Demand-Driven Labor-Market Polarization*

Diego Comin
Dartmouth College

Ana Danieli
Northwestern U.

Martí Mestieri
Northwestern U.

May 15, 2019

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Abstract

We document that income elastic sectors are more intensive in high- and low-skill occupations than income inelastic sectors, which are relatively more middle-skill intensive. As a result, increases in aggregate expenditure have an asymmetric effect on labor demand across occupations and cause labor-market polarization. We quantify the importance of this demand-driven labor market polarization for the US using a general equilibrium model with endogenous job assignment and nonhomothetic demand. Our model is calibrated to aggregate variables from 1980 and household-level estimates of sectoral income elasticity. We find that the increase in aggregate expenditure from 1980 to 2016 accounts for 50% of the increase in the wage bill share of high-skill occupations, 60% of the decline for medium-skill occupations and virtually all of the increase in the wage bill share of low-skill occupations. This mechanism is also quantitatively important to understand the evolution of labor market outcomes across occupations in the period 1950-1980 and in other developed economies.

Keywords: Inequality, Nonhomothetic Demand, Occupations, Workers' Skills.
JEL Classification: E21, E23, J23, J31.

*We thank Gadi Barlevy, Matthias Doepke, Koichiro Ito, Ryan Kellogg, Kiminori Matsuyama, Yongs Shin, Joseph Zeira and attendees at CEMFI, Harris School, TSE, FRAME Conference, Washington U. at St. Louis, Federal Reserve Bank of Chicago, World Bank and Banca d'Italia joint conference and the Northwestern macro lunch for helpful comments and discussions. Comin thanks financial support from the European Commission under the FRAME project and from the NSF. Mestieri thanks CREI and the Chicago Fed for their hospitality during part of this research. All errors are our own. Contact: marti.mestieri@northwestern.edu

1 Introduction

Labor market outcomes in the US have polarized since the 1980s. The wage bill accrued to US high-skill workers relative to middle-skill has increased six-fold since the 1980. The wage bill accrued to low-skill workers relative to middle-skill has increased three-fold.[1] What drives polarization? This question has motivated an enormous literature that has focused on skilled-biased technical change, computerization trade and offshoring, de-unionization,etc.[2]

This paper documents and quantifies a novel mechanism to account for job-market polarization that builds on the nonhomotheticity of demand. We document the novel fact that there is a strong positive correlation between the sectoral intensity of high- and low-skill occupations and the income elasticity of sectoral value added. Since income elastic sectors represent a high share of US value added, this implies that the sectoral distribution of wage bills is concentrated in high-income elastic sectors for high and low- skill occupations, while the wage bill of middle-skill occupations is concentrated mostly in income inelastic sectors.[3] Our demand-driven polarization mechansim follows naturally from this fact. As aggregate expenditure grows, demand shifts to high-income-elastic sectors. Since these sectors are intensive in high- and low-skill occupations, this reallocation of sectoral demand causes an increase in the relative demand for high- and low-skilled workers. This leads to a hollowing out of the wage bill distribution and polarization of workers earnings.[4]

Two empirical observations motivate our mechanism. First, sectoral value added growth over the period 1980-2016 has been fastest in more income-elastic sectors. To document this fact, we estimate the income elasticity parameters of a nonhomothetic CES demand system using US household expenditure data, as in Comin et al. [2015].[5] A key property of this demand system is that there is a one-to-one mapping between sectoral income elasticty parameters and the observed average expenditure elasticity in the data. Figure 1 depicts the estimated income elasticity parameter in the x-axis and sectoral value-added growth across 8 broad sectors of the US economy on the y-axis.[6] There is a clear, strong (0.86) and statistically significant relationship between the two.

[1] We report these numbers in Table 2. Table 6 shows that there is polarization in relative wages and relative employment shares. The polarization of labor markets is a common phenomenon across most Western economies, see the references at the end of this section.

[2] See, among many others, Acemoglu and Autor [2011] and the references therein.

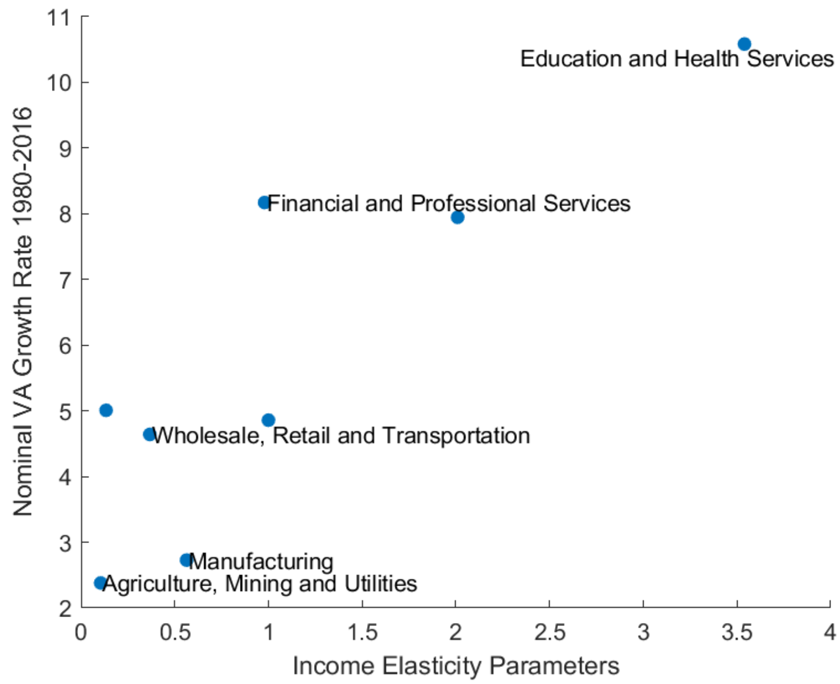
[3] Income elasticities of demand differ significantly across sectors. Among others, Aguiar and Bils [2015] document this heterogeneity across sectors using US household expenditure data. They also show that income elasticities are stable both over time and across the income distribution.

[4] Furthermore, as we discuss below, the share in total value added of high-income elastic sectors tends to increase over this period. As a result, the positive correlation between income elasticity and sectoral distribution of the wage bill for high and low-skill occupations tends to persist over time (see Table 1).

[5] Demand is specified over sectoral value added. We thus combine data from the consumer expenditure survey (CEX) and BEA's input-output tables to estimate demand over value added, as in Buera et al. [2015].

[6] The relationship is robust to both finer and broader sectoral aggregations. We use 8 sectors in our analysis because it is a good compromise between the tradition in the structural change literature, which tipically focuses on 2 or 3 sectors, and the 15 sectors available in the BEA Input-Output tables.

Figure 1: Sectoral Nominal Value-Added Growth (1980-2016) and Income Elasticity Parameters



Sectoral value added measures are from the BEA. The income elasticity parameters correspond to the estimated sector-specific income elasticity parameter of a nonhomothetic CES demand system estimated using the Consumer Expenditure Survey (see Section B in the appendix for details).

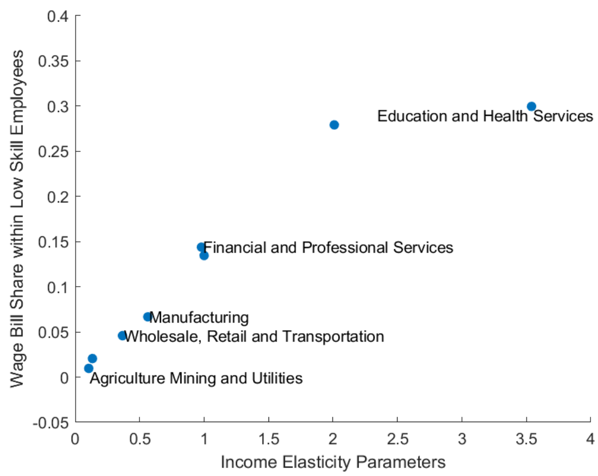
The second empirical observation supporting our mechanism is the correlation between the sectoral distribution of the wage bill and sectoral income elasticity parameters across different occupations. Following Acemoglu and Autor [2011], we classify occupations into three skill categories (high, middle and low skill) according to their average wage in 1980.[7] We then compute the share of the total wage bill accrued by any given occupation that comes from each of the 8 broad sectors. Figure 2 plots, for each occupation, the income elasticity parameter in the x-axis and the sectoral share of the wage bill in 1980 on the y-axis. Figures 2a and 2c show that there is a strong positive correlation between income elasticity and the low- and high-skill shares. The corresponding correlations are 0.57 and 0.95, respectively. In contrast, Figure 2b shows a negative relationship for middle-skilled occupations (with a correlation of -0.36). Perhaps surprisingly, we also document in Table 1 that the correlation patterns between income elasticity and sectoral wage bill shares across occupations have been remarkably stable over the period 1980-2016.

As suggested above, these correlation patterns between income elasticity and sectoral distribution of wage bill shares emerge for two reasons. First, high income elastic sectors are

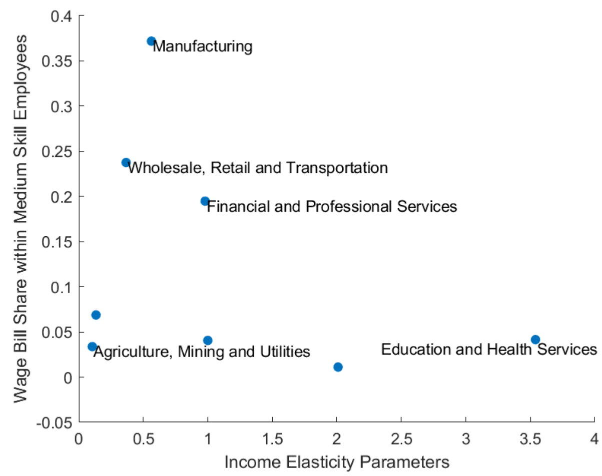
[7] We use the Census IPUMS 1980 5 percent extract. The mean wage in each occupation is calculated using workers' hours of annual labor supply times the Census sampling weights.

Figure 2: Sectoral Wage Bill Share and Income Elasticity Across Skill Groups

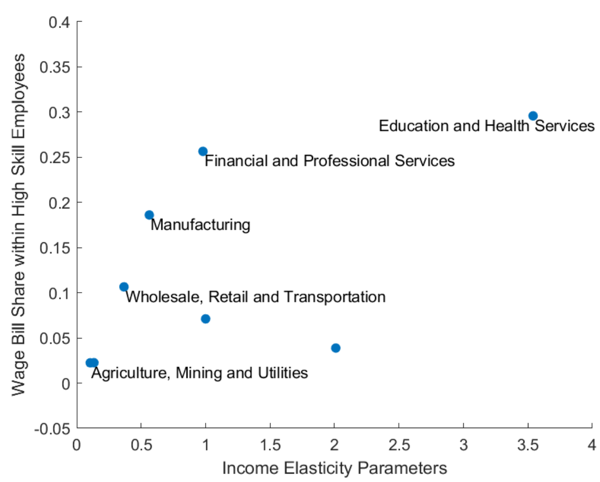
(a) Low-skill



(b) Middle-skill



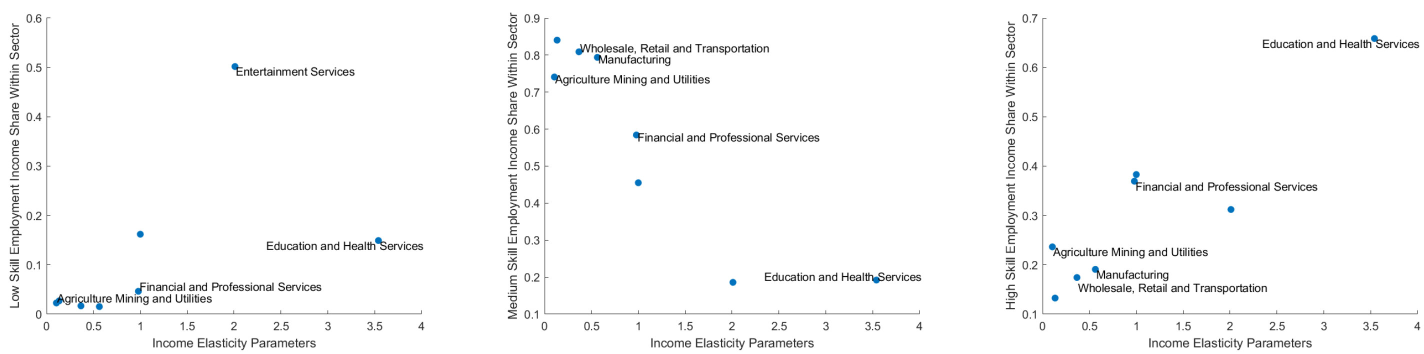
(c) High-skill



Notes: Each dot represents the share of the wage bill in occupation j coming from sector s in 1980. Employment shares are computed from the decennial census. Wages come from the Current Population Survey. See Appendix A for details.

Figure 3: Sectoral Factor Intensity and Income Elasticity

(a) Low-skill (b) Middle-skill (c) High-skill



Notes: Each dot represents the share of the total wage bill in sector s that is paid to occupation j in 1980. Employment shares are computed from the decennial census. Wages come from the Current Population Survey. See Appendix A for details.

Table 1: Correlation of Sectoral Distribution of Occupation Wage Bill and Income Elasticity Parameters

	High	Middle	Low
1980	0.57	-0.36	0.95
1990	0.48	-0.34	0.88
2000	0.45	-0.35	0.87
2016	0.52	-0.34	0.87

intensive in high- and low-skill occupations, while the low-income elastic sectors are intensive in medium-skill occupations. This fact is documented in Figure 3 that plots the share of the sectoral wage bill accrued by a given occupation (in 1980) against the income elasticity of sectoral demand. The correlation between these two variables is 0.9 for high-skill, 0.56 for low-skill and -0.9 for medium-skill occupations. Second, since high-income elastic sectors account for a significant part of total expenditures the vast majority of labor demand for low- and high-skill workers comes from high-income elastic sectors. As a result of these two forces, we obtain the positive correlation between wage bill shares and income elasticities for low- and high-skill workers documented in Figure 2.

To quantitatively evaluate the significance of nonhomotheticicities for labor-market polarization, we develop a general equilibrium multi-sector economy with three key features: *(i)* nonhomothetic preferences with sectoral differences in the income elasticity of demand, *(ii)* sectoral differences in the skill intensity requirements of production and *(iii)* endogenous assignment of workers to occupations.

We calibrate the key parameters in the model using the household-level estimates of the demand parameters and matching the distribution of value added across sectors in 1980. To capture traditional explanations of polarization, our model allows for a time-varying and sector-specific intensity of each occupation. We calibrate these intensity parameters to match, in each sector and year, the share in value added of the wage bill accrued by each occupation. Our key finding is that, because of nonhomotheticities, an increase in aggregate expenditures consistent with the US historical increase in Personal Consumption Expenditures (PCE) per capita and with the increase in the PCE deflator is a key driver of the polarization of labor markets in all its dimensions. This increase in expenditures is responsible for roughly 50% (100%) of the observed increase in the wage bill share of high-skill (low-skill) occupations and 60% of the decline in the wage bill share of medium-skill occupations.

These results highlight the importance of using a multi-sector framework. A one-sector model would incorrectly attribute to changes in (aggregate) skill-intensity the observed reallocation of the wage bill across occupations. Instead, in our setting, we can directly measure the skill-intensity at the sector level and can separately identify the role of changes in the composition of demand on the evolution of the relative wage bills.

