

# THE RACE BETWEEN PREFERENCES AND TECHNOLOGY

JOACHIM HUBMER

Department of Economics, University of Pennsylvania

This paper argues that a unified analysis of consumption and production is required to understand the long-run behavior of the U.S. labor share. First, using household data on the universe of consumer spending, I document that higher-income households spend relatively more on labor-intensive goods and services as a share of their total consumption. Interpreted as nonhomothetic preferences, this fact implies that economic growth increases the aggregate labor share through an income effect. Second, using disaggregated data on factor shares and capital intensities, I document that equipment-intensive goods experienced relatively larger declines in their labor shares. Based on this finding, I estimate that capital and labor are gross substitutes, and that investment-specific technical change reduces the labor share. Given the estimated elasticities, a parsimonious neoclassical model quantitatively matches the observed low-frequency movements in the aggregate labor share since the 1950s, both its relative stability until about 1980 and its decline thereafter.

KEYWORDS: Labor share, investment-specific technological change, consumption.

## 1. INTRODUCTION

WE ARE WITNESSING an era of rapid technological advances, manifesting itself in new, better, or cheaper machines. Stark examples are robots and artificial intelligence. As these new technologies that are embodied in capital goods diffuse in the economy, fears about the future of labor abound. Indeed, the share of labor in national income has been declining in the U.S. as well as globally over the past few decades (Elsby, Hobijn, and Sahin (2013), Karabarbounis and Neiman (2014)). These fears have reemerged continually since the beginning of the Industrial Revolution. Yet, labor has not become redundant. Kaldor (1961) famously mentioned the observed stability of the aggregate labor share as one of the stylized facts of economic growth.

This paper starts by documenting two novel facts about labor shares in the U.S. economy that have implications for the evolution of the aggregate labor share. First, linking cross-sectional household spending data from the Consumer Expenditure Survey (CEX) to good-level labor shares constructed with data from the Bureau of Economic Analysis' (BEA) Detailed Input–Output (I–O) Tables, I establish that richer households spend more on labor-intensive goods and services as a fraction of their total expenditure. Panel (a) of Figure 1 summarizes this fact, plotting households' consumption labor shares as a function of their income percentile, averaged over the sample period (1980–2015). While higher-income households spend relatively more on labor-intensive services including

---

Joachim Hubmer: [jhubmer@sas.upenn.edu](mailto:jhubmer@sas.upenn.edu)

This is a revised version of the first chapter of my dissertation. I am indebted to my advisors Giuseppe Moscarini, Tony Smith, and Per Krusell for their guidance and support. I am grateful to three anonymous referees, Costas Arkolakis, Bill Brainard, Zhen Huo, Loukas Karabarbounis, Ilse Lindenlaub, Michael Peters, Pascual Restrepo, Aleh Tsyvinski, Fabrizio Zilibotti, as well as to seminar participants at the 2018 Minneapolis Fed Junior Scholar Conference, the 2019 NBER Summer Institute, the 2019 SED Meetings, Berkeley, Cologne, Essex, Georgetown, Houston, Maryland, Minnesota, NYU Economics, NYU Stern, Philadelphia Fed, Princeton, University of Pennsylvania, Uppsala, Yale, and Zurich for their comments and feedback. I also thank James O'Brien for generously sharing a concordance between CEX categories and Input–Output Tables with me.

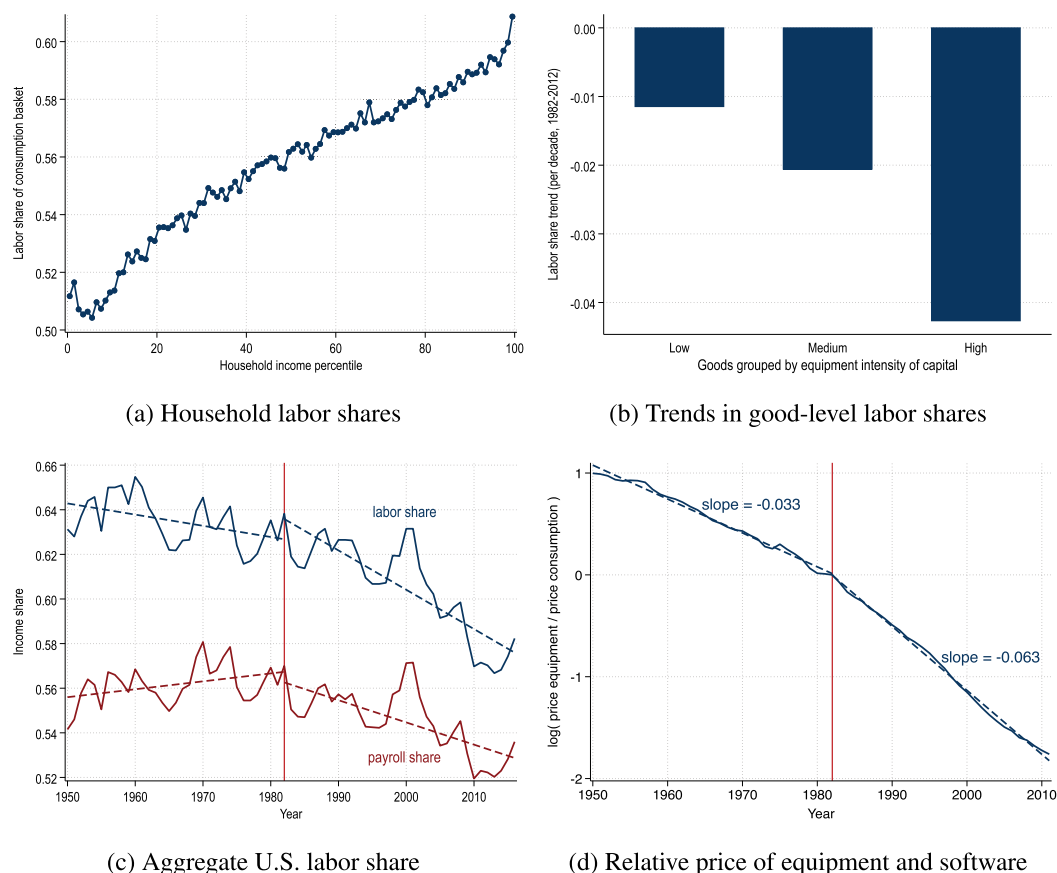


FIGURE 1.—Labor shares in the U.S.: Two novel facts and two aggregate trends. Data sources: (a) BLS; (b) DiCecio (2009); (c) BEA I–O Tables, BEA FAT, NBER-CES Manufacturing Database, own computations; (d) CEX, BEA I–O Tables, own computations.

travel, eating at restaurants, and higher education, lower income-households spend relatively more on capital-intensive necessities such as utilities and food at home. The overall pattern is robust, as it holds across the income distribution, over the entire sample period, and it is not driven by any particular sector, neither by differential import intensities nor differential markups. Holding constant relative prices, this observation suggests that economic growth increases the aggregate labor share through an income effect over time.

Second, I document that over the sample period 1982–2012, those goods and services that are characterized by a relatively high equipment and software intensity of capital experienced much stronger labor share declines (Panel (b) of Figure 1). To establish this fact, I combine the panel data set of good-level labor shares obtained from the I–O Tables with capital stock composition data from the BEA's Fixed Assets Tables and the NBER-CES Manufacturing Industry Database. Panel regressions reveal that across goods, the decline in labor shares can be largely explained by the equipment and software intensity of production, both when measured as a share of total value added, and as a share of total capital compensation. While this paper's focus is on good-level labor shares—which factor in value added along the value chain—I document that this pattern also hold across industries, both across I–O Table industries as well as across industries in the BLS/BEA

Integrated Industry-Level Production Account. This cross-sectional fact suggests a key role for capital-embodied technological changes in the decline of the aggregate U.S. labor share.

The rest of the paper studies the evolution of the U.S. labor share in the post-war era through the lens of a parsimonious neoclassical model, whose key elasticities are estimated using the cross-sectional variation discussed above. Panel (c) of Figure 1 shows that the labor share has been roughly stable until the early 1980s, and declined subsequently.<sup>1</sup> Throughout, we witnessed remarkable technological progress in the sectors that produce equipment and software capital. Following the literature, I use the quality-adjusted relative equipment and software price as a measure of investment-specific technical change. Panel (d) of Figure 1 shows that this relative price declined throughout the entire period, and that the decline accelerated substantially in the early 1980s.<sup>2</sup>

In a general equilibrium framework, I show that the response of the aggregate labor share to different forms of economic growth can be decomposed into two additive components: The first is a substitution effect, operating both on the production side via direct capital–labor substitution, as well as indirectly via a reallocation of consumption in response to changing prices. This substitution effect is proportional to the bias of growth toward capital, and to an aggregate substitution elasticity, which is a convex combination of the capital–labor elasticity in production and the consumers’ substitution elasticity. The second component represents an income effect, and is proportional to the overall rate of economic growth multiplied by the cross-sectional covariance between sectoral labor shares and income elasticities. If this covariance is positive and the relevant aggregate substitution elasticity is above one, then the aggregate labor share is stable if growth exhibits a moderate capital bias, while it declines if the capital bias is strong.

The estimation of the income elasticities is based on cross-sectional variation in expenditure shares across households, using the CEX data linked to the I–O Tables. Holding fixed prices, the income elasticities are recovered by regressing household-good-year expenditure shares on total annual household expenditure, instrumented by household income to deal with measurement error. As suggested by the descriptive evidence, I find that the covariance between labor shares and income elasticities is positive. This nonhomotheticity in consumer demand implies that any form of economic growth increases the aggregate labor share through an income effect.

Next, I turn to estimating the capital–labor elasticity of substitution in production, again relying on the panel of good-level labor (and capital) shares derived from the I–O Tables augmented with data on the composition of capital. The estimation strategy is based on the assumption that the observed secular decline in the quality-adjusted price of equipment and software capital reflects exogenous technical progress. Because in the cross-section of goods, falling labor shares correlate with falling capital costs (high equipment intensity of capital), the estimated capital–labor elasticity is significantly above one. In other words, capital and labor are gross substitutes, implying that declining capital prices trigger falling labor shares. The estimated elasticity represents the shift from labor to capital in response to a fall in the rental rate of capital, relative to the wage rate, along the full

<sup>1</sup>Because there is some ambiguity concerning the treatment of proprietors’ income, I report both the BLS’ headline labor share measure and the narrower payroll share. For all time series in Figure 1, I added separate linear time trends for the pre-1982 and the post-1982 time period for illustrative purposes only. In the model analysis, I relate to the raw annual data.

<sup>2</sup>The series is constructed by DiCecio (2009), building on earlier work by Gordon (1990) and Cummins and Violante (2002). Hulten (1992) and Greenwood, Hercowitz, and Krusell (1997) are seminal references for investment-specific technical change.

value chain, including all upstream production. In robustness exercises, I show that the estimated elasticity is stable when controlling for rising exposure to international trade, rising markups, and other confounders.

Armed with these two sets of estimates, I analyze the evolution of the U.S. labor share since the 1950s through the lens of the model. For this exercise, I assume that the key consumer demand and technology elasticities have been stable over time. The model quantitatively matches the observed low-frequency movement in the aggregate labor share, both its relative stability until about 1980 and its decline thereafter. Up to the early 1980s, the substitution of capital for labor in production was moderate, and as it turns out, entirely offset by the positive income effect. Later on, as investment-specific technical change accelerated, capital–labor substitution became the dominant force.

In the baseline model, I treat factor prices of capital as exogenous, and back out the resulting capital stocks from firms' optimal input demand. This procedure implies a time series of nominal investment rates that can be compared to data. While the investment ratio trend is flat or slightly declining in the data, the baseline model implies a substantial increase. This discrepancy motivates studying an alternative model version that is consistent with national accounts data on investment. In that alternative model, the fall in the labor share is less dramatic, though still quite large at 5.6 percentage points, compared to 7.7 points in the baseline. Why does the capital share increase even if the nominal investment rate and capital–output ratio are relatively stable over time? The reason is that even if nominal investment is flat, investment-specific technical change leads to capital deepening in real terms. Combined with an above-unitary capital–labor elasticity, the capital share increases.

The rest of the paper is organized as follows. Section 2 documents a pervasive positive relation between income and the labor intensity of consumption in the cross-section of households. Section 3 shows that, in the cross-section of goods and services, the decline in labor shares since the 1980s can be fully explained by the equipment and software intensity of production. Section 4 lays out a parsimonious neoclassical model of growth and nonhomothetic consumption that can account for these facts. Section 5 estimates the model based on the cross-sectional variation documented earlier, and Section 6 describes the quantitative implications for the post-war U.S. economy. Section 7 concludes. The Supplemental Material (Hubmer (2023)) contains Appendices with further details on the data (Appendix A), robustness checks for the empirical (Appendix B) and quantitative exercises (Appendix C), and the proof of Proposition 1 (Appendix D).

