

# Inside the decline of the labor share: technical change, market power, and structural change\*

Sergio Feijoo Moreira<sup>†</sup>

University of Bristol

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## Abstract

This paper documents substantial industry-level heterogeneity in the decline of the U.S. labor share and its main components: employment, wages, and value added. The decline is also contemporaneous with a strong process of structural change between manufacturing and services. I analyze both phenomena through the lens of a multi-sector model where sector-specific changes in market power and capital-biased technical change – the most prominent explanations for the declining labor share – also characterize the process of structural change between sectors. I show that increasing market power, which is pervasive across manufacturing and services, accounts for almost two-thirds of the decline in the labor share. Technical change explains the remaining third and is the fundamental driver of structural change between sectors.

**JEL Codes:** O30, O40, O41.

**Keywords:** Labor share decline, capital-biased technical change, market power, structural change.

## 1 Introduction

A decades-long decline in the labor share – the part of national income allocated to labor compensation – has recently been receiving a great deal of attention in the literature

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<sup>†</sup>Address: University of Bristol, School of Economics. The Priors Road Complex, Priors Road, Bristol, BS8 1TU. E-mail: [sergio.feijoo@bristol.ac.uk](mailto:sergio.feijoo@bristol.ac.uk). Web: <https://sergiofeijoo.github.io>.

(Elsby, Hobijn and Sahin, 2013, Karabarbounis and Neiman, 2014, Koh, Santaeuilàlia-Llopis and Zheng, 2020). This decline has been substantially stronger in manufacturing than in service industries and contemporaneous with a process of structural change that has reallocated employment and capital stock from the former to the latter. Although several theories have been proposed to explain the decline in the labor share, its main underlying causes remain unclear. In this sense, it is important to consider how the process of structural change has interacted with other potential causes of the decline in the labor share. In this paper, I build a multi-sector model of structural change and show, both empirically and quantitatively, that the factors that contribute to the process of structural change also explain the decline in the labor share.

A declining labor share raises many relevant macroeconomic and policymaking concerns. For example, it can indicate lower average labor compensation growth relative to labor productivity, leading to increasing inequality and declining consumer purchasing power. As a consequence, it is crucial to understand the reasons underlying the decline.<sup>1</sup> In this paper, I analyze industry-level data from the [U.S. Bureau of Economic Analysis \(2020\)](#) to document the evolution of the U.S. labor share and its main components from 1998 to 2016.<sup>2</sup> At the same time, I examine the contemporaneous process of structural change characterized by the relative reallocation of production inputs – employment and capital stock – from manufacturing to service industries, and the increasing contribution to value added generation of the latter. This analysis establishes the following facts:

1. The evolution of the labor share has been substantially heterogeneous across industries. The (linear) trend of the labor share shows a steeper decline in manufacturing than in services, resulting in a roughly five times larger decline. Moreover, analyzing the main components of the labor share reveals that in manufacturing the average wage has grown at a faster rate than value added, while employment has declined. In contrast, employment in services has increased, and value added has grown at a faster rate than the average wage.
2. There has been a strong (relative) reallocation of labor and capital from manufacturing to service industries and the contribution of services to total value added has increased.
3. Substantial capital deepening has taken place, with the capital-labor ratio of the

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<sup>1</sup>For example, for the design of optimal fiscal policy ([Atesagaoglu and Yazici, 2020](#)).

<sup>2</sup>This is an especially interesting period to consider as the labor share has unambiguously declined regardless of the capitalization of intellectual property products in the national income and product accounts ([Koh et al., 2020](#)). Moreover, although previous research abstracting from capitalization of IPP has established that the decline of the labor share may have already started in the early 1980s, more than half of the decline has taken place since the late 1990s. Besides, the labor share has also declined in some EU countries, as shown in ([Karabarbounis and Neiman, 2014](#)) or ([Kostarakos, 2020](#)).

U.S. economy (in real 2009\$ per hour worked) increasing from 69.5\$/h in 1998 to 91.4\$/h in 2016.<sup>3</sup>

While similar facts have already been documented using different data sources and there has been a substantial effort in understanding the decline, the literature is still far from reaching a consensus when it comes to isolating its main causes. In this sense, previous literature has highlighted two main reasons that underlie the decline in the labor share: technical change (e.g. in the form of automation)<sup>4</sup> and changes in market power (reflected in the increasing profits and concentration of firms)<sup>5</sup>. However, as the labor share of an economy can be computed by appropriately weighting industry-level labor shares, the previous analysis highlights an additional source of variation for the labor share. Provided that the labor shares of manufacturing and services have experienced different declines, an increase in the relative importance of services in the production of total value added will be reflected in the economy's labor share. Therefore, the strong process of structural change from manufacturing to services has a clear effect on the overall decline of the labor share.

In this paper, I develop a two-sector model of structural change – an extended version of the [Álvarez-Cuadrado, Long and Poschke \(2017, 2018\)](#) framework – which stresses the role of the supply side on the process of structural change. Specifically, the model allows for industry-specific technical change and production technology differences across industries. I enrich this framework by incorporating heterogeneous competition levels across sectors, which I model as the ability to charge (exogenous) industry-specific time-varying markups. Consequently, industry-specific technical change, production technology differences, and heterogeneous markups across industries can explain structural change and the evolution of the labor share at the industry and aggregate level. While the effect of markups in explaining the decline of the labor share is well known and has been already studied in ([Karabarbounis and Neiman, 2014](#)) or ([Barkai, 2020](#)), the novel part of the model is that markups can also play a role in explaining structural change. The idea is simple: if one industry can charge higher markups than others, it will affect the relative price between industries. Therefore, higher prices driven by higher markups in one industry will affect the quantity demanded of output from other industries as long as they are (at least) partially substitutable.

According to the theory, technical change and market power can individually deliver industry-level declines in the labor share. However, given the substantial heterogeneity in the decline between manufacturing and services, it is crucial to consider structural

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<sup>3</sup>Capital excludes residential assets and publicly-owned capital.

<sup>4</sup>Some examples are ([Acemoglu and Restrepo, 2019](#)), ([Hémous and Olsen, 2021](#)) or ([Martínez, 2021](#)).

<sup>5</sup>See, among others, ([Autor, Dorn, Katz, Patterson and Van Reenen, 2020](#)), ([Barkai, 2020](#)) or ([De Loecker and Eeckhout, 2021](#)).

change when considering sectoral changes over time. Structural change offers an additional source of variation that allows the joint evolution of technical change and market power over time to be characterized. In particular, the observed process of structural change imposes structure on the evolution of technical change and market power across sectors while delivering a labor share decline consistent with those in the data. The model is intentionally reduced to the main elements that are quantitatively relevant. In this sense, it is restricted to intra-temporal decisions and abstracts from the intertemporal dimension. In other words, I consider a static allocative equilibrium model repeatedly: given an endowment of capital stock and labor, the solution of the model reduces to determining the equilibrium allocations of capital and labor across sectors, abstracting from capital accumulation or labor supply decisions.

I use the model to quantify the contribution of technical change and market power to the decline in the U.S. labor share (both at the aggregate and industry level) and the process of structural change over the last two decades. The quantitative analysis is conducted as follows. First, I obtain the time series of the stock of capital and labor from the data and feed them period-by-period into the model as an endowment. I assume that the deep parameters governing consumption and production are fixed. By contrast, technical change and market power parameters can vary over time. Second, by repeatedly using the first-order and market clearing conditions that characterize the static equilibrium, I retrieve the evolution of technical change and market power that match quantitatively the evolution of both industry labor shares and the process of structural change between sectors. I find that the increase in markups in the manufacturing and service industries is the main reason underlying the decline. Specifically, market power accounts for 64.1% of the decline, being more relevant in manufacturing. The remaining part of the decline is produced by capital-biased technical change,<sup>6</sup> which becomes more important in explaining the decline in the labor share after 2008, especially in service industries. Although market power affects the pace of structural change from manufacturing to services, technical change is its fundamental driver.

Finally, I show that these findings are robust under different estimates of the elasticity of substitution between capital and labor in the production function of manufacturing and service goods. Moreover, given the relevance that previous literature usually attributes to technical change, I consider different assumptions regarding the evolution of market power over time and conclude that without time-varying markups it is not possible to reconcile the heterogeneous labor share decline observed in the data.

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<sup>6</sup>That is, the evolution of technology is such that it increases the relative productivity of capital with respect to labor.

**Literature review.** This paper contributes to the literature on the labor share decline, which is frequently related to technical change in various forms, e.g. the continuously increasing capabilities of computers, artificial intelligence, and robots. Although technological change has always enabled the substitution of human labor for that performed by machines, some recent papers (e.g. [Hémous and Olsen, 2021](#), [Acemoglu and Restrepo, 2019, 2020](#), [Martínez, 2021](#)), develop models with automation and the creation of new tasks in which labor has a comparative advantage, and study the dynamic properties of these environments and implications for the labor share. In this line of research, [Frey and Osborne \(2017\)](#) and [Arntz, Gregory and Zierahn \(2016\)](#) try to quantify the risks of automation and computerization by estimating which activities are more likely to be automated. More recently, the reduction in competition, allowing firms to increase their profits, has been related to the decline in the labor share. For example, [Autor et al. \(2020\)](#) highlight the correlation of the concentration of market share among the so-called superstar firms with the labor share decline. [Barkai \(2020\)](#) documents that the decline in the labor share is further accompanied by a decline in the capital share, and an increase in the profit share. Investigating at firm-level, [De Loecker, Eeckhout and Unger \(2020\)](#) and [De Loecker and Eeckhout \(2021\)](#) document an increase in markups, which is consistent with the decrease in the labor share. In this paper, I document substantial heterogeneity in the decline of the labor share at the industry level and contribute to this literature by developing a multi-sector model where I exploit this heterogeneity to measure the contribution of technical change and market power to the labor share decline both at the industry and aggregate level.<sup>7</sup>

This paper also contributes to the literature on structural change, starting from the seminal contributions of [Ngai and Pissarides \(2007\)](#) and [Acemoglu and Guerrieri \(2008\)](#) that highlight the role of uneven sectoral growth rates across sectors, differences in total factor productivity across sectors, and capital deepening with differences in factor proportions. The industry-level labor share heterogeneity is key to understanding the relationship between the declining labor share and structural change over the last two decades. In this sense, when considering sectoral changes over time, structural change has to be considered at the same time. In this paper, I build upon the [Álvarez-Cuadrado et al. \(2017\)](#) model which further shows that cross-sectoral differences in the substitutability of capital and labor can also have implications for structural change. I contribute to this literature by showing that industry-level changes in the levels of competition affect

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<sup>7</sup>Although this paper is not the first to use industry-level data to analyze the evolution of the labor share (see, e.g. [Diez-Catalan, 2018](#), [Kehrig and Vincent, 2021](#), [Álvarez-Cuadrado et al., 2018](#)) it is, to the best of my knowledge, the first paper that decomposes each industry's labor share into its main components (wage, employment, and value added) and documents their heterogeneous evolution at the industry-level.

the relative allocation of capital and labor across industries and, consequently, the final production of goods. In other words, differences in competition across industries affect the pace of structural change.

**Layout.** This paper is organized as follows. In Section 2, I document the evolution of the main components of the labor share and the process of structural change. In Section 3, I set out the model. In Section 4, I conduct the quantitative analysis. Section 5, concludes. The Appendix includes additional evidence on the decline of the labor share, additional results of the model, and further validation for the quantitative analysis results.

## 2 Labor share and structural change in the U.S.

In this paper, I use data from the online public interactive database published by the [U.S. Bureau of Economic Analysis \(2020\)](#). In particular, I gather aggregate data for the U.S. from 1947 to 2016 and industry-level data for 67 industries from 1998 to 2016. This section establishes a series of facts regarding the evolution of the labor share and the contemporaneous structural change process that has taken place over the last two decades.

### 2.1 Labor share

Several methodologies can be used to compute the labor share.<sup>8</sup> In this section, I follow [Koh et al. \(2020\)](#) – ultimately based on [Cooley and Prescott \(1995\)](#) – by measuring the share of ambiguous income, i.e., the share of income that cannot be unambiguously assigned either to capital or labor, and I distribute this proportionally to the unambiguous retribution of capital and labor.<sup>9</sup> The evolution of the trend of the labor share for the overall economy turns out to be qualitatively similar and quantitatively very close to the evolution of the trend of the naive labor share (namely, compensation of employees over value added), which is much simpler to compute. One of the main drawbacks of using industry-level data is the lack of consistency in the industry definitions, which precludes from obtaining long time series without altering the original data.<sup>10</sup> Therefore, to compute

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<sup>8</sup>For example, [Valentinyi and Herrendorf \(2008\)](#) that use Input-Output tables, [Elsby et al. \(2013\)](#) that use the compensation of employees and estimate the compensation of the self-employed workers, [Karabarbounis and Neiman \(2014\)](#) that focus on computing the labor share of the corporate sector, avoiding many of the problems related with the imputation of the wages of self-employed workers.

<sup>9</sup>Recent work by [Atkeson \(2020\)](#) casts doubts about the BEA's ability to correctly measure firm's investments.

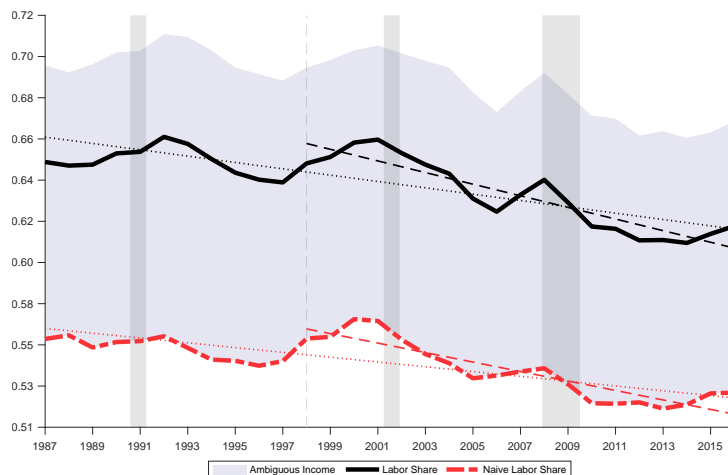
<sup>10</sup>While industry-level data under the Standard Industrial Classification (SIC) classification is available at least from 1947 onwards, the migration to the North American Industry Classification System (NAICS), introduced a break in the time-series data. As [Yuskavage \(2007\)](#) points out, NAICS provides a more

the labor share at the industry-level I use the naive labor share.

### 2.1.1 Aggregate level

Figure 1 shows the U.S. labor share at the aggregate level, the naive labor share, and the share of ambiguous income.<sup>11</sup>

**Figure 1:** U.S. labor income share, 1987 - 2016



*Note:* Vertical shaded areas represent recession periods.

Between 1998 and 2016, the labor share declines from 0.6564 to 0.6030 (an 8.08% reduction), and the naive labor share falls from 0.5625 to 0.5193 (a 7.68% decline). Approximating the time-series of the labor share with a linear trend to compute the labor share variation over a period (fitted change hereafter) yields a decline in the aggregate labor share of 0.0466 (a 7.06% fitted decline), while the naive labor share fell in 0.0353 labor share points during the same period (a 6.27% fitted decline). Together with Figure 1, these results allow the characterization of two aspects of the evolution of the U.S. labor share over the last three decades. First, both labor share measures show a fast decline during this period, which has intensified from 1998 to 2016. Second, the naive labor share qualitatively matches the decline of the labor share. Besides, the declines are quantitatively very close. Ultimately, these findings suggest that the decline of the labor share seems far from being over and has intensified over the last decades.

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consistent classification of establishments into industries based on the similarity of their production processes, rather than considering similarities in the produced output. However, this change in the industry classification hinders the availability of long time series.

<sup>11</sup>Details on the methodology can be found in Appendix A.2.1. Additionally, further results from 1947 to 2016 are shown in Appendix A.2.

### 2.1.2 Industry level

The analysis of the labor share at industry-level bears additional complications due to the data limitations described above. Even in this short and recent period, the industry-level data is not as detailed as the aggregate data, which hinders the computation of the labor share following Koh et al. (2020). To circumvent these complications, I focus on the period from 1998 to 2016. Restricting the analysis to this period is especially interesting for at least two reasons. First, the labor share has unambiguously declined regardless of the capitalization of intellectual property products in the national income and product accounts Koh et al. (2020). This is especially interesting as in the literature there is no agreement as to when the decline in the labor share starts. Second, it enables the exploration of the decline at a disaggregated level with the latest industry-level classification available.

Given the previous findings regarding the aggregate labor share, I rely on the naive labor share to analyze each industry's labor share.<sup>12</sup> Figure 2 shows the resulting manufacturing and service labor shares after aggregating the individual labor shares of all the sub-industries available in the BEA.<sup>13</sup> The decline in manufacturing is much steeper than the one in services: the fitted labor share in manufacturing was 0.5716 in 1998 and 0.4590 in 2016, and thus declined in 0.1126 labor share points during this period (a 19.7% fitted decline), while in services it was 0.6280 in 1998 and 0.6091 in 2016, and thus declined in 0.0189 labor share points during the same period (a 3.01% fitted decline). Given the relative weights of these two industries, the implied labor share declined in 0.0344 labor share points (a 4.48% fitted decline) from 1998 to 2016.<sup>14</sup>

In Appendix A.2, I analyze the evolution of the naive labor share by documenting the evolution of its components: average wage, number of full-time equivalent employees, and the value added generated by each industry. Between 1998 and 2016, manufacturing industries are generally characterized by exhibiting negative employment growth rates, while service industries show positive growth rates. Additionally, value added in service industries grows faster than the average wage, while the opposite happens in manufacturing industries. These observations are remarkably similar for disaggregated manufacturing and service industries. These two findings suggest that the reallocation of workers from

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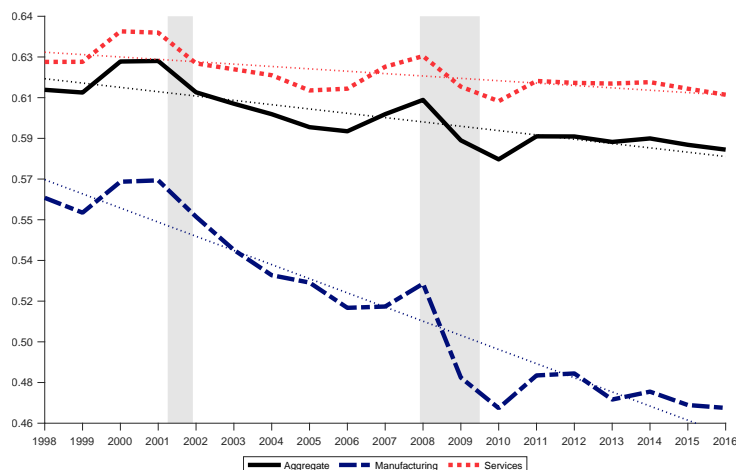
<sup>12</sup>In Appendix A.2 I conduct a detailed analysis for six industries of the U.S. where it is possible to compute the labor share following a similar approach to (Koh et al., 2020) and show that the naive labor share can also deliver a good approximation of the evolution of the true labor share for the period I consider. This is in line with the results of Mućk, McAdam and Growiec (2018).