Beyond the wage bills, our job assignment model also does a good job in terms of dividing the effect of changes in labor demand between changes in relative wages and hours worked. More specifically, we find that non-homotheticities in demand are responsible for similar shares of the evolution of relative wages and hours worked across occupations. These findings are robust to accounting for the wedges between sectoral production and expenditures introduced by net exports, and to the rules used to assign capital income across households.

To conclude our paper, we turn our attention to exploring the role of nonhomotheticities in the evolution of labor market polarization in other developed economies and other historical periods. We explore the polarization of a large number of European economies since 1990, and the US during the 1950-1980 period. We also speculate about the future by studying the transformation of labor markets from 2016 to 2035. In all these three exercises, we document that nonhomotheticities in demand appear to be key to explain the evolution of distributional outcomes in labor markets.

Related literature This paper relates to different strands of literature. First, a vast and rich literature has explored the drivers of wage polarization. Wage polarization was probably first documented by Acemoglu [1999] for the US. Goos et al. [2009] document similar polarization patterns for European countries. Technical change has been the leading explanation to account for labor market polarization. Autor et al. [2003] proposed the "routinization" hypothesis whereby computer capital substituted for workers in routine-intensive occupations. Autor and Dorn [2009, 2013], Goos et al. [2014] also document a substantial increase in low-skill service sector jobs and link it to the fact that they are not routine-intensive. A larger number of papers have subsequently explored different aspects of routinization and polarization.[8]

The paper also relates to the relatively small literature that has linked structural change and relative wages. Lee and Shin [2017] and Bárány and Siegel [2018] link biased technological progress, structural change and labor-market polarization. In contrast to ours, these papers focus on the role of technology and abstract from nonhomotheticity of demand. The rest of this literature has focused on the skill premium and compared labor market outcomes of college versus non-college workers. Our focus is on labor-market polarization, allowing for three skill-levels of occupations in which agents select into.[9] Buera et al. [2015] propose a two-sector, two-skill level (linked to education) model of structural change to account for the evolution of the skill premium. The model borrows from the insights in Buera and Kaboski [2012] who also uses a two-sector model, in which services is more skill intensive. Cravino and Sotelo [2017] extend the previous setting to allow for international trade and show that international trade also affects structural change and the evolution of the skill premium. Our formulation and estimation of the nonhomothetic CES demand system follows Comin et al. [2015]. This formulation has the advantage of allowing for an arbitrary number of sectors (and nesting) with non-vanishing income effects relative to Stone-Geary demand systems.[10]

Finally, our work also relates to the micro literature that has used household expenditure data to document heterogeneity of income elasticities across sectors and differences in consumption patters across the income distribution. Heterogeneity of income elasticities across sectors is a well-known fact, see Aguiar and Bils [2015] and references therein. Leonardi [2015] uses the household expenditure survey to show that educated households consume more high-skill and, to a lesser extent, very low-skill *services*. Leonardi then links an "education-specific elasticity of demand" to the rise of the skill premium in a static general equilibrium model. He finds a small effect for demand shifters in his calibrated model (consistent with Autor and Dorn, 2013 and Goos et al., 2014).[11] Mazzolari and Ragusa [2013] also analyze changes in product demand using household consumption data. They focus their analysis on the consumption of low-skill-intensive services. They argue that when relative wages of skilled workers increases, demand for low-skill services should increase. They estimate that this channel accounts for one-third of the growth of employment of noncollege workers in low-skill services

[8]Offshoring and international fragmentation of production has also been proposed as a potential channel. Basco and Mestieri [2013] show how trade costs have declined more in middle-skill intensive industries and how this can lead to wage polarization in rich countries. See the references therein for trade-based accounts of polarization.

[9]Our proposed channel is present in any model with nonhomotheticities, technological progress and heterogeneity in skill intensity across sectors. As such, the models proposed in Buera et al. [2015] and Cravino and Sotelo [2017] feature our proposed mechanism in a two-skill level setting. However, they do not analyze our proposed channel in isolation from other shocks to the economy.

[10]We abstract from the changes in the quality of goods consumed within a sector as recently emphasized in Jaimovich et al. [2019].

[11]Autor and Dorn, 2013 conclude that demand-pull effects are likely not to drive polarization by studying whether wage increases at the very top of the distribution affected demand for services. In contrast, our results account for the overall increase income at across the income distribution and their effect on the overall sectoral composition of demand.

in the 1990s.

We find instructive to illustrate our mechanism by introducing its key elements one at a time. The structure of the paper reflects this strategy. In Section 2, we focus on the drivers of the relative wage bills across occupations. We first introduce the multi-sector model and document the importance of changes in the composition of value added for the evolution of wage bills. Then, we make the evolution of sectoral value added endogenous by introducing nonhomothetic preferences. We quantify the importance of aggregate expenditures for the evolution of relative wage bills across occupations in this simple set-up. After understanding the key driving forces in the simplest possible setting, we present the fully-fledged model in Section 3. This model features endogenous job assignment and heterogeneous households in addition to the multi-sector production structure and nonhomothetic preferences. In contrast to the simple model, this richer setting has implications for the evolution of both wages and hours worked across occupations. In Section 4, we extend our analysis to the 1950-1980 period for the U.S., to various European countries, and we look into the future polarization of US labor markets circa 2035. Section 5 concludes.

2 Relative Wage Bills: A first pass

This section presents a simple multi-sector model that contains the key quantitative drivers of polarization. We proceed in two steps. First, we introduce the production side of our economy. We use it to perform a decomposition exercise of the evolution of the relative wage bill and quantify the importance of sectoral reallocation of economic activity. Second, we present the demand-side of the economy. It features a representative household with nonhomothetic preferences. This setting suffices to study the sources of changes in the sectoral composition of the economy and assess the importance of nonhomotheticities in driving labor-market polarization.

2.1 Production

We consider an economy with $\mathcal{S} = \{1, \ldots, S\}$ distinct sectors. Each sector $s \in \mathcal{S}$ produces output Y_{st} at time t according to the constant-returns-to-scale Cobb-Douglas production function

$$Y_{st} = A_{st} \prod_{j \in \{H,M,L\}} X_{jst}^{\alpha_{jst}}, \qquad \text{with} \qquad \sum_{j \in \{H,M,L\}} \alpha_{jst} = 1, \tag{1}$$

where A_{st} is a Hicks-neutral technological term in sector s, α_{jst} is the intensity of occupation j in sector s at time t. Since we are allowing $\{\alpha_{jst}\}$ to vary arbitrarily over time, we can flexibly capture any patterns of substitution across factors of production implied by skill-biased technological change, offshoring of production, changes in production wedges, etc. The normalization $\sum_{j\in\{H,M,L\}} \alpha_{jst} = 1$ implies that the contribution of capital (and other omitted factors) to production is captured by the TFP term $\{A_{st}\}$. In Section 3 we relax this assumption by allowing for time-varying sectoral labor shares.

Given a price of sectoral output p_{st} and wages w_{jt}, the demand for occupation j in sector s at time t is

$$w_{jt}X_{jst} = \alpha_{jst}p_{st}Y_{st}. \tag{2}$$

The ratio of the wage bill accrued by two occupations, j and j', in sector s, is

$$\frac{w_{jt}X_{jst}}{w_{j't}X_{j'st}} = \frac{\alpha_{jst}}{\alpha_{j'st}}. \tag{3}$$

Thus, in any sector s, the wage bill of occupation j relative to occupation j' is entirely determined by the ratio of their intensities in production, α_{jst} and $\alpha_{j'st}$, which we can compute using readily available data.

Next, we compute the *aggregate* wage bill of occupation j. Let X_{jt} denote total employment in occupation j (i.e., $X_{jt} = \sum_{s\in\mathcal{S}} X_{jst}$), and VA_{st} nominal value added in sector s. In this simple model, sectoral output coincides with sectoral value-added, $VA_{st} = p_{st}Y_{st}$ (this assumption is relaxed in Section 3). Adding Equation (2) across sectors, we obtain that the aggregate wage bill of occupation j is

$$w_{jt}X_{jt} = \sum_{s\in\mathcal{S}} \alpha_{jst}VA_{st}. \tag{4}$$

This expression simply states that the total wage bill accrued to occupation j is the sum of sectoral value added weighted by the share of the wage bill going to occupation j in sector s.

Accounting for Polarization The production structure laid down so far allows us to unpack observed changes in the wage bill. In particular, we use Equation (4) to decompose the evolution of the wage bill in occupation j. We rewrite $\alpha_{jst}VA_{st}$ as

$$\alpha_{jst}VA_{st} = (\alpha_{js0} + \triangle\alpha_{jst})(VA_{s0} + \triangle VA_{st}), \tag{5}$$

where $\triangle$ denotes the time difference operator between time 0 and t, i.e., $\triangle VA_{st} \equiv VA_{st} - VA_{s0}$. Replacing (5) in (2) and dividing by the initial wage bill, $w_{j0}X_{j0}$, we obtain

$$\frac{w_{jt}X_{jt}}{w_{j0}X_{j0}} - 1 = \frac{\sum_{s\in\mathcal{S}} \alpha_{js0} \triangle VA_{st}}{w_{j0}X_{j0}} + \frac{\sum_{s\in\mathcal{S}} \triangle\alpha_{jst}VA_{s0}}{w_{j0}X_{j0}} + \frac{\sum_{s\in\mathcal{S}} \triangle\alpha_{jst}\triangle VA_{st}}{w_{j0}X_{j0}}.$$

Using equation (4) to replace $w_{j0}X_{j0}$ by $\sum_s \alpha_{js0}VA_{s0}$ yields

$$\begin{aligned}\frac{\triangle\left(w_{jt}X_{jt}\right)}{w_{j0}X_{j0}} \quad = \quad & \overbrace{\sum_{s\in\mathcal{S}}\gamma_{js0}\frac{\triangle VA_{st}}{VA_{s0}}}^{\text{Term 1}} + \overbrace{\sum_{s\in\mathcal{S}}\gamma_{js0}\frac{\triangle\alpha_{jst}}{\alpha_{js0}}}^{\text{Term 2}} \\ & + \underbrace{\sum_{s\in\mathcal{S}}\gamma_{js0}\left[\frac{\triangle VA_{st}}{VA_{s0}}\frac{\triangle\alpha_{jst}}{\alpha_{js0}}\right]}_{\text{Term 3}}. \end{aligned} \tag{6}$$

To interpret expression (6), first note that the weights $\gamma_{js0} \equiv \frac{\alpha_{js0}VA_{s0}}{\sum_s \alpha_{js0}VA_{s0}}$ represents the share of the total wage bill of occupation j that comes from sector s. Expression (6) illustrates the key insight of the multi-sector setting. Changes in the wage bill are not only driven by changes in the factor intensity (Term 2), but also by changes in the sectoral composition of the economy (Term 1), and the covariance between changes in factor intensity and changes in the sectoral composition of the economy (Term 3). As noted by Buera et al. [2015] or Cravino and Sotelo [2017], the structural transformation of the economy may impact the wage bill of occupation j if the sectors where this occupation was initially more intensive have grown faster. Similarly, the impact of changes in the intensity of an occupation on the wage bill depend on how they covary with the initial sectoral share distribution of the occupation.[12]

Contrast with a One-Sector Model In the particular case that there is only one sector in the economy, $S = 1$, Equation (6) simplifies to

$$\frac{\triangle\left(w_{jt}X_{jt}\right)}{w_{j0}X_{j0}} = \frac{\triangle\alpha_{jt}}{\alpha_{j0}} + \frac{\triangle VA_t}{VA_0} + \frac{\triangle\alpha_{jt}}{\alpha_{j0}}\frac{\triangle VA_t}{VA_0}.$$

This implies that the growth in the relative wage bill across occupations j and j' is

$$\frac{\triangle\left(w_{jt}X_{jt}\right)}{w_{j0}X_{j0}} - \frac{\triangle\left(w_{j't}X_{j't}\right)}{w_{j'0}X_{j'0}} = \left(\frac{\triangle\alpha_{jt}}{\alpha_{j0}} - \frac{\triangle\alpha_{j't}}{\alpha_{j'0}}\right)\left(1 + \frac{\triangle VA_t}{VA_0}\right) \tag{7}$$

Expression (7) shows that, in the one-sector setting, differences in the growth of the relative wage bill of workers in occupation j relative to j' can only arise from differences in the growth rate of their factor intensities, α_{jt} and $\alpha_{j't}$. Consequently with this observation, most of the existing theories proposed to account for polarization – such as skill-biased technical change,

[12]Note that this decomposition exercise also holds if we assume a CES production function instead of Cobb-Douglas. To see this, suppose that production is given by a standard CES production function, $Y_{st} = A_{st}\left(\sum_s \alpha_{jst}^{\frac{1}{\sigma}} X_{jst}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$. The wage bill paid to factor of production j is $w_{jt}X_{jst} = \alpha_{jst}\left(\frac{w_{jt}}{p_{st}}\right)^{1-\sigma} p_{st}Y_{st}$, where $p_{st}^{1-\sigma} = \sum_j \alpha_{jst}w_{jt}^{1-\sigma}$. Thus, we can define $\tilde{\alpha}_{jst} \equiv \alpha_{jst}\left(\frac{w_{jt}}{p_{st}}\right)^{1-\sigma}$ and apply the same decomposition as in the Cobb-Douglas case.

de-unionization or offshoring– operate through sectoral changes in occupational intensities $\{\alpha_{jst}\}$.[13]

This analysis makes clear that assuming a one-sector model imposes that *any* change in the wage bill must come from differential trends in α_{jt} and $\alpha_{j't}$. This effect corresponds to Term 2 in our decomposition (6). Thus, assuming a one-sector model shuts down the effect of differential output growth across sectors with heterogeneous skill intensity (Term 1) and its interaction with cross-sectional changes in sectoral skill intensity (Term 3). If these latter two terms are important in driving changes in the wage bill, using a one-sector model may offer a very incomplete picture of the evolution of the wage bill. We turn to this question next.

Assessing the Contribution of the Terms in Decomposition (6) Table 2 quantifies the contribution to the growth in the wage bill of high, medium and low occupations from each of the three terms in decomposition from Equation 6. Specifically, rows 2 through 4 report the contribution of one term. Row 1 reports the total contribution from the three terms.[14] Columns 1 through 3 report the drivers of the total growth in the wage bill for the three occupation types. Column 4 reports the contribution for the wage bill of high-occupations relative to medium as the difference between columns 1 and 2. Column 5 does the same for low relative to medium occupations (i.e. column 3 minus column 2).

We decompose the economy into 8 sectors.[15] Nominal sectoral value added growth comes from the BEA. The occupation intensities in each sector are computed from equation (3) as the share in the sectoral wage bill of each occupation. The weights γ_{js0} are computed as the share of sector s in occupation j's total wage bill. The subscript 0 denotes 1980 and the subscript t denotes the final year, 2016.

The decomposition (6) shows that the change in the sectoral composition of value added, Term 1 in Equation (6), has been the key driver of the growth in the wage bill at all skill levels (first three columns in Table 2). Furthermore, the change in the sectoral composition of the economy has a bigger impact on the evolution of the relative wage bill of high- to middle-skill (column 4) and low- to middle-skill (column 5) than changes in factor intensity. Splitting evenly the contribution of the covariance (term 3) between the first two terms, our decomposition implies that sectoral value added growth accounts for 62% (4.365/7.01) of the increase in the wage bill of the high- to the medium-skill occupations, and for 82% (2.82/3.43) of the increase in the wage bill for low- relative to medium-skill occupations from 1980 to 2016.