### 1.1. *Related Literature*

This paper contributes primarily to the literature on the evolution of the labor share. Elsby, Hobijn, and Sahin (2013) document its decline over the past few decades for the U.S., while Karabarbounis and Neiman (2014) show that it is a global phenomenon. The exact magnitude of the decline is still debated due to measurement issues such as the treatment of the labor portion of proprietor's income (Gollin (2002), Elsby, Hobijn, and Sahin (2013)), intangible capital (Koh, Santaaulàlia-Llopis, and Zheng (2020)), and housing (Rognlie (2015)). There is, however, a consensus that the labor share has been falling in the U.S. Proposed explanations include increased openness to international trade (Elsby, Hobijn, and Sahin (2013)), an increase in concentration that causes increasing markups and profits (Barkai (2020), Autor, Dorn, Katz, Patterson, and Van Reenen (2020), De Loecker, Eeckhout, and Unger (2020)), automation (Hémous and

Olsen (2022), Acemoglu and Restrepo (2018, 2020)), as well as more generally capital–labor substitution that is triggered either by declining investment good prices (Karabarbounis and Neiman (2014), Eden and Gaggl (2018)) or by capital accumulation itself (Piketty (2014)).

This paper contributes to this literature by documenting two novel facts: richer households spend relatively more on labor-intensive goods and services, and the decline in good-level labor shares can be largely explained by the equipment and software intensity of production.<sup>3</sup> In addition, this paper shows that a parsimonious multisector growth model, whose key elasticities are disciplined by these cross-sectional facts, quantitatively matches the observed low-frequency movements in the aggregate U.S. labor share in the post-war era. Relative to the majority of studies in that literature, accounting not only for the period of declining labor shares (post-1980) but also for the relative stability of the labor share earlier on is novel.<sup>4</sup>

Second, this paper also contributes to the literature on estimating the capital–labor elasticity. Chirinko (2008) and León-Ledesma, McAdam, and Willman (2010) summarize the earlier literature. Conceptually, I build on Karabarbounis and Neiman (2014), who also focus on cross-sectional variation in investment good price trends. While their estimate is based on cross-country variation in aggregate factor share and investment good price trends, I exploit differential exposure across goods, within the U.S., to the secular decline in the real national equipment and software price—which I view as a more plausible source of exogenous variation. Relative to that literature, the focus on good-level as opposed to industry-level (or aggregate) factor shares is new. I clarify that my estimated elasticity reflects not only capital–labor substitution within value added of an industry, but also incorporates outsourcing and substitution across intermediate inputs, and note that ignoring the nonhomotheticity in consumer demand biases estimates that are based on aggregate data. To my knowledge, the particular identification strategy of using differential exposure across goods to the secular decline in equipment prices is also novel.

Third, this paper relates to the literature on structural change. As in recent contributions by Boppart (2014) and Comin, Lashkari, and Mestieri (2021), I find that allowing for long-run income effects is crucial in order to understand long-run sectoral reallocation. In contrast to that literature’s focus on broad sectors, I consider a much more disaggregated economy. This is necessary in order to quantitatively capture the contribution of the income effect to the aggregate labor share evolution. Instead of adopting a specific class of structural preferences, I use a log-linear approximation to Engel curves (as, e.g., used by Aguiar and Bilal (2015)). The advantage of this modeling approach is that it allows for more flexibility in the pattern of income and substitution elasticities. In general, a downside is that, without an underlying utility function, welfare statements are not possible. However, this is not a problem in the context of this paper, which conducts an entirely positive analysis.

## 2. CONSUMPTION AND THE LABOR SHARE

This section documents a new fact about how consumption relates to the labor share: in the cross-section of households, there is a pervasive and stable positive relationship between household income and the labor share of a household’s consumption basket.

<sup>3</sup>A version of the former fact has also been established in a business cycle context by Alonso (2016) and Jaimovich, Rebelo, and Wong (2019).

<sup>4</sup>Karabarbounis and Neiman (2019) is a related paper insofar as they also go beyond the period of declining labor shares to argue that some of the proposed explanations are at odds with earlier data.

## 2.1. Data

I start by assembling the data sources. The Bureau of Economic Analysis' (BEA) Detailed Input–Output (I–O) Tables contain the necessary information to construct a panel data set of labor shares for goods and services. Next, I link these to consumption micro data from the Consumer Expenditure Survey (CEX) in order to compute the labor content of consumption baskets in the cross-section of households.

*Input–Output Tables.* The BEA's I–O Tables are available every 5 years; I use the 1982, 1987, ..., 2012 editions.<sup>5</sup> In a given year  $t$ , the *Make Table* specifies the (dollar) amount of good  $i \in I_t$  produced by industry  $j \in J_t$ .<sup>6</sup> The *Use Table* specifies the amount of production inputs used by each industry, where inputs are both value added (labor, capital, production taxes, and subsidies) as well as intermediate inputs. The Use Tables allow for directly computing industry-level labor shares  $\tilde{\theta}_{jt}^L$  as the ratio of labor compensation to value added. Appendix A.1 discusses details: taxes and subsidies are allocated to labor and capital proportionally, the portion of proprietors' income that reflects labor compensation is imputed based on the economy-wide assumption (Gollin (2002), Valentinyi and Herrendorf (2008)), and all data is in producer prices.

In the remainder of this paper, final good labor shares  $\theta_{it}^L$  are the object of interest. My approach to the data is that consumer demand is defined over goods (e.g., a car) instead of over value added by industry (e.g., value added in the car industry). For consistency, subsequently, the production structure will be specified by good as well, and not by industry. Herrendorf, Rogerson, and Valentinyi (2013) label this the *final expenditure approach*, in contrast to the *value added approach*. As shown in Appendix A.1,  $\theta_{it}^L$  is a weighted average of industry-level labor shares, where industry  $j$ 's weight equals the fraction of total value added generated in producing good  $i$  that originates in industry  $j$ .

The economy-wide labor share  $\bar{\theta}_t^L$  can be computed as a weighted average of good-level labor shares. The appropriate weights are in general final demand weights  $(\omega_{it}^{\text{FD}})_{i \in I_t}$ , which can be readily computed from the Use Tables:

$$\bar{\theta}_t^L = \sum_{i \in I_t} \omega_{it}^{\text{FD}} \theta_{it}^L.$$

The I–O industry classifications are time-varying. I first compute  $\theta_{it}^L$  for each  $i \in I_t$  and each  $t$ , and subsequently map these objects into a common set of goods  $i \in I$ . This results in a panel data set of good-level labor shares and expenditure shares, comprising of 362 goods and seven time periods, spanning the period 1982–2012.

*Consumer Expenditure Survey.* I use consumption micro data from the U.S. Consumer Expenditure Survey (CEX), covering 1980–2015. The CEX follows individual households for five consecutive quarters, recording nominal amounts spent on various consumption categories. Aggregating to annual frequency yields a repeated cross-section of annual household expenditures on up to 524 consumption categories (UCCs). Sample selection and further details on the data treatment are relegated to Appendix A.2. After sample selection, the data set consists of 91,894 households, about 2500 per year.

<sup>5</sup>Previous editions are not suitable as value added is not broken down in labor compensation and other components. The 2017 edition is not yet available.

<sup>6</sup>In the language of the I–O Tables, goods and services are called commodities. I will refer to both goods and services simply as goods.



Next, I map CEX spending data into the I–O Tables’ industry classification system. The mapping is based on a manual concordance assembled by [Levinson and O’Brien \(2019\)](#).<sup>7</sup> The final data set contains for each year  $t$  and each household  $h$ : total expenditure  $E_{ht}$ , expenditure weights  $(\omega_{iht})_{i \in I}$ , as well as a vector of household characteristics  $Z_{ht}$  that includes income and other demographic information. I use the reported after-tax household income variable, which includes transfers. Aggregating across households yields aggregate CEX expenditure weights  $(\omega_{it}^{\text{CEX}})_{i \in I}$ .

Given a household’s expenditure weights, its consumption labor share is straightforward to calculate as a weighted average of good-level labor shares:

$$\theta_{ht}^{L, \text{household}} = \sum_{i \in I} \omega_{iht} \theta_{it}^L.$$

## 2.2. Descriptive Evidence on Consumption and the Labor Share

Figure 2 shows the relation between household income and household labor shares, averaged by income percentile and decade. We see that for each time period, richer households spend relatively more on labor-intensive goods and services as a fraction of their total expenditure. The magnitude is economically significant, as the gap between the 90th and 10th percentile amounts to 6–8 percentage points—for comparison, this is similar in size to the decline in the aggregate U.S. labor share. The fact that these labor shares declined over time, conditional on income, reflects primarily technological changes (i.e.,  $\theta_{it}^L$  decreased over time for most  $i \in I$ ), and to a small extent substitution toward capital-intensive goods in response to changing prices.<sup>8</sup>

While Figure 2 is informative about the overall magnitude and monotonicity of the relationship, and its stability over time, it does not tell us which goods are driving this

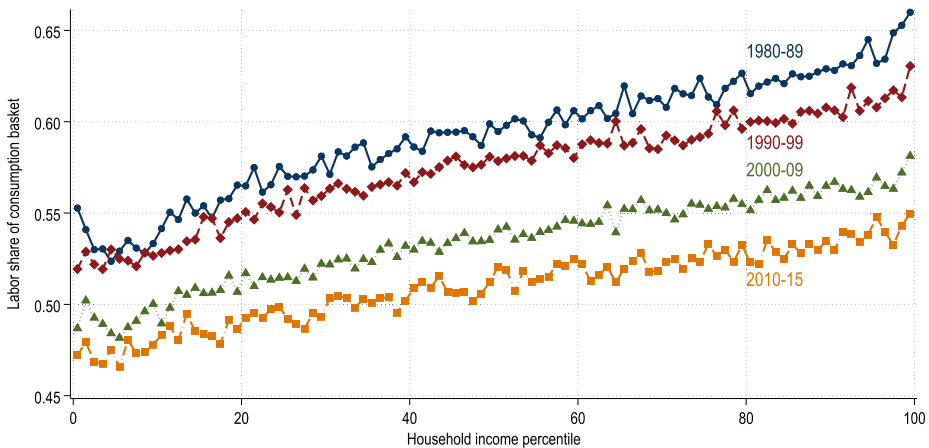


FIGURE 2.—Household income and household labor shares. Source: CEX (household consumption by category and income), BEA I–O Tables (labor shares). Income percentiles are defined to be stable over time, so that households in a given income percentile bin, in any year, have the same real income.

<sup>7</sup>Further details are described in Appendix A.3.

<sup>8</sup>The income percentiles in Figure 2 are defined to be constant across years, so that the level of real income on the horizontal axis is constant across time. Figure B.1(a) in Appendix B shows that the results are comparable when using instead time-varying income percentiles.

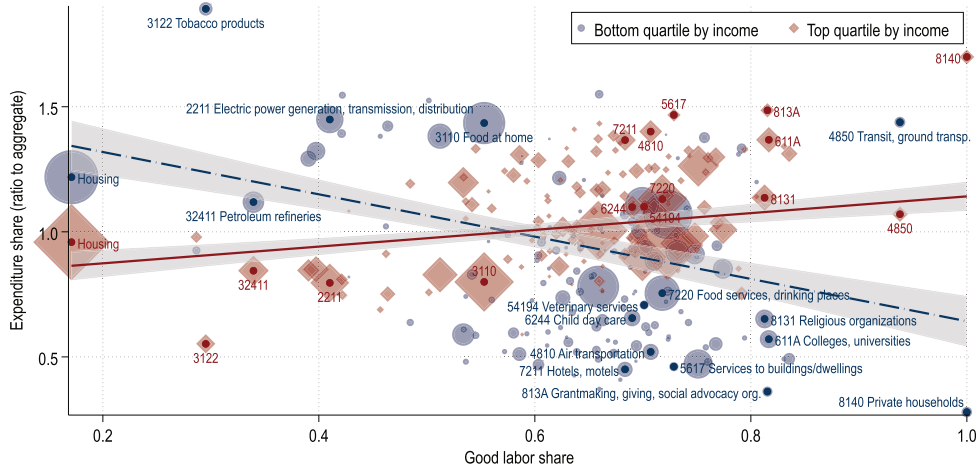


FIGURE 3.—Good-level labor shares and household expenditure shares. Source: CEX (household consumption by category and income), BEA I-O Tables (labor shares). On the horizontal axis, goods are ordered by their (time-averaged) labor shares. The vertical axis reports average expenditure shares for both the top as well as the bottom quartile of households ordered by income, displayed as ratio relative to aggregate expenditure shares. The size of the markers corresponds to goods' aggregate expenditure shares. Some important consumption categories are labeled and highlighted. The dashed lines depict the OLS fit, the shaded areas, the 95% confidence interval.

pattern. Figure 3 correlates goods' labor shares with the expenditure shares of the top, respectively, the bottom, income quartile of households. For example, higher-income households spend relatively more on labor-intensive services including travel, eating at restaurants, and higher education, while spending relatively less on more capital-intensive goods such as utilities or food at home. With the exception of few outliers, the pattern is remarkably consistent for the universe of goods and services. Appendix B.1 establishes robustness of this fact: the relation is neither driven by imports nor by markups, and not quantitatively sensitive to the inclusion or exclusion of any particular sector. Appendix B.1 also contains a full tabulation of the data aggregated to the 2-digit level in Table B.I.

### 2.3. Relation to the Literature and Implications

A benefit of using CEX data linked to national accounts is that it provides a comprehensive picture of personal consumption expenditures. At the same time, the focus is on consumption categories, abstracting from heterogeneity within categories, such as within the restaurant category. There is evidence that higher-income households spend relatively more on high-quality goods (Faber and Fally (2021)), and that high quality correlates with high labor intensity in sectors where such data is available (Jaimovich, Rebelo, and Wong (2019)). Thus, while incorporating within-category heterogeneity comprehensively is not feasible, one would expect the effect to be even stronger when taking such additional heterogeneity into account.