<sup>13</sup>Following previous literature and given the specific evolution of the real estate industry labor share, I exclude this from service industries. The complete list of industries can be found in Appendix A.1.1.

<sup>14</sup>Note that for the purpose of this paper, restricting the analysis to manufacturing and services (and, as a consequence, omitting agricultural activities, mining, utilities, construction, government, and real estate) only changes the results quantitatively.



**Figure 2:** Naive labor share: manufacturing and service industries, 1998 - 2016



Note: Services exclude Real Estate. The overall implied naive labor share is obtained by aggregating the individual labor shares of all the sub-industries available in the BEA after excluding agricultural activities, mining, utilities, construction, government and real estate industries.

manufacturing to service industries, or structural change, together with the different evolution of wages and value added across industries, may explain the differences in the decline of the labor share across industries.

## 2.2 Structural change

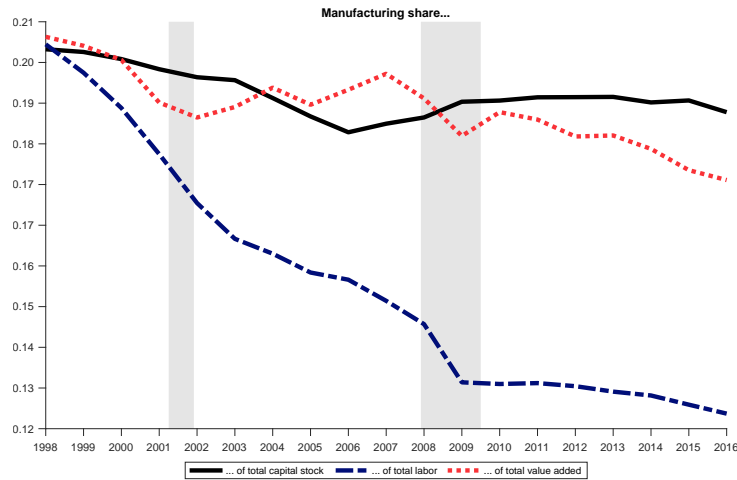
The substantial differences in the growth rates of employment and value added between manufacturing and service industries suggest that contemporaneously to the decline in the labor share, the last two decades have also witnessed an intense structural change period. To examine this, I gather additional data on (non-residential) capital stock and employment from the [U.S. Bureau of Economic Analysis \(2020\)](#).<sup>15</sup>

Figure 3 depicts three series that allow the process of structural change to be evaluated. The solid (black) line represents the share of capital stock in manufacturing with respect to the economy's total capital stock, where the total is the sum of capital in manufacturing and service industries.<sup>16</sup> This relative share has declined slightly over the last two decades, even though the level of the capital stock in manufacturing has increased. The dashed (blue) line represents the share of labor in manufacturing with respect to total labor. The evolution is striking, with a very steep decline implied by the high destruction of employment in manufacturing, as opposed to services, which has grown over the last two decades. The evolution of these two shares shows that there has been an intense relative reallocation of inputs from manufacturing to services. Finally, the dotted (red) line shows

<sup>15</sup>Additional details can be found in Appendix [A.1.2](#).

<sup>16</sup>Total excludes agricultural, mining, utilities, construction, government and real estate industries.

**Figure 3:** Manufacturing share of total capital stock, total labor and total value added, 1998 - 2016



Note: Total excludes agricultural activities, mining, utilities, construction, government and real estate industries.

the share of value added produced by manufacturing industries. The picture is the same from an output perspective, as the contribution of manufacturing to value added has declined over the last two decades.

An implication of the small decline in the share of capital stock employed in manufacturing industries compared to the large reduction in the share of employment is that the capital-labor ratio (in real 2009\$ per hour worked) in manufacturing industries almost doubled during this period, increasing from \$69.3/h in 1998 to \$137.46/h in 2016. As a consequence, the aggregate capital-labor ratio also increased from \$69.5/h in 1998 to \$91.4/h in 2016. Moreover, the capital-output ratio also increased from 1.55 in 1998 to 1.61 in 2016, with a stronger increase in manufacturing, from 1.53 in 1998 to 1.74 in 2016.<sup>17</sup> Before the Great Recession, the capital-output ratios in manufacturing and services were very similar and, despite some fluctuations, remained relatively close. From that point onwards, the two have diverged, staying relatively constant at a higher level in manufacturing and seemingly converging back to its pre-recession level in services.

### 3 Model

In this section, I study how the two main mechanisms that have been put forward to explain the decline in the labor share – technical change and changes in market power – simultaneously affect the process of structural change. I consider a two-sector model where the production side of the economy consists of a single output formed by aggregating manufacturing and service goods. In particular, the model builds upon (Álvarez-Cuadrado

<sup>17</sup>Note that the capital-output ratios exclude residential assets and publicly-owned capital.

et al., 2017, 2018), introducing an intermediate production sector that allows imperfect competition to be modelled in both industries, given by the (exogenous) ability to fix a price equal to a markup over marginal cost. Similar to their model, differences in the evolution of the labor share and structural change across sectors may come from differences in technical change, capital-labor ratios, and differences in the elasticity of substitution between capital and labor or their intensity in the production function. Moreover, the heterogeneous evolution of market power across industries yields two implications. The first one is straightforward and well-known: market power affects the labor share in each industry. The second one is novel: changes in market power across industries can affect the pace of structural change between sectors.

### 3.1 Environment

Time is discrete. At each particular moment in time  $t$ , the economy is formed by a final good and two types of intermediate goods that are produced by aggregating a continuum of differentiated varieties in the unit interval  $i \in [0, 1]$ . In what follows, I describe each agent in detail.

#### 3.1.1 Final good

There is a unique final good in the economy,  $Y_t$ , produced by a single price-taker firm that combines manufacturing goods  $M_t$ , and service goods  $S_t$ , with the technology

$$Y_t = \left[ \gamma M_t^{\frac{\theta-1}{\theta}} + (1-\gamma) S_t^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}},$$

where  $\gamma \in [0, 1]$  and  $\theta \geq 0$  is the elasticity of substitution between manufacturing and service goods. Each of these goods  $J \in \{M, S\}$  is produced by aggregating a continuum of differentiated intermediate inputs  $i \in [0, 1]$ , with the technologies

$$J_t = \left( \int_0^1 j_t(i)^{\frac{\varepsilon_{j,t}-1}{\varepsilon_{j,t}}} di \right)^{\frac{\varepsilon_{j,t}}{\varepsilon_{j,t}-1}}, \quad (1)$$

where  $j_t(i)$ ,  $j \in \{m, s\}$  is the quantity of intermediate variety  $i$  used to produce good  $J$  and  $\varepsilon_{j,t}$  is the time-varying elasticity of substitution across different varieties.

Assuming a perfectly competitive environment, the problem of this firm can be broken into two steps. First, given  $p_{j,t}(i)$ , the price of intermediate variety  $i$  of type  $j$ , the firm optimally chooses  $m_t(i)$  and  $s_t(i)$ ,  $\forall i$ , to minimize the cost of producing some given quantities  $S_t$  and  $M_t$ . Second, given the implied prices  $P_{M,t}$  and  $P_{S,t}$  for manufacturing and service goods, the firm optimally balances  $M_t$  and  $S_t$  to minimize the cost of producing

a given quantity  $Y_t$ . The first step yields the conditional input demand

$$j_t(i) = \left( \frac{p_{j,t}(i)}{P_{J,t}} \right)^{-\varepsilon_{j,t}} J_t, \quad \forall i, \quad J = \{M, S\}, \quad j = \{m, s\}, \quad (2)$$

where  $P_{J,t}$  is the ideal price index.<sup>18</sup> The second step yields the relative demand

$$MRTS_{M,S} = \frac{\gamma}{1-\gamma} \left( \frac{S_t}{M_t} \right)^{\frac{1}{\theta}} = \frac{P_{M,t}}{P_{S,t}}. \quad (3)$$

Normalizing to unity the price of the final good we obtain the price index

$$1 = P_{Y,t} = [\gamma^\theta P_{M,t}^{1-\theta} + (1-\gamma)^\theta P_{S,t}^{1-\theta}]^{\frac{1}{1-\theta}}.$$

### 3.1.2 Intermediate varieties

There exist two types of intermediate goods that are used to produce manufacturing and service goods. Within these two types, there exist a continuum of differentiated varieties in the unit interval  $i \in [0, 1]$ , i.e., each intermediate manufacturing (service) producer supplies an intermediate variety  $m_t(i)$  ( $s_t(i)$ ) which is used as an input in the production of the manufacturing (service) good.

Each variety  $i$  of intermediate type  $j$ , where  $j = m, s$  (henceforth, a pair  $\{i, j\}$ ), is produced using a constant returns to scale technology  $y_{j,t}(i) = F_j[k_{j,t}(i), l_{j,t}(i)]$ . This technology combines capital,  $k_{j,t}(i)$ , rented at a rate  $R_t$ , with labor,  $l_{j,t}(i)$ , hired at a wage  $W_t$ . Each producer of a pair  $\{i, j\}$  takes input prices and aggregate demand as given. Intermediate varieties are produced under monopolistic competition, thus each producer will find it optimal to sell at a price equal to a markup over marginal cost. I assume that the technology for producing a pair  $\{i, j\}$  is given by the constant elasticity of substitution production function

$$y_{j,t}(i) = A_{j,t} \left[ \alpha_j [\tilde{B}_{j,t} k_{j,t}(i)]^{\frac{\sigma_j-1}{\sigma_j}} + (1-\alpha_j) [l_{j,t}(i)]^{\frac{\sigma_j-1}{\sigma_j}} \right]^{\frac{\sigma_j}{\sigma_j-1}}, \quad \forall i \quad j \in \{m, s\},$$

where  $\sigma_j$  is the elasticity of substitution between capital and labor,  $\alpha_j$  is the distributional parameter,  $A_{j,t}$  denotes Hicks-neutral technical change, and  $\tilde{B}_{j,t}$  denotes the factor imbalance of technical change.<sup>19</sup> The profit-maximization problem of the intermediate

<sup>18</sup>As is standard with Dixit-Stiglitz aggregators, the price  $P_{J,t}$  is given by

$$P_{J,t} = \left( \int_0^1 p_{j,t}(i)^{1-\varepsilon_{j,t}} di \right)^{\frac{1}{1-\varepsilon_{j,t}}}.$$

<sup>19</sup>This specification implies that if the imbalance is negative (positive), then technical change is capital-

producer of pair  $\{i, j\}$  is characterized by the equations

$$p_{j,t}(i)F_{j,t}^k(i) = \frac{\varepsilon_{j,t}}{\varepsilon_{j,t} - 1}R_t = \mu_{j,t}R_t, \quad (4)$$

$$p_{j,t}(i)F_{j,t}^l(i) = \frac{\varepsilon_{j,t}}{\varepsilon_{j,t} - 1}W_t = \mu_{j,t}W_t, \quad (5)$$

where  $p_{j,t}(i)$  is the price of the variety pair  $\{i, j\}$ ,  $F_{j,t}^k(i)$  ( $F_{j,t}^l(i)$ ) is the marginal product of capital (labor), and

$$\mu_{j,t} = \frac{\varepsilon_{j,t}}{\varepsilon_{j,t} - 1}, \quad (6)$$

is the (sector-specific) markup over factor prices that, directly depends on the elasticity of substitution between varieties. Profits earned by the variety producer of pair  $\{i, j\}$  represent a constant share of output sold, given by

$$\pi_{j,t}(i) = \frac{1}{\varepsilon_{j,t}}p_{j,t}(i)y_{j,t}(i).$$

### 3.2 Static Allocation

I assume that an exogenous supply of capital  $K_t$  and labor  $L_t$  flow into the economy each period, and that there is no capital accumulation. This assumption allows me to characterize a period-by-period static allocation as in [Acemoglu and Guerrieri \(2008\)](#) and [Álvarez-Cuadrado et al. \(2017\)](#).<sup>20</sup> In this sense, the concept of equilibrium for the purpose of this paper is reduced to finding output prices  $P_m, P_s$ ; input prices  $R_t, W_t$ ; outputs  $M_t, S_t$ ; and allocations of inputs across sectors  $K_m, L_m, K_s, L_s$ ; that clear the labor and capital markets (with exogenously given  $K_t$  and  $L_t$  supplies). As the environment across varieties in the production of intermediates is symmetric, it follows that the static equilibrium satisfies  $m_t(i) = y_{m,t}(i) = M_t$ ,  $s_t(i) = y_{s,t}(i) = S_t$ ,  $p_{m,t}(i) = P_{m,t}$ ,  $p_{s,t}(i) = P_{s,t}$ ,  $k_{m,t}(i) = K_{m,t}$ , and  $k_{s,t}(i) = K_{s,t}$ , for all  $i$  and  $t$ . I define

$$k_t = \frac{K_t}{L_t}, \quad \kappa_t = \frac{K_{m,t}}{K_t}, \quad \lambda_t = \frac{L_{m,t}}{L_t}, \quad (7)$$

as the capital-labor ratio of the economy and the shares of capital and labor allocated to the production of the manufacturing good, respectively. The static equilibrium can then

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be biased (labor-biased) as it decreases (increases) the marginal productivity of capital with respect to labor.

<sup>20</sup>The analysis could be extended by including a typical representative household. The equilibrium could then be broken into two parts: first the static model shown in this section and second a dynamic problem of capital accumulation. [Álvarez-Cuadrado et al. \(2017\)](#) also study the dynamic version of such a model (without markups).

be summarized in the system of equations

$$\frac{1 - \alpha_s}{1 - \alpha_m} \frac{\alpha_m}{\alpha_s} \frac{\tilde{B}_{m,t}^{\frac{\sigma_m-1}{\sigma_m}}}{\tilde{B}_{s,t}^{\frac{\sigma_s-1}{\sigma_s}}} k_t^{\frac{1}{\sigma_s} - \frac{1}{\sigma_m}} \left( \frac{1 - \kappa_t}{1 - \lambda_t} \right)^{\frac{1}{\sigma_s}} \left( \frac{\lambda_t}{\kappa_t} \right)^{\frac{1}{\sigma_m}} = 1, \quad (8)$$

$$\frac{1 - \gamma}{\gamma} \frac{\mu_{m,t}}{\mu_{s,t}} \frac{1 - \alpha_s}{1 - \alpha_m} \left( \frac{A_{s,t}}{A_{m,t}} \right)^{\frac{\theta-1}{\theta}} \frac{g_{m,t}(\kappa_t, \lambda_t, k_t)^{\frac{1}{\theta} - \frac{1}{\sigma_m}}}{g_{s,t}(\kappa_t, \lambda_t, k_t)^{\frac{1}{\theta} - \frac{1}{\sigma_s}}} k_t^{\frac{1}{\sigma_s} - \frac{1}{\sigma_m}} \frac{\lambda^{\frac{1}{\sigma_m}}}{(1 - \lambda_t)^{\frac{1}{\sigma_s}}} = 1, \quad (9)$$

where

$$g_{m,t}(\kappa_t, \lambda_t, k_t) = \left[ \alpha_m \left( \tilde{B}_{m,t} \kappa \right)^{\frac{\sigma_m-1}{\sigma_m}} + (1 - \alpha_m) \left( \frac{\lambda}{k_t} \right)^{\frac{\sigma_m-1}{\sigma_m}} \right]^{\frac{\sigma_m}{\sigma_m-1}},$$

$$g_{s,t}(\kappa_t, \lambda_t, k_t) = \left[ \alpha_s \left( \tilde{B}_{s,t} (1 - \kappa_t) \right)^{\frac{\sigma_s-1}{\sigma_s}} + (1 - \alpha_s) \left( \frac{1 - \lambda_t}{k_t} \right)^{\frac{\sigma_s-1}{\sigma_s}} \right]^{\frac{\sigma_s}{\sigma_s-1}}.$$

The static equilibrium reduces to finding the (unique) solution of the contract curve (8) and the labor mobility condition (9) in the  $(\kappa, \lambda)$  space given  $k_t$  and a set of values for the parameters.<sup>21</sup> The static equilibrium shares the same comparative static properties concerning capital deepening and changes in technical change parameters shown in [Álvarez-Cuadrado et al. \(2017\)](#). As a consequence, I focus on the novel properties of this static model. Once  $\kappa_t$  and  $\lambda_t$  are determined, it is straightforward to obtain the remaining components of the equilibrium and characterize any moment of interest from the model. Consider first the labor share. Given that both intermediate firms exhibit constant returns to scale, from the profit maximizing condition of intermediate producers it follows that

$$J_t = \frac{\mu_{j,t}}{P_{j,t}} (R_t K_{j,t} + W_t L_{j,t}),$$

which allows the sectoral shares of labor  $s_{J,t}^L$ , capital  $s_{J,t}^K$ , and profits  $s_{J,t}^\Pi$  to be defined as

$$s_{J,t}^L = \frac{W_t L_{j,t}}{P_{j,t} J_t} = \frac{W_t L_{j,t}}{\mu_{j,t} (R_t K_{j,t} + W_t L_{j,t})},$$

$$s_{J,t}^K = \frac{R_t K_{j,t}}{P_{j,t} J_t} = \frac{R_t K_{j,t}}{\mu_{j,t} (R_t K_{j,t} + W_t L_{j,t})},$$

$$s_{J,t}^\Pi = 1 - s_{j,t}^K - s_{j,t}^L = 1 - \frac{1}{\mu_{j,t}},$$

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<sup>21</sup>See Appendix A.3 for a step-by-step derivation of (8) and (9), and [Álvarez-Cuadrado et al. \(2017\)](#) for a detailed discussion on the uniqueness of the solution.

with  $j \in \{m, s\}$  and  $J \in \{M, S\}$ .<sup>22</sup> These shares can also be expressed as

$$s_{J,t}^L = \frac{W_t L_{j,t}}{P_{j,t} J_t} = \frac{1}{\mu_{j,t}} \epsilon_{J,t}^L, \quad (10)$$

$$s_{J,t}^K = \frac{R_t K_{j,t}}{P_{j,t} J_t} = \frac{1}{\mu_{j,t}} \epsilon_{J,t}^K, \quad (11)$$

where

$$\begin{aligned} \epsilon_{J,t}^L &\equiv (1 - \alpha_j) \left( \frac{A_{j,t} L_{j,t}}{J_t} \right)^{\frac{\sigma_j - 1}{\sigma_j}}, \\ \epsilon_{J,t}^K &\equiv \alpha_j \left( \frac{A_{j,t} \tilde{B}_{j,t} K_{j,t}}{J_t} \right)^{\frac{\sigma_j - 1}{\sigma_j}}, \end{aligned}$$

are the sectoral elasticities of output with respect to labor,  $\epsilon_{J,t}^L$ , or capital,  $\epsilon_{J,t}^K$ , at time  $t$ . Note that both markups and technology parameters characterize the level of the labor share in each sector.