[13]See, among others, Acemoglu and Autor, 2011), Acemoglu et al. [2001], Basco and Mestieri [2013] and the references therein.

[14]This is not exactly the same as the observed growth in the wage bill as the sectoral labor shares have changed over the period 1980-2016.

[15]These are i) primary+utilities, ii) manufacturing, iii) construction, iv) trade, v) FIRE, information and professional services, vi) health and education vii) food and entertainment and viii) government. These grouping is based on two factors: the traditional aggregation of sectors and the estimates of the income elasticity of demand. The results from the decomposition based on Equation 6 are robust to alternative disaggregations of the economy both with larger and smaller number of sectors.

Table 2: Decomposition of Wage Bill Growth 1980-2016 based on equation (6)

	High	Middle	Low	H−M	L−M
Total Change	10.19	3.18	6.61	7.01	3.43
Δ Sectoral Change (Term 1)	7.05	4.66	7.09	2.39	2.43
Δ Factor Intensity (Term 2)	0.45	-0.22	0.00	0.67	0.22
Covariance (Term 3)	2.69	-1.26	-0.47	3.95	0.79
Contribution of Sectoral Change				62%	82%

Why does this happen? The key driver of our findings is the large correlation between the growth rate of sectoral value added and the sectoral share of high-skill occupations in the economy in 1980 (0.58) and low-skill occupations (0.87), while it is negative for middle occupations (-0.36). This explains the importance of the first term for the growth in the relative wage bill of high- and low-skill. In contrast, the correlation between the growth rate of the factor intensities and the initial sectoral shares for each type of occupation are more negative for high and low skill occupations (-.23 and -.22) than for medium skill occupations (.38). Hence the little contribution of the second term to the relative wage bills.[16]

These findings suggest that to explain the aggregate variation in the relative intensity across occupations, it is critical to explore why the sectoral composition of economic activity has shifted to sectors that were initially more intensively in high and low skilled occupations.

In the Appendix we report the results from applying the decomposition in Equation (6) to three subperiods 1980-1990, 1990-2000 and 200-2016. The dominance of sectoral reallocation of value added over changes in intensity for the evolution of relative wage biils holds in all three subperiods. However, we find that the reallocation of value added becomes more important for the evolution of both relative wage bills over time. In particular its contribution increases from 54% in 1980-90 to 67% in 2000-16 (for the high vs. medium occupations wage bill) and from 83% in 1980-90 to 98% in 2000-16 (for the low vs. medium occupations wage bill).

2.2 Households

Next, we take on the task of understanding what may have driven the observed changes in the distribution of value added. One possibility is that the sectoral transformation of the economy is driven by the same forces that traditionally have been regarded as culprits for inequality such as skill-biased technical change, robotization or international trade. In the next subsection, we explore the role of a distinct driver of sectoral growth. Namely, sectoral heterogeneity in the degree of non-homotheticities in demand.

[16] We still find a positive contribution of Term 2 to the relative wage bill because, on average, the growth in factor intensity is higher for high and low skill occupations than for medium skill occupations. A similar logic explains the positive conribution of Term 3 to the relative wage bill.

To explore this mechanism, we need to specify household preferences for the goods and services produced in the economy. We use the nonhomothetic CES preferences developed by Hanoch [1975] and introduced by Comin et al. [2015] in a general equilibrium setting.

We make two simplifying assumptions. First, we assume that all income accrued by the workers is spent in consumption. Second, we study an economy with a representative household. That is, all the resources earned by the household are pulled together and, given the prevailing prices, the household decides its consumption bundle. We extend the model to heterogeneous households in Section 3.

Preferences The utility of the representative household at time t, U_t, is a nonhomothetic CES aggregator defined over the consumption goods c_{st} available in the economy

$$\sum_{s \in \mathcal{S}} \left(U_t^{\varepsilon_s} \zeta_s\right)^{\frac{1}{\sigma}} c_{st}^{\frac{\sigma-1}{\sigma}} = 1. \tag{8}$$

The parameter σ controls the price elasticity of substitution across goods, while the income elasticity parameter ϵ_s controls the expenditure elasticity of sector s. The constant ζ_s captures the constant taste component of preferences. This formulation of preferences allows for the level of utility $U_t^{\varepsilon_s}$ to enter symmetrically in (8) as an additional taste component. In contrast to ζ_s, this term is variable and endogenously determined. As a result, the weight attached to the consumption of each good depends on the level of utility itself, U, with an elasticity controlled by ε_s. If ε_s is constant across all s, e.g., $\varepsilon = 1 - \sigma$, we have homothetic CES preferences.[17]

Given a set of prices $\{p_{st}\}_{s \in \mathcal{S}}$ and total expenditure E_t, a household maximizing utility (8) subject to the budget constraint $\sum_{s \in \mathcal{S}} p_{st} c_{st} \leq E_t$ chooses

$$c_{st} = \zeta_s \left(\frac{E_t}{p_{st}}\right)^{\sigma} U_t^{\varepsilon_s}. \tag{9}$$

The corresponding expenditure function is given by $E_t^{1-\sigma} = \sum_{s \in \mathcal{S}} \zeta_s U_t^{\varepsilon_s} p_{st}^{1-\sigma}$.

We can normalize one taste parameter $\zeta_s = 1$ (as with homothetic CES) and one income elasticity parameter $\epsilon_s = 1$ for some $s \in \mathcal{S}$. This normalization uniquely defines a price index P_t and a real consumption index C_t of the representative household,

$$U_t = \frac{E_t}{P_t} \equiv C_t, \tag{10}$$

[17] This parametrization of preferences requires that $\epsilon_s > 0$ if $0 < \sigma < 1$ and $\epsilon_s < 0$ otherwise. It is possible to parametrize nonhomothetic CES preferences such that the income elasticity parameters do not change signs depending on whether goods are gross complements or substitutes. For example, the alternative specification of preferences $\sum_s \zeta_s^{\frac{1}{\sigma}} \left(\frac{c_{st}}{U^{\tilde{\varepsilon}_s}}\right)^{\frac{\sigma-1}{\sigma}} = 1$, is well-defined for $\tilde{\varepsilon}_s > 0$ and any $\sigma > 0$. Note that we can go from this specification to our baseline specification (8) with the change of variables $\tilde{\varepsilon}_s = \varepsilon_s/(1-\sigma)$. See Appendix A of Comin et al. [2015] for a more general discussion.

with

$$P_t = \left[\sum_{s \in \mathcal{S}} \left(\zeta_s p_{st}^{1-\sigma} \right)^{\chi_s} \left(x_{st} E_t^{1-\sigma} \right)^{1-\chi_s} \right]^{\frac{1}{1-\sigma}}, \tag{11}$$

where $x_{st} = p_{st} c_{st} / E_t$ denotes the expenditure share in sector s, and $\chi_s \equiv (1-\sigma)/\varepsilon_s$.[18]

2.3 Drivers of Structural Change

After having introduced household preferences, we use the market clearing condition to close our model and decompose the evolution of sectoral value added. The total expenditure of the representative household is given by the total labor income of the economy,

$$E_t = \sum_{s \in \mathcal{S}} \sum_{j \in \{H,M,L\}} w_{jt} X_{jst}. \tag{12}$$

Using the demand for good s, Equation (9), nominal value added in sector s is

$$VA_{st} = p_{st} c_{st} = \zeta_s p_{st}^{1-\sigma} E_t^{\sigma+\varepsilon_s} P_t^{-\varepsilon_s}. \tag{13}$$

Equation (13) illustrates that, in our model, the evolution of sectoral value added is driven by two forces: changes in aggregate expenditures, E_t, and changes in sectoral prices, $\{p_{st}\}$ (note from Equation (11) note that P_t is itself a function of aggregate expenditure and prices).

Supply-side drivers of polarization and inequality such as skill-biased technical change, deunionization or offshoring affect the sectoral composition of value added through their impact in relative sectoral prices. Indeed, in a model with homothetic preferences, changes in relative prices are the only source of sectoral reallocation in value added. To see this, consider the ratio of Equation (13) for two sectors, s and s' when preferences are homothetic (i.e., $\varepsilon_s = 1 - \sigma$ for all s),

$$\frac{VA_{st}}{VA_{s't}} = \frac{\zeta_s}{\zeta_{s'}} \left(\frac{p_{st}}{p_{s't}} \right)^{1-\sigma}.$$

Changes in the relative sectoral composition depend on the evolution of relative prices and are independent of the overall level of expenditure, E_t.

Nonhomotheticicities introduce a distinct, demand-driven, mechanism that affects the evolution of the sectoral composition of value added: aggregate expenditures, E_t. As expenditure increases, consumers shift the composition of expenditure from low income-elastic (low ε_s) to

[18] The expenditure elasticity of sector s is

$$\frac{\partial \ln c_{st}}{\partial \ln E_t} = \sigma + (1-\sigma) \frac{\epsilon_s}{\sum_{s \in \mathcal{S}} x_{st} \epsilon_s}.$$

Thus, whether a good as an expenditure elasticity higher or lower than 1 depends on the total level of expenditure of the household. See also Hanoch [1975] and Comin et al. [2015] for further discussion on the properties of these preferences.

high income-elastic sectors (high ε_s). Even if relative prices were constant, our demand system would imply changes in the sectoral composition of the economy driven by aggregate expenditure,

$$\frac{VA_{st}}{VA_{s't}} = \frac{\zeta_s}{\zeta_{s'}} \left(\frac{E_t}{P_t}\right)^{\varepsilon_s - \varepsilon_{s'}},$$

where we have normalized relative prices to one.

Estimating the demand system An important step in our analysis of the drivers of the evolution of relative labor market outcomes or the sectoral composition of the economy is the estimation of the income elasticity parameters $\{\epsilon_s\}_{s\in\mathcal{S}}$ and the price elasticity σ. Next, we describe the estimation strategy and present the estimates. Our estimation strategy is based on Comin et al. [2015] and is discussed in detail in in section (B) in the appendix. The starting point is a generalization of equation (9) where we allow for a generic unit of observation, n, that may in principle differ from the aggregate economy. Formally, defining the share of sector s expenditure for unit n as $x^n_{st} = \frac{p_{st}c^n_{st}}{E^n_t}$ and taking logs, equation (9) can be expressed as

$$ln(x^n_{st}) = ln(\zeta^n_s) + (\sigma - 1) ln\left(\frac{E^n_t}{p^n_{st}}\right) + \varepsilon_s ln(U^n_t) \tag{14}$$

Without loss of generality, we can normalize the taste and income elasticity parameters of a base sector, $\hat{s}$, to 1. That is, $\zeta^n_{\hat{s}} = \varepsilon_{\hat{s}} = 1, \forall n$. Then we can use expression (14) for the base sector to express $ln(U^n_t)$ as

$$ln(U^n_t) = ln(x^n_{\hat{s}t}) + (1-\sigma) ln\left(\frac{E^n_t}{p^n_{\hat{s}t}}\right)$$

Substituting back in (14) , we obtain the following expression for the relative expenditure share of unit n in sector s relative to the base sector:

$$ln\left(\frac{x^n_{st}}{x^n_{\hat{s}t}}\right) = ln(\zeta^n_s) + (1-\sigma)\, ln\left(\frac{p^n_{st}}{p^n_{\hat{s}t}}\right) + (1-\sigma)\,(\epsilon_s - 1)\, ln\left(\frac{E^n_t}{p^n_{\hat{s}t}}\right) + (\epsilon_s - 1)\, ln(x^n_{\hat{s}t}) \tag{15}$$

We estimate equation (15) using household-level data from the CEX.[19] To this end, we rewrite equation (15) as

$$ln\left(\frac{x^n_{st}}{x^n_{\hat{s}t}}\right) = ln(\zeta^n_s) + (1-\sigma)\, ln\left(\frac{p^n_{st}}{p^n_{\hat{s}t}}\right) + (1-\sigma)\,(\epsilon_s - 1)\, ln\left(\frac{E^n_t}{p^n_{\hat{s}t}}\right) + (\epsilon_s - 1)\, ln(x^n_{\hat{s}t}) + \nu^n_{st}$$

with the assumptions $ln(\zeta^n_s) \equiv \beta_s X^n + \delta_{sr}$ and $\nu^n_{st} \equiv \delta_{st} + \tilde{\nu}^n_{st}$ where $\tilde{\nu}^n_{st}$ is classical measurement error. The first assumption imposes the constraint that the cross-household heterogeneity in

[19] We make the following groupings of the BEA sectors that appear in the input output tables (in parenthesis we report the BEA code): Education and Health Care (6), Arts, Entertainment, Recreation and Food Services (7), Finance, Professional, Information, other services (excl. gov't) (FIRE, PROF, 51, 81), Manufacturing (31G), Retail, Wholesale Trade and Transportation (42, 44RT, 48T), Construction (23), Agriculture, Mining and Utilities (11,21,22).

time-invariant taste parameters can be fully explained as a linear function of the vector X^n of household characteristics discussed above (age, household size, number of earners dummies) and sector-region (*sr*) fixed effects. The second assumption allows for a dyad of sector-time (*st*) fixed effects to absorb potential aggregate consumption shocks. This specification identifies income elasticities based on the within-region covariation between expenditure shares and total household expenditures, controlling for household characteristics. To deal with potential measurement error and endogeneity issues, we use instruments for the observed measures of household expenditures and relative prices. As in [ab15], we instrument household expenditures (total and on the base sector) in a given quarter with the annual household income after taxes and the income quintile of the household. The instruments capture the permanent household income and are therefore correlated with household expenditures without being affected by transitory measurement error in total expenditures. We instrument household relative prices with a 'Hausman' relative-price instrument. Each of the prices used in the relative-price instrument is constructed in two steps. First, for each sub-component of a sector, we compute the average price across regions excluding the own region. Then, the sectoral price for a region is constructed using the average region expenditure shares in each sub-component as weights. These price instruments capture the common trend in U.S. prices while alleviating endogeneity concerns due to regional shocks (and measurement error of expenditure).[20]

Table (3) reports our estimates of the preference parameters in the first column. The second column computes the implied expenditure elasticity for each sector for the average household, and the third column reports the expenditure elasticities obtained by applying the estimation procedure in Aguiar and Bils [2015]. It is reassuring the striking similarity between the implied expenditure elasticities from our model estimates and from the reduced form approach used by Aguiar and Bils.

Quantification of the drivers of structural transformation A natural question to ask at this point is what share of the observed sectoral variation in value added growth between 1980 and 2016 is the result of the increase in aggregate expenditure and how much is due to the increase in sectoral prices. To answer this question we calibrate $\{\zeta_s\}_{s=1}^S$ to match the initial sectoral distribution of private value added,[21] and use the estimates of the income elasticities of demand $\{\varepsilon_s\}_{s=1}^S$ and the elasticity of substitution across sectors (σ) reported in Table 3.

We set the initial values of E_t, P_t and p_{st} to match the values in 1980 of personal consumption expenditures (pce) per capita, the pce deflator, and the sectoral value added deflator for each of the eight sectors.

[20]Using the average price in the U.S. excluding the own region addresses the concern of regional shocks, while capturing the common component of prices across regions. Using average expenditures in the region addresses the concern of mismeasurement of household expenditure shares in that region to the extent that the mismeasurement averages out in the aggregate.

[21]By using information on sectoral value added (instead of expenditure) we take into account the input-output linkages from personal consumption.

