INTERNATIONAL MONETARY FUND

Production Technology, Market Power, and the Decline of the Labor Share

Agustin Velasquez

WP/23/32

2023
FEB

WORKING PAPER

 WP/23/32

IMF Working Paper
Finance Department

Production Technology, Market Power, and the Decline of the Labor Share
Prepared by Agustin Velasquez*

Authorized for distribution by Charleen Gust
February 2023

ABSTRACT: The labor share has been declining in the United States, and especially so in manufacturing. This paper investigates the role of capital accumulation and market power in explaining this decline. I first estimate the production function of 21 manufacturing sectors along time series and including time-varying markups. The elasticities of substitution for most sectors are estimated below one, implying that capital deepening cannot explain the labor share decline. I then track the long-run evolution of the labor share using the estimated production technology parameters. I decompose aggregate labor share changes into sector re-weights, capital-labor substitution, and market power effects. I find that the increase in market power, as reported in recent studies, can account for, at least, 76 percent of the labor share decline in manufacturing. Absent the rise in market power, the labor share would have remained constant in the second half of the 20th century.

JEL Classification Numbers:	E21, E22, E25
Keywords:	Labor share; elasticity of substitution; capital accumulation; market power
Author's E-Mail Address:	avelasquez@imf.org

* The author would like to especially thank Ugo Panizza, Rahul Mukherjee, and Nicolas Depetris-Chauvin. This paper received helpful comments and suggestions from Bas Bakker, Timo Boppart, Julia Cajal Grossi, Mariarosaria Comunale, Gabriela Cugat, Mert Demirer, Woori Lee, Miguel Leon-Ledesma, Flavien Moreau, Chris Papageorgiou, Francesco Pappada, Samuel Pienknagura, Daniele Rinaldo, Nayantara Sarma and the participants of the 19th RIEF meetings, IHEID BBL, and the IMF RESDM seminar. All errors are his own.

1. Introduction

The labor income share in the US economy has been declining in recent decades (Elsby et al., 2013). This decline has been especially prominent in manufacturing, which represents about a third of GDP (Figure 1). What factors can explain declining labor shares? Among many possible explanations, two narratives have received broad attention from researchers and policymakers.

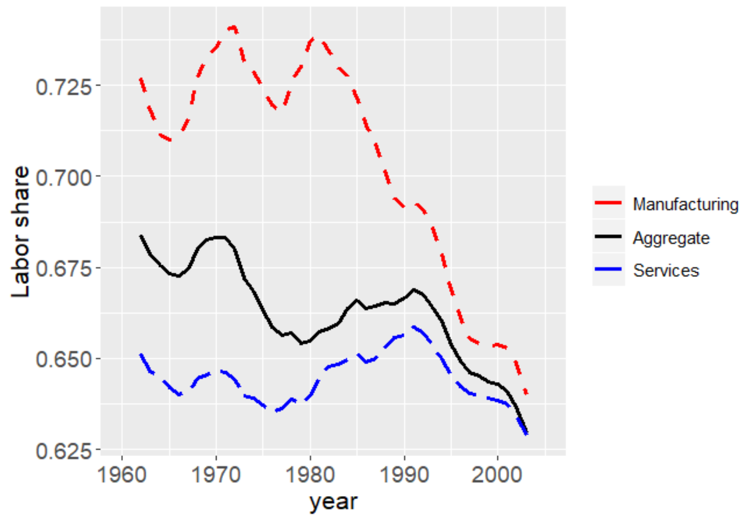
The first one is the 'capital accumulation' narrative, as popularized by Rognlie (2015). Its main argument is that the rate of capital accumulation (i.e. capital deepening) or an increase in its productivity (e.g. due to automation and robotization) have shifted the distribution of income from labor towards capital (Karabarbounis and Neiman, 2014b).[1] Central to this narrative is the magnitude of the elasticity of substitution, henceforth defined as $\sigma \geq 0$. Capital accumulation would cause a decline of the labor share only if capital and labor are gross substitutes, i.e. $\sigma > 1$. In this case more income is allocated to the more abundant production factor. The second popular narrative focuses on the rise in market power as a contributing factor behind falling labor shares. This view states that less market competition has allowed firms to raise markups well above their marginal costs (De Loecker et al., 2020; Philippon, 2019). In turn, this leads to rising profit shares at the expense of lower labor and capital shares, regardless of the magnitude of σ.

This paper investigates the role of the capital accumulation and market power narratives in explaining the stark decline of the labor share in manufacturing.[2] Within manufacturing, the labor share decline presents significant heterogeneity across sectors in terms of timing and magnitude. I evalu-

[1] The main focus of this narrative is on capital deepening. This is defined as the growth of capital per worker.

[2] While services command a larger share of GDP, I focus on manufacturing because is where the labor share decline has been concentrated (see Figure 1).

Figure 1: The labor share in the US economy



Note: Labor income shares are measured in gross value added. Manufacturing comprises 21 sectors and services 7 sectors. The aggregate is composed by 35 sectors. The series reflect 5-year moving averages. Source: 35-sector KLEMS (Jorgenson, 2008)

ate the contribution of each narrative by studying the evolution of the labor share at the sector level. I proceed in two steps. First, I estimate the production function for 21 manufacturing sectors, with the objective to estimate σ, along their time series.[3] Second, I use the estimated production function parameters to track long-run trend changes in labor shares. This allows me to disentangle variations accruing to labor's contribution in production and market power.

To estimate the sectoral production functions I employ the system approach over the 1960-2005 period (León-Ledesma et al., 2010).[4] This methodology allows me to jointly estimate σ and the growth rates of labor and capital's technical progress. The latter is assumed to be deterministic and grow at a constant rate for each factor of production. I extend the system spec-

[3]The estimation of multiple production functions unravels manufacturing's production technology and the potential heterogeneity across its sectors.

[4]The system approach jointly estimates a normalized (CRS) production function and its first order conditions along the time series.

ification to include time-varying markups (as in Jiang and León-Ledesma (2018)). Markups follow the path reported by Barkai (2020), and are assumed independent from production technology.

I find that σ is within the $0.6 - 1$ range for all but one of the 21 manufacturing sectors.[5] Evidence of $\sigma \leq 1$ suggests that capital deepening cannot explain declining labor shares in manufacturing. What about market power? To this aim, I perform an accounting exercise. I build "fundamental" labor shares for each sector based on the estimated production technology parameters. These capture the contribution of effective labor in production as well as markups charged on prices.

Using these fundamental shares, I decompose total labor share changes in manufacturing into three sources of variation: sectoral re-weights, capital-labor substitution, and market power effects. The first one captures variation in sectors' size. The labor share in manufacturing could decline if sectors which have low labor shares expand over time, while those with high ones shrink. Capital-labor substitution effects comprise the re-shifting of income between capital and labor due to relative factor efficiency changes in value added. In other words, the labor share may change depending of the amount of labor (or capital) used in production. Finally, market power effects capture transfers from labor income towards profits triggered by rising markups.

I report two main findings. First, I quantify that capital-labor substitution effects remained stable between 1960 and 2005, despite most sectors having $\sigma \neq 1$. This implies that, abstracting from changes in market power, the labor share in manufacturing would have remained constant in the post-war period. Second, the reported rise in market power from recent studies

[5]The inclusion of time-varying markups is not key to obtain σ below one, although it does correct for a small downward bias. I also find the net bias of technical change to be labor-augmenting for most sectors.

can account for a sizable amount of the labor share decline, but to varying degrees. I find that I can account up to 76 percent of the labor share decline in this period using the reported markups from Barkai (2020). However, alternative markup measures, such as those by Hall (2018) and De Loecker et al. (2020), overestimate the actual labor share decline by more than 200 percent.[6]

Related literature. This paper contributes to the vast literature on the determinants of the labor share and its decline. In a seminal paper, Elsby et al. (2013) draw attention to a declining labor share in the US economy. This trend has also been observed in many other advanced economies (Karabarbounis and Neiman, 2014b) and in developing countries (Dao et al., 2017). Several propositions to explain this decline have been brought forward, such as trade (Elsby et al., 2013), the rising cost of housing (Rognlie, 2015), productivity stagnation (Grossman et al., 2017b), demographics (Glover and Short, 2018), workers' bargaining power (Stansbury and Summers, 2020), and capital mismeasurement (Koh et al., 2018).[7] But, few have gained such momentum as the accumulation and market power narratives.

The capital accumulation narrative claims that there has been a reallocation of income from labor towards capital. Karabarbounis and Neiman (2014b) and Hubmer (2018) argue that this is caused by falling investment prices while Piketty (2014) and Piketty and Zucman (2014) aim at rising savings. Autor and Salomons (2018); Eden and Gaggl (2018); Leduc and Liu (2019); Ray and Mookherjee (2019) claim that recent innovations in robotics and automation have accelerated capital's productivity and reduced the num-

[6] Basu (2019), Bond et al. (2020) and Doraszelski and Jaumandreu (2019)), among others, have recently criticized the 'steep' estimated markup path that these studies find, based on the strong imposed assumptions in their estimation methodology.

[7] Some studies, such as Karabarbounis and Neiman (2014a); Grossman and Oberfield (2022), point that once capital depreciation is accounted for, the decline in labor shares is less steep and lies within historic values.

ber of available jobs and their pay.[8]

My study provides evidence against the capital accumulation narrative which requires $\sigma > 1$ to explain declining labor shares. I estimate $\sigma \leq 1$, following a large literature that exploits time series variations in factor shares and prices (León-Ledesma et al., 2010). I contribute to this literature by providing estimates of σ for manufacturing sub-sectors and highlighting the heterogeneity in production technology across them.[9] My findings are in line with Herrendorf et al. (2015) and Oberfield and Raval (2019) who also estimate $\sigma \leq 1$ in manufacturing.[10] Besides the magnitude of σ, the argument of excessive capital accumulation has also been criticized. Gutiérrez and Philippon (2017b) argue that capital formation has weaken by a preference shift towards intangible assets, while Gutiérrez and Philippon (2017a) and Philippon (2019) pointing at the ongoing rise in market power.

A growing number of studies support the view of market power being an important factor behind the decline of the labor share (Diez et al., 2021; Akcigit et al., 2021). De Loecker et al. (2020) estimate firm-level markups over the past 65 years from public-listed firms and document that they have significantly increased after 1980. They argue that the increase in markups exceeds those in overhead costs (Traina, 2018), leading to rising profit shares. This view has recently been complemented by Autor et al. (2020) and Kehrig and Vincent (2017), who document a rise of 'superstar' firms. These are firms with high productivity, high markups and low labor shares. Over time, these firms expand and drive other firms out of the market, creating more con-

[8]Acemoglu and Restrepo (2017) also point to an increase in robotization as the leading reason behind the labor share decline. However, they focus on a task-based framework where the labor share can decline independently from the magnitude of σ.

