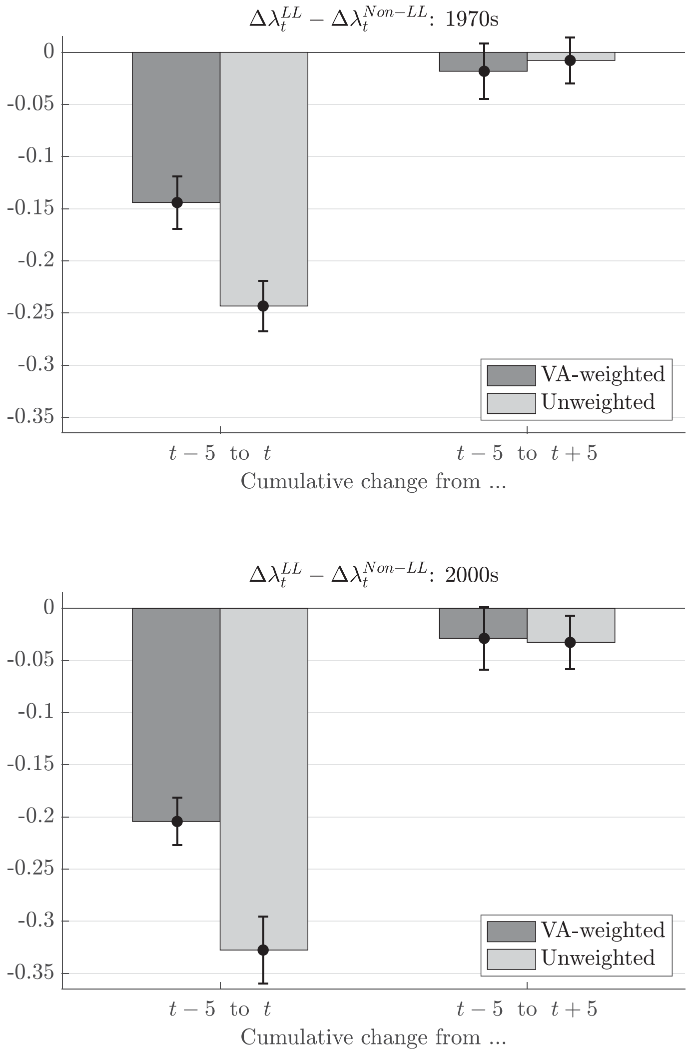


FIGURE XI

Labor Share Change of *LL* versus non-*LL* Establishments over Time

This figure displays the difference in labor share dynamics between *LL* and non-*LL* establishments (corresponding to the $t-5$ to t bars in the top panel of Figure IX) by time period. It shows that *LL* establishments look increasingly different from their peers over time.

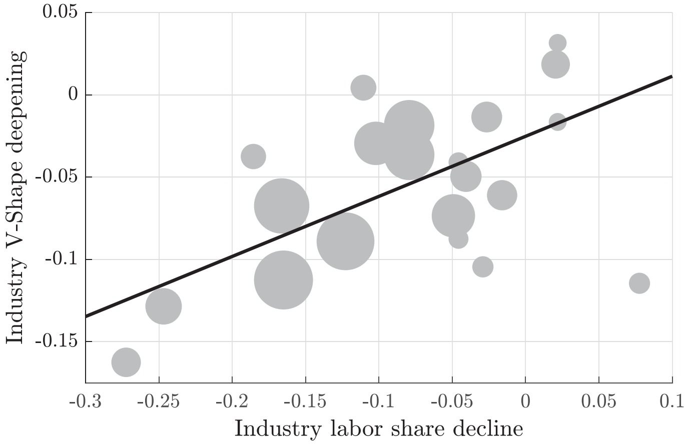


FIGURE XII

Industry Labor Share Declines versus V-Shape Deepening 1987–2012

This figure displays the relationship between industry-specific estimates of the labor share dynamics of its *LL* establishments and the industry labor share decline over the same 1987–2012 time period. Each point represents a three-digit NAICS industry. The size of the circle represents the average value-added share of that industry in the manufacturing sector.

industries that experienced a more pronounced decline in their labor share also tend to be the ones that saw the sharpest deepening of their labor share V-shape of *LL* establishments. The unweighted and weighted correlations between these two measures are 0.49 and 0.62, respectively.