Table 3: Elasticity Parameters $\{\epsilon_s\}$

Sectors	ε_s^1	Avg. Elasticity[2]	Elasticity AB[3]
Education and Health Care (6)	3.50	2.28	2.28
Arts, Entertainment, Recreation and Food Services (7)	2.04	1.57	1.60
Government (G)	1.00	1.10	1.08
Finance, Professional, Information, other services (excl. gov't) (FIRE, PROF, 51, 81	0.98	1.09	1.10
Manufacturing (31G)	0.57	0.89	0.92
Retail, Wholesale Trade and Transportation (42, 44RT, 48T)	0.37	0.80	0.81
Construction (23)	0.14	0.69	0.68
Agriculture, Mining and Utilities (11,21,22)	0.10	0.68	0.67

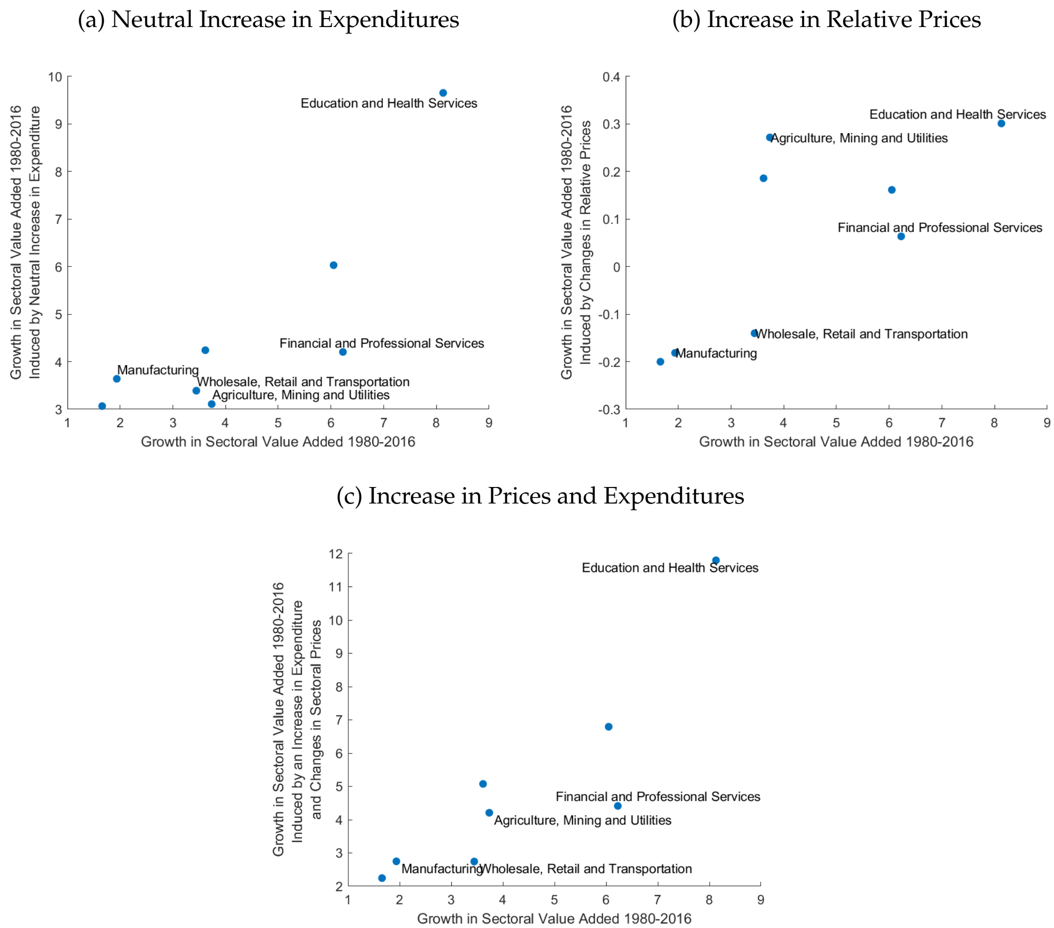
Note:(1) Government sector is normalized to 1. (2) Average expenditure elasticity implied by the model calculated using the 2000-2002 CEX data. (3) Expenditure elasticity estimated using Aguiar and Bils (2015 specification

Then, we use equations (11) and (13) to conduct three different exercises. The first consists in computing the price level and the sectoral value added levels in 2016 if there was a neutral increase in expenditure of the same magnitude as the one we observed between 1980 and 2016. A neutral increase in expenditure is an increase in E_t equal to the observed increase in pce per capita accompanied by an increase in sectoral prices by the same constant by which the pce deflator has increased, so that relative prices do not change. The second exercise consists in computing the sectoral value added and the price index for 2016 if we change the relative sectoral prices by the magnitudes observed in the data.[22] The third exercise simulates the effect on sectoral value added growth of conducting simulatenously the neutral increase in expenditure and the change in relative sectoral prices.

Figure 4 plots the sectoral growth rates induced by each of these exercises vs. the actual growth rates observed in the data. Table 4 reports the covariance between the sectoral growth rates observed in the data and those generated by each of these exercises (relative to the variance of actual sectoral growth). These exhibits yield two conclusions. The first is that the model accounts quite well for the changes in sectoral composition in US from 1980-2016. The covariance between total predicted changes in sectoral value added and those observed in the data from 1980 to 2016 is 106% of the variance of sectoral growth. The second lesson is that while

[22]To be precise, we change the price of each sector by the factor observed in the data relative to the factor by which the pce deflator increases. In this way relative prices change by the same amount as in the data.

Figure 4: Sectoral VA Growth Rate Data vs. Model



the neutral increase in expenditures accounts for 73% of the actual sectoral growth, changes in sectoral relative prices account for only 6% of the actual variation in sectoral growth.

2.4 Drivers of the relative wage bill

Substituting (13) into equation (4), we obtain the following expression for the wage bill accrued by workers in occupation j as a function of total expenditure and prices,

$$\begin{aligned} w_{jt}X_{jt} &= \sum_{s\in\mathcal{S}} \alpha_{jst} VA_{st} \\ &= \sum_{s\in\mathcal{S}} \alpha_{jst}\zeta_s E_t^{\sigma+\varepsilon_s} p_{st}^{1-\sigma} P_t^{-\varepsilon_s}. \end{aligned} \tag{16}$$

Expression (16) allows us to study the role of non-homotheticities in the evolution of the wage bill across occupations. Because our model takes the factor intensity, α_{jst}, as given, we first focus on how the model affects the wage bill through the reallocation of value added across

Table 4: Sectoral VA Growth Rate - Percent of Variance Explained

	Neutral Increase in Expenditures	Increase in Relative Prices	Increase in Prices and Expenditures
% of data variance[1]	0.73	0.058	1.06
% of model variance[2]	0.82	0.18	

(1) Calculated as the covariance between the model generated growth rates and the growth rates observed in the data, relative to the variance of the growth rates observed in the data.

(2) Calculated as the covariance between the growth rates generated in the partial exercise and the growth rates generated in the full exercise, relative to the variance of the growth rates generated in the full exercise.

sectors. That is, Term 1 in the decomposition in Equation (6). Additionally, non-homotheticities also affect wage bills through the covariance between the growth in factor intensities and sectoral growth in value added (Term 3). To capture this effect, we also conduct a second analysis where we study the role of non-homotheticities in the evolution of the all the wage bill for each occupation.

The Drivers of Term 1 We first explore how well the model accounts for the observed contribution of sectoral reallocation to the growth in the wage bills across occupations. To this end, we simulate the evolution of value added in the model after feeding in the observed increase in personal consumption expenditures and the observed sectoral prices from 1980 to 2016 and multiply it by the initial intensities of each occupation in each sector, α_{js1980}. This comparison is presented in the first two rows of table 5. The model accounts for a majority of the observed growth in wage bills induced by sectoral value added growth. The share accounted by the model ranges from 78% for the medium skill occupation to 101% for the low-skilled occupations. The model more than fully accounts for the growth in relative wage bills induced by sectoral growth.

The second exercise we conduct consists in exploring how much of this variation is induced by the neutral increase in personal expenditures and how much by the relative growth in sectoral prices. To this end, we compute the growth in the wage bills of the different occupations after simulating (alternatively) the neutral increase in expenditure we have observed or the increase in relative sectoral prices. Rows 3 and 4 of table 5 report the results. As one would expect from our findings on the relative importance for expenditures and prices for sectoral growth, the former is much more important than the former also for the growth in wage bills and for the evolution of the relative wage bills. Splitting evenly the interaction,[23] we find that the contribution of the neutral expenditure for the growth in the wage bill ranges from 92%

[23]By interaction, here, we refer to the differential growth in the wage bill between the case when we simultaneously adjust both expenditures and sectoral prices, and the sum of the observed growth when we just adjust one of the two types of variables. See section (C) in the appendix for details.

Table 5: Non-homotheticities and the Growth in Wage Bill through Sectoral Value Added Growth

	H	M	L	H-M	L-M
Wage Bill Growth from actual sectoral Growth (Term 1)	7.05	4.66	7.09	2.39	2.43
Wage Bill Growth from Demand Model	6.2	3.63	7.16	2.57	3.53
Neutral Expenditure	5.64	3.91	6.24	1.73	2.33
Growth in sectoral prices	0.08	-0.06	0.16	0.14	0.21
Model/Data	0.88	0.78	1.01	1.08	1.46
Contribution Neutral increase in Expenditure	0.95	1.05	0.92	0.81	0.8

for the low skilled occupation to 105% for the medium skill. The neutral increase in aggregate expenditures generates 80% of the growth in the relative wage bills generated by the model. Therefore, we conclude that non-homotheticities have played a first order role in the observed evolution of relative wage bills across occupations in the US between 1980 and 2016.

The Drivers of Occupational Wage Bill We now move beyond Term 1 and use expression (16) to study the drivers of the entire wage bill for each occupation. In addition to the neutral increase in expenditures and the change in relative sectoral prices, we consider also the change in occupational intensities, α_{jst}. We first use the model to simulate the evolution of the wage bills after feeding in the observed increase in neutral expenditures, relative prices and occupational intensities. This calculation is reported in row 2 of Table XX. Row 3 presents the growth in the wage bills after feeding in only the increase in neutral expenditures. Row four reports the results from feeding in the change in relative sectoral prices and the changes in occupational intensities. evolution of teh wage reports the conduct contributions of the change decompose teh change in teh wage bill

3 Model with Endogenous Labor Supply and Prices

To further investigate the role of non-homotheticties in the polarization of labor markets, it would be desirable to go beyond wage bills and to study the differential effects of non-homotheticities in the number of jobs and the wage rates earned by workers. To pursue these goals, we extend our simple model in several directions. First, we explicitly model the labor supply of workers for the different occupations so that our model has predictions not only for the evolution of the wage bill but also for the relative wages and employment across occupations. Second, we allow for an exogenous varying labor share. Third, we introduce a non-unitary treatment of household consumption decisions.

3.1 Environment

3.1.1 Production

There is a representative firm in each sector that produces final output according to

$$Y_{st} = A_{st} K_{st}^{1-\beta_{st}} \left(\prod_{j \in \{H,M,L\}} \tilde{X}_{jst}^{\alpha_{jst}} \right)^{\beta_{st}}, \tag{17}$$

where $\tilde{X}_{jst}$ denotes the number of efficiency units of labor are employed in occupation j in sector s in year t and $0 < \beta_{st} < 1$ and $\sum_j \alpha_{jst} = 1$. The key difference is that we have now introduced capital in our model. As a result the labor share can vary over time and across sectors. Optimal demand from the representative firm implies

$$\tilde{w}_{jt} \tilde{X}_{jst} = \beta_{st} \alpha_{jst} p_{st} Y_{st} \tag{18}$$

$$r_t K_{st} = (1 - \beta_{st})\, p_{st} Y_{st} \tag{19}$$

The total wage bill in sector s is

$$\sum_{j=1}^{J} \tilde{w}_{jt} \tilde{X}_{jst} = \beta_{st} p_{st} Y_{st} \sum_{j=1}^{J} \alpha_{jst}, \tag{20}$$

$$\beta_{st} = \frac{\sum_{j=1}^{J} \tilde{w}_{jt} \tilde{X}_{jst}}{p_{st} Y_{st}}. \tag{21}$$

Therefore, β_{st} is the labor share in sector s.

The total number of efficiency units demanded for occupation j are

$$\tilde{X}_{jt} \equiv \sum_{s=1}^{S} \tilde{X}_{jst} = \frac{\sum_{s=1}^{S} \beta_{st} \alpha_{jst} p_{st} Y_{st}}{\tilde{w}_{jt}} \tag{22}$$

and the wage bill required to compensate workers employed in occupation j is

$$\tilde{w}_{jt} \tilde{X}_{jt} = \sum_{s=1}^{S} \beta_{st} \alpha_{jst} p_{st} Y_{st} \tag{23}$$

The total revenue accrued by capital owners is

$$r_t K_t = \sum_{s=1}^{S} (1 - \beta_{st}) \, p_{st} Y_{st}. \tag{24}$$

where we have allowed for sectoral hetogeneity in the rental rate of capital, r_{st}. Finally, the price of the sectoral output is

$$p_{st} = \left(\frac{\prod_{j=\{l,m,h\}} \left(\frac{\tilde{w}_{jt}}{\alpha_{jst}}\right)^{\alpha_{jst}}}{\beta_{st}} \right)^{\beta_{st}} \left(\frac{r_t}{1-\beta_{st}} \right)^{1-\beta_{st}}. \tag{25}$$

3.1.2 Household preferences

There is a continuum of households indexed by h from (0,1). Each household inelastically supplies a unit of labor to one of the three occupations. Household income is composed of the labor income plus the rental income accrued from the capital it owns (K_{ht}). We assume that capital is evenly distributed across households, and that every period household expenditure, E_{ht}, equals household income.

The household demand for each of the S good is such that each household maximizes its utility level U_{ht} subject to the constraint that total expenditure cannot exceed its income E_{ht}, where U_{ht} is implictly defined by

$$\sum_{s \in \mathcal{S}} \left(U_{ht}^{\varepsilon_s} \zeta_s \right)^{\frac{1}{\sigma}} c_{hst}^{\frac{\sigma-1}{\sigma}} = 1. \tag{26}$$

Given a set of prices $\{p_{st}\}$ and total expenditure E_{ht}, household h chooses

$$c_{hst} = \zeta_s \left(\frac{E_{ht}}{p_{st}} \right)^{\sigma} U_{ht}^{\varepsilon_s} \tag{27}$$

where E_{ht} is the total expenditure given by $E_{ht}^{1-\sigma} = \sum_{s \in \mathcal{S}} \zeta_s U_{ht}^{\varepsilon_s} p_{st}^{1-\sigma}$.

As with homothetic CES, we can normalize one taste parameter $\zeta_s = 1$ and one income elasticity parameter $\varepsilon_s = 1$ for some s. This uniquely defines a price index P_t and a real consumption index C_t for each household

$$U_{ht} = \frac{E_{ht}}{P_{ht}} \equiv C_{ht} \tag{28}$$

with

$$P_{ht} = \left[\sum_{s \in \mathcal{S}} \left(\zeta_s p_{st}^{1-\sigma} \right)^{\chi_s} \left(x_{hst} E_{ht}^{1-\sigma} \right)^{1-\chi_s} \right]^{\frac{1}{1-\sigma}} \tag{29}$$

where $x_{hst} = p_{st}c_{hst}/E_{ht}$ denotes the expenditure share in sector s, and $\chi_s \equiv (1-\sigma)/\varepsilon_s$.