[9]In contrast, studies of the accumulation narrative usually estimate $\sigma > 1$ by exploiting cross-country differences in factor shares using investment prices as proxies for capital intensity. However, Glover and Short (2019) show that this approach suffers from omitted bias and that once corrected it yields $\sigma = 1$.

[10]A large literature estimate $\sigma \leq 1$. See Chirinko (2008) and Knoblach et al. (2016) for a survey, and Gechert et al. (2022) for an in depth analysis accounting for publication bias.

centrated markets. A rise in markups is also documented in Hall (2018), using aggregate sectoral data and concentration measures derived from the Lerner index, and in Barkai (2020), using financial statements data from public listed firms.[11]

My study contributes to this literature by providing novel quantitative assessment on the effects of reported market power on labor shares. Unlike previous studies that estimate the elasticity of labor shares to markups, I account for the timing and the heterogeneous decline pattern across sectors. In doing so, I track both the stability of the aggregate labor share before 1980 and its decline afterwards. In addition, my approach allows for technology-driven income substitution between capital and labor within sectors, an absent feature in most firm-level studies (Autor et al., 2020; De Loecker et al., 2020).[12] To the best of my knowledge, this is the first study to jointly estimate σ, and analyze the capital accumulation and market power narratives with a unifying methodology and on the same data.[13]

The remainder of the paper is as follows. Section 2 provides the theoretical background on how the accumulation and market power narratives affect the labor share. Section 3 presents the methodology to estimate production functions, and section 4 describes the data. Section 5 presents the production function estimation results for each of the 21 manufacturing sectors. In Section 6, I perform the accounting exercises to evaluate the importance of market power in explaining the labor share decline. Section 7 concludes.

[11] See Grossman and Oberfield (2022) for an extended discussion on the two narratives.

[12] One notable exception is Oberfield and Raval (2019). The authors allow for factor-substitution but do not explicitly measure changes in markups to account for the decline of the labor share.

[13] Alvarez-Cuadrado et al. (2018) also track the evolution of the labor share in manufacturing with $\sigma < 1$. However, while they argue that the main driver of the labor share decline has been a change the bias of technical change, I focus on the rise in markups (a mechanism that is absent in their study).

2. Theoretical Background

This section describes the mechanisms through which the capital accumulation and market power can affect long-run trend changes in labor and capital shares.

Setting. Assume that each sector in manufacturing faces a cost minimization problem taking the form

$$\min_{K(t),L(t)} W(t)L(t) + R(t)K(t) \quad s.t. \quad F\Big(\Gamma^K(t)K(t), \Gamma^L(t)L(t)\Big) = Y(t), \tag{1}$$

where the $K(t)$ and $L(t)$ are the amounts of physical capital and labor employed by the sector in year t. $R(t)$ and $W(t)$ are the user cost of capital and wages in nominal values, respectively, which are taken as given by the sector. Value added $Y(t)$ is produced with a constant returns to scale (CRS) production function $F(.)$.[14] $\Gamma^j(t)$ is the efficiency level of each factor of production $j \in (K, L)$ in each period t. Its evolution over time is known as j-augmenting technical progress. This problem's first order conditions (FOCs) are

$$R(t) - \lambda(t)F_K\Big(\Gamma^K(t)K(t), \Gamma^L(t)L(t)\Big) = 0 \tag{2}$$

$$W(t) - \lambda(t)F_L\Big(\Gamma^K(t)K(t), \Gamma^L(t)L(t)\Big) = 0 \tag{3}$$

$$F\Big(\Gamma^K(t)K(t), \Gamma^L(t)L(t)\Big) - Y(t) = 0, \tag{4}$$

where $\lambda(t)$ is the Lagrange multiplier. I define the production function $F(.)$

[14] Note that the analysis presented here only holds under the CRS assumption (unitary elasticity). De Loecker et al. (2020) estimate these elasticities for various sectors of the US economy and they find their values to be close to one, and nearly constant in the postwar period. In a recent study, however, Ho and Ruzic (2019) cast doubt on whether this assumption holds.

as a constant elasticity of substitution (CES)

$$Y(t) = \left[\pi\Big(\Gamma^K(t)K(t)\Big)^{\frac{\sigma-1}{\sigma}} + (1-\pi)\Big(\Gamma^L(t)L(t)\Big)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}},$$

where $\pi \in (0,1)$ is the weight of physical capital in the production process and $\sigma \in [0,+\infty)$ denotes the elasticity of substitution between capital and labor. Recall when σ approaches zero, the CES approximates the Leontief production function and when σ is close to one the production function becomes Cobb-Douglas. If σ is smaller than one factors are considered gross complements, while if $\sigma > 1$ they are considered gross substitutes. In the limit, if σ tends to $+\infty$ then the production function converges to that of perfect substitutes.

I derive expressions for the capital and the labor shares by multiplying the first and second FOC respectively by $\frac{K(t)}{P(t)Y(t)}$ and $\frac{L(t)}{P(t)Y(t)}$, with $P(t)$ being the selling price. In this setting, the markup is the inverse of the real marginal cost $\mu(t) = \frac{P(t)}{\lambda(t)}$.

$$S^K(t) = \frac{R(t)K(t)}{P(t)Y(t)} = \frac{\pi}{\mu(t)}\left(\Gamma^K(t)\frac{K(t)}{Y(t)}\right)^{\frac{\sigma-1}{\sigma}} \tag{5}$$

$$S^L(t) = \frac{W(t)L(t)}{P(t)Y(t)} = \frac{(1-\pi)}{\mu(t)}\left(\Gamma^L(t)\frac{L(t)}{Y(t)}\right)^{\frac{\sigma-1}{\sigma}}. \tag{6}$$

Finally, I denote $S^{profit}(t)$ to be the share of profits at the sectoral level. Under the assumption that marginal costs equal average costs, the profit share is given by

$$S^{profit}(t) = 1 - S^K(t) - S^L(t) = 1 - \frac{1}{\mu(t)} \tag{7}$$

Analysis. I now analyze how capital accumulation and market power can affect changes in capital and labor shares over time. Equations (5) and (6) depict the negative relationship between market power and factor shares. Assuming no fixed costs, a rise in market power allows sectors to charge higher markups. This manifests in a shift from capital and labor income towards profits. $S^{profit}(t)$ rises while $S^{K}(t)$ and $S^{L}(t)$ decline by the same magnitude. Markups, however, do not change the *relative* distribution of income between labor and capital (as shown below). Most importantly, this mechanism is independent from the magnitude of σ. This makes the market power narrative separate from the accumulation one.

The capital accumulation narrative relates factor payoffs to their contribution in production. The relative distribution of income between capital and income depends on the magnitude of σ. When one factor share rises, it does so at the expense of the other one. This can be better appreciated by the following expression

$$\Theta(t) = \frac{S^{K}(t)}{S^{L}(t)} = \frac{\pi}{1-\pi}\left(\underbrace{\frac{\Gamma^{K}(t)}{\Gamma^{L}(t)}}_{(a)}\underbrace{\frac{K(t)}{L(t)}}_{(b)}\right)^{\frac{\sigma-1}{\sigma}}, \tag{8}$$

where $\Theta(t)$ is defined as the relative capital-to-labor share ratio. An increase in $\Theta(t)$ implies an increasing capital share and a declining labor share.

If $\sigma = 1$, the labor share and capital share are stable over time, reflecting the weight of each factor in production. These are assumed time invariant, implying $\Theta(t) = \frac{\pi}{1-\pi}$. If $\sigma \neq 1$, then changes in relative factor shares depend on relative factor contribution. I analyze changes in $\Theta(t)$ by comparing the growth rate of (a) to that of (b), jointly with the magnitude of σ. The growth rate of (a) refers to the net bias of technical change. It captures technical innovations that make one factor more efficient than the other. This term is unobserved and its evolution may fluctuate over time.[15] (b) denotes

[15]Innovations may be capital-biased in some periods and labor-biased in others. In the long-run, however, there is a consensus that the bias of technical change should be net

the observed stock of capital per worker and its growth is the rate of capital deepening.

For example, imagine that in any given year, the efficiency of capital $\Gamma^K(t)$ experiences an unanticipated positive shock. What would happen to the labor share? The answer depends on the magnitude of σ. If capital and labor are gross complements $\sigma < 1$, then the labor share would increase because the relatively *scarcer* factor (labor) will accrue the largest share of income (as both factors are needed for production). In contrast, if capital and labor are gross substitutes $\sigma > 1$ the labor share would decline. In this case the relatively more *abundant* factor (capital) receives the larger share of income.

In an influential study, Karabarbounis and Neiman (2014b) argued that lower investment prices were leading to an accelerated pace of capital deepening. In my analysis this refers to a sustained increase in the growth rate of (b) in (8), through the accumulation of $K(t)$. But, this argument requires $\sigma > 1$ to cause a decline of the labor share. Similarly, a faster pace of $\Gamma^K(t)$ from automation or robotization, would only cause a labor share decline if $\sigma > 1$. Finally, notice that markups cancel out in (8) illustrating the independence between the accumulation and market power narratives.[16]

In summary, if the elasticity of substitution is larger (smaller) than one, an increase in capital deepening and/or capital-augmenting technical progress leads to a decline (rise) of the labor share and a rise (decline) of the capital share. Independently of the value of the elasticity of substitution, a rise in markups causes both a decline of the labor *and* capital shares.

---

labor-augmenting.

[16]Note that the labor share can also fall with $\sigma < 1$. Based on theory and empirical evidence, we know that in the long run net technical progress should be net labor-augmenting, i.e., $\Gamma^L(t)$ grows at a faster pace than $\Gamma^K(t)$ (León-Ledesma et al., 2015; Antras, 2004; Acemoglu, 2003; Uzawa, 1961). Then the labor share would decline with $\sigma < 1$ if (a) falls at a faster pace than the growth of (b). Alvarez-Cuadrado et al. (2018) investigate this idea in a calibrated growth model with strong assumptions on the bias of technical change (which is not observable).

3. Production Function Estimation

In this section I present the system approach to estimate the elasticity of substitution for each sector. While the standard system approach assumes fixed markups, I extend the specification, as in Jiang and León-Ledesma (2018), to include time-varying markups.

The system approach (Klump et al., 2007; León-Ledesma et al., 2010) refers to constructing a specification system based on a production function and its FOCs. These FOCs are derived from the sector's cost minimization problem discussed in the previous section. The estimation is then carried out along the time series. The CES production function is

$$Y_t = C\left[\pi(\Gamma_t^K K_t)^{\frac{\sigma-1}{\sigma}} + (1-\pi)(\Gamma_t^L L_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{9}$$

where C is a productivity constant. My main parameter of interest is $\sigma \in [0, +\infty)$.