Now define the relative share of labor income as

$$\frac{s_{J,t}^L}{s_{J,t}^K} = \frac{W_t L_{j,t}}{R_t K_{j,t}} = \frac{1 - \alpha_j}{\alpha_j} (\tilde{B}_{j,t} k_{j,t})^{\frac{1 - \sigma_j}{\sigma_j}}. \quad (12)$$

It follows from this expression that both the capital-labor ratio and the imbalance of technical change will affect the relative share of labor income of a sector. In particular, if  $\sigma_j < 1$  and there is capital deepening, i.e.,  $k_{j,t}$  increases over time (the relevant case for the quantitative analysis performed in the next section), a decline in the relative share of labor income can only occur if there is a sufficiently strong decline in  $\tilde{B}_{j,t}$ . Intuitively, if there is more capital, its relative price will decline, and firms will hire more capital. Moreover, if capital and labor are complements, labor demand will also increase, introducing an upward pressure on its relative price. As the former effect dominates the latter, both lead to an increase in the relative share of labor income. However, as  $\sigma_j < 1$ , a decline in  $\tilde{B}_{j,t}$  generates a reduction in both the rental rate and the wage rate, being relatively stronger in the latter. Ultimately, a sufficiently strong decline in  $\tilde{B}_{j,t}$  can completely offset the effect of capital deepening and generate a decline in the relative share of labor income.

The evolution of markups does not directly affect the sectoral relative income shares.

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<sup>22</sup>From (6),  $s_{J,t}^\Pi$  can also be expressed as

$$s_{J,t}^\Pi = 1 - \frac{\varepsilon_{j,t} - 1}{\varepsilon_{j,t}} = \frac{1}{\varepsilon_{j,t}},$$

which shows that profits are simply the inverse of the elasticity of substitution across varieties in each sector.

However, if the evolution of markups differs across sectors it will indirectly affect the sectoral relative income shares by altering the allocation of inputs across sectors (i.e., through structural change). The following proposition establishes this result.

**Proposition 1 (Competition displacement effect).** *Assume  $\theta > 0$  and let  $\eta \equiv \mu_{m,t}/\mu_{s,t}$  be the relative markup between manufacturing and services. Then, a decline (increase) in  $\eta$  shifts up (down) (9) in  $(\kappa, \lambda)$  space.*

*Proof.* The relative markup  $\eta$  only appears in the equilibrium equation (9). Consider a given (constant) parametrization of the deep parameters of the model. The proof is divided into two parts. Suppose first that  $\kappa$  and  $k$  are fixed. If  $\eta$  declines (i.e., markups increase relatively less in manufacturing than in services), then (9) will hold with strict inequality. As the equilibrium adjustment can only be made through  $\lambda$  and (9) is increasing in  $\lambda$ , for each value of  $\kappa$ , more labor will be demanded, and therefore  $\lambda$  must increase. In other words, if the relative markup  $\eta$  declines, the equilibrium resource allocation of capital and labor to manufacturing increases. Following the same reasoning, if  $\eta$  increases,  $\lambda$  must decline. Now suppose that  $\lambda$  is fixed instead of  $\kappa$ . As the equilibrium adjustment can only be made through  $\kappa$  and (9) is increasing in  $\kappa$ , for each value of  $\lambda$ , more capital will be demanded, and therefore  $\kappa$  must increase.  $\square$

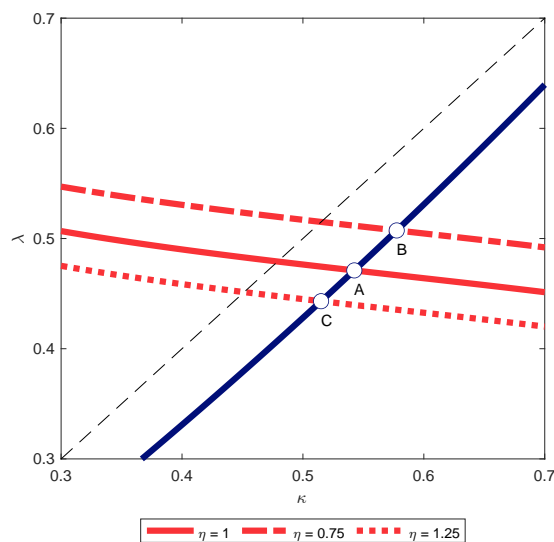
This result is intuitive. Suppose first a one-sector economy with a representative firm. From the firm's perspective, for a given demand for its output, an exogenous increase in markups allows a higher price to be set. To the extent that this exogenous change does not affect its relative demand for capital and labor, it follows from (12) that the increase in markups is neutral for the relative share of labor income. However, in a two-sector model, the competition displacement effect implies that changes in markups affect the allocation of inputs across sectors and, as a consequence, also affect the sectoral capital-labor ratios. To see this, suppose that  $\varepsilon_m$  increases so that the intermediate inputs are more substitutable in the production function of manufacturing goods. This implies a decline in  $\mu_m$ , as the ability to set up higher markups over marginal cost declines. Thus, the relative markup also declines. Consequently, given that any intermediate firm's cost function does not change,  $P_m$  declines, and the relative price across sectors also declines. This finally implies that the production of the final good will become more manufacturing intensive. Thus, both  $\kappa$  and  $\lambda$  will increase or, in other words, (9) shifts up in  $\kappa, \lambda$  space. Therefore, changes in markups (or in the level of competition) can affect the allocation of resources across sectors, generating structural change. This is precisely the competition displacement effect.

The extent to which inputs are reallocated between industries after changes in the relative markups depends both on the elasticity of substitution in the production of the



final good  $\theta$  and on the slopes of the contract curve and the labor mobility condition. First, the strength of the competition displacement effect is increasing in  $\theta$ . This result is also intuitive, as it becomes easier (more difficult) to substitute between manufacturing and service goods, the demand for the final good becomes more (less) sensitive to changes in prices driven by changes in the relative markup  $\eta$ . The second part is similar to the analysis in (Álvarez-Cuadrado et al., 2017): the positive slope of the contract curve reflects the complementarity of capital and labor in production and the slope of the labor mobility condition depends on parameters. For example, assuming that both sectoral elasticities of substitution between capital and labor are greater than the elasticity of substitution between manufacturing and services in the production of the final good (i.e.  $\theta < \sigma_m, \sigma_s$ ), allocating more capital to a sector calls for allocating more labor to the other sector. In other words, substituting in manufacturing and services is easier than in the final sector and implies a negative slope of the labor mobility condition.<sup>23</sup>

**Figure 4:** Competition displacement effect



Parameter values:  $\gamma = \theta = 0.5$ ,  $\sigma_m = 0.8$ ,  $\sigma_s = 0.6$ ,  $\alpha_m = 0.45$ ,  $\alpha_s = 0.35$ ,  $\tilde{B}_m = \tilde{B}_s = A_m = A_s = k = 1$ .

To illustrate the competition displacement effect, Figure 4 shows the results for a numerical example. The (solid blue) curve depicts the contract curve, and the (red solid, dashed, and dotted) curves depict the labor mobility condition for different values of the relative markup  $\eta$ . Their intersection yields the shares of total capital and labor employed in the production of manufacturing goods. The thin dashed black line represents the 45° line, thus the fact that the contract curve lies below it implies that manufacturing is relatively more capital intensive than services.

<sup>23</sup>The converse is true when it is easier to substitute in the final good sector than in the intermediates sector.

Consider the initial equilibrium represented by allocation  $A$  in which both sectors have the same level of markups (i.e.,  $\eta = 1$ ). Now suppose that markups decline in manufacturing so that the relative markup declines. By proposition 1, the contract curve shifts up in  $(\kappa, \lambda)$  space, and the new allocative equilibrium becomes  $B$ . In this new equilibrium, more manufacturing goods are demanded in the production of the final good, and more capital and labor must be devoted to their production, thus  $K_m$  and  $L_m$  increase.<sup>24</sup> Given that the shrinking sector is more labor-intensive, the parallel shifting of the labor mobility condition implies that the capital-labor ratio declines in both sectors, even though the aggregate capital-labor ratio remains constant. As a by-product, the relative share of labor income given by (12) also declines in both sectors. The results are the opposite if, starting from equilibrium  $A$ , the relative markup increases, attaining the allocative equilibrium  $C$ . In general, proposition 1 shows that the evolution of markups may generate structural change both in terms of capital and labor as long as markups vary across industries.

To conclude this section, I define the share of value added generated by sector  $J \in \{M, S\}$  over total valued added as

$$\psi_{J,t} = \frac{P_{J,t}J_t}{Y_t},$$

This allows the overall economy shares of labor,  $s_t^L$ ; capital,  $s_t^K$ ; and profits,  $s_t^\Pi$ , to be derived.<sup>25</sup> These measures are ultimately weighted sums of the sectoral shares, i.e. for  $Z \in \{L, K, \Pi\}$

$$s_t^Z = \psi_{M,t}s_{M,t}^Z + \psi_{S,t}s_{S,t}^Z = \sum_J \psi_{J,t}s_{J,t}^Z.$$

Naturally, changes in the income shares across sectors will affect the overall shares of income with an effect proportional to each sector's value added share.

## 4 Quantitative analysis

In this section, I use the theory to quantify the contribution of technical change and market power to the decline of the labor share and the process of structural change documented in Section 2.

I start by describing the calibration of the model, which yields processes for technical

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<sup>24</sup>As  $K = k = 1$  by assumption, it follows that  $\kappa = K_m$  and  $\lambda = L_m$ . Then  $k_m = \kappa/\lambda$  and  $k_s = (1 - \kappa)/(1 - \lambda)$ .

<sup>25</sup>Note that  $s_t^L$  is the model counterpart of the naive labor share measured in the data. More details on its computation can be found in Appendix A.2. Moreover, it is important to highlight that the data does not allow  $s_t^K$  and  $s_t^\Pi$  to be explicitly distinguished without introducing further measurement assumptions (e.g. as in Barkai, 2020). Therefore, a model has to be used.

change and markups across sectors (henceforth, the unobserved exogenous processes). This procedure finds parameter values such that the model generates time-series for the labor share in manufacturing, the labor share in services and a process of structural change that replicate those observed in the data.

Before discussing the main findings, it is important to highlight the underlying intuition. According to the theory, technical change and market power can individually explain industry-level declines in the labor share. In this sense, in Appendix A.4 I show that by restricting the model to match only labor share moments, the estimated series for either technical change or market power generate a process of structural change that is inconsistent with the data. This is a consequence of the substantial heterogeneity in the decline between manufacturing and services, and highlights the contribution of this exercise: when considering sectoral changes over time, structural change has to be considered at the same time. In particular, structural change offers an additional source of variation that helps identify the joint evolution of technical change and market power. In other words, the observed process of structural change imposes structure on the evolution of technical change and market power across sectors while delivering a labor share decline consistent with the data. Considering both the labor share and the process of structural change jointly turns out to be crucial to derive meaningful conclusions regarding the contribution of technical change and market power to the decline in the labor share.

The results show that to match the data: i) markups must increase over time, and ii) technical change must be capital-biased.<sup>26</sup> I find that the increase in markups is the main driver underlying the decline in the labor share. Technical change is also relevant in the decline, especially for services since 2008, and is the main reason behind the structural change process from manufacturing to services. To stress the baseline experiment results, in Appendix A.6 I conduct a series of additional experiments where I consider different assumptions regarding market power and its evolution over time. I conclude that without industry-specific time-varying markups, the model cannot generate large differences in the level of the labor shares across industries. In other words, both changes in markups and technical change are needed to fully reconcile the decline in the labor share and the transformation of the U.S. into a more service-oriented economy over the last two decades.

## 4.1 Calibration

The model has 12 structural parameters that need to be calibrated, which I partition into two sets.

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<sup>26</sup>In other words, technical change needs to increase the relative productivity of capital and, as a consequence, its relative demand.

### 4.1.1 Parameters fixed without solving the model

I start by fixing some parameters of the model by relying on previous literature. First, regarding the final good production, following [Buera and Kaboski \(2009\)](#) I fix the elasticity of substitution between manufacturing and service goods,  $\theta$ , to 0.5. This implies that manufacturing and service goods are complements in the production of the numéraire of the economy. Moreover, I fix the relative weight of manufacturing and services,  $\gamma$ , to its average value over the period 1998 to 2016.

For the sectoral production functions, I follow [Herrendorf, Herrington and Valentinyi \(2015\)](#) and fix the elasticities of substitution between capital and labor  $\sigma_m = 0.8$  and  $\sigma_s = 0.75$ . Although there exists an extensive literature that tries to identify these elasticities, there is no consensus on whether capital and labor are indeed substitutes or complements in production (see, among others, [Karabarbounis and Neiman, 2014](#), [Herrendorf et al., 2015](#), [Alonso-Carrera, Freire-Serén and Raurich, 2017](#), [Wemy, 2021](#)).<sup>27</sup> Fixing values below unitary elasticity implies that capital and labor are complements in the production of manufacturing and service goods, being more easily substitutable in the production of the former. Additionally, given that using (away from unitary) constant elasticity of substitution production functions necessarily involves dealing with their normalization, fixing the elasticities of substitution outside the model alleviates this problem in my quantitative analysis.<sup>28</sup> Finally, following previous literature, I fix  $1 - \alpha_m$  and  $1 - \alpha_s$  to the geometric average of the labor share in each sector between 1998 and 2016. Table 1 lists the values assigned to these parameters.

**Table 1:** Parameters fixed outside the model

Parameter	Value	Definition	Source
$\gamma$	0.19	Average manufacturing/services	Data
$\theta$	0.5	Subst. elasticity $M$ and $S$	<a href="#">Buera and Kaboski (2009)</a>
$\sigma_m$	0.8	Subst. elasticity $K_m$ and $L_m$	<a href="#">Herrendorf et al. (2015)</a>
$\sigma_s$	0.75	Subst. elasticity $K_s$ and $L_s$	<a href="#">Herrendorf et al. (2015)</a>
$\alpha_m$	0.49	Average manufacturing labor share	Data
$\alpha_s$	0.39	Average service labor share	Data

### 4.1.2 Targeted moments

The next step consists of using moments from the data to infer the unobserved exogenous processes' evolution: technical change and market power. The parameters governing

<sup>27</sup>In Appendix A.5 I show that the results are robust for a wide range of estimates of these elasticities.

<sup>28</sup>See [Klump, McAdam and Willman \(2007b\)](#), [León-Ledesma, McAdam and William \(2010\)](#), [Klump, McAdam and Willman \(2012\)](#), [Temple \(2012\)](#) among others for a detailed analysis on the normalization of CES production functions.

both processes are calibrated to exactly replicate the moments of interest. Technically, the experiment is conducted as follows:

1. For a given  $t$  guess a set of parameters  $\{\tilde{B}_{m,t}, \tilde{B}_{s,t}, A_{m,t}, A_{s,t}, \varepsilon_{m,t}, \varepsilon_{s,t}\}$ .
2. Take  $K_t$  and  $L_t$  (and thus  $k_t$ , the capital-labor ratio of the economy in period  $t$ ) as given, and solve the static model characterized in Sec. 3 by Equations (8) and (9). The solution yields the equilibrium allocation of capital and labor across sectors.
3. Compute the following moments in the model:
  - i. Manufacturing labor share,  $s_{M,t}^L$ ,
  - ii. Service labor share,  $s_{S,t}^L$ ,
  - iii. Capital-output ratio of the economy,  $K_t/Y_t$ ,
  - iv. Capital-labor ratio in manufacturing,  $k_{m,t}$ ,
  - v. Manufacturing share of total capital,  $\kappa_t$
  - vi. Manufacturing share of total labor,  $\lambda_t$ .

Denote this set of moments as  $\hat{g}(\Theta)$ , where  $\Theta$  is the full set of parameters (exogenously fixed and calibrated) needed to solve the model.

4. Compute the distance between the moments generated in the model  $\hat{g}(\Theta)$  and their counterpart in the data,  $g$ . If not close, go back to step 1.

To implement this procedure, I develop an algorithm that performs a random search in the parameter space and employs a minimum-distance criterion function that compares empirical moments from the data to their model-implied counterparts. Technically, it minimizes the weighted sum of squared relative deviations between the moments generated within the model,  $\hat{g}(\Theta)$  and those computed in the data,  $g$ . The calibration procedure is performed jointly. Hence, all the moments are interdependently affected by changes in all the parameters

## 4.2 Results

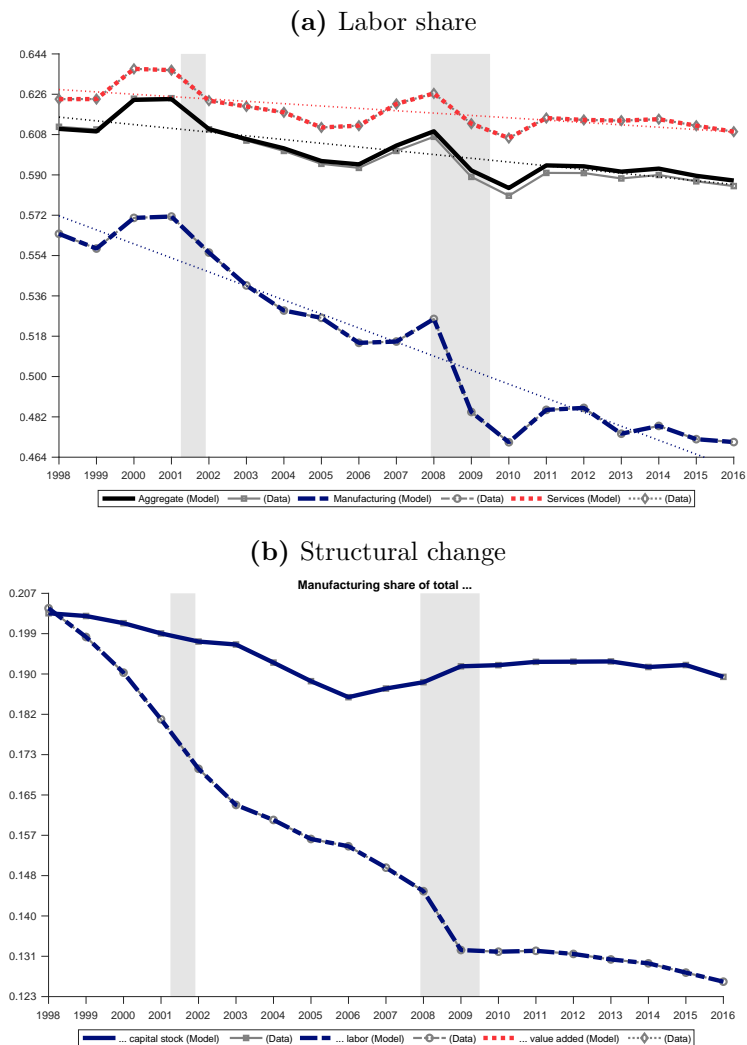
In what follows, I discuss the fit of the model and the estimates obtained for technical change and markups and quantify their contribution to the decline in the labor share. To do that, I first show the baseline experiment results where both technical change and markups vary over time and jointly interact. As a consequence, both shape the evolution of the labor share, generating structural change at the same time. Second, I decompose the effects of technical change and market power by comparing the results of the baseline

economy with two counterfactual (non-recalibrated) economies: i) an economy that shows what the evolution of the U.S. economy would have been had markups evolved as in the baseline experiment but without technical change; ii) an economy that shows what the evolution of the U.S. economy would have been had technical change evolved as in the baseline experiment but without a change in markups.