Given these household-level consumption decisions, the aggregate demand for sectoral output is

$$C_{st} = \int_0^1 \zeta_s E_{ht}^{\sigma+\varepsilon_s} p_{st}^{-\sigma} P_{ht}^{-\varepsilon_s} dh. \tag{30}$$

3.1.3 Occupational Choice

A key difference with the simple model is that now we allow each household to choose an occupation. Each household draws a vector (η_H, η_M, η_L) of efficiency units in each occupation. Given the vector of market prices per efficiency unit for the three occupations $(\tilde{w}_H, \tilde{w}_M, \tilde{w}_L)$, households choose optimally their occupations by maximizing their earnings. Formally,

$$\max_{j\in\{H,M,L\}} \{\eta_j \tilde{w}_j\} \tag{31}$$

The total income accrued by household h is equal to its labor income plus the rental income:

$$\max_{j\in\{H,M,L\}} \{\eta_j \tilde{w}_j\} + rK_h$$

where K_h denotes the household capital holdings.

Let $F(\eta_H, \eta_M, \eta_L)$ be the CDF of the joint distribution of the efficiency units across occupations. We have that the density of a household choosing occupation H is

$$F_H\left(y, \frac{\tilde{w}_H}{\tilde{w}_M}y, \dots, \frac{\tilde{w}_H}{\tilde{w}_L}y\right) \tag{32}$$

where $F_H = \frac{\partial F(\eta_H,\eta_M,\eta_L)}{\partial \eta_H}$. Thus, the share of households choosing occupation H is

$$\pi_H = \int_{y\in\mathcal{Y}} F_H\left(y, \frac{\tilde{w}_H}{\tilde{w}_M}y, \dots, \frac{\tilde{w}_H}{\tilde{w}_L}y\right) dy \tag{33}$$

where $\mathcal{Y}$ denotes the support of the distribution for η_H.

The supply of efficiency units in occupation H is

$$\tilde{X}_{jt} = \int_{y\in\mathcal{Y}} yF_H\left(y, \frac{\tilde{w}_H}{\tilde{w}_M}y, \dots, \frac{\tilde{w}_H}{\tilde{w}_L}y\right) dy \tag{34}$$

and the wage bill accrued by workers in occupation H is

$$\tilde{w}_H\tilde{X}_{jt} = \tilde{w}_H \int_{y\in\mathcal{Y}} yF_H\left(y, \frac{\tilde{w}_H}{\tilde{w}_M}y, \dots, \frac{\tilde{w}_H}{\tilde{w}_L}y\right) dy \tag{35}$$

Analogous expressions to (33), (34) and (35) hold for the other occupations.

To evaluate quantitatively the model, we consider the particular case where the $\eta_j's$ are independent and distributed log-Normal with the mean and standard deviation of $\log \eta_j$ being μ_j and σ_j.[24]

3.2 Competitive Equilibrium

We focus our analysis on the competitive equilibrium of this economy. A competitive equilibrium is defined by a sequence of prices $\{\{p_{st}\}_{s\in\mathcal{S}}, \tilde{w}_{lt}, \tilde{w}_{mt}, \tilde{w}_{ht}\}_{t=0}^{t=T}$, allocations $\{\{c_{hst}\}_{s\in\mathcal{S},h\in\mathcal{H}}\}$ and household occupational choices such that

1. Each household chooses the occupation that maximizes labor income, (31).
2. Household income equals household expenditure E_{ht} period by period. Income is equal to labor income plus the return to capital (which is assumed to be uniform across households).
3. Each household maximizes utility (8) subject to the budget constraint $\sum_{s\in\mathcal{S}} p_{st}c_{hst} = E_{ht}$.
4. Firms maximize profits taking prices as given, max $p_{st}A_{st}K_{st}^{1-\beta_{st}}\left(\prod_{j\in\{H,M,L\}} \tilde{X}_{jst}^{\alpha_{jst}}\right)^{\beta_{st}} - \tilde{w}_{lt}\tilde{X}_{lst} - \tilde{w}_{mt}\tilde{X}_{mst} - \tilde{w}_{ht}\tilde{X}_{hst}$.
5. Aggregate effective labor supply in an occupation (equation 34) equals aggregate demand (equation 22).
6. All goods markets clear at any point in time, $\int c_{hst}dh = Y_{st}$.

3.3 Calibration

To study the drivers of the relative evolution of employment and wages across occupations we must calibrate two types of parameters: those that are fixed, and those that vary exogenously. To calibrate the first, we use data moments from 1980, while for the latter, we use data from 1980 and 2016 to determine their initial and final values, respectively.

Let's start by discussing the calibration of the distributions of the productivity parameters $\{\eta_j\}$. First note that the definition of an efficiency unit is arbitrary, therefore, without loss of generality, we can set $\{\mu_j\}_{j=\{l,m,h\}}$ to 1. To calibrate $\{\sigma_j\}_{j=\{l,m,h\}}$, we take advantage of the fact that our model is modular in the sense that conditional on the relative wage bill across occupations, the distribution of productivities determines the relative wages per worker across occupations, independently of the rest of parameters in the model. To better understand this property, note that equations (34) and (35) determine the wage bill for occupation j supplied

[24] We note that assuming a Fréchet distribution (or a multi-variate Fréchet in the max-stable familiy as described in Lind and Ramondo, 2018) in this setting would have the counterfactual prediction that average wage per worker is equalized across occupations. Authors that have used the Fréchet distribution in this setting need to resort to unobserved costs or worker attributes.

by workers. Additionally, equation (33) determines the share of workers employed in each occupation. These three equations depend only on the distribution of productivities and on the equilibrium efficiency wages ($\{\tilde{w}_j\}_{j=\{l,mh\}}$). Therefore, we can proceed as follows. For any given $\{\sigma_j\}_{j=\{l,m,h\}}$, the requirement that the relative wage bill supplied at each occupation matches the distribution of wage bills in 1980 pins down the equilibrium efficiency wages ($\{\tilde{w}_j\}_{j=\{l,mh\}}$). The dispersion parameters $\{\sigma_j\}_{j=\{m,h\}}$ can be calibrated by additionally requiring that the average wage per capita for h and l occupations relative to the average wage per capita for m occupations match the equivalent ratios observed in 1980.

There are two relevant observations worth noting. The first is that because we match the 1980 relative wage bill and average wage per workers across occupations, we will also match the employment shares across occupations in 1980. The second is that because we only use information on relative wage bills and relative wage per worker across occupations, without loss of generality, we can normalize σ_l to 1.

We calibrate the occupation intensities, $\left\{\{\alpha_{jst}\}_{j=\{l,m,h\}}\right\}_{s=1}^{S}$, by matching the relative wage bill in each sector (equation 3) computed with wage information from the CPS and occupation information from the ACS. We calibrate $\{\beta_{st}\}_{s=1}^{S}$ by matching the sectoral labor share (equation 21) computed from the CPS, ACS and KLEMS.[25] The preference parameters $\{\varepsilon_s\}_{s=1}^{S}$ and σ are estimated from the CEX as described in the Appendix. Given those, we calibrate the taste parameters, $\{\zeta_s\}_{s=1}^{S}$, to match the aggregate value added share of each sector in 1980.

To study the drivers of the evolution of relative wages and employment shares, we consider exogenous changes in three parameters. The changes in the factor intensities, $\{\alpha_{jst}\}$, and labor shares, $\{\beta_{st}\}$, are directly measured in the data. Most importantly, we would like to implement the equivalent in this full-blown model to the neutral increase in aggregate nominal expenditure we have introduced in section 2. This requires the use of two of the parameters to induce the increases in aggregate expenditures and in the price level we have observed in the data.[26] Since the model pins down the equilibrium value of relative wages, the level of wages is a free parameter. This allow us to exogenously induce changes in nominal variables by altering directly one of the wage rates, (e.g., $\tilde{w}_{lt}$). The second instrument we use to induce the neutral increase in expenditure is aggregate TFP. Consequently, we set the increases in TFP

[25]We compute labor shares by computing wage bills using hours worked from the ACS and wages from the CPS. We calibrate the relative values of $\{\beta_s\}$ from the ratio of total wage bill taken from the ACS and CPS to nominal VA in each sector. While these values correctly capture the relative share of employment in each sector, the resulting level is too small. We then adjust the level of $\{\beta_s\}$ by multiplying all values of by min(labor compensation share in KLEMS/β). To calibrate r we use the private sector lending rate from the IMF International Financial Statistics. For our baseline model we use the average value between 1980-2016. We then run robustness checks were we let it vary over time.

[26]To construct the Fisher price index we use as a target for our model we use nominal value added and price deïňĆators for each sector provided by the BEA. We use the values from the baseline year 1980 and each target year to first construct the Laspeyres and Paasche index between the two periods. Then we construct the Fisher index as the geometric mean of the two. The key difference between this index and the one reported by the BEA is that we do not chain it over the years. We construct this alternative price index since our model simulation does not run for each of the years between the two periods we are interested in.

and $\tilde{w}_{lt}$ to simultaneously match the increase in nominal personal consumption expenditure per capita and in the pce deflator observed in the US from 1980 to 2016. Note that these two variables have different effects on real and nominal expenditure because for given inputs, TFP only affects real income while $\tilde{w}_{lt}$ affects both. In our baseline calibration, we set the rental rate of capital equal to the average private sector lending rate from 1980-2016 as reported in the IMF International Financial Statistics. [27]

3.4 Results

The results from our baseline analysis are reported in Table 6. The first two rows report the actual values of the key variables in the data. As before, we study the wage bills of the three occupations but also the relative wages and the share of hours worked in each of the three occupations. Row 3 reports the model simulations for 1980 which, by design, match the data. Rows 4 to 6 report the values of the variables of interest for 2016 produced by the model in different simulations. We consider three exercises. The neutral increase in expenditure (row 4), a simultaneous increase in the sectoral factor intensities and in the sectoral labor shares as the one observed in the data (row 5), and the effect of conducting simultaneously both exercises (row 6). Row 7 reports the fraction of the observed change in each of the variables from 1980 to 2016 that the model produces. Rows 8 and 9 report the contributions of the neutral increase in expenditure and the change in factor intensities and labor shares in the evolution of each variable using the approach detailed in section (C) in the appendix.[28]

There are two key findings of the quantitative evaluation of our model. The first is that the model does a good job in generating the polarization of the labor markets both in terms of the evolution of the relative wages of high vs. medium and low vs. medium skill occupations, and in terms of the hollowing out of medium skill hours worked increasing the share of hours worked in high and low- skill occupations. Specifically, the model slightly over-predicts the 2016 relative wages of low vs. medium (0.87 vs. 0.8 in the data) and high vs. medium (1.57 vs. 1.49 in the data). It virtually nails the increase in the share of hours worked by each occupation (0.125 vs. 0.129 for low, 0.499 vs. 0.488 for medium and 0.376 vs. 0.383 for high-skill occupations). Consequently, the model virtually nails the 2016 wage bill distribution across occupations (0.091 vs. 0.088 for low, 0.416 vs. 0.421 for medium and 0.493 vs. 0.491 for high-skill occupations).

The second key finding from Table 6 is that the neutral increase in aggregate expenditures accounts for a remarkable share of the polarization in labor markets generated by our model both in terms of the evolution of relative wages and hours worked across all occupations. In particular, the neutral increase in expenditure accounts, respectively, for 85% and 55% of the

[27] We conduct robustenss checks using the initial and final values as well as allowing the rental rate to vary over time.

[28] Note that these contributions are relative to the change induced by the model when all the exogenous variables change.

Table 6: Full Quantitative Model

	Year	$\frac{W_L}{W_M}$	$\frac{W_H}{W_M}$	L_s	M_s	H_s	$\frac{W_L L}{\sum_k W_k K}$	$\frac{W_M M}{\sum_k W_k K}$	$\frac{W_H H}{\sum_k W_k K}$	Exercise
Data	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
	2016	0.80	1.49	0.129	0.488	0.383	0.088	0.421	0.491	
Model	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
	2016	0.86	1.44	0.133	0.543	0.324	0.101	0.483	0.416	E
	2016	0.77	1.41	0.095	0.582	0.323	0.066	0.524	0.411	α+β
	2016	0.87	1.57	0.125	0.499	0.376	0.091	0.416	0.493	E+$\beta + \alpha$
Fraction of observed change[1]		2.17	1.32	0.88	0.93	0.95	1.15	1.02	1.01	
Contribution of E		0.85	0.55	1.13	0.63	0.5	1.26	0.6	0.51	
Contribution of $\alpha + \beta$		0.15	0.45	-0.13	0.37	0.5	-0.26	0.4	0.49	

(1) Fraction of the change produced by the full model, with changes in the level of expenditures, factor intensities and in the sectoral labor shares relative to total changed observed in the data.

increases in the low vs. medium and high vs. medium relative wages generated by the model. The neutral increase in expenditure is responsible for a share of the change in the share of hours worked generated by the model that ranges from 50% for high-skill occupations to 113% for low-skill occupations. Finally, the neutral increase in expenditures is responsible for a share of the change in the wage bill shares generated by the model that ranges from 51% for the high-skill occupation to 126% for the low skill occupation.

The relevance of the neutral increase in aggregate expenditure for labor market polarization is quite intuitive in the light of our findings in section 2. As we have documented, non-homotheticities in demand induce income elastic sectors to grow more in response to the increase in aggregate expenditure. These sectors are more intensive in high- and low-skill occupations hence the reallocation of the wage bill. The increase in labor demand for high and low-skill workers translates both into higher relative wages and a higher share of employment in high and low-skill occupations. The log-Normal distribution of productivity draws does a good job in splitting the increase in relative labor demand between changes in relative wages and in relative hours across occupations.

In addition to the direct effect through aggregate expenditure, non-homotheticities also induce labor market polarization indirectly through relative sectoral prices. In particular, because non-homotheticities induce relative increases in the wage per-efficiency unit of high and low-skill occupations, they lead to relative increases in the sectoral prices of sectors that are more intensive in these occupations. Since the elasticity of substitution of demand across sectors is smaller than 1, the increase in relative sectoral prices leads to an additional increase in the (nominal) GDP share of sectors that are intensive in high and low-skill occupations. Hence amplifying the direct effect of non-homotheticities.

3.4.1 Evolution of Polarization: Simulation by Decades

We conclude our analysis of the drivers of the wage polarization in the US from 1980 to 2016 by exploring the drivers in different subperiods. To this end, we simulate the evolution of model after gradually adjusting the exogenous variables. Table 7 reports the resulting evolution of the labor market variables and the contribution of the neutral increase in expenditure to the change of each variable for each of the two subperiods. This exercise allows us to better understand the relevance of both driving forces during each of the two subperiods. The key take away is that the neutral increase in expenditure was very relevant in the labor market polarization during both subperiods, however it was somewhat less important for low-skilled labor in the 2000-2016 period. More specifically, we find that the neutral increase in expenditure observed during the 1980-2000 period more than accounts for the evolution of relative wage and the share of hours for low-skill occupations, and it accounts for 70% and 61%, respectively, of the change in the model simulations for relative wages and the share in hours worked by high-skill occupations. In the 2000s, the contribution of the neutral expenditure decrease but it is still key for the model success in explaining the observed polarization of labor markets. It generates between 50% and 60% of the change in the relative wage, share of hours worked and wage bill for high and medium-skill occupations and around 35% for the low-skill occupations.