Technical progress reflects the evolution of each factor's efficiency level. The system approach presents factor-biased technical progress. This means that changes in capital and labor's efficiency are independent from each other and may have independent evolution paths. Capital and labor's technological progress takes the form

$$\Gamma_t^j = \Gamma_0^j \cdot e^{\alpha_j t} \qquad \forall j \in (L, K),$$

where $t \in (1, \ldots, T)$ represents a time index and α_j is the average annual growth rate of factor j-augmenting technical progress. As shown in León-Ledesma et al. (2010), allowing for biased technological progress leads to a more consistent estimation of the elasticity of substitution compared to using stricter technical progress assumptions (such as Hicks-neutral or Harrod-neutral).

I normalize the production function as suggested in Klump et al. (2007). Normalization is necessary because σ is a point elasticity that needs a common benchmark to be comparable to other families of production functions. This benchmark is achieved by dividing factors and their efficiency levels by their averages (geometric for growing variables and arithmetic for factor income shares and time index). This normalization makes the production function unit-less and, therefore, comparable across different sectors.

For the normalization, I assume $C = \Gamma_0^j = 1$. The normalized production function is

$$\frac{Y_t}{\overline{Y}} = \psi \left[\overline{\pi} \left(e^{\alpha_K (t-\overline{t})} \frac{K_t}{\overline{K}} \right)^{\frac{\sigma-1}{\sigma}} + (1-\overline{\pi}) \left(e^{\alpha_L (t-\overline{t})} \frac{L_t}{\overline{L}} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{10}$$

where the over-lined variables are sample averages. For time and labor weight in production ($\overline{t}, 1-\overline{\pi}$) I use the arithmetic average and the geometric average for value added, capital and labor.

Normalizing helps the identification of the factor augmenting estimates and contributes circumventing Diamond's impossibility theorem (Diamond et al., 1978). This theorem states that since the econometricians cannot observe the weight of factors in the production function, they cannot be estimated differently from their technical progress. By normalizing the production function and introducing $1-\overline{\pi}$ (assumed stable over time) and assuming deterministic technical progress, we are fixing the the production function to a common point which allows for a proper identification of σ, α_L and α_K.

It is common in the system approach literature to introduce a normalization constant ψ which expected value is close to one. I include this parameter to check for possible poor convergence of the estimation algorithm due to the non-linearity of the system, although it does not carry any economic meaning.

As shown in the previous section, the cost minimization problem of any sector's production problem with production function (10) yields the following FOCs

$$\frac{R_t}{\lambda_t} = \frac{\overline{\pi}\overline{Y}}{\overline{K}} \cdot \left(e^{\alpha_K(t-\bar{t})}\right)^{\frac{\sigma-1}{\sigma}} \cdot \left(\frac{Y_t/\overline{Y}}{K_t/\overline{K}}\right)^{\frac{1}{\sigma}} \tag{11}$$

$$\frac{W_t}{\lambda_t} = \frac{(1-\overline{\pi})\overline{Y}}{\overline{L}} \cdot \left(e^{\alpha_L(t-\bar{t})}\right)^{\frac{\sigma-1}{\sigma}} \cdot \left(\frac{Y_t/\overline{Y}}{L_t/\overline{L}}\right)^{\frac{1}{\sigma}}, \tag{12}$$

where λ_t is the Lagrange multiplier.

To include time-varying markups I multiply (11) and (12) respectively by $\frac{K_t}{P_t Y_t}$, and $\frac{L_t}{P_t Y_t}$. A multiplicative error is added to each FOC representing shocks or measurement errors. Applying a logarithmic transformation and combining equations (10) - (12), I form the system

$$\log(\frac{Y_t}{\overline{Y}}) = \log\psi + \frac{\sigma}{\sigma-1}\log\left[\overline{\pi}\left(e^{\alpha_K(t-\bar{t})}\frac{K_t}{\overline{K}}\right)^{\frac{\sigma-1}{\sigma}} + (1-\overline{\pi})\left(e^{\alpha_L(t-\bar{t})}\frac{L_t}{\overline{L}}\right)^{\frac{\sigma-1}{\sigma}}\right] + \epsilon_t^Y \tag{13a}$$

$$\log(S_t^K\mu_t) = \log(\overline{\pi}) + \frac{\sigma-1}{\sigma}\alpha_K(t-\bar{t}) - \frac{\sigma-1}{\sigma}\log\left(\frac{Y_t/\overline{Y}}{K_t/\overline{K}}\right) + \epsilon_t^K \tag{13b}$$

$$\log(S_t^L\mu_t) = \log(1-\overline{\pi}) + \frac{\sigma-1}{\sigma}\alpha_L(t-\bar{t}) - \frac{\sigma-1}{\sigma}\log\left(\frac{Y_t/\overline{Y}}{L_t/\overline{L}}\right) + \epsilon_t^L \tag{13c}$$

where S_t^L and S_t^K are the observed labor and capital shares in value added, and μ_t the time-varying markup.

For clarification, the objective is to jointly estimate σ, α_L, α_K and ψ, using data on S_t^L, S_t^K, Y_t, L_t, K_t and μ_t. I estimate the system with both time-varying and fixed markups ($\mu_t = 1 \quad \forall t$). While the standard system approach ignores markups, it is not clear —ex-ante —how their inclusion would affect the estimated magnitude of the parameters.

I estimate the normalized system (13 a-c) using non-linear three-stage least squares (NL3SLS).[17] The parameters are estimated freely, without imposing any restrictions to their values, but including cross-equation restrictions to improve efficiency.[18] One possible endogeneity concern arises if capital and/or labor adjust within the same time period to current innovations, thus violating exogeneity. This is the classic "transmission bias" (Ackerberg et al., 2015). To prevent this possibility, I perform a non-linear three stages least squares (NL3SLS) procedure.

In the first stage, I instrument the right-hand side variables in the system with their one year lagged values. In the second step, I estimate the parameters of the system via non-linear least squares with the projected covariates, equation by equation. The third stage accounts for contemporaneous correlation of the error terms. It performs feasible generalized least squares to account for heteroskedasticity (Zellner and Theil, 1962).

I use the instruments suggested by Fair (1970), which are standard in the system approach literature (León-Ledesma et al., 2015; Herrendorf et al., 2015). The instruments in the first-stage are the logarithm of lagged normalized value added, capital, labor, labor and capital share, the markup series plus a time trend. Usually, the estimation involving non-linear least squares is highly sensitive to the choice of starting values. For sectors where there are more than one set of convergence estimates, I choose the one that provides the best fit.[19]

[17]The estimation algorithm uses predetermined starting values for all parameters to minimize the estimated vector of residuals. Then, the starting values are slightly modified. After each iteration, the algorithm compares the goodness of fit of the new estimated parameters to the one from the previous iteration. The process continues until it converges to a set of parameters that globally minimize the vector of residuals.

[18]Thus, the estimates are not necessarily consistent with a balanced growth path (see Uzawa (1961), Grossman et al. (2017a)).

[19]I favor the parameters with the smallest log determinant of the estimated residual covariance matrix.

4. Data

I use the 35 sector US KLEM dataset from Jorgenson (2008) to estimate the elasticity of substitution and the growth rates of capital and labor's technical progress. This dataset decomposes the US whole economy into 35 sectors at 2-digit Standard Industrial Classification and provides price and quantity of gross output for each sector spanning from 1960 to 2005. It also comprises sector-specific amounts physical capital and labor (quality adjusted) and their rental cost. Factor prices include taxes, while gross output prices exclude them. Therefore, the data provides a cost minimizing perspective of gross value added creation.[20]

I include a markup series based on the empirical evidence reported by recent studies. Employing different estimation techniques, De Loecker et al. (2020), Hall (2018) and Barkai (2020) document stable market power before 1980, and an increase between 1980 and 2016. De Loecker et al. (2020) compute markups at the firm level using data from public listed companies from Compustat. They recover markups as the wedge between inputs' expenditure share in revenue and its output elasticity. Then, they aggregate these markups across firms and sectors over time. De Loecker et al. (2020) estimate that in manufacturing sectors markups were roughly stable between 1950 and 1977, but rose from 1.55 to 1.75 in the 1977-2002 period.[21] Hall (2018) builds markups from the Lerner index—the ratio of price minus marginal cost over price—using NAICS data. He also documents that markups have risen in different sectors of the US economy by about 0.006 points per year.[22] Barkai (2020) employs an approach which relies on finan-

[20] For a more detail description of the data see Jorgenson and Stiroh (2000) and O'Mahony and Timmer (2009). I utilize gross value added factor shares. In other words, capital depreciation is assumed constant over time.

[21] See Figure 6 panels (a) and (b) in De Loecker et al. (2020). They also document a rise in overhead costs, however, the rise in markups is larger, increasing profits.

[22] One drawback of Hall's methodology is that it only estimates the trend's slope and not

cial corporate data. He estimates capital costs, which often require an estimated rate of return for privately-own physical capital, to disentangle between the capital share and the profit share. He documents a rise in markups (measured in value added) from 1.02 in 1984 to 1.19 in 2014.

Based on these studies, I assume a constant markup equal to one (perfect competition) between 1960 and 1980, and a linearly growing markup for the 1980-2005 period. The series reaches 1.15 by 2005, and is the same for all sectors. My markup series is the closest to Barkai (2020), who also works in value added terms. The series is less steep than those reported by De Loecker et al. (2020) and Hall (2018) when transforming the markup from gross output into value added terms (more on this below).[23]

The inclusion of fixed or variable markups is also important for the construction of value added and factor shares. I observe S_t^L from the data, but the definition of S_t^K depends on the evolution of the markup. To solve this, I proceed as follows. First, I define real value added P_tY_t in each sector by subtracting the total value of intermediate inputs from gross output. P_t is a price index that follows the evolution of the output price. The CRS production function allows me to re-write total value added as: $P_tY_t = P_tF_{K,t}K_t + P_tF_{L,t}L_t$ which can also be expressed as $1 = \frac{R_tK_t}{P_tY_t}\mu_t + \frac{W_tL_t}{P_tY_t}\mu_t$ or $1 = S_t^K\mu_t + S_t^L\mu_t$. Following Jiang and León-Ledesma (2018), I use this last expression to build an accurate measure of the capital share. I build S_t^K as a residual using the expression $1 = S_t^K\mu_t + S_t^L\mu_t$ with the the observed S_t^L and μ_t. For the case of fixed markups, I simply assume $\mu_t = 1$ for all sectors and all years.

Table 1 shows some summary statistics. The first two columns document the shift in the relative importance across sectors (measured as sector's

the time series of markups. See Basu (2019) and Bond et al. (2020) for a discussion on the markup estimation approaches.