What are the implications of this fact for the evolution of the aggregate labor share? Under some assumptions formalized in Section 5.1, the relation can be interpreted as an income effect. Intuitively, the vertical difference between high-income and low-income households in Figure 3 corresponds to a good's income elasticity (minus one). Indeed, in Section 5.1 I estimate the income elasticities precisely based on cross-sectional variation



in expenditure shares and household income. Then, when holding constant relative prices, economic growth leads to a reallocation of consumer spending toward labor-intensive goods, which by itself increases the aggregate labor share over time.

### 3. PRODUCTION AND THE LABOR SHARE

This section documents a new fact about the evolution of labor shares: in the cross-section of goods and services in the U.S. economy, the decline in labor shares since the 1980s can be largely explained by the equipment and software intensity of production.

#### 3.1. Data

In this section, I augment the labor share panel constructed from the I–O Tables with information on capital intensities sourced from the NBER-CES Manufacturing Industry Database and the BEA's Fixed Assets Tables (FAT). The I–O Tables only allow for breaking down total value added into labor income and a residual, which I define to be capital income.<sup>9</sup> Here, I split total capital income into equipment (which includes software) as well as structures capital income by using industry data on capital stocks and the standard user cost formula (Hall and Jorgenson (1967)).<sup>10</sup>

*Equipment Intensities and Factor Shares.* For the manufacturing sector, the NBER-CES dataset (Becker, Gray, and Marvakov (2016)) provides this data at the 6-digit industry level. For all other industries, I rely on data from the BEA's FAT, which is available at a higher level of aggregation only (62 industries). Mapping nominal capital stocks into flows requires further an assumption on the required return on equipment  $\tilde{R}_t^E$ , relative to the one for structures  $\tilde{R}_t^S$ . I use a standard user cost formula; the details are described in Appendix A.4. Given these required returns, the equipment intensity  $\tilde{\kappa}_{jt}$  of industry  $j$  is defined as the ratio of equipment costs to total capital costs,

$$\tilde{\kappa}_{jt} = \frac{\tilde{R}_t^E P_t^E K_{jt}^E}{\sum_{k=E,S} \tilde{R}_t^k P_t^k K_{jt}^k}, \quad (1)$$

where  $P_t^E K_{jt}^E$  ( $P_t^S K_{jt}^S$ ) denotes industry  $j$ 's nominal equipment (structures) capital stock.

Given industry  $j$ 's labor share  $\tilde{\theta}_{jt}^L$ , I compute the equipment, respectively, structures, factor share as

$$\begin{aligned} \tilde{\theta}_{jt}^E &= (1 - \tilde{\theta}_{jt}^L) \tilde{\kappa}_{jt}, \\ \tilde{\theta}_{jt}^S &= (1 - \tilde{\theta}_{jt}^L) (1 - \tilde{\kappa}_{jt}). \end{aligned}$$

<sup>9</sup>In Section 5.2, I relax this assumption, allowing the residual to contain pure profits and incorporating the possibility of rising markups.

<sup>10</sup>This two-way split excludes some types of IPP capital (R&D and artistic originals), for which price indices are difficult to estimate and data availability is limited. Appendix A.4 shows that their contribution to aggregate factor share trends is minor.

*From Industry- to Good-Level Intensities and Factor Shares.* Analogously to the computation of good-level labor shares, I map these industry capital shares into good-level equipment ( $\theta_{it}^E$ ) and structures factor shares ( $\theta_{it}^S$ ); similarly, for equipment intensities  $\kappa_{it}$ . Since time-variation in equipment intensities and factor shares is sensitive to the choice of interest rate (see Figure A.4 in Appendix A.4), I primarily use the respective time-averages ( $\bar{\theta}_i^E$ ,  $\bar{\theta}_i^S$ ,  $\bar{\kappa}_i$ ) in the empirical analysis. Thus, I rely on cross-sectional rather than time-variation in the composition of the capital stock.

As discussed in Section 2.1, good-level factor shares reflect the full value chain of a product. This is desirable, because first they are invariant to a reallocation of production tasks across industries that does not change the capital–labor mix within tasks. Second, and relatedly, changes in good-level labor shares reflect not only substitution between capital and labor within an industry, but also across intermediate inputs.<sup>11</sup>

3.2. Descriptive Evidence on Production and the Labor Share

Table I displays panel regressions of the good-level labor share  $\theta_{it}^L$  on good fixed effects and linear time trends. Column 1 reports that the aggregate labor share declined by 2.5 percentage points per decade, or 7.5 points over the period 1982–2012. Column 2 interacts the time trend with a dummy for the manufacturing sector, showing that the decline is stronger for manufacturing goods as is well known. Yet, there is also a substantial decline outside of manufacturing. Column 3 conveys the main point: The entire decline in

TABLE I  
EXPLORING THE DECLINE IN GOOD-LEVEL LABOR SHARES.

	(1)	(2)	(3)	(4)	(5)
$t$	−0.025 (0.004)	−0.019 (0.005)	0.004 (0.008)	0.002 (0.008)	0.004 (0.011)
$t \times 1_{i \in IM}$		−0.021 (0.008)		−0.006 (0.009)	
$t \times \bar{\theta}_i^E$			−0.168 (0.040)	−0.150 (0.049)	−0.169 (0.044)
$t \times \bar{\theta}_i^S$					−0.001 (0.014)
$R^2$ (within)	0.129	0.148	0.168	0.169	0.168

*Note:* Dependent variable: good-level labor shares. 2534 observations: 362 goods, 7 periods (1982, 1987, ..., 2012). Good fixed effects used in all specifications. Standard errors in parentheses (clustered at good level). Unit of  $t$  is a decade. Observations are weighted by final demand shares. Labor shares and weights based on I–O Tables (BEA). Equipment and structures intensity based on NBER-CES Manufacturing Database, BEA FAT.

<sup>11</sup>To see this, consider the stylized example of a representative firm in industry A producing final good A with \$100 of revenue, spending \$40 on in-house labor, \$20 on intermediate inputs, and residual capital income of \$40. Suppose all intermediate inputs are purchased from industry B, which produces with labor only. While the labor share of industry A equals  $\frac{40}{40+40} = 50\%$ , the labor share of good A equals  $\frac{40+20}{40+40+20} = 60\%$ . Now suppose that the tasks outsourced to B are instead performed within industry A, again using only labor. The labor share of industry A increases to  $\frac{60}{60+40} = 60\%$ , while the labor share of good A is unchanged at 60%. Suppose instead that the tasks outsourced to B are reallocated to industry C, which produces using capital only. In that case, while the labor share of industry A remains at  $\frac{40}{40+40} = 50\%$ , the labor share of good A decreases to  $\frac{40}{40+40+20} = 40\%$ .

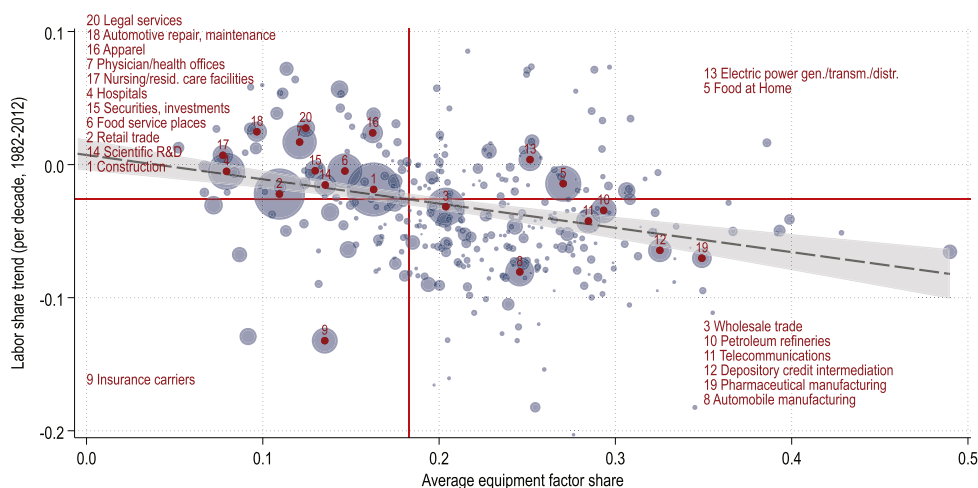


FIGURE 4.—Labor share trends and equipment factor shares. Source: BEA I–O Tables (labor shares); NBER-CES Manufacturing Database and BEA FAT (equipment intensities). On the horizontal axis, goods are ordered by their time-averaged equipment-factor share. The vertical position reports goods' labor share trends (per decade, 1982–2012). The size of the circles corresponds to goods' aggregate expenditure weights. The 20 largest goods are labeled and highlighted. Vertical and horizontal straight lines correspond to economy-wide averages. The dashed line depicts the OLS fit, the shaded area, the 95% confidence interval.

the labor share can be explained by the (average) equipment share of goods.<sup>12</sup> Specifically, when also interacting the time trend with a good's equipment share, the estimated coefficient on the residual time trend becomes small and insignificant. Column 4 shows that the stronger trend decline in manufacturing vanishes when controlling for equipment shares. Finally, column 5 shows that the structures share is orthogonal to the decline in labor shares.

Figure 4 visualizes the cross-sectional relationship between goods' labor share trends and their equipment factor shares. While there is a lot of residual heterogeneity in labor shares (in part because profits are volatile), the main point here is that there is a robust relationship between equipment shares and falling labor shares not specific to any sector. For example, among the 20 largest goods, 17 are either high-equipment share and exhibit stronger than average labor share drops, or are low-equipment share and exhibit weaker than average labor share falls.<sup>13</sup>

While this paper focuses on labor shares of goods and services, much of the literature focuses on industries, where data is more readily available. Table II relates the evolution of industry-level labor shares to the composition of the capital stock by industry. Columns 1 and 2 show that for the 413 industries in the I–O Tables, the labor share decline can be fully explained by an industry's equipment and software intensity, mirroring the pattern across goods in the main data set used in this paper. Columns 3–5 use data from the BLS/BEA Integrated Industry-Level Production Account, a panel of 61 industries over the period 1987–2018 with readily available labor shares. Linking these with data on detailed asset types by industry from the Fixed Assets Tables, columns 3 and

<sup>12</sup>Using instead the equipment intensity produces the same result, regardless of whether the time-average ( $\bar{\kappa}_i$ ) or the initial value ( $\bar{\kappa}_{i,1982}$ ) is used (see Figure B.5(b) in Appendix B.2). In other words, the result is not driven by differential total capital shares, as is also evidenced by column 5.

<sup>13</sup>See also Figure B.5(a) in Appendix B.2 for further robustness.

TABLE II  
LABOR SHARE TRENDS AT THE INDUSTRY LEVEL.

	I–O Table (1982–2012)		BLS/BEA MFP Table (1987–2018)		
	(1)	(2)	(3)	(4)	(5)
$t$	−0.019 (0.006)	0.003 (0.008)	−0.029 (0.005)	−0.002 (0.009)	−0.021 (0.006)
$t \times \bar{\kappa}_i^{\text{equipment \& software}}$		−0.040 (0.013)		−0.044 (0.014)	
$t \times \bar{\kappa}_i^{\text{ICT}}$					−0.025 (0.012)
Observations	2891	2891	1952	1952	1952
Industries	413	413	61	61	61

Note: Dependent variable: industry-level labor shares (columns 1–2 author’s calculations based on I–O Tables; columns 3–5 from BLS/BEA Integrated Industry-Level Production Account). Industry fixed effects used in all specifications. Standard errors in parentheses (clustered at industry level). Unit of  $t$  is a decade. Observations are weighted by value added shares. Capital intensities: column 2 from NBER-CES Manufacturing Database, BEA FAT; columns 4–5 from BEA FAT detailed estimates by industry and type. The ICT classification follows [Eden and Gaggl \(2018\)](#).

4 first confirm that the pattern of industry labor share declines being concentrated in equipment-intensive industries holds in this standard industry data set as well. Column 5 zooms in on the subset of information and communication technology (ICT) capital goods, which have been highlighted to grow rapidly and where price declines have been especially steep ([Eden and Gaggl \(2018\)](#), [Lashkari, Bauer, and Boussard \(2019\)](#)). While ICT-intensive industries do exhibit relatively stronger labor share declines, the results suggest that about two-thirds of the labor share decline cannot be explained by ICT intensity alone—according to the point estimate, 2.1 out of the unconditional 2.9 percentage points decline in the labor share per decade is not associated with an industry’s ICT intensity. Therefore, the focus in this paper is on the broader category of equipment and software.

### 3.3. Relation to the Literature and Implications

The decline in good-level labor shares can be largely explained by good-level equipment and software factor shares (equivalently, intensities). This fact is important and relevant in particular because over the same time period, the relative price of equipment and software has been falling dramatically. As [Figure 5\(a\)](#) shows, the decline in equipment prices has accelerated starting in the 1980s, while the relative price of structures capital hardly moved. In combination, these facts motivate using cross-sectional variation in equipment intensities to estimate the capital–labor elasticity in subsequent sections. In particular, the fact that equipment-intensive industries and goods—which experienced relatively stronger declines in the cost of capital—experienced relatively stronger labor share declines is very suggestive of an elasticity of substitution greater than one.