#### 4.2.1 Fit of the model, parameter values and discussion

Figure 5 shows the fit of the industry-level shares of the baseline economy and the allocation of capital and labor across industries. By construction, it perfectly replicates their evolution throughout the period under consideration.

**Figure 5:** Fit of the model, 1998 - 2016



Concentrating on the labor share, Figure 5a reflects how the calibrated economy in the baseline experiment matches both the observed ups-and-downs and the declining trend in

the industry-level labor shares. This decline is much steeper in the labor share of manufacturing industries (represented by the dashed blue line) than in services (represented by the dotted red line). Although the overall labor share is not targeted – it is obtained by weighting the industry labor shares – it is by construction close to its data counterpart.<sup>29</sup> Regarding structural change moments, Figure 5b reveals that the baseline economy is also consistent with the strong relative reallocation of employment from manufacturing to service industries (the dashed blue line) and the relatively smaller fluctuations of the share of capital stock in manufacturing with respect to the total capital stock of the U.S. economy (the solid blue line).

Figure 6 exhibits the calibrated evolution of markups at the industry and overall (implied) level (Figure 6a) and the TFP growth rates implied by the calibrated evolution of the technical change parameters (Figure 6b).<sup>30</sup> Both mechanisms interact in equilibrium to characterize the phenomena of interest.

The steep increase in markups in manufacturing (the dashed blue line) contrasts with the flatter evolution in services in the benchmark exercise. Both jointly imply an overall increase in the economy-wide markup of 0.05 over the last two decades. The quantitative evolution of markups is aligned with the well-known estimates obtained using COMPUSTAT data by De Loecker et al. (2020) and with the results in Hall (2018). Moreover, markups are highly negatively correlated with the labor share time series, a feature of the data already pointed out by De Loecker and Eeckhout (2021).

Simultaneously, industry-level capital-biased technical change implies a positive average TFP growth in manufacturing, depicted as the dashed blue line, and almost zero TFP growth in services. Besides, TPF growth in both sectors is declining, being much more noticeable in manufacturing. This result has the TFP growth slowdown essence pointed out in (Duernecker, Herrendorf and Valentinyi, 2021). Besides, it is aligned with the commonly accepted view that ongoing low productivity growth is related to competition weakness, reflected in the calibration through markups.

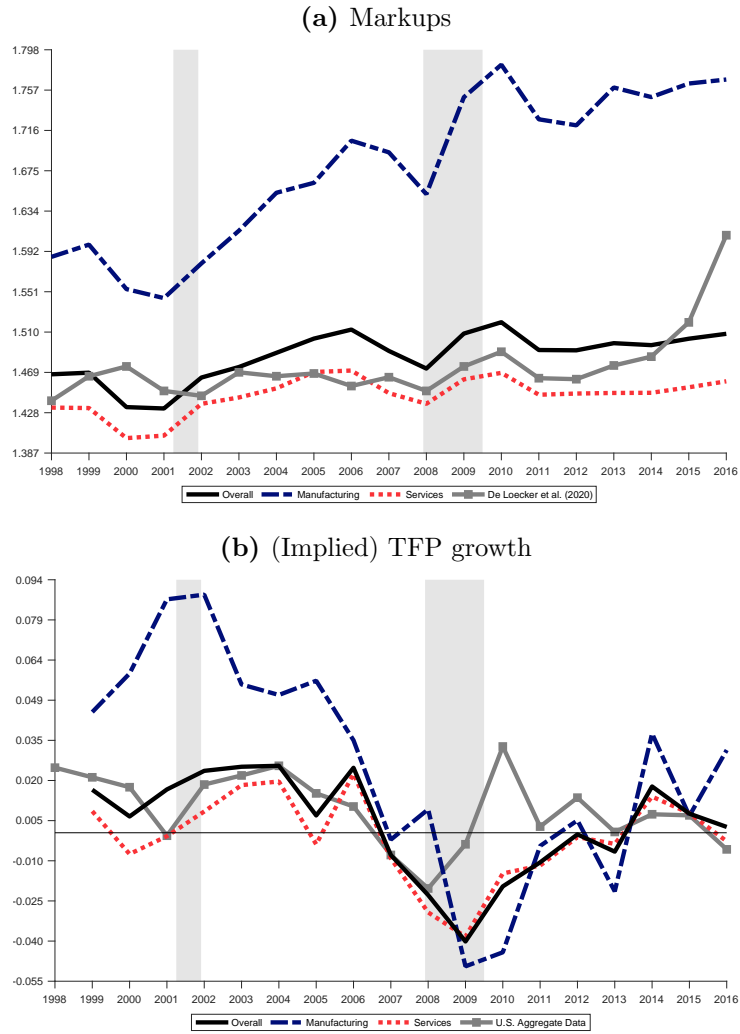
The calibrated series for technical change parameters involve negative growth rates of the factor imbalance ( $\tilde{B}$ ) in both sectors and positive growth rates of neutral technical change ( $A$ ). Through the lens of the model, (10) and (11) imply that the evolution of markups produces a decline in both the labor share and the capital share. Moreover, according to (12), the evolution of technical change implies a decline in the relative share of labor income in both sectors, even though the capital-labor ratio increases. Consequently, the decline in the labor share is driven by a parallel increase in the pure profit share. By

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<sup>29</sup>The smaller decline is a consequence of the resulting higher weight in the value added of manufacturing relative to services obtained in the calibrated model.

<sup>30</sup>The specific evolution of  $\tilde{B}$  and  $A$  can be found in Figure 23 in Appendix A.6. TFP is computed by using Kmenta approximation (see Kmenta, 1967, Klump, McAdam and Willman, 2007a).

**Figure 6:** Calibrated exogenous processes: markups and (implied) TFP growth



Note: U.S. Aggregate Data measure of TFP growth obtained from [Fernald \(2014\)](#). Markups series obtained from [De Loecker et al. \(2020\)](#).

contrast, the capital share remains flat during this period.

#### 4.2.2 Driving processes

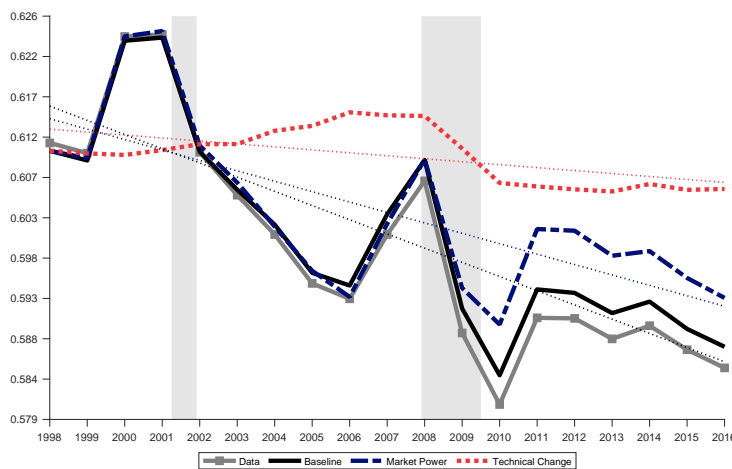
To quantify the contribution of technical change and market power to the decline of the (aggregate) labor share and the process of structural change, I compare the results of the baseline economy with two non-recalibrated counterfactual economies:

1. Market power economy: There is no technical change, and markups vary as in the baseline economy.
2. Technical change economy: There are no changes in market power, and technical change evolves as in the baseline economy.



Figure 7 shows the evolution of the labor share from 1998 to 2016. The baseline exercise is able to explain 87.4% of the decline observed in the data. The main reason underlying this decline is the evolution of market power, as if technical change had not taken place, market power would individually account for 64.1% of the decline as depicted by the dashed blue line. Instead, if there are no changes in market power, technical change would individually account for 18.2% of the decline as depicted by the dotted red line.<sup>31</sup> As a consequence, the increase in markups is the main reason underlying the decline of the labor share since the late 1990s.

**Figure 7:** Labor share, baseline and counterfactual experiments, 1998 - 2016



Focusing on the industry-level labor shares, Figure 8 shows the resulting labor shares in manufacturing and services in the baseline and counterfactual economies. If the only exogenous change (other than capital deepening) had been markups, the labor shares in manufacturing and services would have declined by 61.5% and 38.4%, respectively. In the opposite situation, i.e., if only technical change had taken place, but markups had remained constant at its 1998 level, the labor shares in manufacturing and services would have also declined, accounting for 38.7% and 23.9% of the decline, respectively.<sup>32</sup>

Figure 9 shows the time-series of the shares of total capital and labor employed in manufacturing industries. Following the previous discussion and the theoretical predictions laid out in Section 3, market power generates structural change, but its effect is smaller than that of technical change. According to the dashed blue lines, without technical change, structural change between manufacturing and services in terms of employment

<sup>31</sup>To stress the relevance of these results, in Appendix A.6 I conduct a series of experiments where I recalibrate alternative economies with different assumptions regarding the joint evolution of technical change and market power. In particular, I show that in an economy without markups, technical change can be pushed to explain up to 62.9% of the observed decline in the data. However, this comes at the cost of not being able to match the observed levels and trends of the industry-level labor shares.

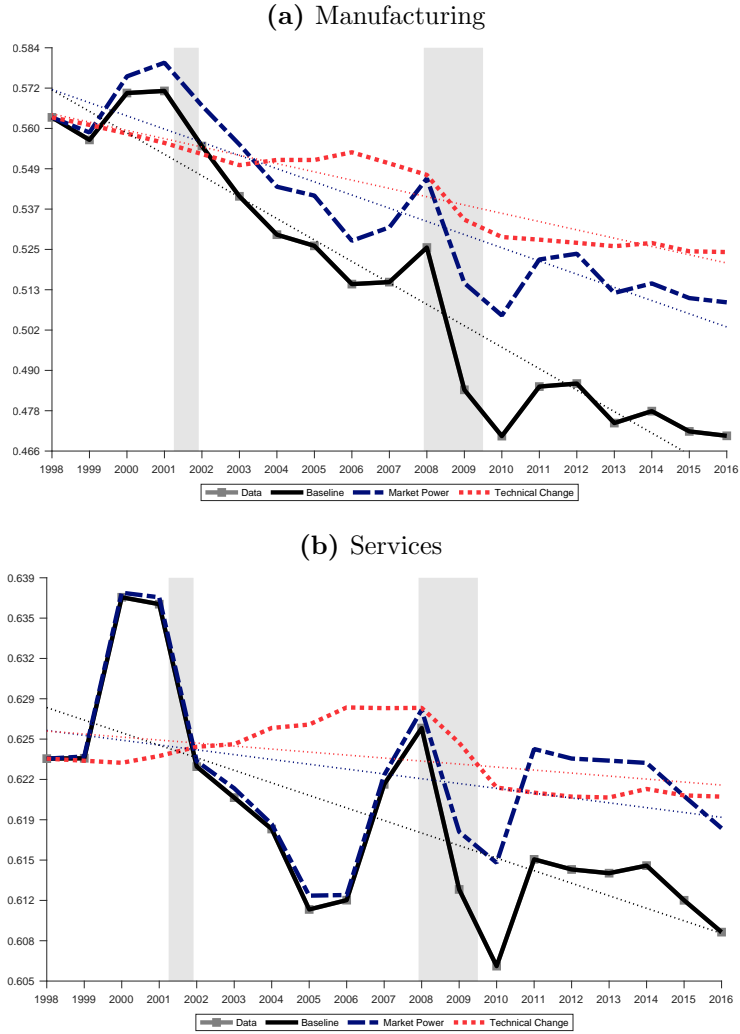
<sup>32</sup>The volatility of both labor shares is lower in the absence of changes in markups. A detailed discussion regarding the volatility of these series can be found in Appendix A.6.

**Table 2:** Decomposition of the effects of market power and technical change, 1998 - 2016

	$s^L$	$s_M^L$	$s_S^L$	$\lambda$	$\kappa$
<i>1998 - 2016</i>					
Both	-3.01	-11.26	-1.89	-7.69	-1.03
Market Power	-2.21	-6.93	-0.72	-0.96	-0.59
Technical Change	-0.62	-4.35	-0.45	-7.03	-0.14
<i>Only Technical Change</i>	-2.16	-12.8	-0.31	-7.58	-1.11
<i>1998 - 2008</i>					
Market Power	-1.76	-4.04	-1.06	-0.47	-0.14
Technical Change	0.55	-1.42	0.54	-5.61	-1.43
<i>2008 - 2016</i>					
Market Power	-0.63	-1.98	-0.19	-0.27	-0.29
Technical Change	-0.66	-1.64	-0.58	-1.11	0.33

Note: 'Both' represents the baseline economy. 'Market Power' and 'Technical Change' values are obtained by allowing technical change and fixing markups at their 1998 level, or by fixing technical change at its 1998 level and changing markups. 'Only Technical Change' shows the results of an alternative recalibrated economy without markups. More details can be found in Appendix A.6.

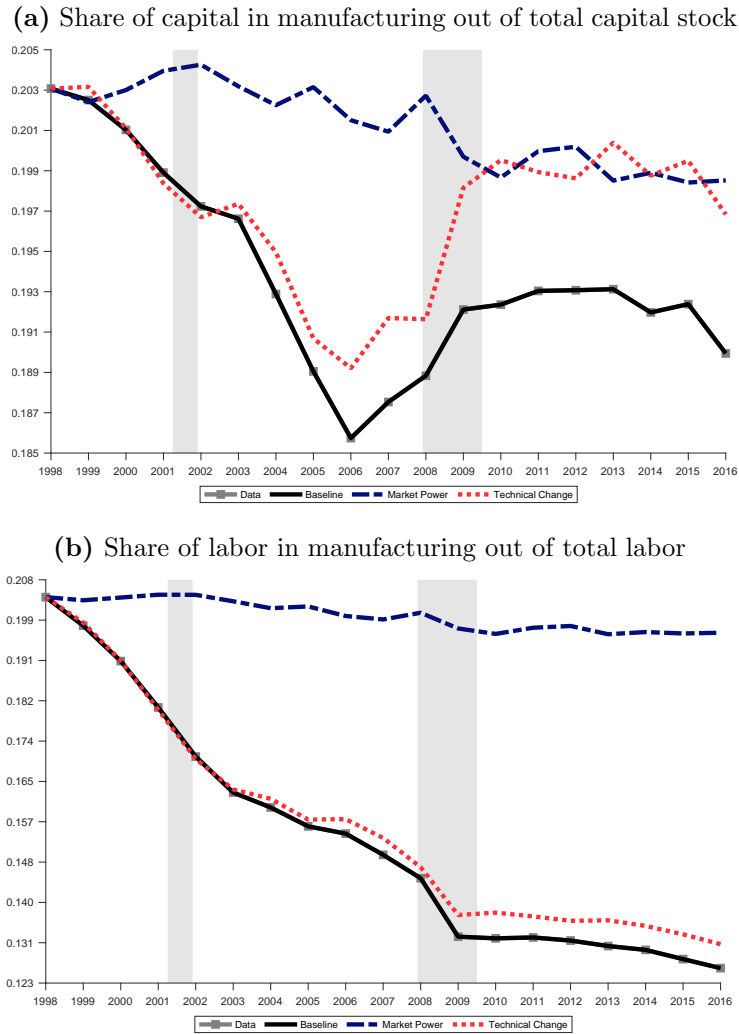
**Figure 8:** Industry labor shares, baseline and counterfactual experiments, 1998 - 2016



would have been almost negligible over the last two decades. In other words, markups alone cannot generate the strong structural change observed in the data, and the evolution of technology accounts for almost all employment reallocation across sectors. This is related to the automation literature, where labor can be easily replaced in manufacturing, further supported by the substantial capital deepening observed in the economy.

Considering the entire period from 1998 to 2016 hides substantial heterogeneity in the relevance of technical change and market power for the moments of interest. Table 2 provides additional results of the baseline economy by considering two sub-periods: 1998 to 2008 and 2008 to 2016. The evolution of market power is key to explaining the decline in the labor share from 1998 to 2008. Specifically, it accounts for 69.7% of the decline in manufacturing and 91.1% of the decline in services. This yields an 87.4% decline at the aggregate level. Technical change can explain up to 24.5% of the decline in manufacturing; however, it would have implied an increase in the labor share in services. As a consequence,

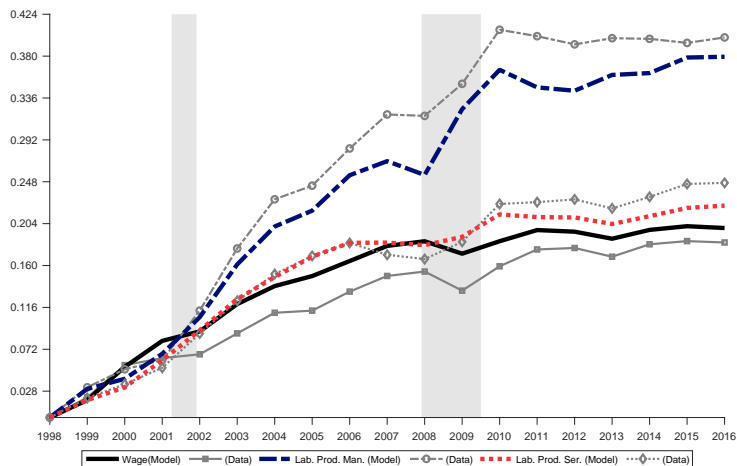
**Figure 9:** Structural change, baseline and counterfactual experiments, 1998 - 2016



in the absence of market power, the estimated technical process would have implied an increase in the aggregate labor share. Market power is still the main reason underlying the decline of the labor share in manufacturing from 2008 to 2016, accounting for 58.9% of the decline, while technical change accounts for 48.8%. Interestingly, in service industries market power is less relevant during this period, accounting for 26.9% of the decline, while technical change becomes much more relevant, accounting for 78.6% of the decline. Overall, technical change is slightly more relevant during this period.