[23]The latter have been recently criticized. For example, Basu (2019) argues that the rise in markups reported by De Loecker et al. (2020) is too large to be consistent with other macroeconomic variables, while Bond et al. (2020) cast doubts on the assumptions imposed on the markup estimator.

value added over total value added in manufacturing) within manufacturing. While some sectors expanded, such as chemicals and allied products, others lost their relative importance (e.g. apparel and textile mill products). The third column shows the labor share at the first year of the sample for each sector. While most labor shares hover around two-thirds, there is still some significant cross-sectoral variation in labor share levels. The last three columns show how the labor share changed between 1960, 1980 and 2005. Note that the labor share fell in almost all sectors between 1960 and 2005, with most of it taking place between 1980 and 2005. Motor vehicles and tobacco manufactures present the sole exceptions to this trend. During the same period, Autor et al. (2020) also register a significant increase in concentration in manufacturing sectors.

5. Estimation Results

I present the estimated production function parameters for 21 manufacturing sectors using the system approach with both fixed and time-varying markups. To allow a better cross-sector comparisons, I present the estimated elasticity of substitution, the growth rate of the labor-augmenting and capital-augmenting technical progress in three figures.

Figure 2 presents the estimates of the elasticity of substitution σ for each manufacturing sector. The figure shows the point estimates with their 95% confidence interval when including fixed markups (in blue) as well as time-varying markups (in red) in system (13). I find σ to be below one in most sectors. This is the case whether I include fixed or time-varying markups in the specification. While ignoring time-varying markups leads to an downward bias, including them still yields σ below, or close to, unity. In the latter case, I find that σ across sectors is less spread and its value appears within the $0.6 - 1$ interval. The median sector exhibits an elasticity of 0.86. A few

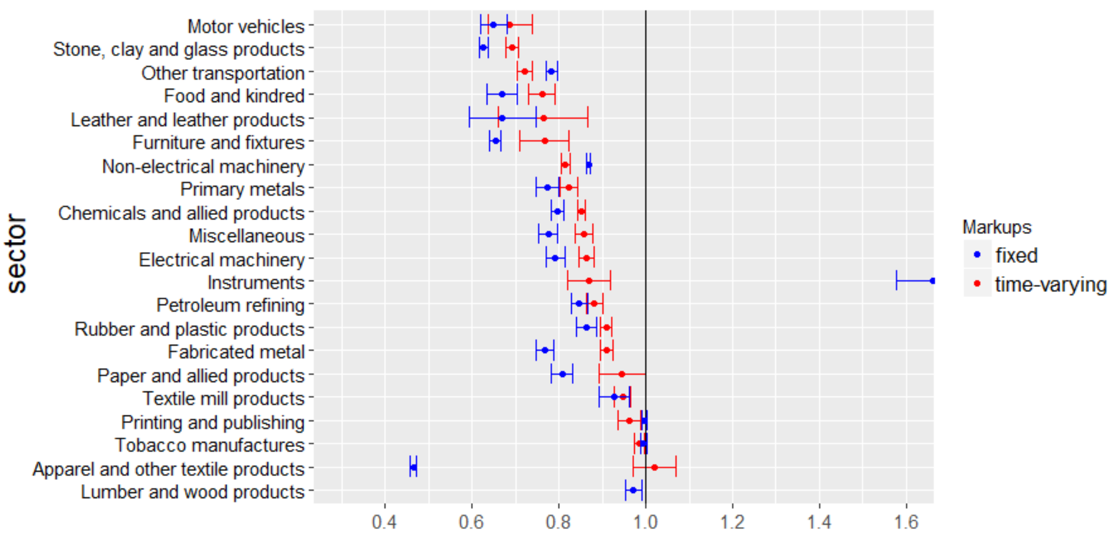
Table 1: Summary statistics

		(1)	(2)	(3)	(4)	(5)	(6)
		% of manuf. GDP		labor share	labor share changes (p.p.)		
ID	Sector	1960	2005	in 1960	1960−1980	1980−2005	1960−2005
1	Food and kindred	9.34	10.20	0.74	0.02	-0.20	-0.18
2	Tobacco manufactures	0.69	0.44	0.39	-0.03	0.10	0.07
3	Textile mill products	3.21	1.14	0.78	0.01	-0.16	-0.16
4	Apparel and other textile products	4.02	0.81	0.90	-0.08	0.06	-0.03
5	Lumber and wood products	2.61	2.52	0.80	-0.15	0.01	-0.14
6	Furniture and fixtures	1.89	2.39	0.80	0.02	-0.02	-0.00
7	Paper and allied products	4.31	3.79	0.65	0.03	-0.05	-0.02
8	Printing and publishing	6.20	7.44	0.77	-0.05	-0.08	-0.13
9	Chemicals and allied products	8.63	12.21	0.55	0.04	-0.20	-0.16
10	Petroleum refining	2.06	4.35	0.56	-0.21	-0.15	-0.36
11	Rubber and plastic products	2.35	4.43	0.76	0.05	-0.10	-0.06
12	Leather and leather products	1.20	0.13	0.84	-0.11	0.02	-0.09
13	Stone, clay and glass products	4.00	3.30	0.69	0.06	-0.13	-0.06
14	Primary metals	7.45	4.04	0.69	0.06	-0.31	-0.25
15	Fabricated metal	8.18	6.74	0.84	-0.07	-0.14	-0.22
16	Non-electrical machinery	9.32	9.83	0.76	-0.01	0.00	-0.01
17	Electrical machinery	7.46	8.03	0.73	0.06	-0.15	-0.09
18	Motor vehicles	5.33	4.50	0.59	0.18	-0.08	0.10
19	Other transportation	6.30	5.85	0.92	-0.04	-0.05	-0.10
20	Instruments	3.62	6.48	0.83	0.00	-0.03	-0.03
21	Miscellaneous	1.81	1.36	0.83	-0.05	-0.23	-0.28
	Total	100.00	100.00				

Note: Column 1 and 2 report the percentage of each sector's value added over total manufacturing GDP. Column 3 reports the labor share in 1960. Columns 4-6 report percentage point changes in labor shares.

sectors, such as printing and publishing and tobacco manufactures, present σ close to unity —Cobb-Douglas technology. Only lumber and wood products display σ significantly larger than one ($\hat{\sigma} = 1.88$).[24]

Figure 2: Elasticity of substitution σ



Note: Each point estimate corresponds to the elasticity of substitution in each sector using the system approach with its respective 95% confidence interval. Red estimates include time-varying markups in the specification, while blue estimates assume them constant. Lumber and wood products has a $\hat{\sigma} = 1.88$ and is significantly larger than one. See also the results in Tables 2 and 3.

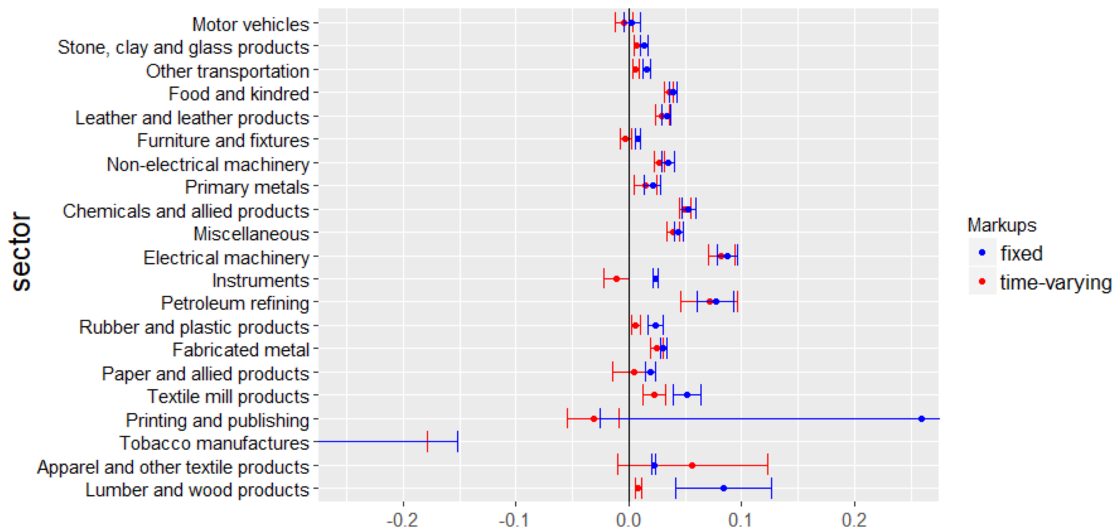
The estimated elasticities are in line with those found in the literature. Most studies report a σ for the aggregate economy smaller than one (see Chirinko (2008) for a survey). Particularly for manufacturing, Herrendorf et al. (2015) estimate the elasticity of substitution to be 0.8 also using the system approach.[25] Oberfield and Raval (2019) use an alternative methodology using micro data from manufacturing establishments. They report an

[24]As shown in Figure 2, only three sectors present large differences in σ when including time-varying markups in the specification. This shows that my estimation is not highly dependent on their inclusion in the system. In addition, the elasticity of substitution is slightly larger when time-varying markups are accounted for(in line with Jiang and León-Ledesma (2018)).

[25]Different from my results, they estimate the elasticity for manufacturing as a whole (not dividing into sub-sectors) and do not include time-varying markups.

elasticity within the 0.5-0.7 interval.

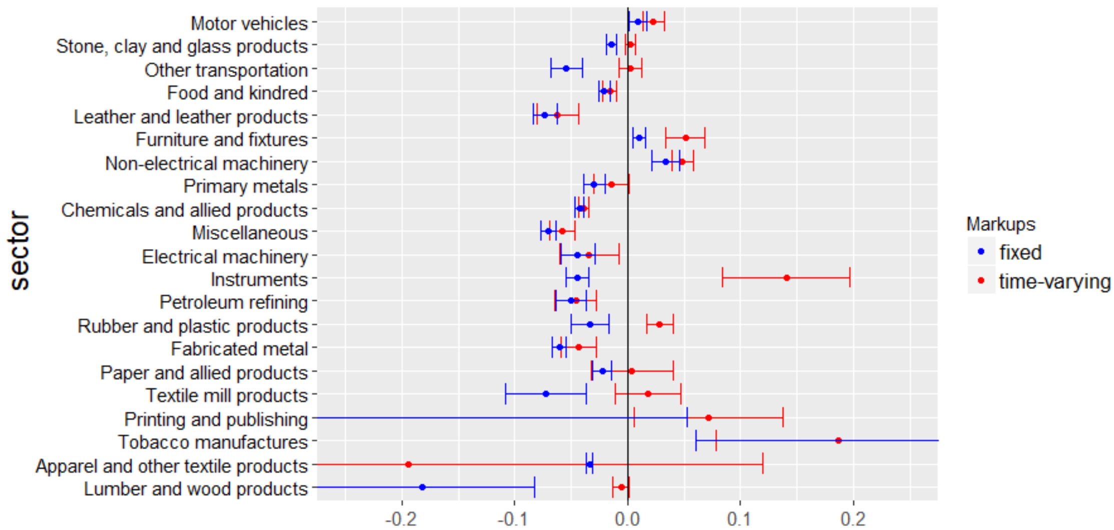
Figure 3: Growth rate of labor-augmenting technical progress α_L



Note: Each point estimate corresponds to the labor-augmenting growth rate α_L in each sector using the system approach with its respective 95% confidence interval. Red estimates include time-varying markups in the specification, while blue estimates assume them constant. See also the results in Tables 2 and 3.