While this paper uses this observation to estimate sectoral production functions that feature a constant capital–labor elasticity, more nuanced interpretations are possible and plausible. In particular, recent contributions to the literature ([Kehrig and Vincent \(2021\)](#), [Autor et al. \(2020\)](#)) show that the labor share decline is far from uniform across firms. The labor shares of most firms have not declined, even within industries and sectors that exhibit strong aggregate labor share declines such as manufacturing, while some large and growing firms experienced steep labor share decreases. In [Hubmer and Restrepo \(2021\)](#),

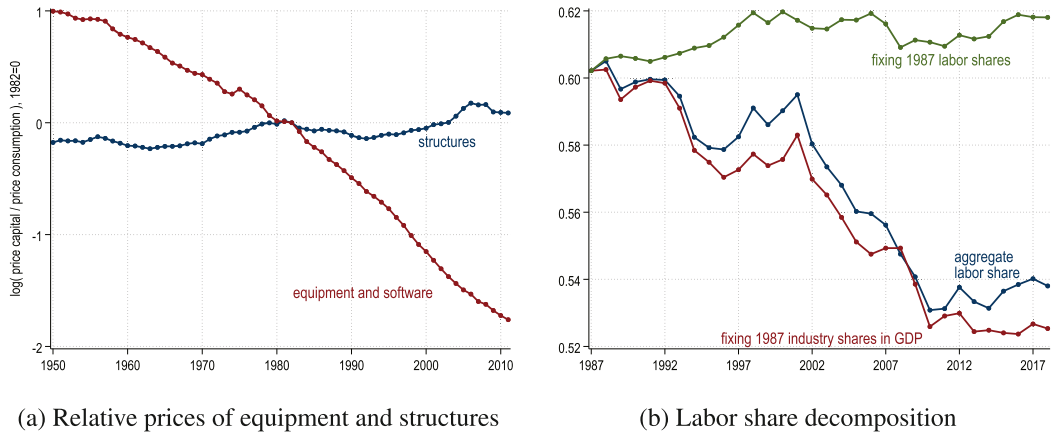


FIGURE 5.—Aggregate capital prices and labor share decomposition. Source: (a) BEA (structures); DiCecio (2009) (equipment & software). (b) BLS/BEA Integrated Industry-Level Production Account.

we propose a model of firm dynamics where firms have to make costly upfront investments to adopt capital-intensive technologies. Crucially, that richer framework reproduces the firm-level evidence on labor shares and market shares in response to falling capital prices, while in the long run likewise generating a constant aggregate capital–labor elasticity at the sectoral level.<sup>14</sup> In this sense, the simple aggregate production representation used in this paper is not inconsistent with recent firm-level evidence on labor shares. Rather than that, it can be interpreted as the reduced form of the aggregate dynamics implied by a richer production structure with firm heterogeneity, which quantitatively reproduces the observed firm-level labor share dynamics in response to the same shock, falling capital prices.

The two empirical facts established in this and the previous section predict that the labor share decline occurred within industries and sectors. Figure 5(b) shows that this prediction holds, using the data from the BLS/BEA Industry Account. When fixing 1987 industry shares in GDP to isolate the within-industry contribution, the counterfactual aggregate labor share declines even more (–7.7 pp) than the observed aggregate labor share (–6.1 pp). Conversely, when fixing 1987 industry labor shares to isolate the reallocation component, the counterfactual aggregate labor share increases by 1.6 pp.<sup>15</sup>

#### 4. GROWTH MODEL WITH NONHOMOTHETIC DEMAND

Based on the empirical findings in the previous sections, this section introduces a parsimonious neoclassical growth model that speaks to the evolution of the labor share in the postwar U.S. economy. The aim is to formalize how various types of economic growth affect the labor share. If growth is biased toward a particular production factor—Figure 5(a) suggests a strong, accelerating bias toward equipment capital—relative factor

<sup>14</sup>The key modeling element is an upfront fixed cost of automating additional tasks. This assumption, backed by firm-level evidence on the adoption of new capital-intensive technologies, implies that most firms initially do not automate additional tasks in response to falling capital prices, while large and growing firms immediately take advantage of falling capital prices and increasingly substitute capital for labor. In the long run, all firms in the economy converge on using the same, more capital-intensive, production technology.

<sup>15</sup>Table C.I in Appendix C.2.1 confirms this finding when adopting a good-level perspective as in the remainder of the paper, using the data from the I–O Tables for the 1982–2012 period.

prices change. In turn, the optimal capital–labor ratio increases. Whether capital shares increase as well depends on how substitutable capital and labor are in production—the cross-sectional evidence in Section 3 suggests that substitution is strong enough such that this is indeed the case. Moreover, any form of economic growth increases real income. Unless consumer demand is restricted to be homothetic, rising real income affects expenditure shares. The cross-sectional findings in Section 2 suggest that necessities tend to be capital-intensive and luxuries labor-intensive, implying that economic growth has a positive impact on the aggregate labor share through an income effect.

#### 4.1. Model Setup

The baseline model is reduced to the elements that I found to be quantitatively relevant for the key channels addressed in this paper. There is no explicit role for consumer heterogeneity. Markets are competitive. I focus on intratemporal consumption decisions, and do not model the intertemporal consumption-savings choice. Finally, the economy is closed.<sup>16</sup>

*Production.* There are multiple sectors  $i \in I$ . In each of them, a representative firm combines labor  $L_{it}$  and a sector-specific capital aggregate  $K_{it}$  to produce  $Y_{it}$  units of the final good  $i$  according to a constant-elasticity-of-substitution (CES) production technology,

$$Y_{it} = A_{it} \left( (1 - \alpha_i)^{\frac{1}{\eta}} (A_{it}^L L_{it})^{\frac{\eta-1}{\eta}} + \alpha_i^{\frac{1}{\eta}} (K_{it})^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \quad (2)$$

where the capital aggregate combines equipment capital  $K_{it}^E$  and structures capital  $K_{it}^S$ ,

$$K_{it} = \left( \frac{A_{it}^E K_{it}^E}{\alpha_i^E} \right)^{\alpha_i^E} \left( \frac{A_{it}^S K_{it}^S}{1 - \alpha_i^E} \right)^{1 - \alpha_i^E}. \quad (3)$$

The parameters  $\alpha_i$ ,  $\alpha_i^E$  are sector-specific and control factor share levels.  $\eta$  is the elasticity of substitution between capital and labor, assumed to be constant across sectors.  $A_{it}$  denotes factor-neutral technology, while  $A_{it}^L$ ,  $A_{it}^E$ , and  $A_{it}^S$  represent, respectively, labor-augmenting, equipment-augmenting, and structures-augmenting technology.

The representative firm takes the factor prices of labor  $W_t$  and capital  $R_t^E$ ,  $R_t^S$  as given, and maximizes profits. The labor share of good  $i$  is defined as  $\theta_{it}^L \equiv \frac{W_t L_{it}}{W_t L_{it} + R_t^E K_{it}^E + R_t^S K_{it}^S}$ , and by profit maximization equal to

$$\theta_{it}^L = (1 - \alpha_i) \left( \frac{\tilde{P}_{it}}{W_t / A_{it}^L} \right)^{\eta-1}, \quad (4)$$

where  $\tilde{P}_{it}$  is the TFP-neutral price of good  $i$ , a weighted average of factor prices in efficiency units:

$$\tilde{P}_{it} = A_{it} P_{it} = \left( (1 - \alpha_i) (W_t / A_{it}^L)^{1-\eta} + \alpha_i (R_{it})^{1-\eta} \right)^{\frac{1}{1-\eta}}, \quad (5)$$

$$R_{it} = (R_t^E / A_{it}^E)^{\alpha_i^E} (R_t^S / A_{it}^S)^{1 - \alpha_i^E}. \quad (6)$$

<sup>16</sup>Investment is addressed in Section 6.2, and consumer heterogeneity in Appendix C.3. Rising markups are discussed in Section 6.3, and accounted for in the estimation.



*Consumer Demand.* Consumers are endowed with  $\bar{K}_t^E$  ( $\bar{K}_t^S$ ) units of equipment (structures) capital and  $\bar{L}_t$  units of labor. Consumer demand is characterized by a common compensated substitution elasticity  $\sigma_t$ , and by good-specific income elasticities  $\gamma_{it}$ . Expenditure shares  $\omega_{it} \equiv \frac{C_{it}P_{it}}{E_t}$  are exogenously given for some base period  $t = \tau$ . They change over time according to

$$d \ln \omega_{it} = (1 - \sigma_t) d \ln \frac{P_{it}}{P_t} + (\gamma_{it} - 1) d \ln \frac{E_t}{P_t}, \quad (7)$$

where  $P_{it}$  is the price of good  $i$ , and  $E_t = W_t \bar{L}_t + R_t^E \bar{K}_t^E + R_t^S \bar{K}_t^S$  is total nominal expenditure. The price deflator is defined as  $d \ln P_t \equiv \sum_{i \in I} \omega_{it} d \ln P_{it}$ , and the budget constraint imposes  $\sum_{i \in I} \omega_{it} \gamma_{it} = 1$ .

*Discussion.* The analysis in this paper imposes equation (7) as an ad hoc specification of demand. One can also interpret (7) as a first-order approximation to the demand system implied by some underlying primitive utility function.<sup>17</sup> The positive analysis in this paper does not require to derive consumer demand from a primitive utility function. Among others, a log-linear demand system has recently been employed by Aguiar and Bils (2015).

## 4.2. Equilibrium

It is convenient to choose the wage rate as the numeraire ( $W_t = 1$ ). Then, solving for the equilibrium reduces to finding the rental rates of capital  $R_t^E$ ,  $R_t^S$  such that given these factor prices, and given the implied good prices, factor and good markets clear.

Formally, an equilibrium consists of factor prices ( $W_t$ ,  $R_t^E$ ,  $R_t^S$ ), good prices  $(P_{it})_{i \in I}$ , consumer demand  $(C_{it})_{i \in I}$  and expenditure  $E_t$ , final good output  $(Y_{it})_{i \in I}$ , and factor input choices  $(L_{it}, K_{it}^E, K_{it}^S)_{i \in I}$ , such that:

1. consumer demand is given by  $C_{it} = \frac{\omega_{it} E_t}{P_{it}}$ , where  $\omega_{it}$  is exogenously given for  $t = \tau$  and evolves according to (7);
2. given good prices  $(P_{it})_{i \in I}$  and factor prices ( $W_t$ ,  $R_t^E$ ,  $R_t^S$ ), final good output  $(Y_{it})_{i \in I}$ , and factor input choices  $(L_{it}, K_{it}^E, K_{it}^S)_{i \in I}$  are consistent with profit maximization subject to (2) and (3);
3. all final good markets clear,  $C_{it} = Y_{it}$ ;
4. and all factor input markets clear,  $\bar{L}_t = \sum_{i \in I} L_{it}$ ,  $\bar{K}_t^E = \sum_{i \in I} K_{it}^E$ , and  $\bar{K}_t^S = \sum_{i \in I} K_{it}^S$ .

## 4.3. Comparative Statics

We are interested in general equilibrium changes in the aggregate labor share in response to changes in the aggregate fundamentals of this economy. To simplify the exposition, assume for the proposition and discussion in this section that there is just one type of capital (denoted by  $\bar{K}_t$ ), and that factor-neutral ( $A_t$ ) and factor-augmenting ( $A_t^L$ ,  $A_t^K$ )

<sup>17</sup>A previous version of this paper, available on request, discussed two classes of structural preferences (generalized Stone–Geary and nonhomothetic CES) that give rise to such a demand system locally. While the overall findings are comparable, each of these specific utility functions implies some restrictions on the pattern of income and substitution elasticities that are at odds with the data, either at a point in time (nonhomothetic CES utility) or over time (Stone–Geary).

technology is common across sectors. Then the aggregate labor share in this economy, denoted by  $\bar{\theta}_t^L$ , is given by

$$\bar{\theta}_t^L \equiv \frac{W_t \bar{L}_t}{W_t \bar{L}_t + R_t \bar{K}_t} = \sum_{i \in I} \omega_{it} \theta_{it}^L,$$

and Proposition 1 characterizes its response to various types of aggregate growth.

**PROPOSITION 1:** *The general equilibrium response of the aggregate labor share to changes in TFP, in the effective labor input, and in the effective capital input is given by*

$$d\bar{\theta}_t^L = \frac{\tilde{\eta}_t - 1}{\tilde{\eta}_t} \bar{\theta}_t^L (1 - \bar{\theta}_t^L) (d \ln A_t^L \bar{L}_t - d \ln A_t^K \bar{K}_t) + \frac{g_t}{\tilde{\eta}_t} \text{Cov}_t(\theta_{it}^L, \gamma_{it}), \quad (8)$$

where  $\tilde{\eta}_t$  is a convex combination of  $\eta$  and  $\sigma_t$ ,

$$\tilde{\eta}_t = \frac{\sigma_t \mathbb{V}_t[\theta_{it}^L] + \eta \mathbb{E}_t[\theta_{it}^L (1 - \theta_{it}^L)]}{\bar{\theta}_t^L (1 - \bar{\theta}_t^L)}, \quad (9)$$

$\text{Cov}_t(\theta_{it}^L, \gamma_{it})$  refers to the cross-sectional covariance between sectoral labor shares and income elasticities (weighted by expenditure shares),

$$\text{Cov}_t(\theta_{it}^L, \gamma_{it}) = \sum_{i \in I} \omega_{it} (\gamma_{it} \theta_{it}^L - \bar{\theta}_t^L),$$

and  $g_t \equiv d \ln \frac{E_t}{P_t} = d \ln A_t + \bar{\theta}_t^L d \ln A_t^L \bar{L}_t + (1 - \bar{\theta}_t^L) d \ln A_t^K \bar{K}_t$ , denotes the overall growth rate.