There are several reasons for the stronger role of the neutral increase in expenditures on the model polarization during the 1980-2000 period. First, both nominal and real expenditure per capita increased more during the 1980-2000 period than during the 2000-2016 period. Second, the intensity of low-skill occupations (in the sectors that make up most of their wage bill) was higher in the 1980s than in the 2000s. As a result, the increase in expenditure during the 2000s did not lead to as large of an increase in demand for low-skill workers.[29]

3.5 Extensions

After showing the relevance of non-homotheticities for wage polarization in our baseline calibration, next we show that the quantification we have just conducted is robust to reasonable alternatives in some of the choices we have made. First we bring into our analysis the gap between value added and expenditure that arises as a result of international trade. Second, we consider alternative distributions of capital across households. Finally, we explore in the

[29] Additionally, the fact that the expenditure increase generates an excessive increase in the low-skill occupation wage induces a mechanical mean reversion in the contribution of aggregate expenditure.

Table 7: Model Simulation by Subperiods

	Year	$\frac{W_L}{W_M}$	$\frac{W_H}{W_M}$	L_s	M_s	H_s	$\frac{W_L L}{\sum_k W_k K}$	$\frac{W_M M}{\sum_k W_k K}$	$\frac{W_H H}{\sum_k W_k K}$	Exercise
Data	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
Data	2000	0.79	1.44	0.100	0.576	0.324	0.070	0.514	0.416	
Model	2000	0.83	1.40	0.126	0.566	0.308	0.095	0.514	0.391	E
	2000	0.72	1.32	0.080	0.629	0.291	0.054	0.586	0.360	α+β
	2000	0.79	1.44	0.102	0.566	0.332	0.072	0.504	0.424	E+$\beta + \alpha$
Data	2016	0.80	1.49	0.129	0.488	0.383	0.088	0.421	0.491	
Model	2016	0.81	1.47	0.107	0.548	0.345	0.076	0.479	0.444	E
	2016	0.85	1.54	0.119	0.516	0.364	0.086	0.439	0.475	α+β
	2016	0.87	1.58	0.126	0.497	0.377	0.092	0.413	0.495	E+$\beta + \alpha$
Contribution	80-00	1.60	0.70	3.79	0.86	0.61	5.63	0.79	0.63	
of E	00-16	0.38	0.50	0.35	0.51	0.59	0.35	0.53	0.57	

Appendix the consequences of allowing for time-varying interest rates as another driving force for household income.

3.5.1 Accounting for International Trade

So far, our analysis has assumed a closed economy equilibrium. This section extends our analysis to account for the possibility to import and export goods in some sectors. We account for this possibility in a parsimonious way through the use of sector specific TFP shocks. (rather than fully modeling a world economy with multiple countries)

We start from the identity that aggregate production equals domestic consumption plus net exports, $p_{st}Y_{st} = p_{st}C_{st} + NX_{st}$. Rearranging we have that

$$p_{st}C_{st} = (1 - \tau_{st})p_{st}Y_{st}, \tag{36}$$

where $\tau_{st} \equiv \frac{NX_{st}}{p_{st}Y_{st}}$ captures the wedge between domestic production and consumption. If net exports are positive, we have a magnifying effect of trade on domestic production (and labor demand), while if they are negative they dampen domestic aggregate demand.

To obtain our measures of $\{\tau_{st}\}$, we proceed by computing US sectoral net exports in terms of value added over US value-added production (see details in Appendix D). We note that this wedge correction only affects two of our eight sectors: Agriculture, Mining and Utilities and Manufacturing. Quantitatively most of the action is on the manufacturing sector. We find that the wedge for manufacturing in 1980 is a small and positive number. The wedge becomes

Table 8: Model Simulation with Trade

	Year	$\frac{W_L}{W_M}$	$\frac{W_H}{W_M}$	L_s	M_s	H_s	$\frac{W_L L}{\sum_k W_k K}$	$\frac{W_M M}{\sum_k W_k K}$	$\frac{W_H H}{\sum_k W_k K}$	Exercise
Data	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
	2016	0.80	1.49	0.129	0.488	0.383	0.088	0.421	0.491	
Model	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
	2016	0.85	1.43	0.131	0.549	0.320	0.100	0.491	0.409	E
	2016	0.78	1.42	0.100	0.573	0.327	0.070	0.513	0.417	α+β+τ
	2016	0.88	1.59	0.131	0.489	0.381	0.096	0.404	0.500	E+$\beta + \alpha$+τ
Fraction of observed change[1]		2.33	1.40	1.06	0.99	0.98	1.40	1.08	1.05	
Contribution of E		0.75	0.51	0.93	0.57	0.47	1.04	0.55	0.48	
Contribution of $\alpha + \beta$		0.25	0.49	0.07	0.43	0.53	-0.04	0.45	0.52	

(1) Fraction of the change produced by the full model, with changes in the level of expenditures, factor intensities and in the sectoral labor shares relative to total changed observed in the data.

increasingly negative over the period 1980-2016, reflecting the increasing US trade deficit in manufactured products, reaching a value of -0.15 in 2016.

We re-do our baseline analysis imposing the observed wedges in the data. The wedges in the initial period $\{\tau_{s,1980}\}$ affect our calibration of $\{\zeta_s\}$ since now sectoral value-added shares are amended by the trade wedges as implied by Equation (36). We allow trade also to affec the effective change in demand in the final period of our simulations (see Appendix D for further details). Table 8 reports our simulation results. The main take away is that the key findings from our baseline calculations about the drivers of labor market polarization are completely unaffected by taking into account the effect of international trade. The neutral increase in aggregate expenditures still accounts for a remarkable share of the polarization in labor markets generated by our mode. In particular, it accounts, respectively, for 75% and 51% of the increases in the low vs. medium and high vs. medium relative wages generated by the model and between 47% to 93% of the change in the share of hours worked. Furthermore, the neutral increase in expenditures is responsible for a share of the change in the wage bill shares generated by the model that ranges from 51% for the high-skill occupation to 104% for the low skill occupation, which is strikingly close to the results from our closed economy model.

Table 9: Model Simulation with Capital Ownership by High-Skilled Households

	Year	$\frac{W_L}{W_M}$	$\frac{W_H}{W_M}$	L_s	M_s	H_s	$\frac{W_L L}{\sum_k W_k K}$	$\frac{W_M M}{\sum_k W_k K}$	$\frac{W_H H}{\sum_k W_k K}$	Exercise
Data	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
	2016	0.80	1.49	0.129	0.488	0.383	0.088	0.421	0.491	
Model	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
Only High	2016	0.83	1.39	0.124	0.570	0.306	0.094	0.518	0.388	E
	2016	0.76	1.39	0.091	0.592	0.317	0.062	0.537	0.401	α+β
	2016	0.83	1.51	0.115	0.529	0.356	0.082	0.455	0.462	E+$\beta + \alpha$
Fraction of observed change[1]		1.5	1.08	0.59	0.75	0.79	0.70	0.84	0.85	
Contribution of E		0.89	0.50	1.33	0.59	0.45	1.64	0.55	0.46	
Contribution of $\alpha + \beta$		0.11	0.50	-0.33	0.41	0.55	-0.64	0.45	0.54	

(1) Fraction of the change produced by the full model, with changes in the level of expenditures, factor intensities and in the sectoral labor shares relative to total changed observed in the data.

3.5.2 Assigning all capital income to high-skill households

Next, we study the robustness of our findings to alternative assumption about the ownership of capital. Given that most capital is owned by the richest households, a more realistic assumption about the capital ownership distribution is that capital is fully owned by the workers in high-skill occupations.[30]

Table 9 reports our simulation results and shows that our key findings are robust to alternative assumptions about the ownership of capital in the economy. Both the total change in labor market polarization generated by the model and the contribution by the neutral increase in expenditures do not differ much from those in the baseline calibration. Overall, the model generates a slightly smaller polarization in labor markets because by assigning all capital income to the workers in high-skill occupations, their share in expenditure increases, and we need a smaller increase in $\tilde{w}_{lt}$ to match the observed increase in the pce deflator from 1980 to 2016. Despite this, the neutral increase in expenditures accounts, respectively, for 89% and 50% of the increases in the low vs. medium and high vs. medium relative wages generated by the model and between 45% to 133% of the change in the share of hours worked. Furthermore, the neutral increase in expenditures is responsible for a fraction of the change in the wage bill shares generated by the model that ranges from 46% for the high-skill occupation to 164% for

[30]Naturally, we assume that workers do not take into account the assignment of capital to high-skill occupations when making their occupational choice.

the low skill occupation, which is quite close to the results from our closed economy model.

4 Additional Exercises

The forces introduced by our model – non-homotheticities that induce changes in the sectoral composition of the economy and labor demand – have surely been relevant in other periods of history and in other geographies. In this section we explore this possibility. Specifically, we study the role of non-homotheticities in explaining labor market dynamics in the US during the period 1950-1980 and the polarization of labor markets in other advanced economies during the period 1980-2016. We conclude our analysis by using our framework to look into the evolution of distributional labor market outcomes over the next 15-20 years.

4.1 Back-tracking 1950-1980

Now that we have used our model to better understand the drivers of US labor market polarization from 1980 to 2016, a natural question to ask is what drove the the evolution of wages and hours worked across occupations during period 1950-1980. This exercise is particularly interesting because much of the job polarization debate concerns the post-1980 period with the implicit assumption that some new developments triggered the polarization in labor markets. Yet, as documented by Siegel and Barany (), the labor market polarization dates back, at least to 1950 (See rows 1 and 2 in Table 10). Therefore, by conducting the back-tracking simulation we can study whether the same forces that have been important in the polarization wave from 1980 to 2016 may be responsible for the rise of the middle class we observed from 1950 to 1980 in the US.

To conduct our simulation, we use the same values for the preference parameters that we have used in section 3.4. As in our baseline calculation, we measure directly the sectoral intensity of each occupation and the labor shares. We calibrate the neutral increase in expenditure so that the model's level of aggregate expenditure per capita and the Fisher price index match the levels observed in 1950.

Rows 3-5 of Table 10 contain the labor market outcomes generated by the model for 1950 in response to the neutral decline in expenditure (row 3), the change in factor intensities and labor shares (row 4), and simultaneously conducting both types of changes in the exogenous variables (row 5). The first observation we can draw is that the model accounts quite well for the change in labor market outcomes from 1950 to 1980 (row 7). In particular, it over predicts the change in the relative wage of high-skill occupations but under predicts the relative wage of low-skill occupations. It accounts for a significant share of the change in the share of hours worked in middle and high-skill occupation with values of 107% and 104% respectively, and somewhat less for low-skill occupations with a value of 45%. The model also provides a good account of the changes in the occupational wage bills which represent from 71% of the ob-

Table 10: Model Simulation 1950-1980

	Year	$\frac{W_L}{W_M}$	$\frac{W_H}{W_M}$	L_s	M_s	H_s	$\frac{W_L L}{\sum_k W_k K}$	$\frac{W_M M}{\sum_k W_k K}$	$\frac{W_H H}{\sum_k W_k K}$	Exercise
Data	1950	0.70	1.15	0.106	0.731	0.163	0.075	0.736	0.189	
	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
Model	1950	0.68	1.17	0.074	0.702	0.224	0.049	0.693	0.258	W_L
	1950	0.79	1.18	0.122	0.660	0.218	0.094	0.651	0.254	α+β
	1950	0.72	1.06	0.100	0.730	0.171	0.073	0.743	0.184	W_L+$\beta + \alpha$
	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
Fraction of observed change[1]		0.50	2.00	0.45	0.99	0.91	0.71	1.07	1.04	
Contribution of E		3.25	0.53	-4.30	0.77	0.46	-4.00	0.69	0.48	
Contribution of $\alpha + \beta$		-2.25	0.47	-5.30	0.23	0.54	5.00	0.31	0.52	

(1) Fraction of the change produced by the full model, with changes in the level of expenditures, factor intensities and in the sectoral labor shares relative to total changed observed in the data.

served change for low-skill to 107% for medium skill occupations. Looking specifically at the contribution to the model performance of the neutral change in aggregate expenditure, we find that it plays an important role in all the dimensions other than for the evolution of the share of hours worked and wage bill accrued by low-skill workers. In particular, for high-skill occupations, it accounts for approximately 50% of the model's increase in the relative wage, share of hours worked and wage bill from 1950 to 1980. For medium skill occupations, the neutral increase in expenditure accounts for 77% of the model generated change in hours worked and 69% of the wage bill. For the low-skill occupations, the model accounts for all the increase in relative wages, but it does not account for any of the decline in the share of hours worked and in the wage bill.

Intuitively, between 1950 and 1980 there was significant sectoral variation in value added growth. As in our baseline period, there is a strong correlation between sectoral growth and the sectoral share in employment for high and low-skill occupations. Additionally, the model does a great job in predicting sector level growth from 1950 to 1980 (See panel A in Figure x). This is largely due to the differential effect of the neutral increase in expenditure on value added across sectors. In particular, the covariance between actual nominal sectoral growth and sectoral growth produced by the model in resposne to the neutral increase in expenditure represents 97% of the variance of actual sectoral growth between 1950 and 1980. Hence, the model's ability to capture the evolution of the wage bill distribution across occupations.

As in the post 1980- period, our model would split the evolution of the wage bill between relative wages and the distribution of hours worked. This works for medium and high-skill occupations but not for low-skill occupations that experience an increase in relative wages but a decline in the share of hours worked. Given the simplicity of our job assignment model, no single driving force can explain this negative co-movement between hours worked and wages of an occupation. So, how is it that the model does a great job in explaining both? The explanation is that while the neutral expenditure force induces an increase in the wage bill of low-skill occupations, during the 1950-80 period, the intensity in production of low skill workers declined causing a reduction in their demand. This second force tends be dominant for hours worked and the wage bill but not for the relative wages of low-skill occupations. Hence the model ability to explain the 1950-80 changes in labor outcomes for all occupational groups.

4.2 Polarization in Other Economies

TO BE ADDED

4.3 Looking into the future of US labor markets: 2016-2035

We conclude our analysis by looking at the future and using the model to forecast the state of labor markets around 2035. To this end, we simulate our model economy if starting in 2016 there was an neutral increase in aggregate expenditures similar to half of that observed from 1980 to 2016. Note that in our simulations we assume that factor intensities and labor shares remain constant at the 2016 levels. Our model predicts a continuation of the labor market polarization. The relative of low-skill occupations increases from 0.8 to 0.93, while the relative wage of high-skill occupations increases from 1.49 to 1.7. The share of hours worked for low and high-skill occupations increases, respectively from 0.12 to 0.142 and from 0.384 to 0.414, while the share of hours worked in medium skill occupations declines by 5 percentage points. These changes in wages and hours worked imply a reallocation of the wage bill from medium skill to low- and especially to high-skill occupations. Specifically, the wage bill of medium skill occupations declines by 8 percentage points, while the wage bill of low- and high-skill occupations increases, respectively, by 2 and almost 6 percentage points.

The magnitude of these changes are quite significant both in absolute terms and compared to the polarization observed during the 1980-2016 period. This is especially the case for relative wages which our model predicts will increase by proportionately more than in the 1980-2016 period. The share of hours worked and the wage bill for low-skill occupations will also increase by proportionately more from 2016-2035 than in 1980-2016. However, the shares of hours worked and the wage bills for medium and high-skill occupations will increase by between 22% and 38% of the overall increase in 1980-2016. Though these are very significant increases, they suggest that the pace at which the wage bill has been reallocated from medium

Table 11: Model Prediction for 2035

	Year	$\frac{W_L}{W_M}$	$\frac{W_H}{W_M}$	L_s	M_s	H_s	$\frac{W_L L}{\sum_k W_k K}$	$\frac{W_M M}{\sum_k W_k K}$	$\frac{W_H H}{\sum_k W_k K}$	Exercise
Data	2016	0.80	1.49	0.129	0.488	0.383	0.088	0.421	0.491	
Model, E	2035	0.93	1.70	0.142	0.444	0.414	0.104	0.347	0.549	
% increase of 1980-2016	2035	2.17	0.84	0.96	0.34	0.23	0.157	0.39	0.31	

to high-skill occupations will slow down slightly.