Figure 3 presents the estimation of the growth rate of labor-augmenting technical progress. α_L is positive and varies between 0 and 0.10. These values are within the expected range. It translates that labor becomes between 0 to 10 percent more efficient each year in these sectors. It is important to highlight that α_L, as well as α_K, can only be identified when σ is not equal to one. This is because there is a discontinuity in the production function (see equation 13a in 13), and the estimating algorithm becomes ill-behaved when σ is close to one. For example, this is the case in tobacco manufacturers and apparel and other textile products. Therefore, α_L and α_K have implausible values in these sectors. Finally, the inclusion of time-varying markups does not appear to significantly change the point estimate of α_L for sectors with $\sigma < 1$. We can observe that the confidence interval with fixed and flexible markups almost overlap.

Figure 4: Growth rate of capital-augmenting technical progress α_K



Note: Each point estimate corresponds to the capital-augmenting growth rate α_K in each sector using the system approach with its respective 95% confidence interval. Red estimates include time-varying markups in the specification, while blue estimates assume them constant. See also the results in Tables 2 and 3.

In Figure 4, I present the estimates for the growth rate of capital-augmenting technical progress α_K. In terms of its magnitude, there is no clear pattern. Many sectors present a negative and significant α_K, while others are close to zero, and a few are even positive. Estimating negative capital-augmenting technical progress is not uncommon in the system approach literature (see Antras (2004); Frieling and Madlener (2016), among others).[26] As in the labor case, α_K is imprecisely estimated in sectors where σ is close to one (such as tobacco manufactures and apparel and other textile products).

I find that net technical progress $\alpha_L - \alpha_K$ is labor-augmenting for most sectors. I present the magnitude for each sector in Figure 9 in the Appendix. In addition, I also present the estimated normalization constant ψ in Figure 10. As expected, they are all close to one.

[26]In line with Jiang and León-Ledesma (2018), the point estimate of α_K is larger when I include time-varying markups in the specification. However, they find that this turns α_K from negative to positive. I find this change in sign only in a few sectors.

Taking stock. Section 2 shows that capital deepening would only cause a decline of the labor share if σ is larger than one. The estimation results show that all sectors —but one —present σ smaller or close to one. This sole sector represents only 2.5 percent of total value added in manufacturing. This evidence suggests that the capital accumulation narrative cannot explain the overall decline of the labor share in manufacturing.

6. Tracking the Labor Share in Manufacturing

In this section I perform an accounting exercise to measure how much of the decline of the labor share can be attributed to the rise in market power reported in the literature. To this aim, I build 'fundamental' labor shares for each manufacturing sector. These labor income shares depend on labor's contribution in production as well as the amount of market power. Then, I aggregate these shares across sectors. I decompose total changes in the aggregate fundamental labor share into sectoral re-weights, capital-labor substitution and market power effects. Finally, I assess how much these separate components help track the long-run trend in observed labor share.

Based on (6), I define the fundamental labor share in sector i as

$$\hat{S^L}_{it} = \frac{(1-\pi_i)}{\mu_{it}} \left(\frac{\hat{\Gamma^L}_{it} L_{it}}{Y_{it}} \right)^{\frac{\hat{\sigma}_i - 1}{\hat{\sigma}_i}} \quad with \quad \hat{\Gamma^L}_{it} = e^{\hat{\alpha}_{Li} \cdot t}, \tag{14}$$

where hat refers to the estimated production parameters discussed in the previous section. $\hat{S^L}_{it}$ expresses the income share accruing to labor given the sector's market power (captured by $1/\mu_{it}$) and labor's contribution in production (the remainder terms). As discussed in Section 2, a rise in market power materializes into higher markups, profit shares and lower labor shares.

Labor's contribution is stable in Cobb-Douglas sectors, $\hat{S^L}_{it} = (1-\pi_i)/\mu_{it}$. But when $\hat{\sigma_i} \neq 1$, it presents two opposite forces. The parenthesis in (14) captures the contribution of effective labor to value added (labor's average efficiency times its total amount). Its evolution over time would raise or lower the labor share depending on the magnitude of $\hat{\sigma_i}$. For sectors with $\sigma < 1$, the fundamental labor share declines if $\hat{\Gamma^L}_{it} L_{it}$ grows at a faster pace than Y_{it}. This would represent a more abundant contribution of labor (relative to capital) in value added. On the contrary, the fundamental labor share rises if $\hat{\Gamma^L}_{it} L_{it}$ grows at a slower pace than Y_{it}.

Figure 5 presents the results for the 21 manufacturing sectors.[27] As expected, the fundamental labor shares track well the labor share in each sector.[28] This is the case for sectors with a steady labor share decline, e.g food and kindred, as well as those which exhibit an upward trend, e.g. non-electrical machinery. In the only sector where capital and labor are gross complements, lumber and wood products, the fundamental series also track well the observed labor share.

Next, I build an aggregate fundamental labor share for manufacturing $\hat{S^L}_t$ by computing the weighted average across all sectors. For this I define

$$\hat{S}_t^L = \sum_{i=1}^{N} \theta_{it} \hat{S^L}_{it}, \tag{15}$$

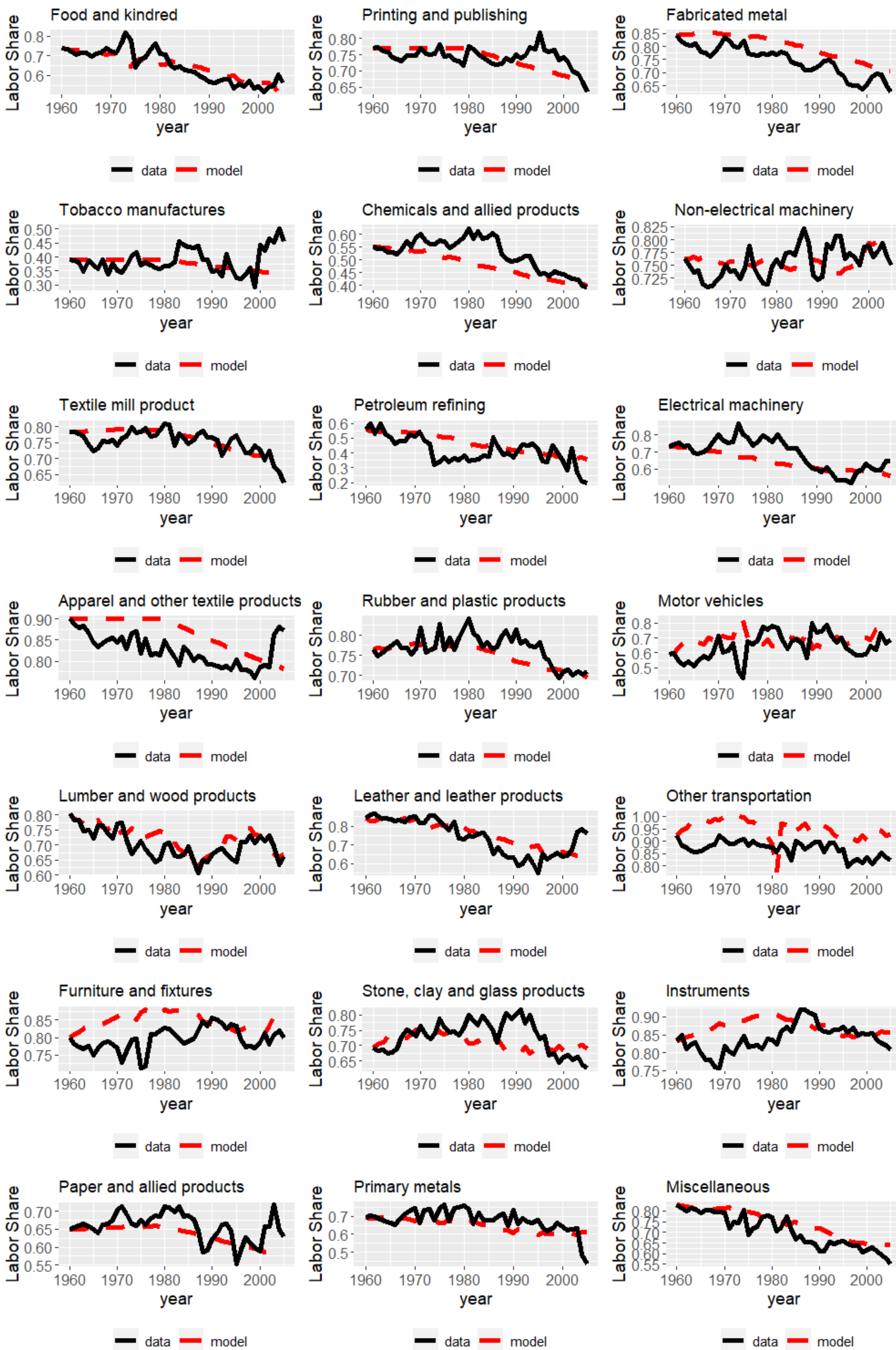
where the weight θ_{it} is value added over total manufacturing GDP. As shown in Table 1, θ_{it}'s also change over time due to structural transformation.

I decompose $\hat{S}_t^L$ into sectoral re-weights, capita-labor substitution and market power effects. These series and the observed labor share is presented

[27] I replace (14) with the estimated elasticity of substitution, growth-rate of labor-augmenting technical progress, markup, labor and value added from Table 2. Sectors with $\hat{\sigma}$ within the $0.97 - 1.03$ interval are replaced with 1. For $\hat{\alpha}_L$ I use the point estimate of each sector that is positive and significantly different than zero, otherwise I replace it with a zero value.

[28] These results display the goodness of fit of my production technology parameters.