**PROOF:** See Appendix D.

*Q.E.D.*

To understand this proposition, consider first the standard one-sector growth model. If there is just one sector, the covariance term in (8) vanishes, and from (9) we see that the relevant aggregate substitution elasticity equals the capital–labor elasticity in production,  $\tilde{\eta}_t = \eta$ . Then, as is well known, factor shares are stable if and only if either (i)  $\eta = 1$  or (ii) all growth is labor-augmenting (then  $d \ln A_t^L \bar{L}_t = d \ln A_t^K \bar{K}_t$ , as capital is the elastic factor). If part of growth is capital-augmenting or -embodied, such that  $d \ln A_t^L \bar{L}_t < d \ln A_t^K \bar{K}_t$ , then the labor share increases if capital and labor are gross complements ( $\eta < 1$ ) and decreases if they are gross substitutes ( $\eta > 1$ ).

This effect is also present with multiple sectors, the difference being that the relevant aggregate substitution elasticity  $\tilde{\eta}_t$  depends on the consumers' substitution elasticity  $\sigma_t$  as well. As factor prices change, relative good prices change as well in equilibrium, in turn inducing changes in consumer demand, which are proportional to  $\sigma_t$ . The strength of this channel depends on how variable factor shares are across sectors, as can be seen from (9). In the data, the weight on  $\eta$  averages 82%, with little time variation. Therefore,  $\tilde{\eta}_t$  is close to  $\eta$ , and capital–labor substitution depends primarily on technology, not on preferences.<sup>18</sup>

Moreover, with multiple sectors and nonhomothetic demand, the covariance term in (8) does not vanish. The intuition is straightforward: If high-income elasticity goods tend

<sup>18</sup>This finding is in line with Oberfield and Raval (2021).

to be relatively more labor-intensive, such that the covariance term is positive, then an income effect pushes up the aggregate labor share. This income effect is proportional to the overall growth rate  $g_t$ ; it does not depend on the source of growth.<sup>19</sup>

## 5. ESTIMATION

Proposition 1 and the subsequent discussion highlight that the income elasticities  $(\gamma_i)_{i \in I}$  as well as the capital–labor elasticity  $\eta$  are the key structural parameters that govern the evolution of the aggregate labor share. In this section, I proceed to estimate them based on the cross-sectional variation described in Sections 2 and 3. In particular, the fact that higher-income households spend relatively more on labor-intensive goods and services suggests that the latter have higher income elasticities. Moreover, the fact that equipment-intensive goods experienced stronger labor share declines suggests that  $\eta$  is greater than one. Using cross-sectional variation to estimate  $\eta$  builds among others on Karabarbounis and Neiman (2014) and Oberfield and Raval (2021), and I discuss the relation to these papers at the end of this section. Finally, this section also contains the calibration of the remaining model parameters.

### 5.1. Income Elasticities

The estimation of the demand system proceeds in two steps: here, I first estimate the income elasticities in the cross-section of households, holding prices fixed. In a second step, I use the full model to estimate the substitution elasticity parameter, by projecting residual demand variation on relative price variation.

The starting point is the expression for the change in the expenditure share (7) in time  $t$ , for good  $i$ . To identify the relative income elasticity of good  $i$ , I consider the expression in the cross-section of households  $h$ , relative to some reference good 0:

$$\ln\left(\frac{\omega_{iht}}{\omega_{0ht}}\right) = \tilde{\zeta}_{it} + (1 - \sigma_t) \ln\left(\frac{P_{it}}{P_{0t}}\right) + (\gamma_{it} - \gamma_{0t}) \ln\left(\frac{E_{ht}}{P_t}\right).$$

Assuming that consumers are facing the same prices, conditional on time and control variables, prices are absorbed by a good-year fixed effect  $\tilde{\zeta}_{it}$ . Adding a set of controls  $Z_{ht}$  (age, race, family composition, region, urban/ rural) and an error term  $\xi_{iht}$ , I estimate

$$\ln\left(\frac{\omega_{iht}}{\omega_{0ht}}\right) = \tilde{\zeta}_{it} + (\gamma_{it} - \gamma_{0t}) \ln E_{ht} + \Gamma'_{it} Z_{ht} + \xi_{iht} \quad (10)$$

for all  $i \in I \setminus \{0\}$  and  $t$  separately in the cross-section of households. An attractive feature of this specification is that the income elasticity estimates are robust to good-time specific measurement error, which is absorbed by  $\xi_{iht}$ .

A few comments are in order: First, a standard concern in estimating such a demand system is that measurement error in expenditure on individual goods, as well as the presence of durable goods, implies that total expenditure  $E_{ht}$  is correlated with the residual

<sup>19</sup>The impact of  $g_t$  on the aggregate labor share is dampened (amplified) in general equilibrium if  $\tilde{\eta}_t > 1$  ( $\tilde{\eta}_t < 1$ ), relative to the partial equilibrium shift in consumption. To see this, consider the case of a positive covariance term: the partial equilibrium shift of consumption toward labor-intensive goods in response to an increase in real income leads to an increase in the relative wage rate, which further increases the labor share if and only if  $\tilde{\eta}_t < 1$ . Therefore,  $g_t$  is divided by  $\tilde{\eta}_t$  in (8).

$\xi_{iht}$ . Therefore, I use current after-tax income, education, and occupation (proxies for permanent income) as instruments for total expenditure.

Second, an identifying assumption is that conditional on the observables  $Z_{ht}$ , unobserved cross-sectional heterogeneity in prices or preferences is orthogonal to permanent income as proxied by the instruments mentioned above. Appendix B.1 discusses robustness of this assumption.

Third, I estimate relative income elasticities ( $\gamma_{it} - \gamma_{0t}$ ). The levels  $\gamma_{it}$  are easily recovered since their expenditure-weighted average has to equal one, a restriction imposed by the budget constraint.

The estimated income elasticities are in fact quite stable over time. A pooled regression of  $\gamma_{it}$  on the time-averages  $\bar{\gamma}_i$  yields an  $R^2$  of 0.955.<sup>20</sup> Figure B.3 in Appendix B.1 plots time-averages of the estimated income elasticities against labor shares. The income elasticities closely resemble the raw expenditure share differentials by income groups shown earlier in Figure 3. This is expected: as the estimating equation (10) reveals, I estimate the income elasticities based on cross-sectional variation in household income. Appendix B.1 also reports a complete (aggregated) tabulation, as well as the covariance between income elasticities and good-level labor shares for varying degrees of disaggregation. The bottom line is that to capture the income effect quantitatively, one needs to consider a sufficiently disaggregated version of the U.S. economy.

## 5.2. Capital–Labor Elasticity

The estimation of the capital–labor elasticity  $\eta$  relies on variation in the extent to which different goods and services are exposed to the secular decline in national equipment and software prices. Formally, using the FOC for labor (4), dividing by the analogous one for the capital aggregate, and taking logs yields

$$\ln\left(\frac{\theta_{it}^L}{1 - \theta_{it}^L}\right) = \left(\frac{1 - \alpha_i}{\alpha_i}\right) + (\eta - 1)(\ln(R_{it}) - \ln(W_t/A_{it}^L)). \quad (11)$$

This expression says that a good's labor share decreases over time if  $\eta > 1$  and its capital costs are falling, in efficiency units, and relative to its labor costs. To simplify the notation, let lowercase letters denote log changes from the base year, for example,  $w_t \equiv \ln W_t - \ln W_{1982}$ , and  $a_{it}^L \equiv \ln A_{it}^L - \ln A_{i,1982}^L$ . From (6), we can write the log change in capital costs as weighted average of the two types of capital,

$$r_{it} = \alpha_i^E (r_t^E - a_{it}^E) + (1 - \alpha_i^E) (r_t^S - a_{it}^S), \quad (12)$$

where the parameter  $\alpha_i^E$  maps into good  $i$ 's observed average equipment intensity  $\bar{\kappa}_i$ .<sup>21</sup> Thus, plugging (12) into (11) and adding a good fixed effect  $\tilde{\alpha}_i$ , which absorbs all constant terms, yields

$$\ln\left(\frac{\theta_{it}^L}{1 - \theta_{it}^L}\right) = \tilde{\alpha}_i + (\eta - 1)(\bar{\kappa}_i(r_t^E - a_{it}^E) + (1 - \bar{\kappa}_i)(r_t^S - a_{it}^S) - (w_t - a_{it}^L)).$$

<sup>20</sup> Aguiar and Bils (2015), who also use CEX data and a similar log-linear demand specification with coarser consumption categories, likewise find that income elasticities are very stable over time.

<sup>21</sup> By Shephard's lemma, (12) is true more generally for any neoclassical production function with  $\alpha_i^E$  replaced by the time-varying  $\kappa_{it}$ . In that general case, the empirical strategy pursued here is valid as a first-order approximation.

Adding a time fixed effect ( $\lambda_t$ ) that absorbs the wage rate as well as any other common trend outside the model (e.g., uniformly rising markups), and collecting unobserved good-time-specific technology in an error term ( $\xi_{it}$ ), the estimated equation in the first specification is

$$\ln\left(\frac{\theta_{it}^L}{1 - \theta_{it}^L}\right) = \tilde{\alpha}_i + \lambda_t + (\eta - 1)(\bar{\kappa}_i r_t^E + (1 - \bar{\kappa}_i) r_t^S) + \underbrace{\xi_{it}}_{=(\eta-1)(\bar{\kappa}_i(a_{it}^L - a_{it}^E) + (1-\bar{\kappa}_i)(a_{it}^L - a_{it}^S))}. \quad (13)$$

This regression results in an estimate  $\eta > 1$  if labor shares are falling relatively more for equipment-intensive goods (if  $\bar{\kappa}_i$  is large), given that  $r_t^E$  is falling strongly over time and  $r_t^S$  is roughly constant. I assume that the secular decline in the price of equipment capital was due to exogenous technical progress. Consequently, I use  $\bar{\kappa}_i r_t^E$  as an instrument for the potentially endogenous regressor  $(\bar{\kappa}_i r_t^E + (1 - \bar{\kappa}_i) r_t^S)$ . There are two related concerns with this strategy that I address in what follows.

*Correlated Error Terms.* First, the error term ( $\xi_{it}$ ) in (13) interacts good-factor-specific technology growth with the equipment intensity  $\bar{\kappa}_i$ . If the change in the bias of technology over time (e.g.,  $a_{it}^L - a_{it}^E$ ) is orthogonal to  $\bar{\kappa}_i$ , then  $\eta$  is identified. A concern is that the technology terms are correlated with  $\bar{\kappa}_i$ . In practice, this concern is alleviated by the fact that equipment prices declined massively, at an average annual rate of 6.3% over the sample period 1982–2012 (see Figure 5(a) earlier). In turn, variation in these technology terms would have to be of the same order of magnitude to significantly bias the estimator. While the technology terms are fundamentally unobservable, it is possible to proxy for them using measured TFP variation. Appendix B.2 contains a Monte Carlo simulation, showing that in the empirically relevant range of parameter values, the estimate of  $\eta$  is largely unchanged. Furthermore, if technical change is directed such that equipment-intensive sectors experienced faster equipment-augmenting technical progress, then the absolute value of  $(\eta - 1)$  is biased upwards, but the sign of  $(\eta - 1)$  is unbiased.<sup>22</sup> More broadly, there is a concern about other omitted variables such as markup growth and exposure to international trade that I address later in this section.

*Quality-Adjustment of Prices.* Second, measuring quality-adjusted capital prices is inherently difficult. I assume that changes in capital costs are equal to changes in quality-adjusted capital prices (Figure 5(a)). Related to the argument above, if the measured annual decline of 6.3% understates (overstates) the true decline in equipment capital costs, then I will overestimate (underestimate) the absolute value of  $(\eta - 1)$ . Crucially, such potential mismeasurement does not affect how much of the aggregate labor share decline is explained by capital–labor substitution: it is only the product of  $(\eta - 1)$  and the decline in capital costs that matters in that regard, as equation (13) shows. Furthermore, for the estimate of  $(\eta - 1)$  to have the wrong sign, it would have to be the case that the relative cost of equipment capital has *increased* over time. I find that the magnitude of observed price changes makes this improbable.

<sup>22</sup>This is because, in this case, capital costs in efficiency units fell even more than observed capital prices in equipment-intensive sectors. In turn, larger variation in the regressor in (13) implies a smaller absolute value of its coefficient  $(\eta - 1)$ .