3. Employment Has Become More Disconnected from Value Added. In finding (iv), we showed that nominal labor productivity was central to understanding the labor share response of *LL* establishments. By definition, large fluctuations in labor productivity must imply that labor and value added do not move in lockstep. In fact, we show next that the comovement of employment to output has been markedly different during the recent period of declining manufacturing labor share (2000s) relative to the early part of the sample, when the labor share was more stable (1970s). We repeat the exercise of Section VI.A by estimating equations (17) and (18) for wages, employment, and value added but for the early and late samples separately. Figure XIII displays the

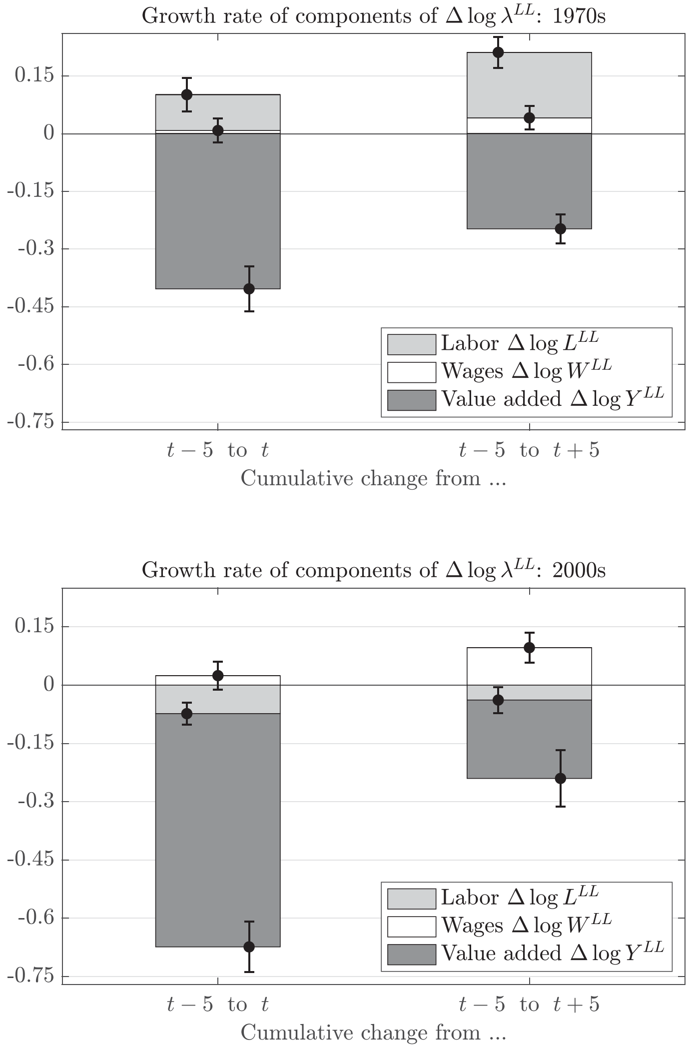


FIGURE XIII

1970s versus 2000s

contributions of these three components to the labor share growth rate of *LL* establishments relative to non-*LL* establishments.

In the 1970s, the majority of the adjustment in the five-year period preceding census year *t* was driven by a rise in value added (negative contribution to the labor share): the average *LL* establishment's labor productivity growth was 40 percentage points higher than that of non-*LL* establishments. The relative change in labor share would have been more pronounced were it not for the fact that employment growth was 10 percentage points higher for *LL* establishments. In the five following years, almost all the labor share growth differential disappears. This occurs mainly because of two factors: a retreat of value added following the time-t peak but also a more robust relative response of employment for *LL* establishments whose hiring seems to respond to the strong value-added growth but with a delay. This picture is consistent with the notion that hiring frictions delay the employment response of *LL* establishments, which tie it instead to the longer-run dynamics of value added. Ultimately, while the value added of *LL* establishments has clearly grown more over the 10-year span than that of their peers, relative labor productivity is more or less back to where it was initially because employment and, to a lesser extent, wages catch up with value added.

The dynamics in the 2000s are very different at many levels. First, the value-added growth advantage of *LL* establishments between $t-5$ and t is larger, at 60 percentage points instead of 40 percentage points in the 1970s. Second, the V-shaped pattern is now more pronounced: not only is the value-added growth differential sharper initially, but after 10 years, only 20 percentage points remain in the 2000s, compared to 25 percentage points in the 1970s. Third, the response of employment is noticeably different from the early part of the sample: between $t-5$ and t, employment growth is 7 percentage points lower for *LL* establishments relative to their non-*LL* peers despite the sharp increase in value added. By $t+5$, the cumulative employment growth differential is close to zero.