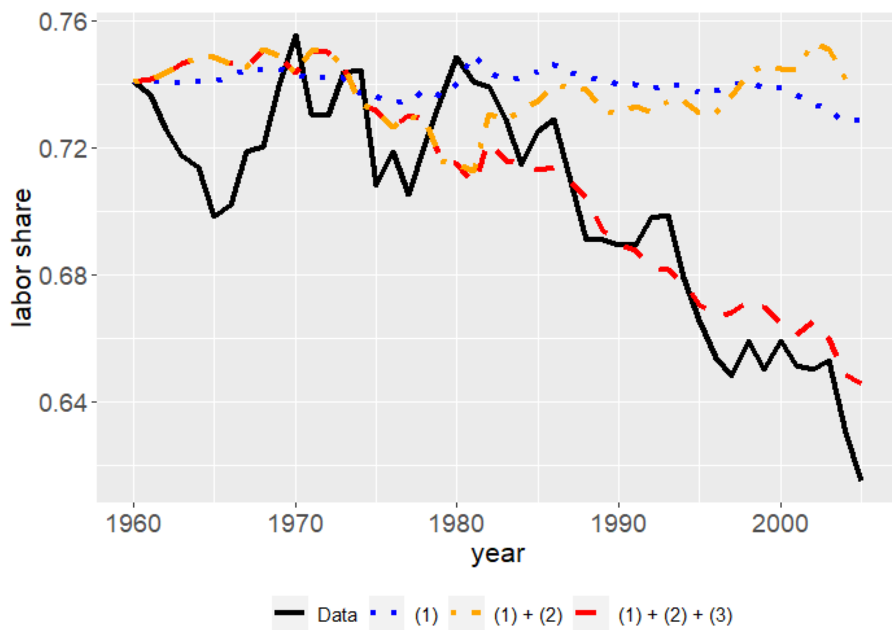
Figure 5: The labor share in individual sectors



Note: The black solid series denotes the observed labor share in value added in each sector. The red dotted series denotes the fundamental labor shares built using eq. (14).

in Figure 6. The blue dotted series, labelled (1), measures the change in the labor share that is due to changes in sectors' weight only. Imagine all sectors have Cobb-Douglas technology and fixed markups, the labor share can still decline if sectors that have low labor shares expand over time, while those with high labor share shrink. As seen in Figure 6, sectoral re-weights played almost no role in explaining the decline of the labor share in manufacturing.

Figure 6: Tracking the labor share in manufacturing



Note: (1): sectoral re-weight effects. (2): capital-labor income substitution effects. (3): market power effects. This figure shows the observed labor share in value added in manufacturing (black solid line). The blue dotted series denotes the change in the labor share due to change in sectors weights. The yellow dotted series adds the contribution of effective labor in value added. The red dashed line adds the effects of markups.

The series $(1)+(2)$ adds labor's contribution to the sectoral reweighing effect. Now the labor share can rise or decline depending on the magnitude of the elasticity of substitution and the weight of effective labor in value added. Markups are still assumed fixed. This series shows a constant fundamental labor share between 1960 and 1970, with a slight decline between 1970 and 1980, and a positive trend from 1980 to 2005. Between 1960 and 2005, the series displays no level changes. This evidence suggests that the weight of effective labor in manufacturing GDP did not decline throughout this period.

The series $(1)+(2)+(3)$ in Figure 6 adds the contribution of market power. The effects of time-varying markups become visible starting in 1980. The rise in markups shifts income from labor towards profits, driving the labor share downwards. Interestingly, the slope of the labor share decline in my aggregated series is similar to that observed in the data. Between 1960 and 2005, the labor share fell by 17 percent in the data. For this period, my accounting exercise predicts a decline of 13 percent. In other words, the rise in market power accounts for 76 percent of the decline. Both series are also end at similar levels. The labor share is 0.62 in 2005, while my accounting predicts a value of 0.65 for that year. These results suggest that the rise in markups, at least those reported by Barkai (2020), can account for most of the observed labor share decline in manufacturing.

In sum, this accounting exercise delivers two findings. First, I find that labor's contribution in production has remained stable in manufacturing in the post-war period. Despite numerous sectors having $\sigma < 1$, the predicted labor share is fairly constant. Second, the reported rise in market power by Barkai (2020) can explain a large share of the labor share decline in manufacturing. Finally, the combination of both findings delivers a counterfactual scenario where the labor share remains stable between 1960 and 2005.

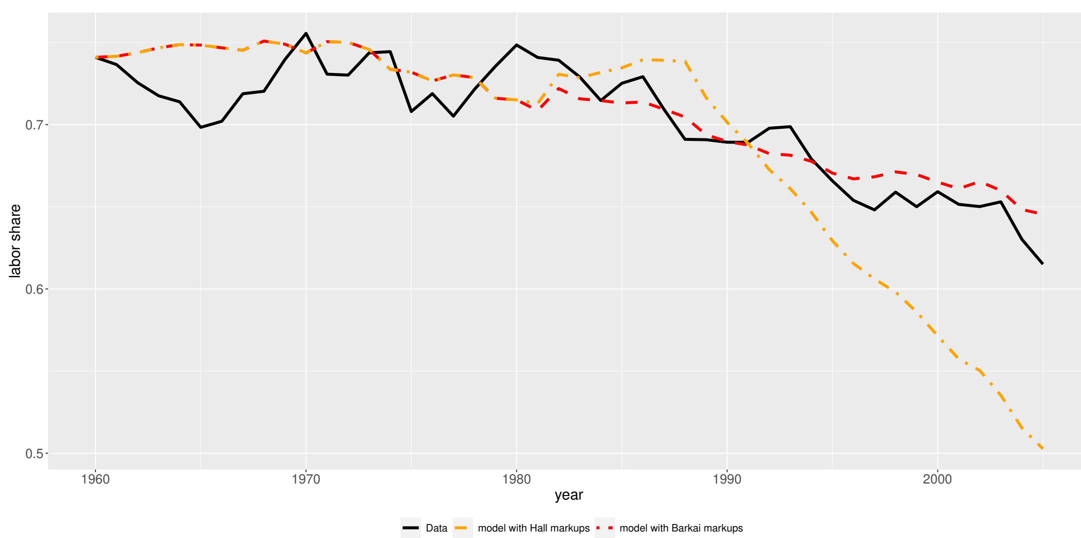
6.1 Sensitivity analyses

Here I present two exercises. First, I show that the extent to which market power can explain the labor share decline is highly dependent on the estimated growth path of markups. Second, given the estimated production technology parameters, I find that factor contribution alone cannot explain the labor share decline. Here I show that this finding is not driven by the assumed path for markups in the estimation of the production function.

6.1.1 Alternative markup series

Figure 6 shows that the increase in market power reported by Barkai (2020) can explain up to 76 percent of the labor share decline. How would these results change with an alternative growth path of markups? Hall (2018) reports similar growth in markups as Barkai (2020), but his markups are estimated on gross output. To include this series into my accounting exercise, I transform the markups into value added ones. To this aim, I follow Basu (2019), and assume a share of intermediate inputs of 0.5 as is standard in the literature.[29] Hall's markup series becomes much steeper than Barkai's, increasing from 1.3 in 1980 to 1.7 in 2005.

Figure 7: Tracking the labor share in manufacturing (with alternative markups)



Note: This figure shows the observed labor share in value added in manufacturing (black solid line). The red dotted series replicates the accounting method of Figure 6, which uses Barkai (2020) markup series . The orange dotted series replaces Barkai's markup series with the one from Hall (2018).

[29]The formula to adjust from gross output markups μ^G to value added markups μ^V is: $\mu^V = \frac{\mu^G(1-S)}{1-\mu^G S}$, with s being the share of intermediate inputs.

Figure 7 presents the results of my accounting exercise replacing Barkai's markup series (red dotted series) with Hall's (orange dotted series). The new series predicts a much steeper decline of the labor share to about 0.5, or 200 percent of the actual decline of the labor share. De Loecker et al. (2020) report an even larger increase in markups than Hall. If we would account for the transformation into value added, the markups would reach a value of 4 (Basu, 2019), and the labor share would be no larger than 0.2 in 2005.

These results show that, while there may be a growing consensus on the growth of market power in the literature, some of the most influential studies seem to report a growth path in markups that is too large to be compatible with the actual labor share decline.

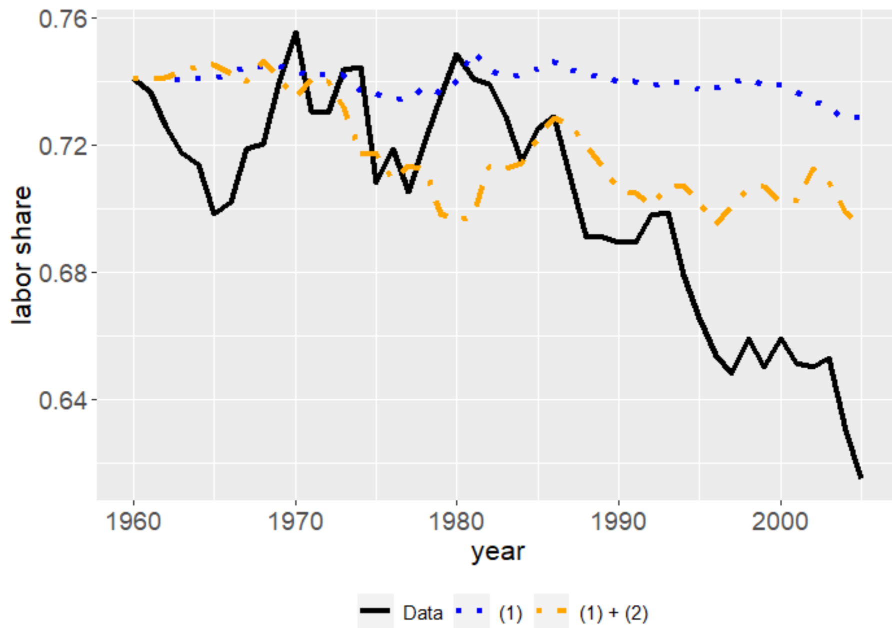
6.1.2 Alternative estimated parameters of the production function

Despite the high sensitivity of accounting to markups, these do not significantly affect the accounting contribution of factors in production. As shown in the previous section, the estimated production technology parameters are sensitive to the inclusion of markups. Here I replicate same accounting exercise to study the capital-labor substitution effects but using alternative production technology estimates. I build fundamental labor shares (eq .14) for all sectors, but with the $\hat{\sigma}$ and $\hat{\alpha_L}$ using fixed markups in the econometric specification. Then I aggregate the shares using (15). Given the slight change in the production parameters, the tracking of the labor share at sectoral level changes, but not much.[30]

Figure 8 presents the results. I observe that capital-labor substitution effects do not help track the decline of the labor share. The $(1) + (2)$ series predicts a slight labor share decline, from 0.74 to 0.7, but its timing is concentrated in the pre-1980 period. Since then it presents a stable series. Com-

[30] By assuming no markup variation, I replace $\mu_{it} = 1 \quad \forall i, t$ in (14).