*Second Specification.* Measured capital shares sometimes fluctuate close to zero. In order to be able to take the logarithm, I bound labor shares symmetrically from above and below ( $\theta_{it}^L \in [0.05, 0.95]$ ). I also consider an alternative specification that does not suffer from this shortcoming. It is based on the firm's FOC for labor (4) only. Taking logs yields

$$\ln \theta_{it}^L = (1 - \alpha_i) + (\eta - 1)(\ln \tilde{P}_{it} - \ln(W_t/A_{it}^L)), \quad (14)$$

where  $\tilde{P}_{it}$  is the TFP-neutral price (5). Log-differentiating (5) yields

$$\tilde{p}_{it} = \theta_{it}^L(w_t - a_{it}^L) + (1 - \theta_{it}^L)r_{it}. \quad (15)$$

Plugging (15) and (12) into (14), rearranging, and adding time and good fixed effects, the estimated equation in the second specification is

$$\ln \theta_{it}^L = \tilde{\alpha}_i + \lambda_t + (\eta - 1)(\bar{\theta}_i^E(r_t^E - w_t) + \bar{\theta}_i^S(r_t^S - w_t)) + \underbrace{\xi_{it}}_{=(\eta-1)(\bar{\theta}_i^E(a_{it}^L - a_{it}^E) + \bar{\theta}_i^S(a_{it}^L - a_{it}^S))}. \quad (16)$$

This equation is very similar to the first specification, except that the dependent variable is  $\ln \theta_{it}^L$  instead of  $\ln(\frac{\theta_{it}^L}{1 - \theta_{it}^L})$ , and that the relative equipment factor price is interacted with the equipment factor share  $\bar{\theta}_i^E$ , instead of with the equipment intensity  $\bar{\kappa}_i$  (likewise for structures). Thus, this specification results in an estimate  $\eta > 1$  if labor shares are falling relatively more for high-equipment-share goods (if  $\bar{\theta}_i^E$  is large). Furthermore,  $w_t$  is not absorbed in the time fixed effect. I use model generated wage growth (in efficiency units, wages grow at an annual rate of 1.5%).<sup>23</sup>

*Estimates of  $\eta$ .* Table III displays various estimates of  $(\eta - 1)$ . The key variation in the data that generates  $\eta > 1$  is that labor shares have decreased relatively more for goods

TABLE III  
ESTIMATES OF  $(\eta - 1)$ .

	Baseline (FOC L)	FOC K and L	Compustat	PCE only
	(1)	(2)	(3)	(4)
OLS	0.470 (0.087)	0.341 (0.160)	0.455 (0.083)	0.379 (0.092)
IV (only equipment)	0.385 (0.158)	0.281 (0.165)	0.484 (0.106)	0.416 (0.095)
N	2534	2534	2534	1603

*Note:* Each column reports both OLS and IV estimates of  $(\eta - 1)$ . Columns 1–3 weigh goods by final demand shares, (4) by personal consumption expenditure (I–O Tables). Time and good fixed effects are used in all specifications. Standard errors, in parentheses, are clustered at the good level. Columns 1, 3, and 4 refer to equation (16), column 2 to equation (13). Equipment intensities for the manufacturing sector are taken from the NBER-CES manufacturing database. For nonmanufacturing, they are based on the more aggregated BEA's Fixed Assets Table 3.1 (current-cost net stock of private equipment and software, respectively, structures, by industry) in columns 1, 2, and 4; respectively on Compustat data in column 3.

<sup>23</sup>The model is matching average wage growth in the data mostly by construction, since GDP growth is targeted and the labor share declines in model and data are similar.



with high equipment intensities (or high equipment shares)—as documented in Section 3, in fact the entire decline in goods’ labor shares has been proportional to goods’ equipment intensities (or shares). Since changes in goods’ capital costs are weighted averages of changes in national equipment and structures prices, and the price of equipment has been falling relative to the price of structures, equipment-intensive goods experienced faster falling capital costs. Since faster falling capital costs are associated with faster falling labor shares in the cross-section, the capital–labor elasticity estimate is above one.

I treat the second approach, based on the FOC for labor, as the baseline, since it does not require winsorization, and because it produces estimates that are less volatile across specifications. The remaining columns show estimates corresponding to (2) the first specification based on the FOC for capital and labor, (3) sourcing nonmanufacturing equipment intensities from Compustat instead of from industry groups in the BEA’s Fixed Assets Tables, and (4) restricting the analysis to consumption goods. OLS estimates for  $\eta$  range from 1.34 to 1.47, and IV estimates from 1.28 to 1.48. All specifications result in statistically significant positive estimates, implying a capital–labor elasticity above one. I use 1.35 as my preferred value for the model analysis to follow, which corresponds roughly to the mid-point of estimates.

*Robustness to Omitted Variables.* Identification of  $\eta$  requires that goods’ equipment shares are uncorrelated with the error terms  $\xi_{it}$ . Besides the good-factor-specific technological progress terms discussed earlier, omitted variables that vary at the good-year level are more generally a threat to identification. For example, if exposure to international trade has increased relatively more for equipment-intensive goods, then this could lead to an upward bias of  $\eta$ . Table IV reports robustness exercises relating to these concerns. Column 2 employs two-digit good by year fixed effects, in addition to the good and year fixed

TABLE IV  
ROBUSTNESS OF CAPITAL–LABOR ELASTICITY ESTIMATE.

	(1)	(2)	(3)	(4)	(5)	(6)
$(\eta - 1)$	0.385 (0.158)	0.379 (0.186)	0.376 (0.157)	0.409 (0.156)	0.371 (0.142)	0.386 (0.147)
Import share <sub>it</sub>			−0.033 (0.077)			
$t \times \text{COLLEGE}_{i,1980}$				−0.080 (0.069)		
Compustat markup $\ln \mu_{it}$					−0.115 (0.099)	
KLEMS markup $\ln \mu_{it}$						−0.045 (0.043)
Good fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
2-digit good by year FE		✓				

*Note:* Dependent variable: good-level labor shares  $\ln \theta_{it}^L$ . 2534 observations (362 goods, 7 time periods), weighted by final demand shares. Standard errors in parentheses (clustered at good level). All regressions are based on equation (16), and use both time and good fixed effects. Column 2 uses in addition interacted fixed effects at the two-digit I–O code by year level. Column 3 controls for import shares, and 4 for goods’ initial skill intensities interacted with a linear time trend (skill intensity measured as fraction of college educated workers based on the 1980 census sourced from IPUMS, see [Ruggles et al. \(2019\)](#)). Columns 5 and 6 add measures of time-varying log markups as controls. Column 5 uses markup estimates based on Compustat data, following the approach in [De Loecker, Eeckhout, and Unger \(2020\)](#). Column 6 uses estimates from KLEMS, provided by [Hall \(2018\)](#).

effects used in the main specification in column 1. Columns 3 and 4 control for goods' time varying import intensities, respectively, goods' initial skill intensities interacted with a time trend. Overall, the stability of  $\eta$  across specifications is reassuring.

*Markups as a Confounding Factor.* The baseline approach in this paper assumes a competitive economy, where payments to capital and labor sum to total value added. In such a setting, relatively faster falling labor shares of equipment-intensive goods imply that  $\eta > 1$ , because movements in the labor share are driven by changes in production. An alternative explanation is that markups have increased relatively more for these goods. Any economy-wide increase in markups is already subsumed in the fixed effects; therefore, it would not contaminate the estimation of  $\eta$ . In principle, given data on markups  $\mu_{it}$ , one can correct for them when estimating  $\eta$ . Assuming monopolistic competition, such that input decisions are not distorted, the firms' cost-minimization problem is unchanged. In turn, labor shares of cost  $\theta_{it}^{L, \text{cost}}$  evolve as under perfect competition, and the observed labor share of value added  $\theta_{it}^L$  equals the labor share of cost scaled down by the markup:

$$\theta_{it}^L = \frac{\theta_{it}^{L, \text{cost}}}{\mu_{it}}. \quad (17)$$

From (17), since the log labor share of value added under monopolistic competition equals the log labor share of value added in the competitive benchmark (16) minus the log markup, it is appropriate to control for  $\ln \mu_{it}$  linearly. In practice, separating the contributions of capital–labor substitution and rising markups is more challenging, because estimating the markup typically requires estimating the output elasticities (or cost shares) in the first place.<sup>24</sup> With these caveats in mind, columns 5 and 6 of Table IV control for available markup estimates from Compustat (De Loecker, Eeckhout, and Unger (2020)), respectively, from KLEMS (Hall (2018)). These methods allow for time-variation in the output elasticities, consistent with the mechanism of this paper. The estimate of  $\eta$  hardly changes, reflecting that the measured rise in markups is largely orthogonal to the equipment intensity of production. While these findings are suggestive, a thorough joint treatment of the interaction between capital–labor substitution and rising market power is beyond the scope of the present paper and left for future research.<sup>25</sup>

*Relation to the Literature on Estimating the Capital–Labor Elasticity.* The literature on estimating the capital–labor elasticity is voluminous. Karabarbounis and Neiman (2014) is closest to the present paper as their strategy is also based on long-run, cross-sectional

<sup>24</sup>The popular ratio estimator inverts equation (17) and recovers the markup as

$$\mu_{it} = \frac{\varepsilon_{it}^V}{\theta_{it}^V} \quad (18)$$

for any variable input  $V$ , where  $\varepsilon_{it}^V$  is the output-to-variable input elasticity (equal to the cost share  $\theta_{it}^{V, \text{cost}}$  under constant returns to scale) and  $\theta_{it}^V$  the observed revenue share of that variable input. In this approach,  $\varepsilon_{it}^V$  is first estimated using firm-level variation within industries and time periods (Olley and Pakes (1996), Akerberg, Caves, and Frazer (2015)). Among others, this is the method used by De Loecker, Eeckhout, and Unger (2020). The recent literature has shown that this approach suffers from identification and estimation issues given the available data for the U.S. economy (Flynn, Gandhi, and Traina (2019), Bond, Hashemi, Kaplan, and Zoch (2021), Basu (2019)).

<sup>25</sup>For example, Hubmer and Restrepo (2021) consider a model with endogenous automation, endogenous markups, and firm-level heterogeneity.

variation in the price of capital. While this paper zooms into the U.S. economy and constructs the price of capital by detailed industry (and subsequently for each good) as a weighted average of national capital prices, Karabarbounis and Neiman (2014) analyze cross-country variation. Their preferred estimate is 1.25, roughly in line with my findings. One advantage of my approach is that the shift-share design addresses the concern that falling capital prices might reflect not only the supply of (i.e., technology), but also the demand for capital goods. In general, the findings in the present paper imply that estimates based on aggregate data (e.g., Antràs (2004)) are potentially confounded by the nonhomotheticity in consumer demand.<sup>26</sup>

In light of the shortcomings of using aggregate data, estimating the capital–labor elasticity at the firm-level as in the innovative contribution by Oberfield and Raval (2021) is promising. Using residual regional wage variation, they estimate a lower elasticity of around 0.4 across manufacturing plants, and show how this implies an elasticity of around 0.7 for the manufacturing sector (i.e., when factoring in reallocation across plants with differential factor intensities). Given the nature of their identifying variation, I interpret these elasticities as capturing the short- to medium-run response of factor shares at the average firm to changes in relative factor prices. Through the lens of a firm dynamics model with costly capital–labor substitution within tasks as in Hubmer and Restrepo (2021), a low short- to medium-run elasticity at the firm level can be interpreted as recovering the response of factor shares when holding the allocation of tasks across capital and labor as fixed, while the higher long-run good-level elasticity estimated in the present paper accounts also for the reallocation of tasks from labor to capital. For example, reallocating some tasks previously performed by workers to industrial robots involves a time lag and significant upfront fixed costs for the reorganization of the production process. The evidence on firm-level labor and market share dynamics since the 1980s in the U.S. (Autor et al. (2020), Kehrig and Vincent (2021)) lends some credence to this interpretation, as these dynamics are reproduced by the task-based model in Hubmer and Restrepo (2021)—in response to falling capital prices—with a short-run elasticity of 0.4 and a long-run elasticity of 1.35. As pointed out earlier, it is crucial to note that such a more elaborate production structure is perfectly consistent with a *constant* long-run capital–labor elasticity at the good (or industry) level. Therefore, the sectoral CES production function used in the present paper, with the estimate  $\eta = 1.35$ , can be viewed as the reduced form of a richer underlying micro production structure with firm heterogeneity. In particular, we expect that the model in this paper matches low-frequency movements in the labor share well; however, we would not expect its predictions to be accurate at higher frequencies.

Lastly, another advantage of the approach pursued here—constructing a panel of factor shares at the level of goods and services—is that the recovered elasticity reflects not only capital–labor substitution within industries, but also across intermediate inputs. In other words, capital–labor substitution along the full value chain.<sup>27</sup>

<sup>26</sup>As the quantitative results in Section 6 demonstrate, the multisector model in the present paper generates a roughly constant aggregate labor share until the early 1980s, even though the relative price of capital is declining. Through the lens of a one-sector aggregate production function, this would be interpreted as  $\eta \approx 1$ , even though the model is parametrized with  $\eta = 1.35$ .