The implications of the baseline economy non-targeted dimensions are well aligned with the data. The growth rates of value added, employment and wages across sectors exhibit the same pattern as in the data: the average wage growth is higher than that of value added in manufacturing and smaller than that of services. Besides, the average employment growth rate is negative in manufacturing and positive in services. Additionally, Figure 10 shows the cumulative growth rate of labor productivity and wages. The joint

**Figure 10:** Cumulative growth rate of labor productivity and wage, baseline economy, 1998 - 2016



combination of technical change and market power implies an incomplete pass-through of labor productivity gains to wages, a well-known fact, documented in previous literature. Through the lens of the model, this gap has increased steadily since 1998, being particularly noticeable and persistent in manufacturing. Since the start of the Great Recession, the gap is also noticeable in services.

Additionally, in Appendix A.6 I conduct a series of additional exercises where I consider alternative assumptions on the joint evolution of technical change and market power. In particular, following the narrative on the relevance of technical change, I focus on explanations that stress its crucial role while considering different assumptions on both the level and the evolution of markups over time. These assumptions consider different levels of flexibility in the evolution of market power. I start by considering an economy without market power and show that it is not possible to match the declining trend of the labor share in services. Moreover, without market power, the levels of the labor shares across sectors are similar, opposite to what is observed in the data. Allowing for market power but assuming that markups are homogeneous across industries and constant over time improves the fit of the model. However, the level of the labor shares is still far from what I observe in the data, and the declining trend in the labor share of both industries is more pronounced than in the data. Finally, assuming that markups are heterogeneous but constant over time, the model can generate a difference in the average level of the labor shares as observed in the data. Nevertheless, it produces a stronger declining trend of the labor share in services. This reinforces the baseline quantitative analysis results, concluding that markups must be heterogeneous across industries and increase over time to match the data.<sup>33</sup>

To conclude the analysis, in Appendix A.5 I conduct a series of robustness exercises

<sup>33</sup>Moreover, if markups do not change over time, the process of technical change is very strong and highly volatile, especially compared to the baseline quantitative analysis.

assuming different values of the elasticity of substitution between capital and labor, a parameter fixed outside the model in the baseline exercise. These elasticities play a fundamental role in determining the allocation of capital and labor across sectors, each industry’s capital-labor ratio, and its labor share. Most of the literature estimating these elasticities have found values below one, i.e., capital and labor are slight complements in the production process. Therefore, to provide additional validation for the baseline exercise results, I consider two alternative estimates where capital and labor are substitutes in either manufacturing or both manufacturing and services. I find that the results do not change qualitatively. In other words, the contribution of market power and technical change to the decline in the labor share and the process of structural change is robust to the specification of the elasticity of substitution between capital and labor in the production of manufacturing and service goods.

## 5 Conclusion

The decline in the labor share experienced in the majority of advanced economies is one of the most troubling facts of modern macroeconomics. The commonly accepted, albeit recently challenged view, is that this decline started in the early 1980s and has intensified over the last two decades. This paper uses U.S. industry-level data from 1998 to 2016 and shows that this decline is heterogeneous and pervasive across industries and is also contemporaneous to an intense structural change process from manufacturing to services. A simple decomposition of the (naive) labor share into its main components shows that manufacturing and service industries experience a different evolution. The former are generally characterized by exhibiting negative employment growth rates, while on the contrary, service industries exhibit positive growth rates. Besides, value added in service industries grows at a higher rate than that of wages, while the opposite happens in manufacturing industries.

Despite the numerous contributions to the literature on the decline in the labor share, there is still no consensus on the causes underlying this decline. Intuitively, the two leading explanations for the decline of the labor share, namely technical change (e.g., in the form of automation) and changes in the level of competition (e.g., rise in the concentration of firms), can also affect the contemporaneous pace of structural change. With this idea in mind, and to understand the industry-level evolution of the labor share and the process of structural change from manufacturing to services, I develop an extension of the model proposed by [Álvarez-Cuadrado et al. \(2017, 2018\)](#). This is a multi-sector model with several supply-side mechanisms that allow for structural change and changes in factor shares, which I augment with heterogeneity in the level of markups across industries.

Therefore, in the proposed model, industry-specific technical change, production technology differences across industries, and heterogeneous markups play a role in explaining both changes in the labor share and in structural change.

The model is then taken to the data to perform a quantitative analysis. The baseline experiment results show that both time-varying markups and capital-biased technical change are necessary to explain the observed decline in the labor share and the reallocation of labor and capital from manufacturing to services. Through the lens of the model, markups are the main driver of the decline in the labor share of manufacturing and service industries. Technical change has also contributed to the decline, especially since 2008, and is the fundamental reason underlying structural change from manufacturing to services. I also show that if markups are not allowed to vary over time, technical change can go a long way to explaining the decline of the labor share, but it cannot replicate the levels of the labor share across sectors while being consistent with the process of structural change.

Consequently, the results of this paper are aligned with the literature that relates the decline of the labor share with a decline in competition, which then favors an increase in markups. Other phenomena such as automation and the rise of AI (which could be understood as a type of capital-augmenting technical change) also play a role in the decline in the labor share, especially after 2008, and are the reasons underlying the process of structural change from manufacturing to services over the last two decades.

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# A Appendix

## A.1 Data

### A.1.1 Industries

The industries are defined according to the 2007 North American Industry Classification System (NAICS). The relationship between the chosen level of detail (BEA summary) and the 2007 North American Industry Classification System (NAICS) code structure can be found on the BEA methodology website.

#### **Others: Agricultural activities, Mining, Utilities and Construction**

1. Farms (NAICS 111)
2. Forestry, fishing, and related activities (NAICS 113[4,5])
3. Oil and gas extraction (NAICS 211)
4. Mining, except oil and gas (NAICS 212)
5. Support activities for mining (NAICS 213)
6. Utilities (NAICS 221)
7. Construction (NAICS 23)

#### **Manufacturing**

8. Wood products (NAICS 321)
9. Nonmetallic mineral products (NAICS 327)
10. Primary metals (NAICS 331)
11. Fabricated metal products (NAICS 332)
12. Machinery (NAICS 333)
13. Computer and electronic products (NAICS 334)
14. Electrical equipment, appliances, and components (NAICS 335)
15. Motor vehicles, bodies and trailers, and parts (NAICS 3361[2,3])
16. Other transportation equipment (NAICS 3364[5,6,9])
17. Furniture and related products (NAICS 337)
18. Miscellaneous manufacturing (NAICS 339)
19. Food and beverage and tobacco products (NAICS 311)

20. Textile mills and textile product mills (NAICS 313)
21. Apparel and leather and allied products (NAICS 315[6])
22. Paper products (NAICS 322)
23. Printing and related support activities (NAICS 323)
24. Petroleum and coal products (NAICS 324)
25. Chemical products (NAICS 325)
26. Plastics and rubber products (NAICS 326)

### **Private Services**

27. Wholesale trade (includes durable goods and nondurable goods) (NAICS 42)
28. Motor vehicle and parts dealers (NAICS 441)
29. Food and beverage stores (NAICS 445)
30. General merchandise stores (NAICS 452)
31. Other retail (NAICS 4424, 4468, 451, 4534)
32. Air transportation (NAICS 481)
33. Rail transportation (NAICS 482)
34. Water transportation (NAICS 483)
35. Truck transportation (NAICS 484)
36. Transit and ground passenger transportation (NAICS 485)
37. Pipeline transportation (NAICS 486)
38. Other transportation and support activities (NAICS 487[8])
39. Warehousing and storage (NAICS 493)
40. Publishing industries (includes software) (NAICS 511)
41. Motion picture and sound recording industries (NAICS 512)
42. Broadcasting and telecommunications (NAICS 515)
43. Information and data processing services (NAICS 518[9])
44. Federal Reserve banks, credit intermediation, and related activities (NAICS 521[2])
45. Securities, commodity contracts, and investments (NAICS 523)
46. Insurance carriers and related activities (NAICS 524)
47. Funds, trusts, and other financial vehicles (NAICS 525)

48. Real estate (NAICS 531)
49. Rental and leasing services and lessors of intangible assets (NAICS 532[3])
50. Legal services (NAICS 5411)
51. Computer systems design and related services (NAICS 5415)
52. Miscellaneous professional, scientific, and technical services (NAICS 5412[2,3,4,6,7,8,9])
53. Management of companies and enterprises (NAICS 55)
54. Administrative and support services (NAICS 561)
55. Waste management and remediation services (NAICS 562)
56. Educational services (NAICS 61)
57. Ambulatory health care services (NAICS 621)
58. Hospitals (NAICS 622)
59. Nursing and residential care facilities (NAICS 623)
60. Social assistance (NAICS 624)
61. Performing arts, spectator sports, museums, and related activities (NAICS 711[2])
62. Amusements, gambling, and recreation industries (NAICS 713)
63. Accommodation (NAICS 721)
64. Food services and drinking places (NAICS 722)
65. Other services, except government (NAICS 81)

## **Government**

66. Federal government, includes general government and government enterprises (NAICS n/a)
67. State and local government, includes general government and government enterprises (NAICS n/a)

### **A.1.2 Capital stock and employment**

One of the main data statistics needed to take the model to the data is the capital-labor ratio. Given that, by definition, capital and labor measure intrinsically different goods, the capital-labor ratio is not a unit-free measure, and thus it is key to define the measurement units of both the numerator and the denominator properly. In this paper, the capital-labor ratio is measured in real 2009 dollars per hour. In this Appendix, I explain how to obtain the appropriate measure for capital and labor (or employment).

**Capital Stock** The capital stock is computed as the current-cost net stock of private fixed assets by adding Equipment (BEA, table 3.1.E), Structures (BEA, table 3.1.S), and IPP (BEA, table 3.1.I). These tables include residential assets, but given the model used in the paper, the relevant measure of capital shall not include these types of assets.<sup>34</sup> However, the BEA does not provide a sufficiently detailed disaggregation of private non-residential fixed assets. Thus, I need to construct that series from the available data.

To do so, I also collect data on the current-cost net stock of private nonresidential fixed assets by industry group and legal form of organization (BEA, table 4.1). The BEA definition of nonfarm nonmanufacturing includes service industries and other industries as utilities or construction. Therefore, to compute the level of nonresidential fixed assets for service industries, I assume that the share of private fixed assets including residential fixed assets (but omitting real estate) in nonfarm nonmanufacturing is the same as in private nonresidential fixed assets.<sup>35</sup> Finally, chain-type quantity indexes for the net stock of private fixed assets are used to obtain the measure of real capital stock.

**Labor (Employment)** To construct hours worked in each industry, I combine use data on hours worked by full-time and part-time employees by industry (BEA, tables 6.9C and 6.9D). The within-industry classification (which type of firms are included in which industry) changes slightly in 2000. To solve this, I smooth out the existing discrepancy across tables by assuming that the employment share between 1998 and 2000 across industries is constant at its 2000 level, allowing aggregate employment to vary as in the data.

The data available aggregates hours worked in finance and insurance, real estate, rental, and leasing (FIRERL), thus for consistency reasons, I need to exclude those hours worked in real estate industries. To do this, I also gather data on the number of full-time equivalent employees by industry (BEA, table 6.5D), which allows the number of employees in each of the sub-industries of FIRERL to be separately identified. A crucial step is assuming that hours distribute evenly among all these sub-industries. Under this assumption, the value of hours in manufacturing and services excluding real estate can finally be pinned down.

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<sup>34</sup>Including (or excluding) residential private fixed assets only makes an enormous difference for the real estate industry. In any case, as it is explained in Section 2, I omit the real estate industry.

<sup>35</sup>The difference between the aggregate value of both series after omitting real estate is indeed very small.

## A.2 Labor share

### A.2.1 Methodology

Following Koh et al. (2020), the labor share at time  $t$ ,  $LS_t$ , is obtained as

$$LS_t = 1 - \frac{DEP_t + UCI_t + ACI_t}{Y_t},$$

where  $DEP_t$  is depreciation,  $UCI_t$  is unambiguous capital income,  $ACI_t$  is ambiguous capital income and  $Y_t$  is a measure of value added generated in period  $t$ . The variable  $UCI_t$  is defined as

$$UCI_t = RI_t + CP_t + NT_t + CSGE_t,$$

where  $RI_t$  is rental income,  $CP_t$  are corporate profits,  $NT_t$  is net interest and  $CSGE_t$  are current surplus government enterprises. Moreover, the variable  $ACI_t$  is obtained as

$$ACI_t = \theta_t AI_t,$$

where, on the one hand,  $AI_t$  is ambiguous income and can be computed as

$$AI_t = PI_t + TPS_t + BCTP_t + SD_t,$$

where  $PI_t$  is proprietors' income,  $TPS_t$  are taxes on production net of subsidies,  $BCTP_t$  are business current transfers payments and  $SD_t$  is statistical discrepancy. On the other hand,  $\theta_t$  is the share of ambiguous income assigned to capital, which is obtained as

$$\theta_t = \frac{UCI_t}{UI_t}$$

where

$$UI_t = UCI_t + DEP_t + CE_t,$$

is unambiguous income and  $CE_t$  is the compensation of employees in period  $t$ .

The naive labor share any industry  $i$  at time  $t$ ,  $NLS_{it}$ , is computed as

$$NLS_{it} = \frac{CE_{it}}{Y_{it}}. \quad (13)$$

Then, the naive labor share at the aggregate level (or overall naive labor share of the

economy) at time  $t$  can be obtained as

$$NLS_t = \frac{\sum_i CE_{it}}{\sum_i Y_{it}} = \frac{\sum_i CE_{it}}{Y_t} = \sum_i \frac{Y_{it}}{Y_t} \frac{CE_{it}}{Y_{it}} = \sum_i \eta_{it} NLS_{it}, \quad (14)$$

which implies that the overall naive labor share of the economy is a weighted average of the naive labor shares of each industry, with weights given by  $\eta_{it} = \frac{Y_{it}}{Y_t}$ , the relative size of each industry in value added generation. In the data, all these variables are measured in nominal terms.<sup>36</sup> As a measure of value added I use the nominal gross value added of each industry, which in the data is obtained as the sum of expenditures on labor or  $CE_{it}$ , gross operating surplus  $GOS_{it}$  and taxes on production and imports minus subsidies  $TPIS_{it}$ , i.e.

$$Y_{it} = CE_{it} + GOS_{it} + TPIS_{it}.$$

The allocation between capital and labor of  $TPIS_{it}$  is unclear (see [Mućk et al. \(2018\)](#)). While in previous research these taxes are usually not allocated, in this paper I allocate them to capital.<sup>37</sup> By doing so, the resulting naive labor share coincides with the labor share of [Koh et al. \(2020\)](#) if the share of ambiguous income is totally assigned to capital, i.e., when  $\theta_t = \theta_{it} = 1$ , for all  $i$  and  $t$ .

To further explore the evolution of the naive labor share, I decompose compensation of employees (the numerator of (14)) for each industry  $i$  at time  $t$  into

$$CE_{it} = WS_{it} + SUPL_{it} = W_{it}L_{it} + ECGSI_{it} + ECEPIF_{it},$$

where  $WS_{it}$  are wage and salary accruals and disbursements.  $SUPL_{it}$  are supplements to wages and salaries. According to the BEA methodology, the term  $WS_{it}$  comprehends the monetary remuneration of employees, including the compensation of corporate officers; commissions, tips, and bonuses; voluntary employee contributions to certain deferred compensation plans and receipts in kind that represent income. It can be further decomposed into the product of the average wage of each industry  $W_{it}$  and the number of full-time equivalent employees within that industry  $L_{it}$ . Moreover, the term  $SUPL_{it}$  consists of employer contributions for government social insurance  $ECGSI_{it}$  and employer contributions for employee pension and insurance funds  $ECEPIF_{it}$ .

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<sup>36</sup>Therefore, without loss of generality, in the proposed notation  $Y_{it} = P_{it}^Y Y_{it}^R$ , where  $Y_{it}^R$  is value added measured in goods and  $P_{it}^Y$  is its price.

<sup>37</sup>If not allocated, then (13) would be

$$NLS_{it} = \frac{CE_{it}}{Y_{it} - TPIS_{it}}.$$

However, as the share of  $TPIS_{it}$  is relatively constant during the period analyzed both at the aggregate and industry-level, allocating taxes only changes the results quantitatively.



### A.2.2 Aggregate level

This section extends the analysis of the labor share of Section 2. Figure 11 shows the labor share between 1947 and 2016. While a linear fit from 1947 to 2016 exhibits a clear decreasing trend, it seems that a more appropriate fit should consider at least two different trends for the periods before and after 1980. In doing so, I show the labor share was almost constant before 1980, while it is decreasing ever after. As shown in the main text, the same result holds if we also introduce a break in the late 1990s.