Figure 8: Tracking the labor share in manufacturing (with fixed markups)



Note: (1): reallocation effects. (2): capital-labor income substitution effects. This figure shows the observed labor share in value added in manufacturing (black solid line). The blue dotted series denotes the change in the labor share due to change in sectors weights. The yellow dotted series adds the contribution of effective labor in value added.

pared to the baseline results in Figure 6, the size change in σ and α_L across different sectors modify the behavior of the aggregate series. Consistent with the analysis in Figure 6, the results in Figure 8 show that the labor's contribution alone cannot account for the decline of the labor share in manufacturing.

7. Conclusions

This paper studies the role of the accumulation and market power narratives as two possible explanations for the decline of the labor share in the manufacturing. By estimating sectoral production functions using the system approach, I find that capital and labor are gross complements in production. The elasticity of substitution σ lies between 0.6 and 1 for most sectors.

The magnitude of the estimated σ eliminates the possibility of capital accumulation as the main driving factor behind falling labor shares.

With the estimated parameters of production technology, I quantify the impact of rising market power, reported in recent studies, in explaining the labor share decline across all sectors in manufacturing. I document two main findings. First, absent any rise in markups, the labor share would have remained stable at the post-war level. Given the estimated production technology, the effective contribution of labor to value added predicts a constant labor share throughout the second half of the 20th century.

Second, assuming a rise in markups closely following Barkai (2020), I account that the rise in market power tracks well up to 76 percent of the labor share decline in manufacturing. However, the magnitude of the decline is sensitive to the assumed growth path in markups. When accounting for the path reported by Hall (2018) and De Loecker et al. (2020), I find that the predicted labor share decline is significantly larger than the actual one. As pointed out in Basu (2019), such differences in market power across studies calls for further exploration.

References

Acemoglu, Daron, "Labor- and Capital-Augmenting Technical Change," *Journal of the European Economic Association*, 2003, *1* (1), 1–37.

— and Pascual Restrepo, "Robots and Jobs: Evidence from US labor markets," *NBER Working Paper No. 23285*, 2017.

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Akcigit, Ufuk, Wenjie Chen, Federico Diez, Romain Duval, Philipp Engler, Jiayue Fan, Chiara Maggi, Marina Mendes-Tavares, Daniel Schwarz, Ippei Shiabata, and Carolina Villegas-Sanchez, "Rising Corporate Market Power: Emerging Policy Issues," *IMF Staff Discussion Notes*, 2021, *2021/001.*

Alvarez-Cuadrado, Francisco, Ngo Van Long, and Markus Poschke, "Capital-labor substitution, structural change and the labor income share," *Journal of Economic Dynamics and Control*, February 2018, *87*, 206–231.

Antras, Pol, "Is the US aggregate production function Cobb-Douglas? New estimates of the elasticity of substitution," *Contributions in Macroeconomics*, 2004, *4* (1).

Autor, David and Anna Salomons, "Is Automation Labor Share-Displacing? Productivity Growth, Employment, and the Labor Share," *Brookings Papers on Economic Activity*, 2018, *2018* (1), 1–87.

— , David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen, "The Fall of the Labor Share and the Rise of Superstar Firms," *The Quarterly Journal of Economics*, 2020, *135* (2), 645–709.

Barkai, Simcha, "Declining Labor and Capital Shares," *Journal of Finance*, 2020, *Forthcoming.*

Basu, Susanto, "Are Price-Cost Markups Rising in the United States? A Discussion of the Evidence," *Journal of Economic Perspectives*, August 2019, *33* (3), 3–22.

Bond, Steve, Arshia Hashemi, Greg Kaplan, and Piotr Zoch, "Some Unpleasant Markup Arithmetic: Production Function Elasticities and their Estimation from Production Data," Technical Report w27002, National Bureau of Economic Research, Cambridge, MA April 2020.

Chirinko, Robert S., "σ: The long and short of it," *Journal of Macroeconomics*, 2008, *30* (2), 671–686.

Dao, Mai, Mitali Das, Zsoka Koczan, and Weicheng Lian, "Why is Labor Receiving a Smaller Share of Global Income? Theory and Empirical Evidence," *IMF Working Paper No. 17/169*, 2017.

Diamond, Peter, Daniel McFadden, and Miguel Rodriguez, "Measurement of the Elasticity of Factor Substitution and Bias of Technical Change," in "Production Economics: A Dual Approach to Theory and Applications" Melvyn Fuss and Daniel McFadden, eds. 1978.

Diez, Federico, Jiayue Fan, and Carolina Villegas-Sanchez, "Global declining competition?," *Journal of International Economics*, 2021, *132* (103492).

Doraszelski, Ulrich and Jordi Jaumandreu, "Using Cost Minimization to Estimate Markups," *Working Paper*, 2019.

Eden, Maya and Paul Gaggl, "On the welfare implications of automation," *Review of Economic Dynamics*, July 2018, *29*, 15–43.

Elsby, Michael WL, Bart Hobijn, and Ayşegül Şahin, "The decline of the US labor share," *Brookings Papers on Economic Activity*, 2013, *2013* (2), 1–63.

Fair, Ray C., "The Estimation of Simultaneous Equation Models with Lagged Endogenous Variables and First Order Serially Correlated Errors," *Econometrica*, May 1970, *38* (3), 507.

Frieling, Julius and Reinhard Madlener, "Estimation of Substitution Elasticities in Three-Factor Production Functions: Identifying the Role of Energy," *Working Paper*, 2016.

Gechert, Sebastian, Tomas Havranek, Zuzana Irsova, and Dominika Kolcunova, "Measuring capital-labor substitution: The importance of method choices and publication bias," *Review of Economic Dynamics*, July 2022, *45*, 55–82.

Glover, Andrew and Jacob Short, "Demographic Origins of the Decline in Labor's Share," *Working Paper*, 2018.

_ and _ , "Can Capital Deepening Explain the Global Decline in Labor's Share?," *Review of Economic Dynamics*, 2019, *Forthcoming.*

Grossman, Gene M. and Ezra Oberfield, "The Elusive Explanation of the Declining Labor Share," *Annu. Rev. Econ. 14*, 2022.

_ , Elhanan Helpman, Ezra Oberfield, and Thomas Sampson, "Balanced Growth Despite Uzawa," *American Economic Review*, April 2017, *107* (4), 1293–1312.

_ , _ , _ , and _ , "The Productivity Slowdown and the Declining Labor Share: A Neoclassical Exploration," *Working Paper*, 2017.

Gutiérrez, Germán and Thomas Philippon, "Declining Competition and Investment in the U.S.," Technical Report w23583, National Bureau of Economic Research, Cambridge, MA July 2017.

_ and _ , "Investment-less Growth: An Empirical Investigation," *Brookings Papers on Economic Activity*, 2017, (Fall).

Hall, Robert, "Using Empirical Marginal Cost to Measure Market Power in the US Economy," Technical Report w25251, National Bureau of Economic Research, Cambridge, MA November 2018.

Herrendorf, Berthold, Christopher Herrington, and Ákos Valentinyi, "Sectoral Technology and Structural Transformation," *American Economic Journal: Macroeconomics*, October 2015, *7* (4), 104–133.

Ho, Sui-Jade and Dimitrije Ruzic, "Returns to Scale, Productivity Measurement, and Trends in U.S. Manufacturing Misallocation," *Working Paper*, 2019.

Hubmer, Joachim, "The Race Between Preferences and Technology," *Working Paper*, 2018.

Jiang, Wei and Miguel León-Ledesma, "Variable markups and capital-labor substitution," *Economics Letters*, 2018, *171*, 34–36.

Jorgenson, Dale W., "35 Sector KLEM," *Harvard Dataverse*, 2008.

Jorgenson, Dale Weldeau and Kevin J. Stiroh, "Raising the speed limit: US economic growth in the information age," *Brookings papers on economic activity*, 2000, *2000* (1), 125–210.

Karabarbounis, Loukas and Brent Neiman, "Capital depreciation and labor shares around the world: measurement and implications," Technical Report, National Bureau of Economic Research 2014.

— and — , "The Global Decline of the Labor Share," *The Quarterly Journal of Economics*, February 2014, *129* (1), 61–103.

Kehrig, Matthias and Nicolas Vincent, "The Micro-Level Anatomy of the Labor Share Decline," *NBER Working Paper No. 25275*, 2017, (124).

Klump, Rainer, Peter McAdam, and Alpo Willman, "Factor substitution and factor-augmenting technical progress in the United States: a normalized supply-side system approach," *The Review of Economics and Statistics*, 2007, *89* (1), 183–192.

Knoblach, Michael, Martin Rössler, and Patrick Zwerschke, "The Elasticity of Factor Substitution Between Capital and Labor in the US Economy: A Meta-Regression Analysis," CEPIE Working Paper No. 03/16 2016.

Koh, Dongya, Raul Santaeulalia-Llopis, and Yu Zheng, "Labor Share Decline and Intellectual Property Products Capital," *Working Paper*, 2018.

Leduc, Sylvain and Zheng Liu, "Are Workers Losing to Robots?," *FRBSF Economic Letter*, 2019, *2019-25.*

León-Ledesma, Miguel A, Peter McAdam, and Alpo Willman, "Identifying the Elasticity of Substitution with Biased Technical Change," *American Economic Review*, September 2010, *100* (4), 1330–1357.

León-Ledesma, Miguel A., Peter McAdam, and Alpo Willman, "Production Technology Estimates and Balanced Growth," *Oxford Bulletin of Economics and Statistics*, February 2015, *77* (1), 40–65.

Loecker, Jan De, Jan Eeckhout, and Gabriel Unger, "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal of Economics*, January 2020, *135* (2), 561–644.

Oberfield, Ezra and Devesh Raval, "Micro Data and Macro Technology," 2019.

O'Mahony, Mary and Marcel P. Timmer, "Output, input and productivity measures at the industry level: the EU KLEMS database," *The Economic Journal*, 2009, *119* (538), F374–F403.

Philippon, Thomas, *The Great Reversal: How America Gave Up on Free Markets*, Belknap Press: An Imprint of Harvard University Press, 2019.

Piketty, Thomas, *Capital in the Twenty-First Century*, Harvard University Press, 2014.

_ and Gabriel Zucman, "Capital is Back: Wealth-Income Ratios in Rich Countries 1700-2010," *Quarterly Journal of Economics*, 2014, *129* (3), 1255:1310.

Ray, Debraj and Dilip Mookherjee, "Growth, Automation and the Long Run Share of Labor," *NBER Working Paper No. 26658*, 2019.