<sup>27</sup>To see this, consider again the stylized example of a representative firm in industry A producing final good A with \$100 of revenue, spending \$40 on in-house labor, \$20 on intermediate inputs sourced from industry B that uses labor only, and residual capital income of \$40. Suppose that, in response to falling capital prices, the firm switches from supplier B to supplying industry C, which produces with higher capital intensity. Assuming unchanged labor and capital compensation within industries, an econometrician would infer an industry-level capital–labor elasticity of one, but a good-level capital–labor elasticity above one.

### 5.3. Remaining Model Parameters

The previous sections discussed estimation of the income elasticities and the capital–labor elasticity based on cross-sectional variation. I turn to calibrating the remaining model parameters, given these estimates.

By construction, the model matches all expenditure and factor shares in the base year 1982. Then I repeatedly solve for the static equilibrium over 1950–2012, calibrating growth in factor stocks and technology to match the time series of aggregate output and of relative factor prices. The decline in capital prices is informative about how much of aggregate growth can be attributed to capital. Then there is a growth residual, attributed to human capital and/or TFP. Model-generated changes in good prices pin down the consumers' elasticity of substitution  $\sigma$ . Capital stocks, technology terms, and  $\sigma$  are jointly calibrated to match the data targets.

*Technology and Capital Stocks.* The calibration targets three time series over the sample period 1950–2012: real per capita GDP, as well as the relative prices of equipment and software and of structures.<sup>28</sup> The user cost of capital per dollar of capital is assumed to be constant in the baseline; that is, real rental rates are growing at the observed rate of real capital prices. To match these two capital price time series, I pick the evolution of the capital stock  $(\bar{K}_t^E, \bar{K}_t^S)_{t=1950}^{2012}$  in efficiency units. In terms of the model, this is isomorphic to changing the common component of capital-augmenting technology. In terms of the mapping to the data, this assumes that all capital-biased technical change is embodied in capital, as measured by relative quality-adjusted prices.

The residual part of economic growth could be attributed to TFP ( $A_{it}$ ) or labor-augmenting technological progress ( $A_{it}^L$ ). I impose that the respective good-specific terms are constant; that is, technological improvements are common to all goods. In the benchmark calibration, I assume that all residual growth is labor-augmenting in the tradition of the neoclassical growth model:  $\Delta A_t = 0$  and  $\Delta A_t^L$  is chosen to match output growth (jointly with capital growth). As a robustness check, I tie  $\Delta A_t^L$  to an index of human capital, and attribute the remaining growth residual to TFP ( $\Delta A_t$ ).

*Consumers' Substitution Elasticity.* The parsimonious baseline calibration uses model-generated changes in relative good prices ( $P_{it}$ ) to estimate the elasticity of substitution  $\sigma$  in consumer demand. Since technical progress is assumed to be uniform across goods in the baseline, variation in the evolution of relative prices is entirely driven by variation in factor shares. In particular, equipment-intensive goods become relatively cheaper over time. As a robustness check, I consider a richer calibration with good-specific technological progress, disciplined by matching the observed evolution of relative good prices in the BEA's Industry Economic Accounts.

To identify the substitution elasticity  $\sigma_t$ , the demand shifters as well as the effect of demographic controls are required to be time-invariant:  $\zeta_{it} = \zeta_i$  and  $\Gamma_{it} = \Gamma_i$ . Then

$$\Delta \ln \omega_{it}^{\text{CEX}} = (1 - \sigma_t) \Delta \ln \left( \frac{P_{it}}{P_t} \right) + (\gamma_{it} - 1) \Delta \ln \left( \frac{E_t}{P_t} \right) + \Gamma_i' (\Delta Z_t) + \xi_{it}.$$

<sup>28</sup>Real output is computed consistently in the model and data using Fisher's chained-price index.

Given prices, I estimate  $\sigma_t$  by regressing the change in residual aggregate expenditure shares on the change in relative prices:

$$\Delta \ln \hat{\omega}_{it}^{\text{CEX}} = (1 - \sigma_t) \Delta \ln \left( \frac{P_{it}}{P_t} \right) + \xi_{it},$$

where  $\Delta \hat{\omega}_{it}^{\text{CEX}} \equiv \Delta \ln \omega_{it}^{\text{CEX}} - (\gamma_{it} - 1) \Delta \ln \left( \frac{E_t}{P_t} \right) - \Gamma'_i(\Delta Z_t)$ .

In practice, measurement error in prices creates attenuation bias when estimating  $\sigma_t$ . As the model predictions for relative price changes are more reliable in the long run, I prefer using long changes. Hence, I assume that  $\sigma$  is constant over time. The point estimate is  $\sigma = 1.55$  (standard error: 0.06).<sup>29</sup>

*Earlier Time Period (1950–1981).* The calibration of capital stocks and technology is completely analogous to the later period, as the aggregate time series on output and capital prices extend back. I assume that the capital–labor elasticity  $\eta$  and consumer demand parameters have been stable. In particular, I set relative income elasticities ( $\gamma_i - \gamma_0$ ) to their respective time-averages over the sample period 1982–2012. As noted earlier, they are very stable over the sample period. Each year, I recover their level from the budget constraint by imposing that their expenditure-weighted average equals one.

## 6. QUANTITATIVE RESULTS

In this section, I first report on the main results: the evolution of the aggregate labor share in the model economy contrasted with the data, as well as a model-based decomposition into technological and preference components. In this first part, Section 6.1, the analysis is restricted to consumption spending. Subsequently, in Section 6.2, I extend the framework to cover investment, which allows for disciplining the model by data on investment rates, as well as a more comprehensive comparison to national accounts data. Finally, I discuss how these findings relate to the broader debate on the labor share decline, including other channels such as the rise in the aggregate markup.

### 6.1. Baseline Model Findings

Figure 6 displays the evolution of the aggregate labor share in the model, contrasted to the data.<sup>30</sup> By construction, the series agree in 1982. Let us first focus on the sample period 1982–2012: The model performs well in replicating the overall fall in the labor share. The fall in the quality-adjusted relative price of equipment capital was drastic over that time period, implying that technological progress was mostly investment-specific. Given that I estimate capital and labor to be gross substitutes ( $\eta > 1$ ), good-level labor shares decrease, and so does the aggregate labor share. Note that even though I used trends in good-level labor shares over the same time period 1982–2012 to estimate  $\eta$ , the model does not fit the data trend by construction: First, when estimating  $\eta$  I employed time

<sup>29</sup>As documented in an earlier working paper version of this article available on request, when splitting the sample in three time periods, the null of a constant elasticity cannot be rejected.

<sup>30</sup>The data series refers to the labor share constructed using the CEX demand weights as well as the good-level labor shares from the I–O Tables for 1982–2012:  $\bar{\theta}_t^L = \sum_{i \in I} \omega_{it}^{\text{CEX}} \theta_{it}^L$ . Neither CEX expenditure data nor detailed good-level labor shares are available prior to 1982. I use an aggregate time series from the BLS for the U.S. business sector for the earlier time period, rescaled such that it aligns with the CEX-based one in 1982. See Figure A.2 in Appendix A.1 for a comparison of labor share series.

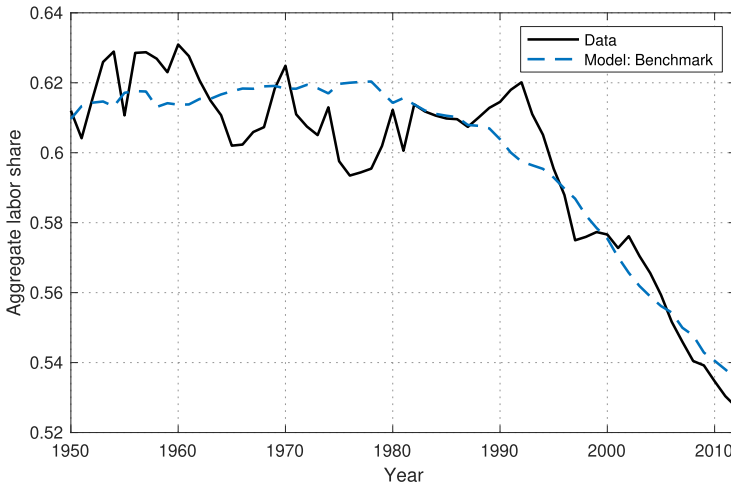


FIGURE 6.—Aggregate labor share in the baseline model. Data sources: BLS, BEA I–O Tables, CEX.

fixed effects to control for economy-wide factors outside of the model. Thus,  $\eta$  reflects cross-sectional variation in equipment intensities and labor share trends. Second, changes in consumer demand impact the aggregate labor share as well. For the 1950–1982 period (out-of-sample), in the data the aggregate labor share fluctuates without any, or perhaps a slight downward trend. The model does not feature the high-frequency fluctuations, but exhibits a comparable flat trend behavior.

*Model-Based Decomposition of Labor Share Change.* Why was the labor share stable until the early 1980s, and why did it subsequently decline? Through the lens of the model, we can decompose changes in the aggregate labor share into the following three components: (i) capital–labor (K–L) substitution in the production process ( $\eta \neq 1$ ), (ii) an income effect operating through nonhomothetic preferences (generally  $\gamma_i \neq 1$ ), and (iii) a substitution effect on the demand side ( $\sigma \neq 1$ ). To isolate each of the three channels, I shut down the remaining two margins by setting the respective elasticities to one, each time recalibrating technology parameters and capital stocks so that aggregate growth and relative capital prices are unchanged. For example, to isolate K–L substitution in production,  $\eta = 1.35$  as in the baseline, but  $\sigma = \gamma_i = 1$ , so that expenditure shares are fixed as if resulting from Cobb–Douglas preferences.

The second column in Figure 7 displays the results of this exercise for the benchmark model. K–L substitution in production has been the dominant force, decreasing the labor share by 13.4 percentage points (pp) cumulatively. Driven by a steep decline in the price of equipment and software capital, this force accelerated from the 1980s onwards. On the consumer demand side, rising real income has had a strong positive effect on the labor share throughout (+7.6 pp cumulatively), while substitution toward capital-intensive products has played only a minor role (–1.3 pp). Looking at the two subperiods, I find that until the early 1980s K–L substitution in production was offset by the income effect, shifting consumer demand toward labor-intensive goods in proportion to overall economic growth. Subsequently, the former effect dominated, as the annual decline in the relative price of equipment and software capital roughly doubled, which the model interprets as a doubling of investment-specific technological progress (see Figure 1(d)).



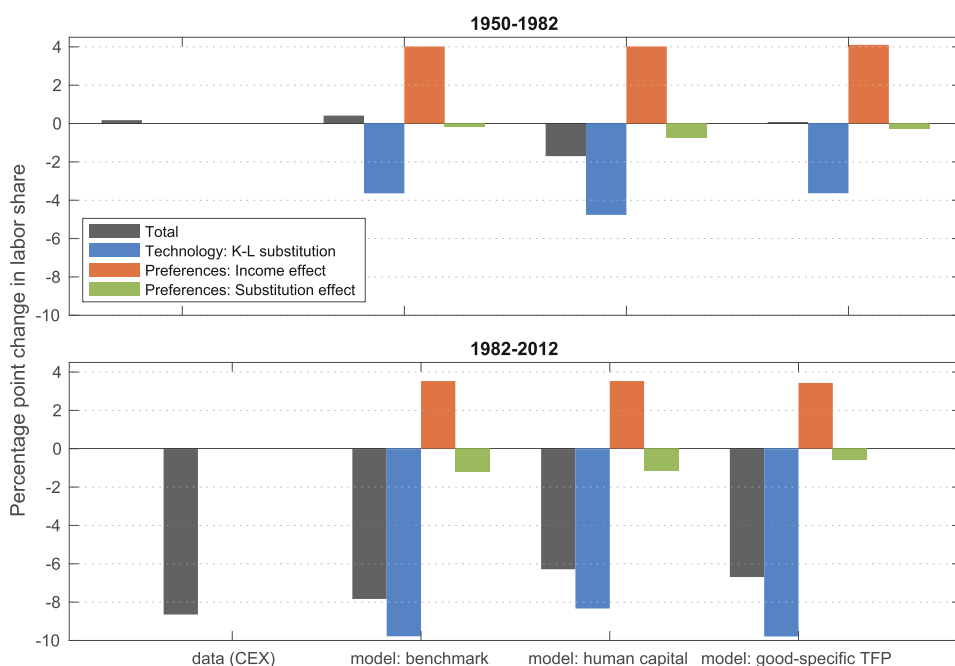


FIGURE 7.—Decomposition of changes in aggregate labor share. Data sources: BLS, BEA I–O Tables, CEX. In the benchmark model, all residual growth (i.e., that is not accounted for by investment-specific technical change) is labor-augmenting. In the human capital calibration, growth in labor-augmenting technology is tied to an index of human capital, and the remaining residual is attributed to TFP. The model with good-specific TFP differs from the baseline insofar as there is a good-specific component of TFP growth, calibrated to match the evolution of relative good prices.