Together, the findings in this section highlight two significant developments in the dynamics of labor shares at the manufacturing establishment level. First, there has been a deepening over time of the V-shaped labor share pattern of *LL* establishments, which we find to be related to the size of the labor share decline across industries. This pattern is mostly due to a sharper response of value added relative to their peers. In the context of the conceptual framework, this can be interpreted as an increase in the volatility of the demand factors that underlie the micro-level dynamics of the labor share. With such extremely positive demand shocks, *LL* establishments will find themselves in a very inelastic part of their demand curve, where most of the demand shock is passed through into higher prices rather than into higher employment. This means that our second documented change, the disconnect between value added and labor input, has become stronger over time. This is in line with recent work documenting the decline in the economy's responsiveness to shocks; see, for example Table 5 in Ilut, Kehrig, and Schneider (2014) or the work by Pugsley, Sedláček, and Sterk (forthcoming), Decker et al. (2017, 2020), and Cooper, Haltiwanger, and Willis (2017).

VII. Discussion and Conclusion

Our study highlights the importance of micro-level dynamics in shaping aggregate labor share trends. In particular, we show that the drastic reallocation of economic activity toward the lower end of the labor share distribution was not mainly driven by compositional forces, entry/exit, or the outsized growth of superstar establishments that were initially more productive than their peers. Instead, it was propelled by units whose labor share fell at the same time as they grew in size. We show that low labor share (*LL*) establishments are characterized by high revenue labor productivity, not low wages, and charge higher prices than their peers for similar products. Moreover, we find that *LL* status is very transient, a pattern that has become more pronounced over time. In the context of a simple conceptual framework, we conclude that among the leading theories proposed in the literature to explain the decline in the manufacturing labor share, only demand factors are consistent with all of our empirical findings.

Under this demand-driven interpretation, an establishment hit by a positive demand shock experiences a pronounced increase in value added and a decrease in its labor share. In Online Appendix C, we show that these patterns, their anatomy, and their increasing salience are also present at the firm level. Unfortunately, the anonymized nature of the Census of Manufacturing does not allow us to identify what the nature of these demand factors could be. We instead turn our attention to the sample of manufacturing firms in Compustat and draw from publicly available information sources such as annual reports to illustrate through four case studies the types of forces that may be at work. Despite Compustat's strong bias toward large and diversified public firms and a small share of observations with information on labor compensation, we can identify dynamics similar to those we documented in the universe of manufacturing firms in the census.[22]

- DuPont de Nemours: From a value of 70% in 1985, DuPont's labor share fell to 36% by the late 1980s before rising back to 59% in 1993. Over the same time frame, its share of industry value added rose and then fell by about 70%. Despite its highly diversified nature, one can reasonably attribute the success of DuPont over this period to the rising popularity of its Lucre stretch polymer. While the patent had expired and its generic version, "spandex", was already in circulation, DuPont was the only major manufacturer. By the early 1990s, profits associated with the textile segment accounted for more than a quarter of the firm's total operating profit.
- Nokia: Nokia's labor share fell from 54% in 1995 to a trough of about 23% between 2000 and 2003, before rebounding to 52% by 2010. Over the same time period, Nokia's share of industry value added quadrupled before declining again dramatically. These variations are largely accounted for by the mobile phone segment. The company's heavy investment in hardware innovation (first U.S. camera phone with the Nokia 3650 in 2003, the introduction in 2005 of its extremely popular N series), ancillary services (e.g., ringtones), and market segmentation (e.g., business versus entry-level phones) led it to become the dominant market leader for many years. This success came to a halt in the late 2000s with greater competition from Apple and Samsung.
- Eastman Kodak: Between 1987 and 1992, Kodak saw its labor share fall by 18 percentage points, from 74% to 56%. This drop coincided with a pronounced rise in its market share, from 12.6% to 18.4% of the total value added in its industry. This period coincides with the extremely successful introduction of the 35mm single-use camera, as well as important growth in the health segment.

22. We compute value added as the difference between sales (item SALE) and the cost of good solds (item COGS), and the labor share as the ratio of staff expense (item XLR) and value added. A firm's value added share is computed as a fraction of the total value added in its three-digit NAICS industry.