Rognlie, Matthew, "Deciphering the fall and rise in the net capital share: accumulation or scarcity?," *Brookings papers on economic activity*, 2015, *2015* (1), 1–69.

Stansbury, Anna and Lawrence Summers, "The Declining Worker Power Hypothesis: An explanation for the recent evolution of the American economy," Technical Report 27193, National Bureau of Economic Research May 2020.

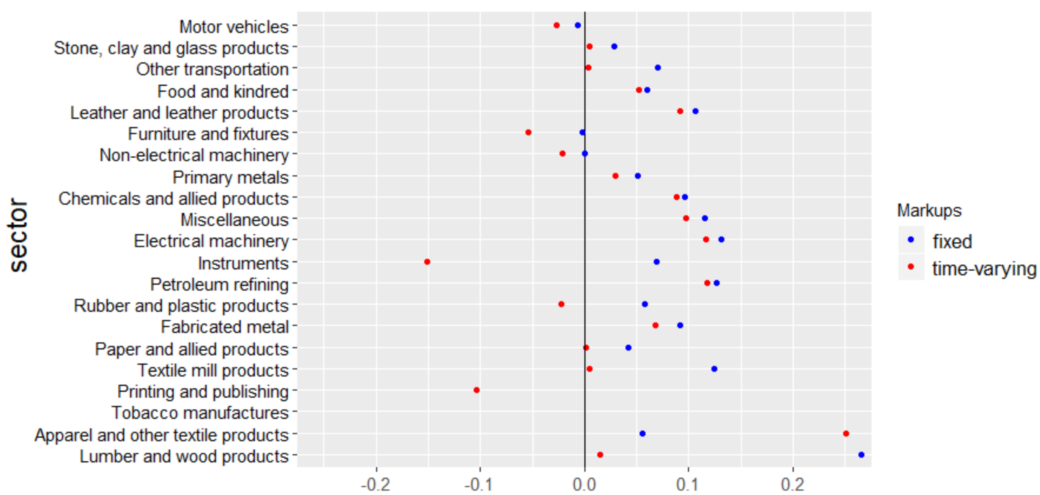
Traina, James, "Is Aggregate Market Power Increasing? Production Trends Using Financial Statements," *Stiegler Center Working Paper Series*, 2018, (17).

Uzawa, H., "Neutral Inventions and the Stability of Growth Equilibrium," *The Review of Economic Studies*, February 1961, *28* (2), 117.

Zellner, Arnold and H. Theil, "Three-Stage Least Squares: Simultaneous Estimation of Simultaneous Equations," *Econometrica*, 1962, *30* (2), 54–78.

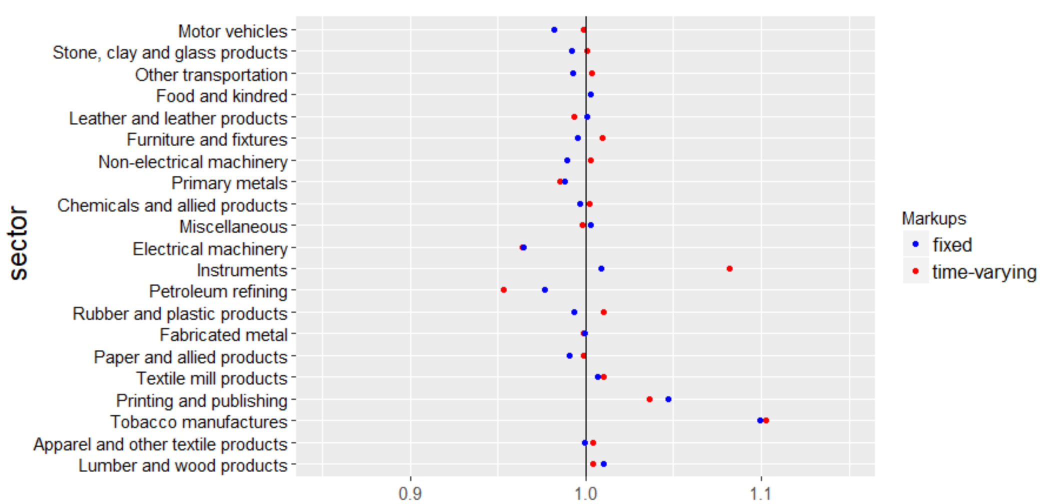
Appendix

Figure 9: Net technical progress $\hat{\alpha}_L - \hat{\alpha}_K$



Note: Each point corresponds to net technical progress $\hat{\alpha}_L - \hat{\alpha}_K$ in each sector. Red estimates include time-varying markups in the specification, while blue estimates assume them constant.

Figure 10: Normalization constant ψ



Note: Each point estimate corresponds to the normalization constant ψ in each sector using the system approach. Red estimates include time-varying markups in the specification, while blue estimates assume them constant. See also the results in Tables 2 and 3.

Table 2: System estimation with time-varying markups (NL3SLS)

ID	σ	α_L	α_K	ψ	ldrcov
1	0.76	0.036	-0.016	1.003	-18.084
	(0.015)	(0.002)	(0.003)	(0.005)	
2	0.986	-0.348	0.187	1.103	-17.441
	(0.006)	(0.087)	(0.055)	(0.020)	
3	0.947	0.023	0.018	1.010	-21.213
	(0.009)	(0.005)	(0.015)	(0.004)	
4	1.02	0.057	-0.194	1.004	-13.745
	(0.025)	(0.034)	(0.161)	(0.012)	
5	1.884	0.009	-0.006	1.004	-17.952
	(0.048)	(0.001)	(0.004)	(0.002)	
6	0.766	-0.003	0.051	1.010	-16.111
	(0.029)	(0.002)	(0.009)	(0.007)	
7	0.945	0.005	0.004	0.999	-19.284
	(0.028)	(0.010)	(0.018)	(0.006)	
8	0.961	-0.032	0.072	1.037	-19.287
	(0.013)	(0.012)	(0.033)	(0.008)	
9	0.852	0.05	-0.039	1.002	-19.768
	(0.004)	(0.003)	(0.002)	(0.003)	
10	0.882	0.071	-0.046	0.953	-12.954
	(0.009)	(0.013)	(0.010)	(0.018)	
11	0.908	0.006	0.029	1.010	-20.738
	(0.007)	(0.002)	(0.006)	(0.003)	
12	0.763	0.03	-0.062	0.993	-15.725
	(0.053)	(0.003)	(0.009)	(0.007)	
13	0.691	0.007	0.002	1.000	-17.473
	(0.007)	(0.001)	(0.002)	(0.002)	
14	0.822	0.015	-0.014	0.986	-16.162
	(0.010)	(0.005)	(0.008)	(0.006)	
15	0.91	0.024	-0.044	0.999	-20.359
	(0.007)	(0.003)	(0.008)	(0.004)	
16	0.815	0.027	0.048	1.002	-15.437
	(0.005)	(0.002)	(0.005)	(0.006)	
17	0.864	0.082	-0.034	0.964	-13.792
	(0.009)	(0.006)	(0.013)	(0.016)	
18	0.687	-0.004	0.023	0.999	-13.073
	(0.026)	(0.004)	(0.005)	(0.010)	
19	0.722	0.006	0.003	1.003	-15.808
	(0.009)	(0.001)	(0.005)	(0.003)	
20	0.868	-0.011	0.14	1.082	-14.605
	(0.025)	(0.006)	(0.029)	(0.015)	
21	0.858	0.039	-0.058	0.998	-18.056
	(0.011)	(0.003)	(0.006)	(0.006)	

This table shows the estimation of all parameters in the system and its respective standard errors using NL3SLS including time-varying markups. Observations: 44 for each sector. Standard errors in parentheses. Sector refers to the sector ID (see Table 1 for the name of each sector). ldrcov refers to log of the determinant of the residual covariance matrix.

Table 3: System estimation with fixed markups (NL3SLS)

ID	σ	α_L	α_K	ψ	ldrcov
1	0.668	0.039	-0.021	1.003	-17.375
	(0.018)	(0.002)	(0.003)	(0.005)	
2	0.994	-0.572	0.327	1.099	-18.565
	(0.004)	(0.215)	(0.136)	(0.019)	
3	0.926	0.052	-0.073	1.007	-20.215
	(0.018)	(0.006)	(0.018)	(0.006)	
4	0.464	0.022	-0.034	0.999	-20.477
	(0.004)	(0.001)	(0.001)	(0.001)	
5	0.972	0.084	-0.182	1.010	-18.619
	(0.010)	(0.022)	(0.051)	(0.014)	
6	0.653	0.008	0.01	0.995	-20.224
	(0.007)	(0.001)	(0.003)	(0.002)	
7	0.807	0.019	-0.023	0.990	-20.693
	(0.012)	(0.002)	(0.004)	(0.003)	
8	0.997	0.259	-0.774	1.047	-20.751
	(0.003)	(0.145)	(0.421)	(0.011)	
9	0.797	0.053	-0.043	0.997	-18.254
	(0.008)	(0.003)	(0.002)	(0.005)	
10	0.847	0.077	-0.05	0.977	-12.721
	(0.010)	(0.008)	(0.007)	(0.017)	
11	0.864	0.024	-0.034	0.993	-20.108
	(0.012)	(0.003)	(0.009)	(0.004)	
12	0.670	0.033	-0.073	1.001	-15.463
	(0.039)	(0.002)	(0.006)	(0.007)	
13	0.626	0.013	-0.014	0.992	-18.217
	(0.005)	(0.002)	(0.002)	(0.002)	
14	0.772	0.021	-0.03	0.988	-15.572
	(0.013)	(0.003)	(0.005)	(0.007)	
15	0.768	0.031	-0.061	0.999	-19.106
	(0.010)	(0.001)	(0.003)	(0.004)	
16	0.868	0.034	0.034	0.989	-19.714
	(0.002)	(0.003)	(0.006)	(0.003)	
17	0.791	0.087	-0.044	0.964	-13.05
	(0.011)	(0.004)	(0.008)	(0.014)	
18	0.65	0.003	0.009	0.982	-14.248
	(0.015)	(0.004)	(0.004)	(0.006)	
19	0.783	0.016	-0.054	0.993	-18.308
	(0.006)	(0.002)	(0.007)	(0.003)	
20	1.661	0.024	-0.045	1.009	-17.797
	(0.042)	(0.001)	(0.005)	(0.003)	
21	0.775	0.044	-0.071	1.002	-17.589
	(0.011)	(0.002)	(0.003)	(0.005)	

This table shows the estimation of all parameters in the system and its respective standard errors using NL3SLS assuming fixed markups. Observations: 44 for each sector. Standard errors in parentheses. Sector refers to the sector ID (see Table 1 for the name of each sector). ldrcov refers to log of the determinant of the residual covariance matrix.