5 Conclusion

This paper makes two contributions. First, it documents a positive correlation between sectoral income elasticity and low- and high-skill occupation intensity. Based on this fact, we propose a demand-driven labor market polarization mechanism: as income grows and demand shifts to high-income-elastic sectors, the relative demand of high- and low-skilled workers increases. We quantify this mechanism in a multi-sector general equilibrium framework and find that it accounts for a substantial part of the US labor market polarization.

References

Daron Acemoglu. Changes in unemployment and wage inequality: An alternative theory and some evidence. *American Economic Review*, 89(5):1259–1278, December 1999. doi: 10.1257/aer.89.5.1259. URL http://www.aeaweb.org/articles?id=10.1257/aer.89.5.1259.

Daron Acemoglu and David Autor. *Skills, Tasks and Technologies: Implications for Employment and Earnings*, volume 4 of *Handbook of Labor Economics*, chapter 12, pages 1043–1171. Elsevier, 2011. URL https://ideas.repec.org/h/eee/labchp/5-12.html.

Daron Acemoglu, Philippe Aghion, and Giovanni L. Violante. Deunionization, technical change and inequality. *Carnegie-Rochester Conference Series on Public Policy*, 55(1):229–264, December 2001. URL https://ideas.repec.org/a/eee/crcspp/v55y2001i1p229-264.html.

Mark Aguiar and Mark Bils. Has consumption inequality mirrored income inequality? *American Economic Review*, 105(9):2725–56, September 2015. doi: 10.1257/aer.20120599. URL http://www.aeaweb.org/articles?id=10.1257/aer.20120599.

David Autor and David Dorn. This job is "getting old": Measuring changes in job opportunities using occupational age structure. *American Economic Review*, 99(2):45–51, May 2009. doi: 10.1257/aer.99.2.45. URL http://www.aeaweb.org/articles?id=10.1257/aer.99.2.45.

David H. Autor and David Dorn. The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, 103(5):1553–97, August 2013. doi: 10.1257/aer.103.5.1553. URL http://www.aeaweb.org/articles?id=10.1257/aer.103.5.1553.

David H. Autor, Frank Levy, and Richard J. Murnane. The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333, 2003. URL https://ideas.repec.org/a/oup/qjecon/v118y2003i4p1279-1333..html.

Zsófia L. Bárány and Christian Siegel. Job polarization and structural change. *American Economic Journal: Macroeconomics*, 10(1):57–89, January 2018. doi: 10.1257/mac.20150258. URL http://www.aeaweb.org/articles?id=10.1257/mac.20150258.

Sergi Basco and MartÃ■ Mestieri. Heterogeneous trade costs and wage inequality: A model of two globalizations. *Journal of International Economics*, 89(2):393–406, 2013. doi: 10.1016/j.jinteco.2012.08. URL https://ideas.repec.org/a/eee/inecon/v89y2013i2p393-406.html.

Francisco J. Buera and Joseph P. Kaboski. The rise of the service economy. *American Economic Review*, 102(6):2540–69, May 2012. doi: 10.1257/aer.102.6.2540. URL http://www.aeaweb.org/articles?id=10.1257/aer.102.6.2540.

Francisco J Buera, Joseph P Kaboski, and Richard Rogerson. Skill biased structural change. Working Paper 21165, National Bureau of Economic Research, May 2015. URL http://www.nber.org/papers/w21165.

Diego A. Comin, Danial Lashkari, and MartÃ■ Mestieri. Structural Change with Long-run Income and Price Effects. NBER Working Papers 21595, National Bureau of Economic Research, Inc, September 2015. URL https://ideas.repec.org/p/nbr/nberwo/21595.html.

Javier Cravino and Sebastian Sotelo. Trade Induced Structural Change and the Skill Premium. NBER Working Papers 23503, National Bureau of Economic Research, Inc, June 2017. URL https://ideas.repec.org/p/nbr/nberwo/23503.html.

Maarten Goos, Alan Manning, and Anna Salomons. Job polarization in europe. *American Economic Review*, 99(2):58–63, May 2009. doi: 10.1257/aer.99.2.58. URL http://www.aeaweb.org/articles?id=10.1257/aer.99.2.58.

Maarten Goos, Alan Manning, and Anna Salomons. Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review*, 104(8):2509–2526, August 2014. URL https://ideas.repec.org/a/aea/aecrev/v104y2014i8p2509-26.html.

Giora Hanoch. Production and Demand Models with Direct or Indirect Implicit Additivity. *Econometrica*, 43(3):395–419, May 1975. URL https://ideas.repec.org/a/ecm/emetrp/v43y1975i3p395-419.html.

Jerry Hausman, Gregory Leonard, and J. Douglas Zona. Competitive Analysis with Differentiated Products. *Annales d'Economie et de Statistique*, (34):159–180, 1994.

Jerry A. Hausman. Valuation of New Goods under Perfect and Imperfect Competition. In *The Economics of New Goods*, NBER Chapters, pages 207–248. National Bureau of Economic Research, Inc, March 1996.

Nir Jaimovich, Sergio Rebelo, and Arlene Wong. Trading down and the business cycle. *Journal of Monetary Economics*, 102:96 – 121, 2019. ISSN 0304-3932. doi: https://doi.org/10.1016/j.jmoneco.2019.01.026. URL http://www.sciencedirect.com/science/article/pii/S0304393219300339. Carnegie-Rochester-NYU ConferenceSeries on Public PolicyÃćÂĂÂIJA Conference Honoring the Contributions ofCharles Plosser to EconomicsÃćÂĂÂİHeld at the University of RochesterSimon Business SchoolApril 20-21, 2018.

Sang Yoon Lee and Yongseok Shin. Horizontal and vertical polarization: Task-specific technological change in a multi-sector economy. Working Paper 23283, National Bureau of Economic Research, March 2017. URL http://www.nber.org/papers/w23283.

Marco Leonardi. The effect of product demand on inequality: Evidence from the united states and the united kingdom. *American Economic Journal: Applied Economics*, 7(3):221–47, July

2015. doi: 10.1257/app.20130359. URL http://www.aeaweb.org/articles?id=10.1257/app.20130359.

Nelson Lind and Natalia Ramondo. Trade with Correlation. NBER Working Papers 24380, National Bureau of Economic Research, Inc, March 2018. URL https://ideas.repec.org/p/nbr/nberwo/24380.html.

Francesca Mazzolari and Giuseppe Ragusa. Spillovers from high-skill consumption to low-skill labor markets. *The Review of Economics and Statistics*, 95(1):74–86, 2013. URL https://EconPapers.repec.org/RePEc:tpr:restat:v:95:y:2013:i:1:p:74-86.

Table 12: Wage Bill Decomposition by Decades

		H-M	L-M
1980-2000:	Overall	3.26	1.10
	Incr Sect Shares	0.79	0.73
	Incr alpha	0.38	0.09
	Cov	2.09	0.28
2000-2016:	Overall	3.75	2.33
	Incr Sect Shares	1.60	1.69
	Incr alpha	0.29	0.13
	Cov	1.86	0.51

A Data Description

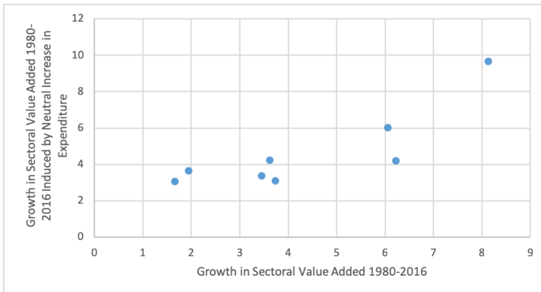
In this section we briefly detail our data sources. We take it from previous work and, thus, we provide a relatively brief description and relegate the interested reader to the original papers for further details.

A.1 Labor-Market Outcomes

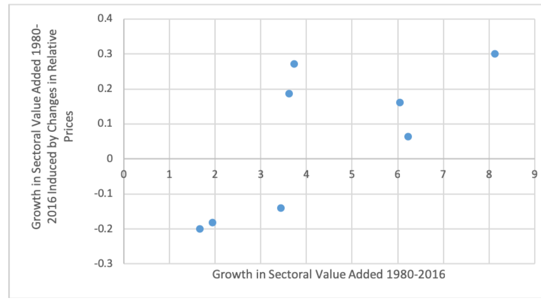
We follow Acemoglu and Autor [2011] in the construction of the baseline data on occupations, wages and employment shares that we want our model to match. Here we provide a brief overview and refer the reader to the original work by Acemoglu and Autor for the details. The data for employment come from IPUMS USA and it includes the decennial censuses between 1980-2000 (with 10 years intervals) and annual data from the American Community Survey (ACS) between 2000-2007.The sample is restricted to individuals aged 16-64 who were employed in the previous year and are assigned to a known occupation (i.e., not n/a or unemployed). We further restrict the sample to exclude the top and bottom 5% of the hourly wage distribution. Wage data comes from the Current Population Survey (CPS) to compute wages

Figure 5: Predicted vs. Actual Value-Added Growth

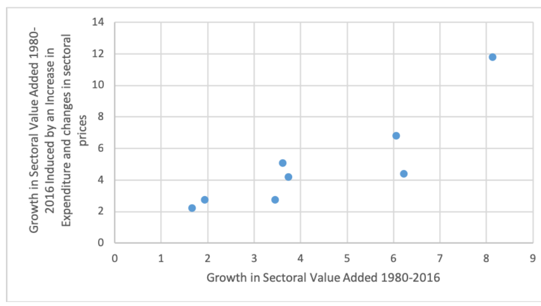
(a) Increase in E



(b) Increase in α



(c) Increase in E and α



Simulation Results on the $y-$axis, actual data in the $x-$axis.

per occupation. We follow Acemlogu and Autor on this choice because the data in the ACS is not consistent across years. Specifically, weeks worked last year has only intervals starting in 2007. Occupations and industries are classified based on the 1990 Census Bureau classification scheme that is consistent for all the sample years. These industries are mapped to the BEA industry classification through mutual mapping to the NAICS codes. For each BEA industry, we compute the share of individuals within each occupation.

Our occupation classification is also taken from Acemoglu and Autor [2011]. They divide the 382 original occupations into 4 broader categories that are characterized by their skill level: (1) managerial, professional and technical occupations; (2) sales, clerical and administrative support occupations; (3) production, craft, repair and operative occupations; and (4) service occupations. The first group is characterized by high skill occupations, the second and third groups are characterized by middle skill occupations and the last group is characterized by low skill occupations. They measure skill by the average hourly wage of individuals in the occupation in 1980 and group (2) and (3) into middle-skill occupations.[31]

[31] Our results on the negative correlation between occupation shares in middle-skill workers and income elasticity parameters are robust to decomposing middle-skill between groups (2) and (3). We report these correlations in Table **??** in the appendix.

A.2 Household Expenditure Data

We use cross-sectional data on household expenditure from the Consumer Expenditure Survey (CEX) to estimate the elasticity parameters of our nonhomothetic CES demand system, $\{\sigma, \varepsilon_s\}_{s\in\mathcal{S}}$. We use data from the 2000-2002 period.[32] We follow the procedure described in Aguiar and Bils [2015] to clean the data. In particular, we restrict our sample to urban households with ages of the reference person between 25 and 64. We drop households if they report spending less than 100 dollars in food in 3 months per individual in the household, they have negative total or food consumption expenditure, total income is reported incomplete, they have not responded all (four quarterly) interviews , income is below 50% of minimum wage or if they earn money but do not work. To mitigate measurement error concerns, we drop the top and bottom 5% richest households according to their total income (after taxes) and we winsorize top and bottom 5% sectoral expenditures.[33] We then follow the procedure described in Buera et al. [2015] and convert the final good expenditures reported in the CEX into value added expenditures using the BEA's 2000 input-output tables. We do so by matching the finest level of expenditure categories in the CEX (called UCCs) to each sector in the BEA table.[34] Following Comin et al. [2015], we also use sectoral, regional urban price series provided by the BLS for our estimation of price elasticities.[35]

B Estimation of Demand Elasticities

We next discuss our estimation procedure of the income elasticity parameters $\{\epsilon_s\}_{s\in\mathcal{S}}$ and the price elasticity σ using the household CEX survey data.[36] As we have discussed, there is one degree of freedom in taste parameters and one in the income elasticity parameters that needs to be pinned down ex-ante. We proceed by normalizing to 1 the taste parameter and income elasticity for one sector, denoted $\hat{s}$. That is, $\zeta_{\hat{s}} = \epsilon_{\hat{s}} = 1$. Our estimation method builds on Lemma 4 of Comin et al. [2015] and proceeds along the lines of the two-step estimation suggested in online Appendix I of the same paper. They show that this two-step method has the advantage of being faster (and more robust in their Monte-Carlo simulations) when the data has a large number of sectors.

[32] We have experimented with different time frame periods, between 1999 and 2007. The estimates are very stable across subsamples. Aguiar and Bils [2015] also report a similar finding in their estimated income elasticities.

[33] Total income after taxes is computed as in Aguiar and Bils [2015].

[34] We use the correspondence in Buera et al. [2015]. We extend the correspondence for the few cases in which there are UCCs from 2000-2002 missing from their original list.

[35] When possible, we create a household-specific Stone price index for each sector from more disaggregated possible price series categories that belong to each sector. We then also convert final expenditure prices to value added prices by assuming a Cobb-Douglas production function and perfect competition, such that the log price of a sector is the input-share weighed mean of log-prices.

[36] We make the following groupings of the BEA sectors that appear in the input output tables (in parenthesis we report the BEA code): Education and Health Care (6), Arts, Entertainment, Recreation and Food Services (7), Finance, Professional, Information, other services (excl. gov't) (FIRE, PROF, 51, 81), Manufacturing (31G), Retail, Wholesale Trade and Transportation (42, 44RT, 48T), Construction (23), Agriculture, Mining and Utilities (11,21,22).

Our empirical specification of the demand equation assumes that there are household specific taste parameters $\{\zeta_{sh}\}$. We follow Aguiar and Bils [2015] and assume that these depend on household size, age of primary earner and number of earners plus a sector specific intercept. That is, we parametrize $\ln \zeta_{hs} = \alpha_s + \Gamma_s Z_h$ where the term Z_h is a vector of demographic dummies based on age range (25-37, 38-50, 51-64), number of earners (≤ 2, 2+), and household size (≤ 2, 3-4, 5+). Note that we allow the coefficient vector on demographics Γ_s to vary across sectors.

In our first step of the estimation, we estimate the log-linear projection of real consumption $C(E_{ht}, \{p_{sht}\})$ on its components.[37] We assume that expenditure shares are measured with error, so that the relative expenditure shares across good s and a reference good $\hat{s}$ can be expressed as

$$\ln \frac{x_{hst}}{x_{h\hat{s}t}} = \Gamma_{0s} + \Gamma_s X_h + \sum_s \gamma_s \ln \frac{p_{sht}}{p_{sh't}} + \beta_s \ln E_{ht} + u_{hst} \tag{37}$$

where u_{hst} denotes the error term. Comin et al. [2015] show that, absent endogeneity concerns, this equation estimates the difference of income elasticity parameters between s and $\hat{s}$ up to a proportionality constant, $\beta_s = \frac{1}{\lambda}(\varepsilon_s - 1)$ for some $\lambda > 0$, such that $\frac{\beta_s}{\beta_{s'}} \to_{\text{plim}} \frac{\varepsilon_s - 1}{\varepsilon_{s'} - 1}$ (see also Footnote 37 in this appendix).