- Infineon Technologies: The semiconductor manufacturer experienced a dramatic V-shaped labor share pattern in the 2000s, falling by more than 40 percentage points between 2001 and 2005 before rebounding by 35 percentage points in the following five years. Value added followed a mirror pattern, with a value-added share more than doubling in the first time period before falling by a factor of three afterward. The company's initial growth was achieved by higher average selling prices for memory products as well as the favorable evolution of the exchange rate but came to a halt due to dramatic declines in market prices for memory chips.

The examples of Nokia, Kodak, and DuPont highlight the central role played by demand factors in driving value-added and labor share dynamics. In all three case, the introduction of highly popular products allowed these firms to rapidly become market leaders. Yet these advantages are not immutable. Instead, the combination of volatile demand shocks and a winner-take-all market structure gives rise to shooting stars, corporate champions whose fortunes are fleeting and at the mercy of changing tastes and new competing products. Moreover, our finding that labor share V-shaped patterns have become more pronounced over time appears to indicate that the volatility of the underlying demand factors is higher than it was a few decades ago. One potential reason is increased market integration: globalization has expanded the varieties available to customers, but also the reach of market leaders—and the potential set of competitors to replace them.

In turn, higher potential gains may arguably lead firms to expand additional resources to sell the product that will be highly sought after in the future or make their customer base more immune to competition. This could include more intensive advertising activity or selling valuable new services along with a product. Ultimately, by making their demand curve less elastic, demand shocks would translate into stronger price increases relative to the physical output and employment responses. To explore this hypothesis, we exploit the data on advertising expenditures collected by the census since 1997.[23] We compute establishment i's advertising expenses per employee in year t, $\frac{ca_{it}}{l_{it}}$, and scale that

23. A caveat is that the data set only contains advertising expenditures at the establishment level, while such expenditures at the headquarter or firm level are missing along with other aspects of customer-related marketing investments.

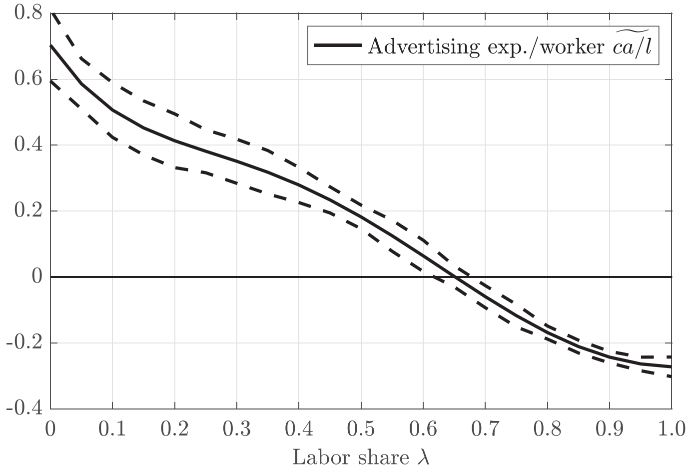


FIGURE XIV

Cost of Advertising per Employee and Labor Shares

The figure displays the cross-sectional differences in relative cost of advertising expenditures per employee $\frac{\widetilde{ca}}{l}$ against the labor share 2002–2012 (when those data are available). All relative measures denote log-point differences vis-à-vis their peers as defined in equation (12). Dashed lines denote 95% error bands.

number analogously to the other nominal variables, as illustrated in equation (12). The resulting variable, $\widetilde{\frac{ca_{it}}{l_{it}}}$, denotes the log point difference of an establishment's advertising expenditures per employee relative to that of their peers in the same industry, state, and year. As in Section V, we nonparametrically regress this variable on the labor share and plot the estimates in Figure XIV.

The figure reveals that low labor share establishments spend significantly more on advertising than their peers. Our estimates indicate that a typical unit with a labor share of 0.1 spends about $\exp(0.51) = 1.67$ times more on advertising per employee than the average plant in its sector and region, while high labor share establishments ($\lambda = 1$) spend about 25% less. Although it should not be interpreted as causal at this point, we view this evidence as consistent with a central role played by demand factors, as well as their heightened influence over time: it has been documented that advertising spending has been steadily increasing over time (Gourio and Rudanko 2014).

Ultimately, we view our findings as a guide for researchers intent on understanding and modeling the forces that underlie not only the decline in the manufacturing labor share but also establishment- or firm-level dynamics more generally.

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Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

Data Availability

Code replicating the figures and tables in this article can be found in Kehrig and Vincent (2021), in the Harvard Dataverse doi: 10.7910/DVN/JMIRHK.

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