**Figure 11:** U.S. labor share, 1947 - 2016.

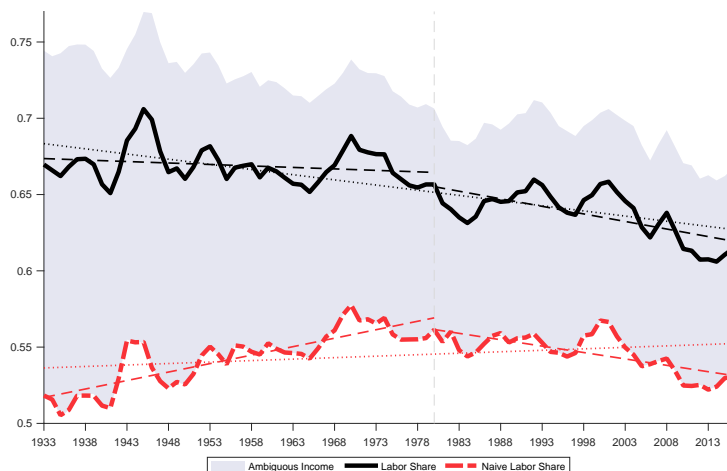
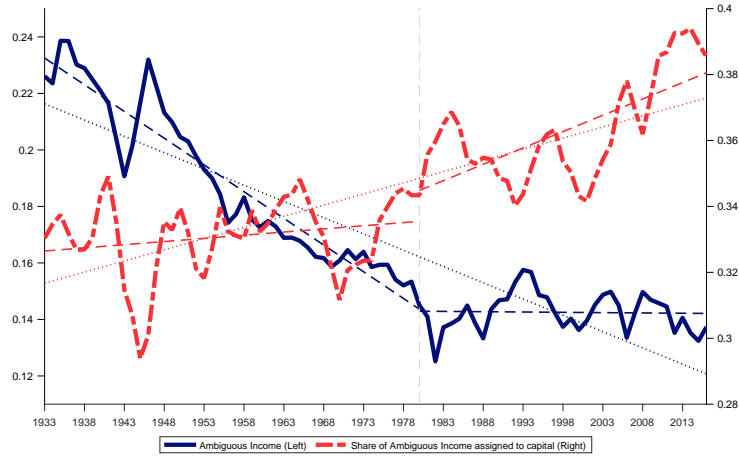


Figure 11 also represents the evolution of the naive labor share. As Mućk et al. (2018) argue, it shows a clear hump-shaped pattern, which is not present in the labor share. However, focusing on the period starting in 1980, the trend of both measures is remarkably similar. In other words, while the labor share can only be adequately measured by following the proposed methodology, since the early 1980s an approximation to its trend can be obtained by just computing the naive labor share. Finally, Figure 11 also shows the evolution of the AI share of income (the grey shaded area), which has shrunk since 1947, when its level was 0.223, and remains roughly stable since the 1980s at around 0.145, i.e., 14.5 labor share points.

The AI component is crucial for the precise computation of the labor share. Both the evolution of the AI share and the parameter  $\theta$ , which measures the part of ambiguous income that accrues to capital, are shown in Figure 12. Contrary to what happened with the AI share, the value of  $\theta$  has been steadily increasing since the 1960s, especially since the 1980s. Therefore, over the last decades, at the same time as the compensation of employees has been declining, the share of ambiguous income that is assigned to labor has also been declining, due to the increase of  $\theta$  and the decrease of AI.

**Figure 12:** U.S. AI share (left axis) and  $\theta$  (right axis), 1933 - 2015.



### A.2.3 Industry level

The lack of data mentioned in the main text prevents following (Koh et al., 2020) to compute the labor share at industry-level, especially when trying to compute the labor share at a very disaggregated level. However, it is possible to adapt the methodology for a small subset of six industries by redefining the following variables:

1. Unambiguous Capital Income (UCI) = Corporate Profits + Net Interest.
4. Ambiguous Income (AI) = Gross Operating Surplus (GOS) - Corporate Profits - Net Interest - DEP + Taxes on Production - Subsidies.

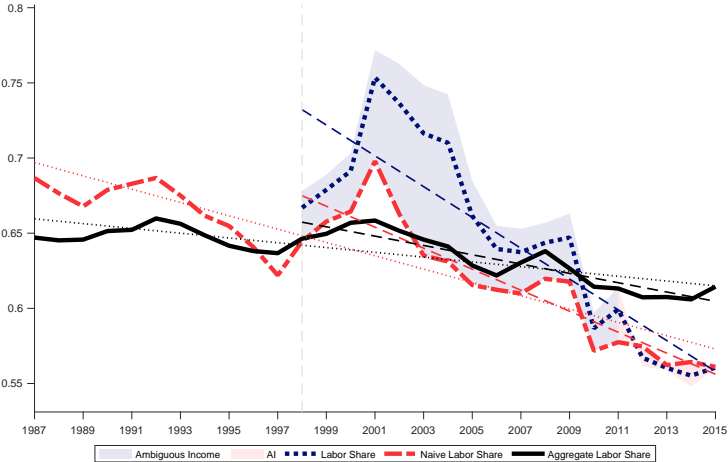
The main difference in this methodology is that AI is now computed as a residual instead of arising as a definition from the data. Besides, as a measure of aggregate output, I use the gross domestic product (GDP), which is still the sum of total unambiguous income and ambiguous income, i.e.,  $Y = \text{UCI} + \text{DEP} + \text{CE} + \text{AI} \equiv \text{GDP}$ .

In the following figures, I show the results for six industries of the U.S. For each industry, each figure shows its labor share under this modified methodology, its naive labor share, its AI share, and, as a benchmark, the aggregate labor share of the economy. Note that the labor share is only computed for the period 1998 to 2015, the unique period when it is possible to obtain detailed data under the NAICS classification. From 1987 to 1997, the best that one can do is computing the naive labor share, as the BEA only provides a series of converted data for compensation employees CE from SIC to NAICS for this period. Unfortunately, obtaining longer series is not possible, as the aggregation of industries is not consistent before 1987.

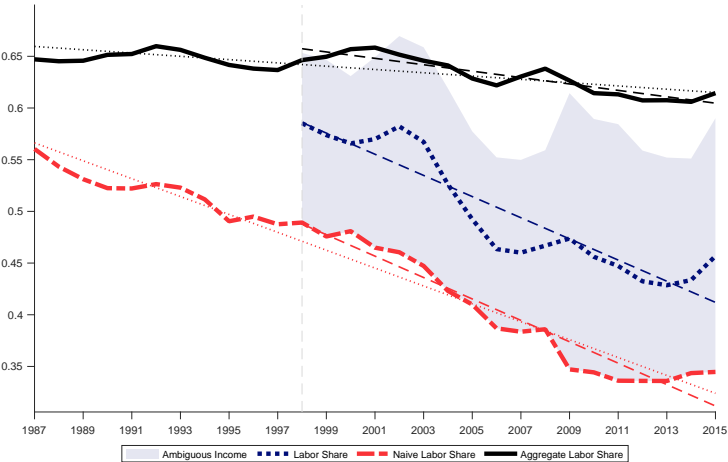
Figures 13 and 14 focus on the manufacturing sector, where the data available allows

considering the manufacturing industry of durable goods and the manufacturing industry of nondurable goods independently. The labor share in manufacturing has declined much faster than the aggregate labor share. These results are aligned with the results of [Álvarez-Cuadrado et al. \(2018\)](#), though in contrast to them, this computation shows that in 1998 the manufacturing sector’s labor share was lower than the aggregate labor share of the whole economy.

**Figure 13:** U.S. Manufacturing (durable goods) industry labor share, 1987 - 2015.



**Figure 14:** U.S. Manufacturing (nondurable goods) industry labor share, 1987 - 2015.

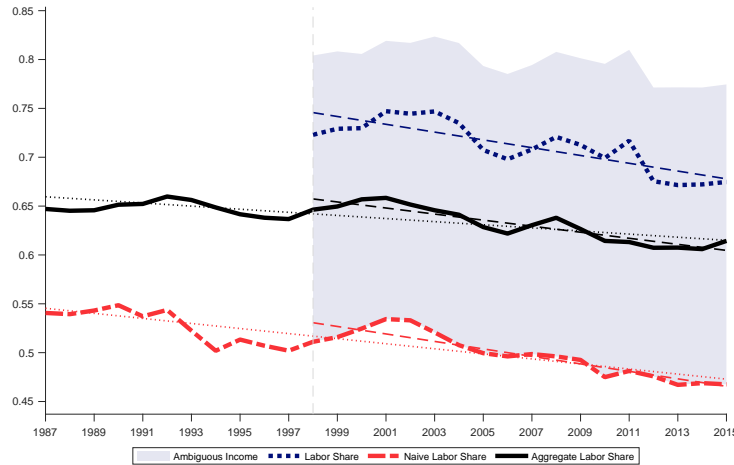


The labor share level is very different in the durable and nondurable goods industries, although both constitute the manufacturing industry. Both industries show a decreasing labor share, as the manufacturing industry, and much faster than the aggregate labor share. The labor share in the durable goods industry in 1998 is 0.667, while in the nondurable goods industry, the labor share is 0.585, eight labor share points lower. In 2015 the values were 0.560 and 0.457, respectively, which implies that the gap has widened in 3 labor share points. Omitting the period 2011 - 2015, the differences between both

industries in the AI share are noticeable.<sup>38</sup> In particular, in the durable goods industry, it is decreasing very fast, while in the nondurable goods industry, I find that the AI share has increased since 1998, passing from 0.164 to 0.245. In the manufacturing industry and the nondurable goods industry, the naive labor share can match the labor share trend.

Regarding service industries, Figures 15 and 16 show the wholesale trade industry and the retail trade industry, respectively. In 1998, both industries had a higher labor share than the aggregate labor share of the economy, which remains true during all the timeframe analyzed. In 1998, the wholesale trade industry labor share was 0.723, and the retail trade labor share was 0.768, while in 2015 were 0.675 and 0.666, respectively. Consequently, the trend of the labor share in the former is flatter than in the latter. Besides, the wholesale trade industry trend has followed the aggregate labor share trend closely, while the retail trade industry trend has been much steeper.

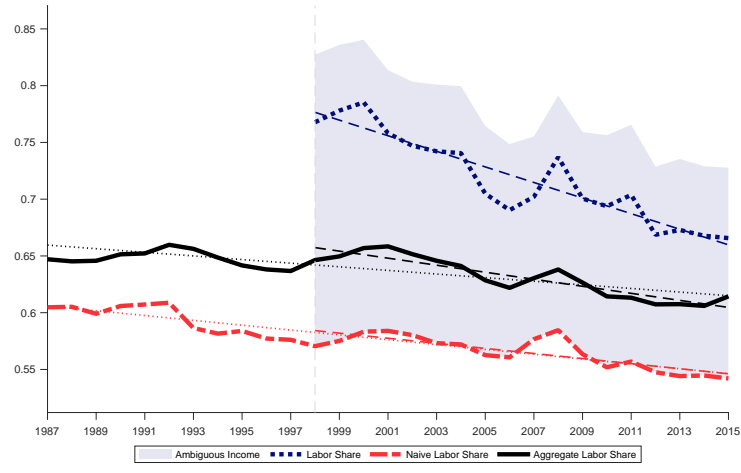
**Figure 15:** U.S. Wholesale trade industry labor share, 1987 - 2015.



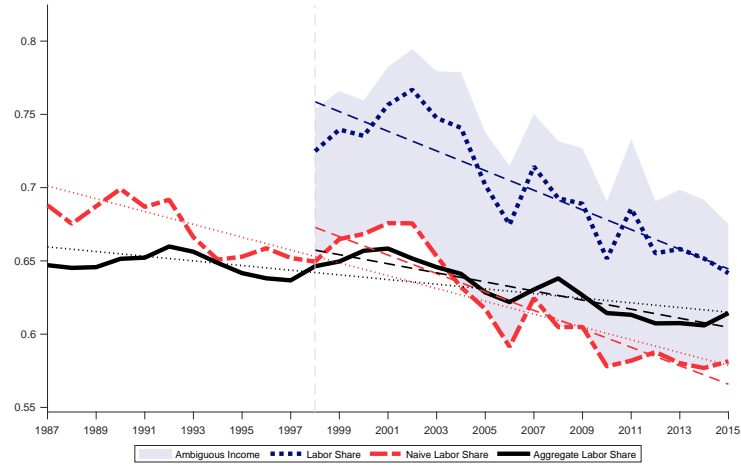
Both wholesale and retail trade industries have a more significant AI share than the aggregate labor share, an expected result due to its computation. However, while in the wholesale trade industry, this share remains roughly constant over this period at around 0.300, in the retail trade industry, it has diminished from 0.255 to 0.186, a decrease of 7 labor share points. The difference between both industries in 2015 is higher than 11 labor share points. Finally, we can point out that the naive labor share delivers a good

<sup>38</sup>Notice that during this period, the labor share in the durable goods industry is smaller than the naive labor share. This happens because the AI share is also negative for this period, a drawback of the developed methodology for the industry-level. Recall that the AI share is computed as a residual, which implies that in this case, the sum of gross operating surplus plus taxes (net of subsidies) on production is smaller than the sum of corporate profits, net interest, and depreciation. According to the proposed methodology, when the AI share is negative, and for a given value of  $\theta$ , when computing the labor share we effectively add a negative value to the CE, which results in a lower labor share than the naive labor share. In this case, we must stick with the naive labor share in the durable goods industry for the period 2011 - 2015. Without more detailed data, it is not possible to pin down the source of the negativeness of the AI share of income.

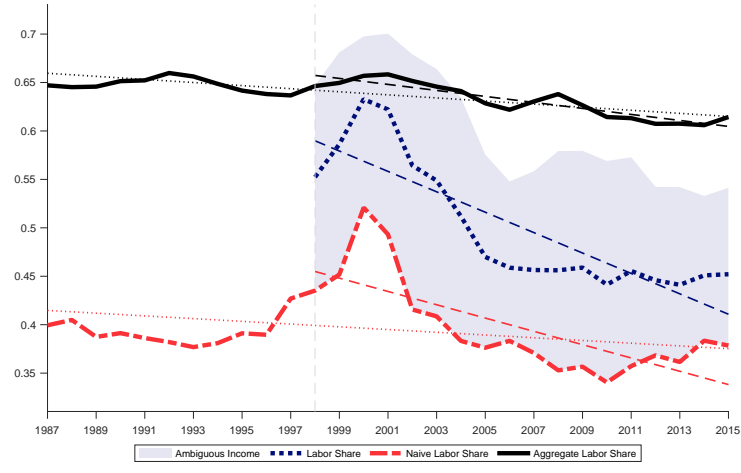
**Figure 16:** U.S. Retail trade industry labor share, 1987 - 2015.



**Figure 17:** U.S. Transportation and warehousing industry labor share, 1987 - 2015.



**Figure 18:** U.S. Information industry labor share, 1987 - 2015.



approximation of the trend of the labor share in the wholesale trade industry, but this is not the case for the retail trade industry. Figure 17 shows the results for transportation

and warehousing. As the previous service industries analyzed, the transportation industry exhibits a higher labor share than the aggregate labor share over this period. However, its decline is substantially stronger, from 0.725 in 1997 to 0.642, almost eight labor share points lower. The AI share remains roughly constant in this industry, averaging 0.117, and the naive labor share delivers a good approximation of the trend of the labor share. Figure 18 shows the results for the information industry. This industry presents a different behavior than the previous ones, increasing in the late 1990s, peaking in the early 2000s, undoubtedly motivated by the boom of the dot-com firms, and decreasing ever after. In any case, considering the labor share pre-peak value in 1998, which was 0.552, the labor share has declined to 0.452, exactly ten labor share points, though it peaked in 2000, being 0.633. The AI share has slightly decreased and averaged 0.206, again higher than the aggregate share of AI. The naive labor share again delivers a good approximation of the labor share, though the trend is somewhat flatter.

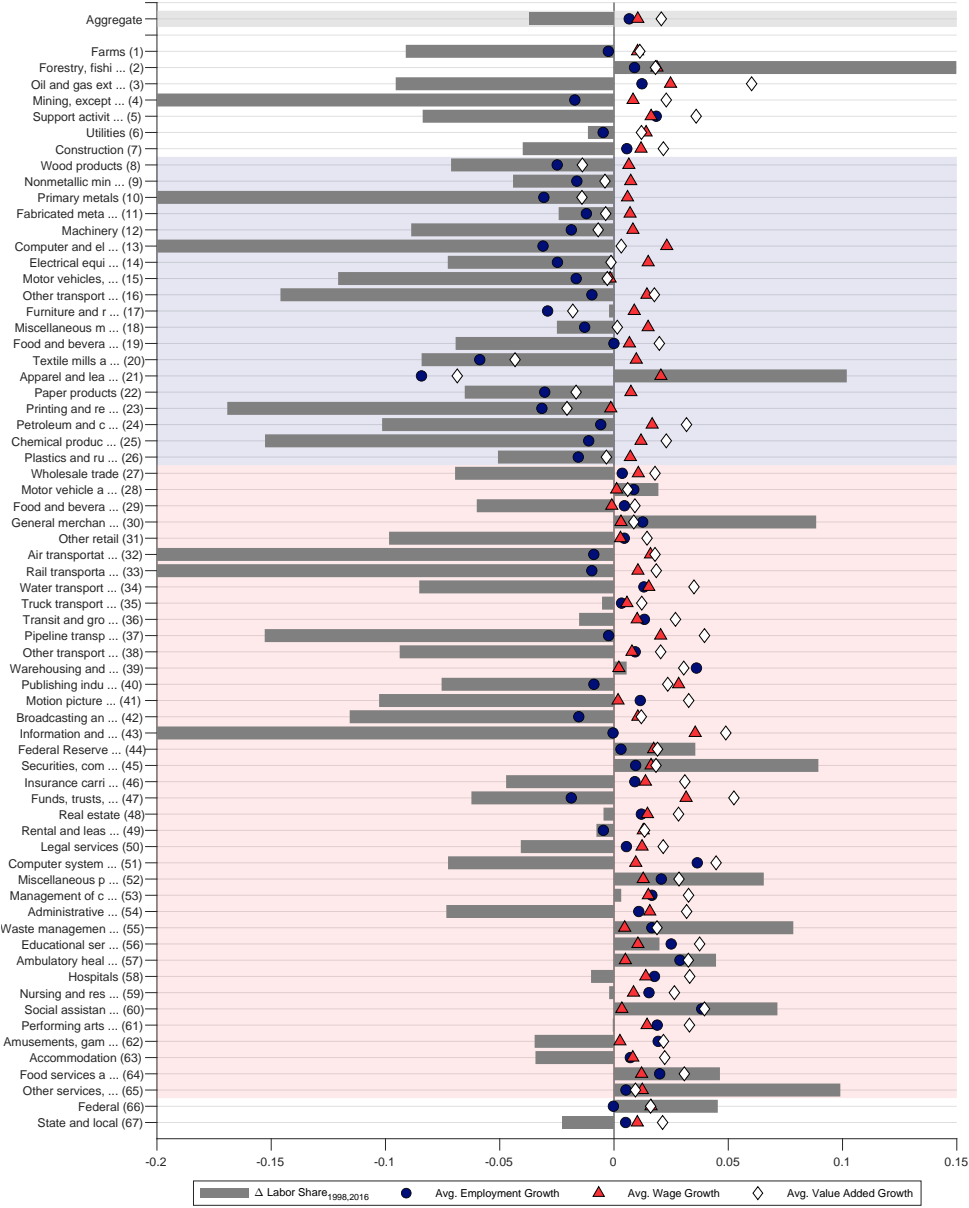
As it turns out, even in the absence of detailed data to follow Koh et al. (2020), the naive labor share still delivers a decline that closely follows that of the true labor share. As a consequence, I rely exclusively on the naive labor share for the rest of the analysis. Moreover, to obtain a deeper understanding about the movements of the naive labor share, I decompose compensation of employees (the numerator of the naive labor share) into wages and employment. Figure 19 shows the fitted change of the naive labor share for 67 industries between 1998 and 2016.<sup>39</sup> Besides, it also represents the average growth rate of the number of full-time equivalent employees, the average growth rate of real wages, and the average growth rate of real gross value added in each industry during this period. Manufacturing industries ([8, 26]) are shaded in blue and services industries ([27, 65]) are shaded in red.