Perhaps interestingly, Equation (37) becomes analogous to the one in Aguiar and Bils [2015] if one controls for relative prices using fixed effects.[38] We follow Aguiar and Bils [2015] and instrument total household expenditure, E_{ht}, with dummies for the household's income quintile group (after taxes) computed from a separate question in the CEX on total income. The logic behind the instrument is that total expenditure reflects permanent income and is thus correlated with current income. We proceed by estimating Equation (37) for each sector (except the reference sector, which we take to be the government sector) by 2SLS. To mitigate concerns on measurement error changing over time or across regions, we control in each regression for year-quarter fixed effects interacted with region fixed effects.

[37] A theoretical underpinning for this step stems from a first-order approximation of real consumption around the sample average expenditure $\ln \bar{E}$ and prices $\{\ln \bar{p}\}$, denoted $\ln \bar{C}(\ln \bar{E}, \{\ln \bar{p}\})$. We have that

$$\ln C(E_{ht}, \{p_{sht}\}) = \ln \bar{C} + \ln C_E \cdot (\ln E_{ht} - \ln \bar{E}) + \sum_s C_s \cdot (\ln p_{sht} - ln \bar{p}_s) + o(\Delta E_{ht}, \{\Delta p_{sht}\}),$$

where C_E denotes the partial derivative with respect E evaluated at $\bar{E}, \{\bar{p}\}$, the analogous notation holds for C_s and $o(\cdot)$ denotes higher order terms. Combining this result with the relative expenditure shares of a household (which follows from Equation 27) between sectors s and s',

$$\ln \frac{x_{hst}}{x_{hs't}} = \ln \frac{\zeta_{hs}}{\zeta_{hs'}} + (1-\sigma) \ln \frac{p_{sht}}{p_{sh't}} + (\varepsilon_s - \varepsilon_{s'}) \ln C_{ht},$$

we obtain the log-linear equation

$$\ln \frac{x_{hst}}{x_{hs't}} = \tilde{\alpha}_s + \Gamma_s X_h + \sum_s \gamma_s \ln \frac{p_{sht}}{p_{sh't}} + (\varepsilon_s - \varepsilon_{s'}) C_E \ln E_{ht}$$

where $\tilde{\alpha}_s$ collects all constants appearing in the equation.

[38] Using time fixed effects interacted with region of residence without controlling for prices in (37) yields very similar estimates of β_s.

Table 13: Demand Estimation

	First Stage	Second Stage
Education and Health Care (6)	1.28	
	(0.09)	
Arts, Entertainment, Recreation and Food Services (7)	0.53	
	(0.04)	
Finance, Professional, Information, other services (excl. gov't) (FIRE, PROF, 51, 81)	-0.01	
	(0.02)	
Manufacturing (31G)	-0.22	
	(0.02)	
Retail, Wholesale Trade and Transportation (42, 44RT, 48T)	-0.32	
	(0.02)	
Construction (23)	-0.44	
	(0.03)	
Agriculture, Mining and Utilities (11,21,22)	-0.46	
	(0.02)	
Price Elasticity σ		0.63
		(0.01)
Scale Parameter λ		1.65
		(0.03)

Notes: Standard errors clustered at the household level shown in parenthesis. The parenthesis corresponds to the BEA classification code of the sector. The F-statistic for the first stage of 2SLS is greater than 50 in each regression that we run. The reference sector $\hat{s}$ is Government.

Table 14 reports our estimates for β_s. Our reference sector is government services. Positive estimates imply a higher income elasticity than government services and negative, lower. We find an intuitive ranking whereby the most income-elastic sector is education and health care and the least, agriculture, mining and utilities.

Our second step in the estimation uses the estimated $\{\beta_s\}$ and our normalizations $\zeta_{\hat{s}} = \varepsilon_{\hat{s}} = 1$ to write an exact demand system consistent with the particular normalization of utility we have chosen. We next show that the estimation boils down to estimate only two parameters: the price elasticity σ and a scale parameter λ to pin down $\{\epsilon_s\}$. We start from Equation (27) for sectors s and $\hat{s}$. We re-write them in terms of expenditure shares and use that $\zeta_{\hat{s}} = \varepsilon_{\hat{s}} = 1$ (see Comin et al. [2015] for details) to obtain

$$\ln\left(\frac{x_{hst}}{x_{h\hat{s}t}}\right) = \ln \zeta_{hs} + (1-\sigma)\ln\left(\frac{p_{hst}}{p_{h\hat{s}t}}\right) + (1-\sigma)(\epsilon_s - 1)\ln\left(\frac{E_{ht}}{p_{h\hat{s}t}}\right) + (\epsilon_s - 1)\ln x_{h\hat{s}t} \tag{38}$$

We then use the fact that $\varepsilon_s - 1 = \lambda\tilde{\beta}_s$, where λ is a constant (independent of s) and $\tilde{\beta}_s$ denotes

Table 14: Elasticity Parameters $\{\epsilon_s\}$

Sectors	ε_s^1	Avg. Elasticity[2]	Elasticity AB[3]
Education and Health Care (6)	3.50	2.28	2.28
Arts, Entertainment, Recreation and Food Services (7)	2.04	1.57	1.60
Government (G)	1.00	1.10	1.08
Finance, Professional, Information, other services (excl. gov't) (FIRE, PROF, 51, 81	0.98	1.09	1.10
Manufacturing (31G)	0.57	0.89	0.92
Retail, Wholesale Trade and Transportation (42, 44RT, 48T)	0.37	0.80	0.81
Construction (23)	0.14	0.69	0.68
Agriculture, Mining and Utilities (11,21,22)	0.10	0.68	0.67

Note:(1) Government sector is normalized to 1. (2) Average expenditure elasticity implied by the model calculated using the 2000-2002 CEX data. (3) Expenditure elasticity estimated using Aguiar and Bils (2015 specification

the estimated β_s in the first stage. Making this substitution in the previous equation, we obtain the estimating system of equations

$$\ln\left(\frac{x_{hst}}{x_{h\hat{s}t}}\right) = \alpha_s + \Gamma_s X_h + (1-\sigma)\ln\left(\frac{p_{hst}}{p_{h\hat{s}t}}\right) + (1-\sigma)\lambda\tilde{\beta}_s \ln\left(\frac{E_{ht}}{p_{h\hat{s}t}}\right) + \lambda\tilde{\beta}_s \ln x_{h\hat{s}t} + \nu_{hst} \quad (39)$$

where ν_{hst} denotes the error term arising from mis-measurement in expenditure shares. Since we are using the estimated $\{\tilde{\beta}_s\}$ in (39), it only remains to identify σ and λ to fully characterize our demand system. These two parameters appear simultaneously in all equations. We thus estimate them using a generalized method of moments (GMM) where we impose the parametric restrictions in the coefficients of (39) implied by our theory. We use the same set of instruments for household quarterly expenditure, E_{ht} as in our first stage. For prices, we follow Hausman et al. [1994], Hausman [1996] and use as instrument the average price paid in sector s by households that do not reside in the same region as household h. The rationale for this instrument is that price changes in other locations are not contaminated by contemporaneous demand regional shocks. Note also that we keep the same parametrization for taste parameters $\ln\zeta_{hs} = \alpha_s + \Gamma_s X_h$ as in the first stage. Table 14 reports the results of this estimation. We find that these sectors are complements, with a price elasticity of $\sigma = 0.63$. Finally, we estimate the scale parameter to be $\lambda = 1.65$. This allows us to compute the scale of $\{\epsilon_s\}$ consistent with our normalization. Table 14 reports the implied values for these elasticities.

C Calculation of contribution of different exogenous factors to the evolution of an endogenous variable

In this section we briefly describe how we calculate the contribution to the evolution of a given variable when there are multiple factors that impact it. For simplicity, consider the case where there are two exogenous drivers (a and b) for the endogenous variable v. Our model provides a mapping between the exogenous vector (a, b) and v. In a slight abouse of notation, we denote this mapping also by $v(.)$. The change in v between times 0 and F can be expressed as

$$\triangle v = v(a_F, b_F) - v(a_0, b_0), \tag{40}$$

where we have used subscripts F and 0 to denote the times.

We are interested in decomposing the change in v between the contribution from a and b. Note that $\triangle v$ can be decomposed in two different ways:

$$\begin{aligned} v(a_F, b_F) - v(a_0, b_0) &= v(a_F, b_F) - v(a_0, b_F) + v(a_0, b_F) - v(a_0, b_0) = \frac{\triangle v}{\triangle a}|_{b_F} + \frac{\triangle v}{\triangle b}|_{a_0} \\ v(a_F, b_F) - v(a_0, b_0) &= v(a_F, b_F) - v(a_F, b_0) + v(a_F, b_0) - v(a_0, b_0) = \frac{\triangle v}{\triangle b}|_{a_F} + \frac{\triangle v}{\triangle a}|_{b_0} \end{aligned}$$

where we have used the notation $\frac{\triangle v}{\triangle a}|_{b_F}$ to denote the change in v when a changes keeping b at its value in the final period, for example. Taking the average of both expressions, it follows that

$$v(a_F, b_F) - v(a_0, b_0) = \frac{1}{2}\left[\frac{\triangle v}{\triangle a}|_{b_F} + \frac{\triangle v}{\triangle b}|_{a_0}\right] + \frac{1}{2}\left[\frac{\triangle v}{\triangle b}|_{a_F} + \frac{\triangle v}{\triangle a}|_{b_0}\right] \tag{41}$$

Dividing throughout by the LHS we obtain the following expression for the contributions of changes in a and b to v:

$$1 = \overbrace{\frac{\frac{1}{2}\left[\frac{\triangle v}{\triangle a}|_{b_F} + \frac{\triangle v}{\triangle a}|_{b_0}\right]}{v(a_F, b_F) - v(a_0, b_0)}}^{\text{Contribution by } a} + \overbrace{\frac{\frac{1}{2}\left[\frac{\triangle v}{\triangle b}|_{a_F} + \frac{\triangle v}{\triangle b}|_{a_0}\right]}{v(a_F, b_F) - v(a_0, b_0)}}^{\text{Contribution by } b} \tag{42}$$

By construction, the sum of the contributions adds up to 1. Implicitly, this computation evenly assigns the effect of jointly changing a and b on v between the two drivers.

D Construction of the Value-Added Trade Data

We use the consolidated Input-Output table for the US from the World Input Output Database (available at http://www.wiod.org) to compute the share of value-added relative to total gross inputs by sector, α_s, $j = 1, \ldots, S$. We compute the average across all years available for the

2013 WIOD release (1995-2011).[39] Armed with the sectoral value-added shares $\{\alpha_s\}$, we compute the value-added content of net exports by sector and year. We use COMTRADE data on sectoral trade flows for 1980 and 2016 (since the WIOD input output table does not span a sufficiently long horizon). We also map sectoral trade flows and value-added shares into our eight sectors. The only sectors with positive trade flows are: Agriculture, Mining and Utilities and Manufacturing.

Note that we are imputing the US value-added shares to US imports (in addition to exports). The reason is that we are interested in understanding the effects of trade diversion on the US economy. Thus, a reduction in demand to US producers due to increased imports translates into a decline in labor demand of US producers. In order to capture this effect appropriately we need to use US value-added shares for imports.

Calibration Details To account for international trade we calibrate $\{\zeta_s\}$ and a sector specific TFP terms. We calibrate $\{\zeta_s\}$ so that the domestic aggregate demand in the model matches the domestic VA shares in each sector observed in 1980. We calibrate the sector specific TFP terms that so that the domestic demand augmented by the factor $(1 - \tau_{s,1980})^{-1}$ as discussed in equation (36) matches the total VA share in each sector observed in 1980. The calibration of the distribution parameters of effective units are done to match relative average wages and employment shares. They are done as in the baseline calibration since this part is independent from the trade module. In our main exercise for 2016 we augment each sector specific TFP term by a factor of $(1 - \tau_{s,2016})$ as well as adjust factor and labor intensity parameters α_{st}, β_{st} and then re-calibrate the change in $\tilde{w}_{lt}$ and a TFP shock that is common to all sectors to match the increase in nominal personal consumption expenditures per capita and the price index.

E Further robustness checks

E.1 Time-varying interest rates

sec:time-var int

[39] We have checked that there are no significant trends in value-added shares for agriculture and manufacturing. If we regress value-added shares on year and a constant we find a non-significant coefficient on time for agriculture and a significant but economically very small coefficient of 0.18% for manufacturing (this coefficient implies an increase over 16 years of 2.9% over a base of 34.6%).

Table 15: Model Simulation with Time Varying Interest Rate

	Year	$\frac{W_L}{W_M}$	$\frac{W_H}{W_M}$	L_s	M_s	H_s	$\frac{W_L L}{\sum_k W_k K}$	$\frac{W_M M}{\sum_k W_k K}$	$\frac{W_H H}{\sum_k W_k K}$	Exercise
Data	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
	2016	0.80	1.49	0.129	0.488	0.383	0.088	0.421	0.491	
Model	1980	0.74	1.24	0.095	0.653	0.252	0.068	0.630	0.302	
Time varying r	2016	0.88	1.49	0.138	0.523	0.338	0.106	0.456	0.438	W_L
	2016	0.85	1.53	0.118	0.519	0.363	0.085	0.441	0.473	α+β
	2016	0.88	1.60	0.129	0.486	0.386	0.093	0.399	0.508	W_L+$\beta+\alpha$
Fraction of observed change[1]		2.33	1.44	1.00	1.01	1.02	1.25	1.11	1.09	
Contribution of E		0.61	0.44	0.79	0.49	0.41	0.92	0.47	0.42	
Contribution of $\alpha+\beta$		0.39	0.56	0.21	0.51	0.59	0.08	0.53	0.58	

(1) Fraction of the change produced by the full model, with changes in the level of expenditures, factor intensities and in the sectoral labor shares relative to total changed observed in the data.

F Discussion on the use of Log-Normal

Consider low types first l. The terms appearing in the integrals to the three moments $m_{l,i}$ for $i = 0, 1, 2$ are

$$m_{l,i} = \int_0^\infty z^i \frac{1}{z\sigma_l\sqrt{2\pi}} \exp\left(-\frac{(\ln z-\mu_l)^2}{2\sigma_l^2}\right) \cdot F\left(\frac{(\ln(w_l z/w_m)-\mu_m)^2}{2\sigma_m^2}\right) \cdot F\left(\frac{(\ln(w_l z/w_h)-\mu_h)^2}{2\sigma_h^2}\right) dz \tag{43}$$

where F is a function related to the CDF of the log-normal distribution. From here we see that changing μ or σ is equivalent if we do not pin down wages separately. Thus, since we target relative wages, we can normalize all means and one variance.

To elaborate a little more on this note that:

$$\frac{(\ln(w_l z/w_h)-\mu_h)^2}{2\sigma_h^2} = \left(\ln z^{\frac{1}{\sqrt{2}\sigma_h}} + \frac{1}{\sqrt{2}\sigma_h}\ln\frac{w_l}{2w_h\sigma_h} - \mu_h\right)^2 \tag{44}$$

$$= (\ln y - \tilde{\mu})^2 \tag{45}$$

So it is clear that the average changes with both μ and σ. Since we do not observe z we can always renormalize things as in the last line and only use μ or σ for the calibration.