The decline is characterized by the remarkable heterogeneity in the evolution of the naive labor share at the industry level, both between manufacturing and service industries and also within these two aggregations of industries. Focusing on manufacturing industries, only apparel and leather products (industry 21) delivers a positive trend. In contrast, the remaining industries show a negative trend, with the highest declines taking place in computer and electronic products (industry 13), primary metals (industry 10), and printing and related support activities (industry 23). Within service industries, the highest declines have happened in rail transportation (industry 33) and air transportation (industry 32). It has also declined in industries as relevant as wholesale trade (industry 27) or administrative and support services (industry 54). Among the industries outside

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<sup>39</sup>Motor vehicles, bodies and trailers, and parts (industry 15); information and data processing services (industry 43) and securities, commodity contracts, and investments (industry 45) show a naive labor share bigger than 1 during some periods. Moreover, those values are, in general, very far from the remaining observations.

**Figure 19:** Naive labor income share fitted change and average growth rates of employment, wages and nominal value added at the industry-level, 1998 - 2016.



Note: Light blue shaded area comprehends manufacturing industries (industries 8 to 26). Light red shaded area comprehends private service industries (industries 27 to 65); Industries 1 to 7 are agricultural activities, mining, utilities, and construction; Industries 66 and 67 are government industries. The exhaustive list of industry index identifiers is available in Appendix A.1.1. The labor share fitted change of some industries are off-scale to simplify the exposition of the results. Their specific values are: -0.2756 (4, mining except oil and gas), -0.2095 (10, primary metals), -0.2311 (13, computer and electronic products), -0.2678 (32, air transportation), -0.2822 (33, rail transportation), -0.5475 (43, information and data processing services).

manufacturing and private services, the most substantial decline has happened in mining, except oil and gas (industry 4) and the strongest increase in forestry, fishing, and related activities (industry 2). Although the decline in labor share is pervasive across industries,

there exist 16 industries that show a positive trend during this period.

The heterogeneity in the evolution of the naive labor share is a consequence of the underlying heterogeneity in the growth rates of employment, wages, and value added across industries. Figure 19 also shows that the average growth rate of employment has been either negative or very close to zero in all manufacturing industries. Interestingly, pooling all manufacturing observations from 1998 to 2016, I find that the correlation between the growth rate of employment and the decline in the trend of the naive labor share is very close to zero, which implies that industries with higher declines in the labor share are not necessarily those in which more employment is destroyed. Moreover, except in four industries, the average growth rate of wages in manufacturing industries has been higher than that of value added. The joint effect of these two facts causes the generalized and robust decline of the manufacturing industries' naive labor share. On the contrary, in service industries I find the opposite situation: with a few exceptions, employment growth has been either positive or close to zero. Besides, except in two industries, the average growth rate of wages in service industries has been lower than that of value added. The joint combination of these two effects explains the declining naive labor share trend in many service industries.

### A.3 Model

The static equilibrium equations are

$$\mu_{m,t}R_t = P_{m,t}\alpha_m(A_{m,t}\tilde{B}_t^m)^{\frac{\sigma_m-1}{\sigma_m}}\left(\frac{M_t}{K_{m,t}}\right)^{\frac{1}{\sigma_m}}, \quad (15)$$

$$\mu_{m,t}W_t = P_{m,t}(1-\alpha_m)A_{m,t}^{\frac{\sigma_m-1}{\sigma_m}}\left(\frac{M_t}{L_{m,t}}\right)^{\frac{1}{\sigma_m}}, \quad (16)$$

$$\mu_{s,t}R_t = P_{s,t}\alpha_s(A_{s,t}\tilde{B}_{s,t})^{\frac{\sigma_s-1}{\sigma_s}}\left(\frac{S_t}{K_{s,t}}\right)^{\frac{1}{\sigma_s}}, \quad (17)$$

$$\mu_{s,t}W_t = P_{s,t}(1-\alpha_s)A_{s,t}^{\frac{\sigma_s-1}{\sigma_s}}\left(\frac{S_t}{L_{s,t}}\right)^{\frac{1}{\sigma_s}}, \quad (18)$$

$$\frac{P_{m,t}}{P_{s,t}} = \frac{\gamma}{1-\gamma}\left(\frac{S_t}{M_t}\right)^{\frac{1}{\theta}}, \quad (19)$$

$$1 = [\gamma^\theta P_{m,t}^{1-\theta} + (1-\gamma)^\theta P_{s,t}^{1-\theta}]^{\frac{1}{1-\theta}},$$

$$M_t = A_{m,t}\left[\alpha_m(\tilde{B}_{m,t}K_{m,t})^{\frac{\sigma_m-1}{\sigma_m}} + (1-\alpha_m)L_{m,t}^{\frac{\sigma_m-1}{\sigma_m}}\right]^{\frac{\sigma_m}{\sigma_m-1}}, \quad (20)$$

$$S_t = A_{s,t}\left[\alpha_s(\tilde{B}_{s,t}K_{s,t})^{\frac{\sigma_s-1}{\sigma_s}} + (1-\alpha_s)L_{s,t}^{\frac{\sigma_s-1}{\sigma_s}}\right]^{\frac{\sigma_s}{\sigma_s-1}}, \quad (21)$$



together with the market clearing conditions

$$\begin{aligned} K_t &= K_{m,t} + K_{s,t}, \\ L_t &= L_{m,t} + L_{s,t}. \end{aligned}$$

Given a value for  $k_t$ , the equilibrium allocation of the static model is characterized by the solution of a system of two equations in two unknowns,  $(\kappa_t$  and  $\lambda_t)$ , where  $k_t$ ,  $\kappa_t$  and  $\lambda_t$  are defined as in (7). To obtain these two equations proceed as follows. On the one hand, arbitrage ensures that in equilibrium the interest rate will be equated across industries, which from (15) and (17) implies

$$R_t = \frac{1}{\mu_{m,t}} P_{m,t} \alpha_m (A_{m,t} \tilde{B}_{m,t})^{\frac{\sigma_m-1}{\sigma_m}} \left( \frac{M_t}{K_{m,t}} \right)^{\frac{1}{\sigma_m}} = \frac{1}{\mu_{s,t}} P_{s,t} \alpha_s (A_{s,t} \tilde{B}_{s,t})^{\frac{\sigma_s-1}{\sigma_s}} \left( \frac{S_t}{K_{s,t}} \right)^{\frac{1}{\sigma_s}},$$

or, equivalently,

$$\frac{\mu_{s,t}}{\mu_{m,t}} \frac{P_{m,t}}{P_{s,t}} \frac{\alpha_m}{\alpha_s} [A_{m,t} \tilde{B}_{m,t}]^{\frac{\sigma_m-1}{\sigma_m}} \left( \frac{M_t}{K_{m,t}} \right)^{\frac{1}{\sigma_m}} [A_{s,t} \tilde{B}_{s,t}]^{-\frac{\sigma_s-1}{\sigma_s}} \left( \frac{S_t}{K_{s,t}} \right)^{-\frac{1}{\sigma_s}} = 1. \quad (22)$$

The same is true for the equilibrium wage, thus following the same procedure with (16) and (18), substituting in the previous equation and rewriting yields

$$\frac{1 - \alpha_s}{1 - \alpha_m} \frac{\alpha_m}{\alpha_s} \frac{\tilde{B}_{m,t}^{\frac{\sigma_m-1}{\sigma_m}}}{\tilde{B}_{s,t}^{\frac{\sigma_s-1}{\sigma_s}}} \left( \frac{K_{s,t}}{L_{s,t}} \right)^{\frac{1}{\sigma_s}} \left( \frac{L_{m,t}}{K_{m,t}} \right)^{\frac{1}{\sigma_m}} = 1. \quad (23)$$

By using (7), (23) can be expressed as

$$\frac{1 - \alpha_s}{1 - \alpha_m} \frac{\alpha_m}{\alpha_s} \frac{\tilde{B}_{m,t}^{\frac{\sigma_m-1}{\sigma_m}}}{\tilde{B}_{s,t}^{\frac{\sigma_s-1}{\sigma_s}}} k_t^{\frac{1}{\sigma_s} - \frac{1}{\sigma_m}} \left( \frac{1 - \kappa_t}{1 - \lambda_t} \right)^{\frac{1}{\sigma_s}} \left( \frac{\lambda_t}{\kappa_t} \right)^{\frac{1}{\sigma_m}} = 1, \quad (24)$$

which determines the first equilibrium equation.

On the other hand, the equilibrium prices given by (16) and (18) can be substituted in (19) to obtain

$$\frac{\mu_{m,t} W_t \frac{1}{1 - \alpha_m} A_{m,t}^{-\frac{\sigma_m-1}{\sigma_m}} \left( \frac{M_t}{L_{m,t}} \right)^{-\frac{1}{\sigma_m}}}{\mu_{s,t} W_t \frac{1}{1 - \alpha_s} A_{s,t}^{-\frac{\sigma_s-1}{\sigma_s}} \left( \frac{S_t}{L_{s,t}} \right)^{-\frac{1}{\sigma_s}}} = \frac{\gamma}{1 - \gamma} \left( \frac{S_t}{M_t} \right)^{\frac{1}{\theta}}, \quad (25)$$

which can be rewritten as

$$\frac{\mu_{m,t}}{\mu_{s,t}} \frac{1 - \alpha_s}{1 - \alpha_m} \frac{A_{s,t}^{\frac{\sigma_s-1}{\sigma_s}}}{A_{m,t}^{\frac{\sigma_m-1}{\sigma_m}}} \frac{M_t^{\frac{1}{\theta} - \frac{1}{\sigma_m}}}{S_t^{\frac{1}{\theta} - \frac{1}{\sigma_s}}} \frac{L_{m,t}^{\frac{1}{\sigma_m}}}{L_{s,t}^{\frac{1}{\sigma_s}}} \frac{1 - \gamma}{\gamma} = 1. \quad (26)$$

Now, rewrite (20) and (21) as

$$M_t = K_t A_{m,t} \left[ \alpha_m \left( \tilde{B}_{m,t} \kappa \right)^{\frac{\sigma_m-1}{\sigma_m}} + (1 - \alpha_m) \left( \frac{\lambda}{k_t} \right)^{\frac{\sigma_m-1}{\sigma_m}} \right]^{\frac{\sigma_m}{\sigma_m-1}} \equiv K_t A_{m,t} g_{m,t}(\kappa_t, \lambda_t, k_t),$$

$$S_t = K_t A_{s,t} \left[ \alpha_s \left( \tilde{B}_{s,t} (1 - \kappa_t) \right)^{\frac{\sigma_s-1}{\sigma_s}} + (1 - \alpha_s) \left( \frac{1 - \lambda_t}{k_t} \right)^{\frac{\sigma_s-1}{\sigma_s}} \right]^{\frac{\sigma_s}{\sigma_s-1}} \equiv K_t A_{s,t} g_{s,t}(\kappa_t, \lambda_t, k_t).$$

Then, using (7) and after some algebra (26) can be expressed as

$$\frac{1 - \gamma}{\gamma} \frac{\mu_{m,t}}{\mu_{s,t}} \frac{1 - \alpha_s}{1 - \alpha_m} \left( \frac{A_{s,t}}{A_{m,t}} \right)^{\frac{\theta-1}{\theta}} \frac{g_{m,t}(\kappa_t, \lambda_t, k_t)^{\frac{1}{\theta} - \frac{1}{\sigma_m}}}{g_{s,t}(\kappa_t, \lambda_t, k_t)^{\frac{1}{\theta} - \frac{1}{\sigma_s}}} k_t^{\frac{1}{\sigma_s} - \frac{1}{\sigma_m}} \frac{\lambda^{\frac{1}{\sigma_m}}}{(1 - \lambda_t)^{\frac{1}{\sigma_s}}} = 1, \quad (27)$$

which determines the second equilibrium equation.

#### A.4 Labor share and structural change: individual effects of technical change and market power

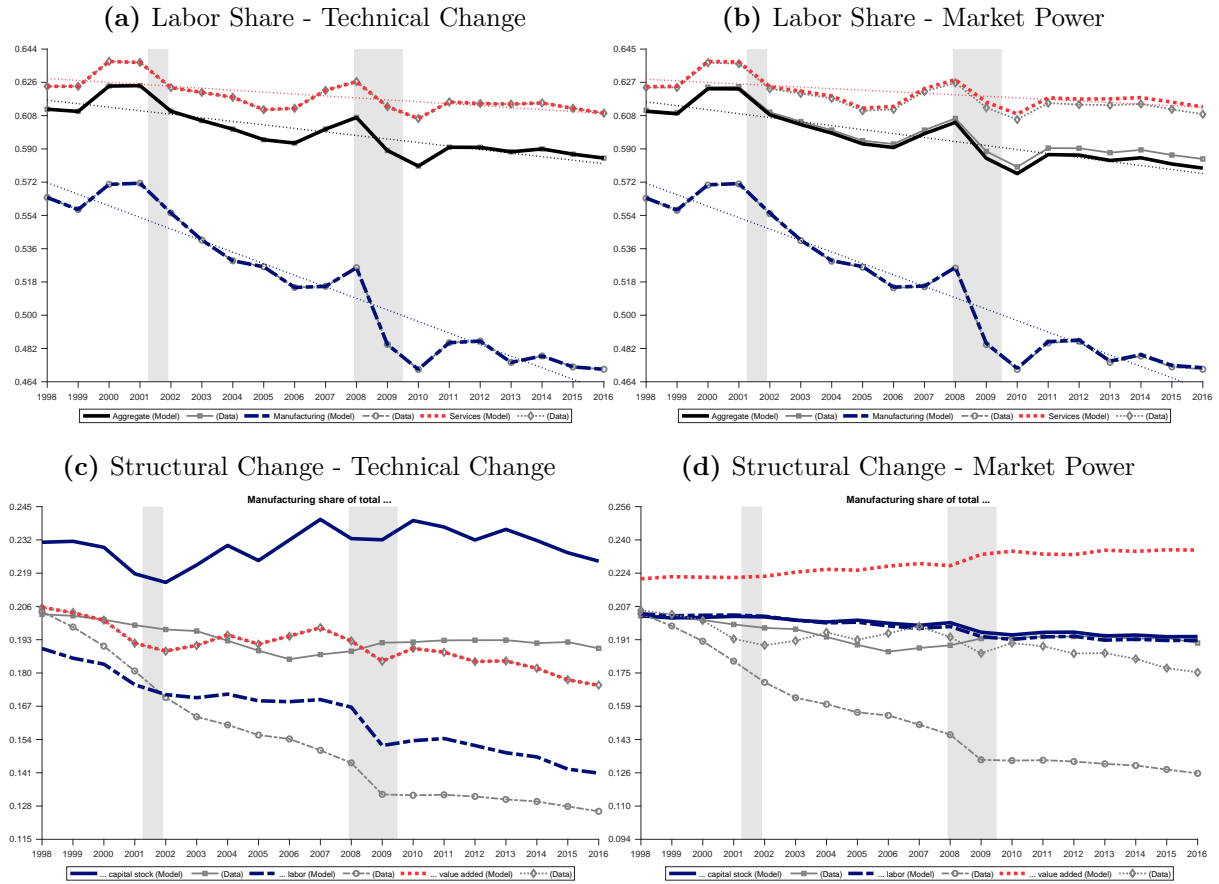
This Section shows the resulting paths for the labor share and structural change that are obtained when targeting the aggregate and industry-level labor shares and individually estimating technical change and market power. As prescribed by the theory, Figure 20 shows that technical change or market power can individually replicate the observed declined in the labor shares of manufacturing and service industries. However, this comes at the cost of obtaining capital and labor allocations across industries that are far from those observed in the data.

#### A.5 Robustness

The elasticities of substitution between capital and labor in manufacturing and services are crucial parameters of the model. These elasticities play a fundamental role in determining the evolution of the capital-labor ratio of each industry and, ultimately, its labor income share. Given the wide spectrum of available estimates in the literature, I repeat the baseline exercise considering different values for these elasticities. In particular, I consider the following alternative estimates:

1. ‘High  $\sigma$ ’, where I take the estimate  $\sigma = 1.25$  from [Karabarbounis and Neiman \(2014\)](#)

**Figure 20:** Technological change or market power, 1998 - 2016.



and assume is the same for both industries so that  $\sigma_m = \sigma_s = 1.25$ . This implies that capital and labor are slightly substitutes in the production of manufacturing and service goods,

2. ‘Low  $\sigma$ ’, where I take the estimate  $\sigma = 0.406$  from [Chirinko and Mallick \(2017\)](#) and assume is the same for both industries so that  $\sigma_m = \sigma_s = 0.406$ . This exercise reinforces the complementarity between capital and labor relative to the baseline exercise.

Table 3 summarizes each channel’s contribution to the decline in the labor share, both at the aggregate and industry-level. I find that the baseline exercise’s main result is preserved under different specifications of the capital-labor elasticity. In other words, the increase in markups is the main reason underlying the decline in the overall labor share of the U.S. As Figure 21 depicts, the level of markups recovered declines as the elasticity of substitution increases. However, the upward trend is remarkably consistent across specifications.

Finally, Figure 21 shows the evolution of markups and implied TFP from the evolution

**Table 3:** Robustness: Contribution to the decline in the labor share: markups vs. technical change

	$s^L$	$s_M^L$	$s_S^L$
<i>Baseline</i>			
Both	-3.01	-11.26	-1.89
Market Power	-2.21	-6.93	-0.72
Technical Change	-0.62	-4.35	-0.45
<i>High <math>\sigma</math></i>			
Both	-2.99	-11.26	-1.87
Market Power	-6.94	-6.06	-7.19
Technical Change	2.89	-7.07	4.29
<i>Low <math>\sigma</math></i>			
Both	-3.00	-11.26	-1.89
Market Power	-4.19	-11.26	-1.89
Technical Change	0.43	0.00	0.00

Note: Non-recalibrated decomposition. ‘Both’ includes technical change and market power. ‘Market Power’ and ‘Technical Change’ values are obtained by allowing technical change and fixing markups at its 1998 level, or fixing technical change and changing markups.

of technical change.

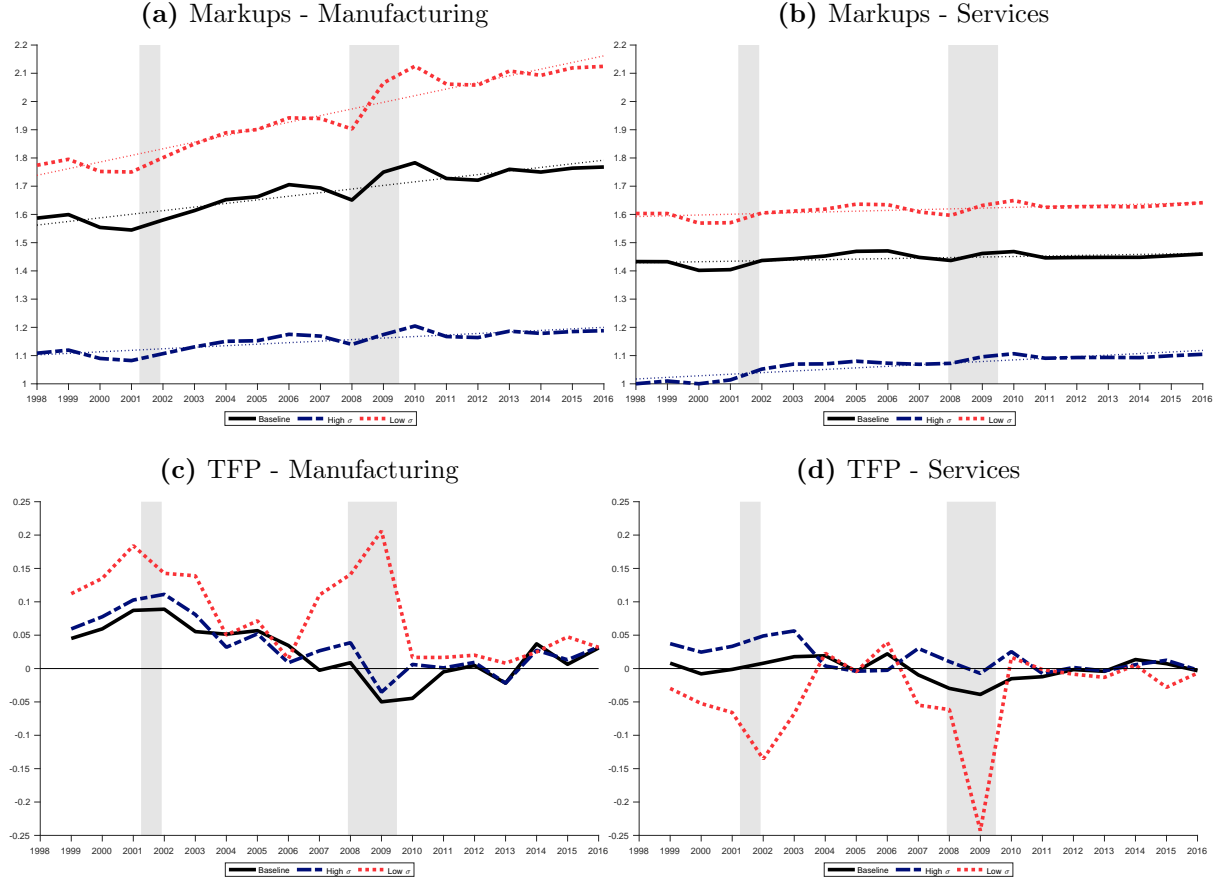
## A.6 Alternative experiments

In the baseline experiment, both technical change and the level of markups are heterogeneous across industries and are allowed to vary over time. The results show that to match the data: i) markups must be heterogeneous across industries and increase over time, and ii) technical change must be capital-biased. To stress the baseline experiment results, I conduct three additional experiments where I consider alternative assumptions of both the level and the evolution of markups over time. Many explanations for the decline of the labor share have been put forward, particularly those stressing the crucial (and sometimes, solely) role of technical change. In this Section, I perform a series of experiments with alternative specifications on the joint evolution of technology and markups, stressing the former’s explanatory power.

To assess the performance of these different explanations against the baseline experiment, I recalibrate the model under these new specifications and compare the results with those from the baseline experiment. The specific alternative specifications that I consider are:

- AE1: technical change is allowed to vary over time while markups are homogeneous

**Figure 21:** Evolution of markups and industry total factor productivity (TFP) for different specifications of the elasticity of substitution between capital and labor, 1998 - 2016.



across sectors and are fixed at a value  $\mu_{m,t} = \mu_{s,t} = 1.25, \forall t$ ;

- AE2: technical change is allowed to vary over time while there are no markups in the economy, that is  $\varepsilon_{j,t} \rightarrow \infty$  so that  $\mu_{j,t} \rightarrow 1, j = \{m, s\}, \forall t$ , and thus intermediate producers behave as price takers (this is, in spirit, an application to a different dataset of the mechanism proposed by [Álvarez-Cuadrado et al. \(2018\)](#));
- AE3: technical change is allowed to vary over time while markups are heterogeneous across sectors, but are constant at the average level calibrated for the baseline economy.

The results of the alternative experiments exhibit that, in the absence of variation over time in the level of markups, technical change can go a very far way in explaining the declining trend in the labor share across sectors. Regardless of the assumption on markups, the calibrated exogenous processes for technical change under experiments AE1, AE2, and AE3 can generate substantial declines in the labor share of manufacturing, in the labor share of services, or both. Given that markups are constant in these three

alternative settings, according to (12), the predicted labor share declines are accompanied by a parallel increase in the capital share.

**Figure 22:** Labor share, baseline and alternative experiments, 1998 - 2016.

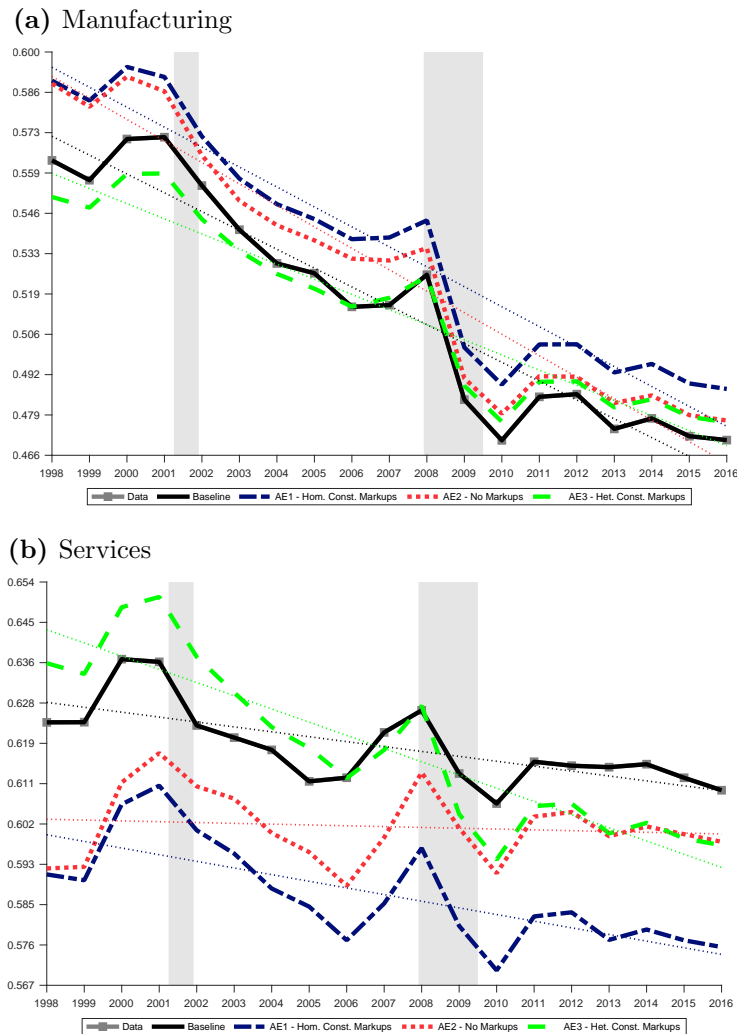
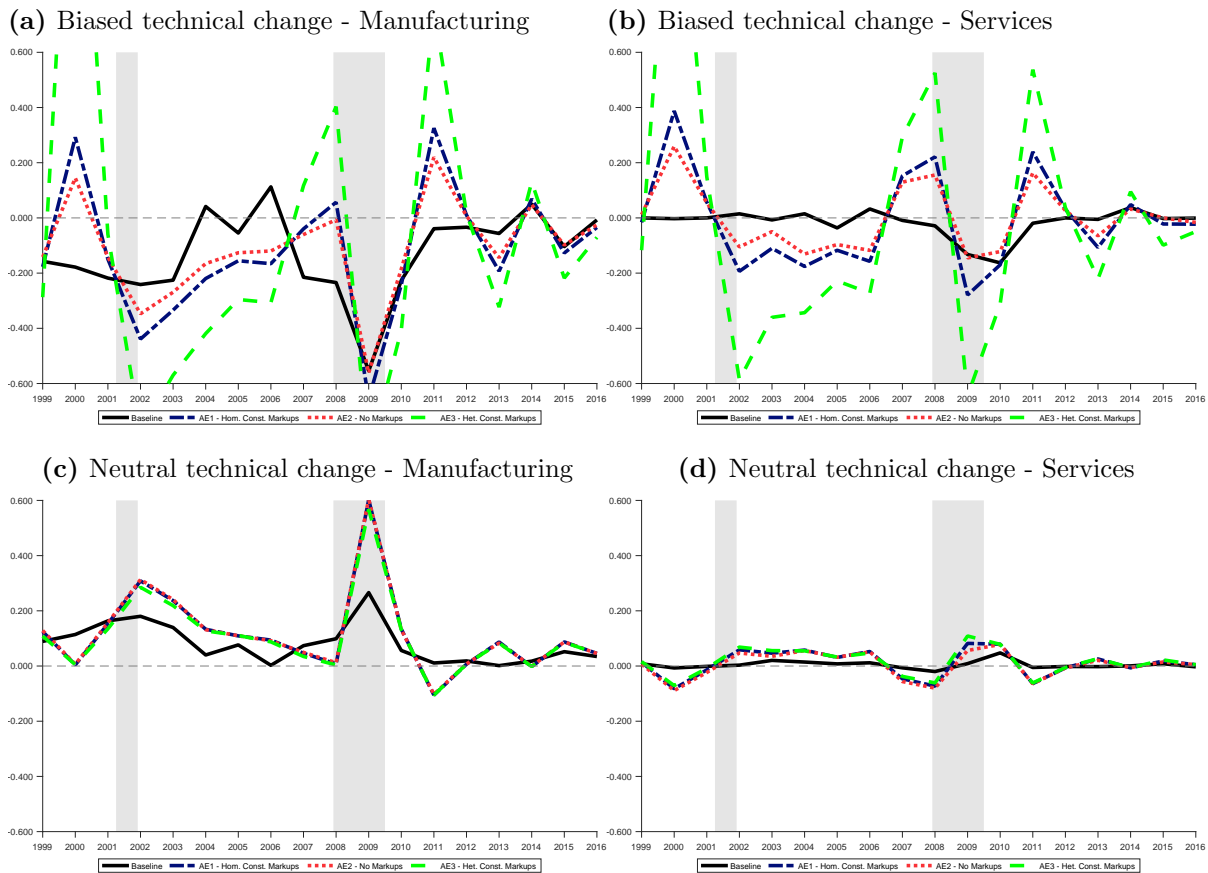


Figure 22 shows the labor shares' time series for manufacturing and service industries, comparing the baseline experiment with the alternative specifications. Noticeably, if markups are homogeneous across sectors (either positive, depicted as the dashed (blue) line, or zero, depicted as the dotted (red) line), the model fails to match the levels of the labor shares while being consistent with the process of structural change. Technical change can then replicate the declining trend of the labor share but at the cost of delivering a smaller average labor share in services and a higher average labor share in manufacturing. In other words, so long as markups are homogeneous, the model cannot generate a big gap between both labor shares, like the one measured in the data.

Allowing for heterogeneity in markups and recalibrating the model delivers a new technical change process that yields an evolution of the labor shares of manufacturing

and services much closer to the results obtained with the baseline economy (or those observed in reality). However, this comes at the cost of a slight under-prediction of the decline in the trend of the labor share of manufacturing and a high over-prediction of the decline in the trend of the labor share of service industries. The fitting of structural change moments is remarkably good no matter what is the assumption regarding markups considered.

**Figure 23:** Technical change parameters, baseline and alternative experiments, 1998 - 2016.

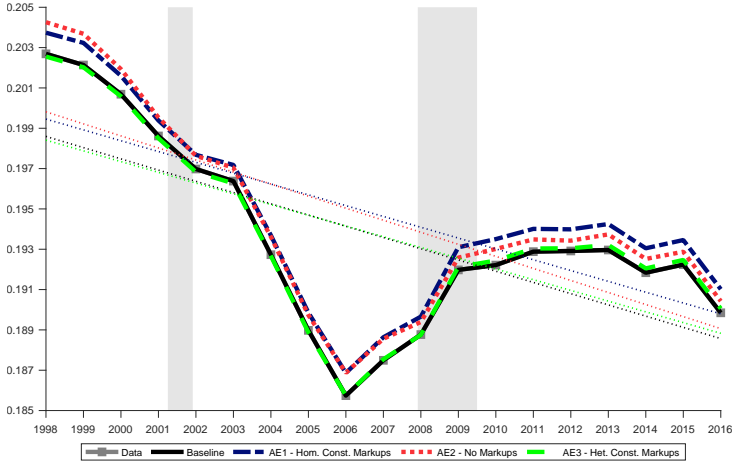


The joint analysis of all the results discussed so far suggests a strong link between the decline in labor share and structural change. In particular, if markups are not heterogeneous and are not allowed to vary over time, technical change alone cannot replicate the levels of the labor share across sectors while being consistent with structural change. If the only interest lies in the labor share's evolution, the model can be pushed even further by targeting only labor share moments. In that case, the model can perfectly reproduce the level and the trend of the labor share in this period, but that comes at the cost of being inconsistent with the observed structural change process.

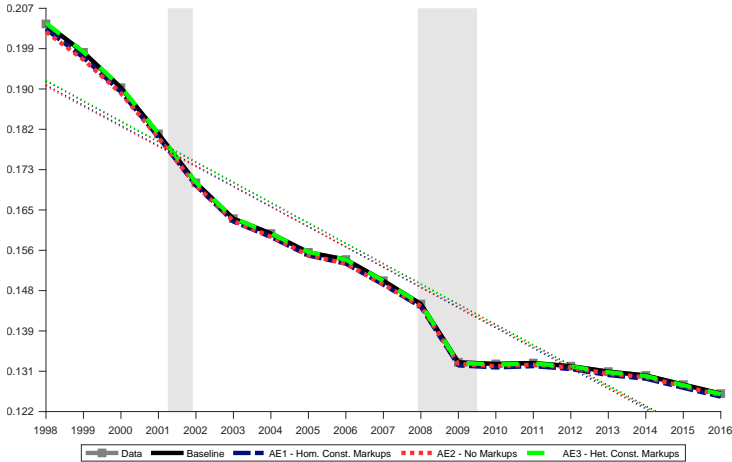
All experiments exhibit similar qualitative results concerning the evolution of the capital-output ratio across sectors, the wage-value added growth gap, and employment

growth. All specifications over-predict structural change in terms of value added, resulting from the substantial decline in the relative price between manufacturing and service goods.

**Figure 24:** Share of capital in manufacturing out total capital stock, baseline and alternative experiments, 1998 - 2016.



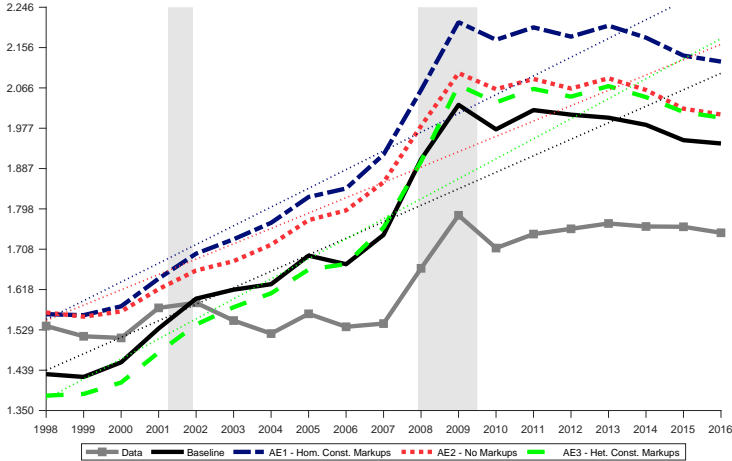
**Figure 25:** Share of labor in manufacturing out of total labor, baseline and alternative experiments, 1998 - 2016.



The evolution of technology is qualitatively similar across the different experiments. However, the volatility of the series of technical change parameters is widely heterogeneous across different specifications. Figure 23 shows that the smallest volatility of these series is attained in the baseline economy, while it is remarkably higher in the counterfactual economies where markups are kept fixed. Intuitively, fixing markups reduces the degrees of freedom to match the data, and therefore the calibrated processes of technical change need to be more volatile to match the evolution of the moments of interest. Compared to the remaining experiments, experiment (Exp6), where markups are heterogeneous and constant, is the experiment in which higher volatility is needed.



**Figure 26:** Manufacturing capital-output ratio, baseline and alternative experiments, 1998 - 2016.



Figures 24 - 26 show the evolution of the share of capital in manufacturing, the share of labor in manufacturing, and the capital-output ratio in manufacturing. Although there are no significant differences across the different specifications for the shares of capital in manufacturing and services, the exercises where markups are homogeneous – either zero or positive, but constant over time – fail in delivering the correct level of capital allocated to manufacturing. As there are no market power differences across sectors, the equilibrium allocation of capital in manufacturing is more significant than in the other experiments. Consequently, the resulting capital-output ratio in manufacturing is also higher than its counterpart in the data.

Consequently, all the results point towards the need for heterogeneity in both technical change and markups across sectors to explain the observed declines in the labor share and the strong relative reallocation of labor from manufacturing to services. Through the lens of the model, markups are the main driver of the decline in the labor share in manufacturing and service industries, while technical change is the main driver of structural change.