To reiterate, since estimates of the key elasticities ( $\eta$  and  $\gamma_i$ ) result from cross-sectional variation, the fact that the model largely replicates the data trend, across both time periods, is a success of the model. However, this paper does not provide a deep answer as to why these forces roughly offset each other until the early 1980s. Instead, the constancy of the labor share is a coincidence; “a bit of a miracle” as stated by Keynes (1939). Likewise, while this paper identifies accelerating capital-embodied technological progress as the proximate cause of the subsequent labor share decline, it is agnostic about the fundamental reason for the changing nature of technological progress.<sup>31</sup>

**Robustness.** The benchmark calibration loads all residual growth (i.e., that is not accounted for by investment-specific technical progress) on the labor-augmenting term, which should be interpreted as an upper bound. The third column in Figure 7 displays the results from the alternative human capital calibration, which limits labor-augmenting technological progress to a measure of human capital growth, and loads the residual on the factor-neutral term. The quantitative differences are small overall; the main discrepancy is that K–L substitution is 1.1 pp stronger over 1950–1982, and 1.4 pp weaker over 1982–2012. These results reflect that the measured contribution of human capital does not differ too much from the overall growth residual.

<sup>31</sup>Acemoglu, Manera, and Restrepo (2020) argue that the U.S. tax code increasingly favors capital relative to labor.

The baseline and the human capital calibration arguably bracket the extent of labor-augmenting technological progress. Therefore, the similarity of the findings across the two model versions demonstrates that the kink in the evolution of the aggregate labor share is a consequence of the acceleration of investment-specific technical change as measured by relative capital prices.

Furthermore, the benchmark calibration simplifies by disregarding good-specific technological progress  $\Delta A_{it}$ . The last column in Figure 7 shows results from a richer calibration that ties  $\Delta A_{it}$  to the observed evolution of relative good prices in the data. The key observation is that differential relative good price trends only affect the substitution effect on the consumer side. As this channel is relatively minor to begin with, the sensitivity of the overall findings is limited.<sup>32</sup>

## 6.2. Results From Model With Investment

So far, I treated consumption as the only component of aggregate demand. In this section, I incorporate investment spending for the following two purposes. First, investment is a sizable fraction of aggregate demand, and differs from consumption with respect to its sectoral composition and changes therein over time. Second, and more importantly, in the baseline approach I back out capital stocks from profit-maximizing behavior of firms, given data and assumptions on the user cost of capital. Introducing investment allows for constructing the capital stock as a result of past investment instead, and thus answering the following two related questions: How do the investment rates implied by the baseline model compare to the data? If we assume that in the data investment rates are measured correctly, how different are the model predictions?

*Investment as a Component of Aggregate Demand.* I begin by incorporating private fixed investment (PFI) as a component of final demand. Figure A.1 in Appendix A.1 plots the aggregate labor share for different definitions of final demand. The aggregate labor share is falling a bit faster, by about one percentage point, when accounting for PFI in addition to personal consumption expenditures (PCE). Government purchases and net exports do not alter the aggregate trend; therefore, I continue to exclude them. Over the sample period 1982–2012, the investment labor share fell by 13.1 points while the one of consumption fell by 5.5 points. Statistically, we can further decompose this difference into a within-sector and a between-sector, or reallocation, component. Table C.I in Appendix C.2.1 shows that investment spending did not shift toward labor-intensive goods, in contrast to consumption. This is not surprising as the notion of an income effect is unclear for investment. Moreover, relative to consumption, investment spending is also concentrated in sectors with faster declining labor shares.

As nominal investment spending, relative to consumption, has been fairly flat (see Figure A.5 in Appendix A.6), I do not model the optimal consumption–savings choice. Instead, I take nominal investment rates directly from the data. As for the composition, I model investment into equipment and software ( $E$ ), respectively, structures ( $S$ ), as homothetic CES aggregators:

$$I_t^k = A_t^k \left( \sum_{i \in I} (\omega_i^k)^{\frac{1}{\sigma^k}} (Q_{it}^k)^{\frac{\sigma^k - 1}{\sigma^k}} \right)^{\frac{\sigma^k}{\sigma^k - 1}}, \quad k \in \{E, S\}, \quad (19)$$

<sup>32</sup>See Appendix C.1 for details on the calibration of these alternative model versions.

where  $Q_{it}^k$  is the quantity of good  $i$  used for type  $k$  investment in period  $t$ , and  $\omega_i^k$  the share parameter. Appendix C.2.1 contains the details. I find that with this specification, the model successfully captures the broad reallocation patterns for both consumption and investment, and that the overall investment labor share is falling faster relative to the one of aggregate consumption.

*Matching Investment Rates in the Data.* In the baseline approach followed in this paper, I back out capital stocks from the first-order conditions of profit maximizing firms, given the estimate of  $\eta$ , and feeding in an exogenous factor price of capital:

$$P_t^k \tilde{R}_t^k = P_{it} \frac{A_{it} \partial F_i(K_{it}^E, K_{it}^S, A_{it}^L L_{it})}{\partial K_{it}^k}, \quad k \in \{E, S\}, i \in I,$$

where  $P_t^k$  is the relative price of type  $k$  capital, and  $\tilde{R}_t^k$  is the required return. I take  $P_t^k$  from the data and assume  $\tilde{R}_t^k$  is constant over time, which is a conservative assumption: applying the user cost formula (A.2) would generate a declining return post-1980s given falling real interest rates, and consequently more capital deepening than in the baseline.

Given capital demand, and given the standard law of motion of capital,

$$K_{t+1}^k = (1 - \delta_t^k) K_t^k + I_t^k, \quad k \in \{E, S\}, \quad (20)$$

the baseline model implies time series of nominal investment rates that can be compared to the data.<sup>33</sup> The left panels of Figure 8 display the respective trend components. The fact that data and model series agree, on average, over 1950–1982, results from a normalization of the level of the user cost of capital. The content of these graphs concerns the later period (1982–2012). While in the data the overall investment rate slightly falls from 19.7% to 18.5%, on average, across the two periods, in the baseline model the implied investment rate increases to an average of 24.3%. Thus, the baseline model implies missing investment of on average 5.8% of output over 1982–2012.

This raises an immediate follow-up question: If we assume that the nominal investment rate is measured without error and let the capital stock evolve accordingly, how different are capital stocks and factor shares in such an alternative model? I refer to this as the I-Model, to contrast it to the baseline. In the I-Model, nominal investment rates and capital prices are taken from the data. Importantly,  $\eta = 1.35$  is maintained, since the estimation of the capital–labor elasticity  $\eta$  does not rely on investment data. For capital market clearing, the user cost of capital needs to adjust; that is,  $\tilde{R}_t^k$  is endogenous (and time-varying). I calibrate this alternative model such that it agrees with the baseline on average over 1950–1982, likewise replicating a stable aggregate labor share.<sup>34</sup>

The top right panel of Figure 8 compares the nominal capital–output ratio in the baseline to the one generated by the I-Model. The difference can be interpreted as missing capital. Missing total capital is in relative terms lower than missing investment, reflecting in particular the low depreciation rate of structures (which include residential structures).

The bottom right panel of Figure 8 contrasts the evolution of the labor share in the I-Model to the data and to the baseline model approach. By construction, the two model versions' trends agree over 1950–1982. There are two key observations: First, as investment is lower in the I-Model post-1982 (relative to the baseline), capital stocks are lower,

<sup>33</sup>See Appendix C.2.2 for details.

<sup>34</sup>See Appendix C.2.3 for details.

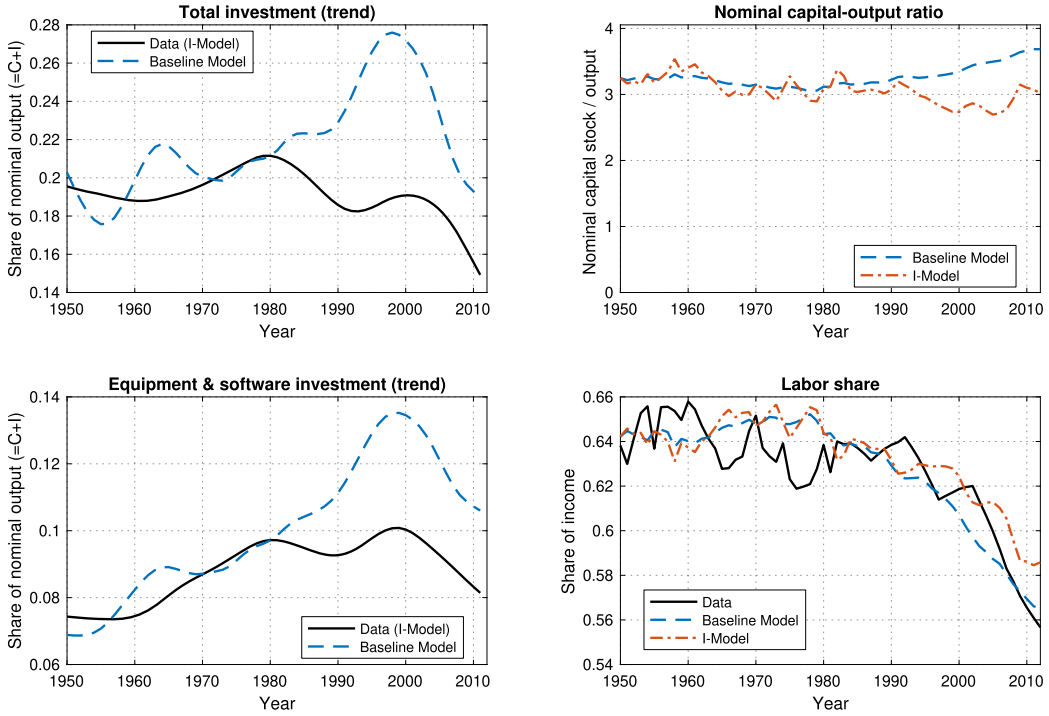


FIGURE 8.—Investment, capital, and the labor share. Data: Investment rates refer to nominal BEA aggregates (see Appendix A.6). Trend components are obtained from HP-filtering the data with smoothing parameter 100. The I-Model exactly matches the investment data; the capital stock is then constructed accordingly from its law of motion. The baseline model backs out capital stocks from profit-maximizing behavior of firms, given observed capital prices; required investment rates are then computed given the same law of motion of capital.

and consequently (given that  $\eta > 1$ ) the labor share decline is less pronounced. However, even though nominal investment rates (and nominal capital-output ratios) stay flat or even decrease slightly, the capital share nevertheless increases substantially. This is because the physical capital-output ratio still increases in response to investment-specific technical change, which increases the capital share (given that  $\eta > 1$ ). Quantitatively, the cumulative change in the labor share is  $-5.6$  percentage points in the I-Model, as opposed to  $-7.7$  points in the baseline.

Second, the user cost per dollar of capital ( $\tilde{R}_t^k$ ), which is constant in the baseline, is increasing over time in the I-Model. Given observed capital prices, lower investment rates (relative to the baseline) require  $\tilde{R}_t^k$  to increase for capital markets to clear. In turn, this implies an increasing wedge between observed real risk-free rates and the rate used by firms when making investment decisions, reflecting the arguments in Caballero, Farhi, and Gourinchas (2017) and Karabarbounis and Neiman (2019).<sup>35</sup>

To summarize, the baseline approach followed in this paper imputes the capital stock, and by implication investment, from firms' factor demand given observed relative capital prices and the estimate of  $\eta = 1.35$ . The latter does not rely on the time series of in-

<sup>35</sup> Appendix C.2.4 explains these two aspects through the lens of a simple one-sector model. This channel is also active if the increasing capital share is driven by automation; see Moll, Rachel, and Restrepo (2022).

vestment. This baseline approach implies a rising discrepancy between the model-implied and the measured investment rate. Alternatively, assuming that investment is measured without error, but maintaining that the model replicates observed capital prices as well as  $\eta = 1.35$ , the contribution of capital–labor substitution to the fall in the labor share is somewhat smaller but still accounts for the majority of the decline. This alternative approach implies an increasing wedge between the real return on productive capital and the real return on safe assets. The conclusion here is that given the estimates of the crucial elasticities, which are based on cross-sectional data, these two approaches bracket the model predictions for the neoclassical component of the aggregate labor share decline. The residual, unexplained, component ranges from 0.8 to 2.9 percentage points (or 1.5 to 5.1 log points).

### 6.3. Discussion and Relation to the Literature

The prime candidate for this residual component of the labor share decline is a rise in the aggregate markup  $\bar{\mu}_t$  (Barkai (2020), De Loecker, Eeckhout, and Unger (2020)). Appropriately defined, it drives a wedge between the observed labor share (of national income)  $\bar{\theta}_t^L$  and the labor share of cost  $\bar{\theta}_t^{L,\text{cost}}$ :

$$\bar{\theta}_t^L = \frac{\bar{\theta}_t^{L,\text{cost}}}{\bar{\mu}_t}.$$

With market power, the findings in this paper have to be interpreted as applying to  $\bar{\theta}_t^{L,\text{cost}}$ .<sup>36</sup> Thus, the quantitative results in the previous section are consistent with a rise in  $\bar{\mu}_t$  of 1.5 to 5.1 log points, which is on the lower end but within the range of estimates in the literature.<sup>37</sup>

Relative to the flexible framework in Karabarbounis and Neiman (2019), the approach pursued in this paper narrows down the contribution of the increase in the capital share to the labor share decline. Again using the quantitative findings from the previous section, the increase in the capital share as predicted by the model accounts for 65–90% of the observed labor share decline. This narrower prediction results from the use of a particular, high value of  $\eta$ , estimated from cross-sectional U.S. data, and a tighter calibration procedure for factor-augmenting technology, in particular ruling out technological regress. Given  $\eta$  (and other elasticities), the model analysis implies that there is either missing

<sup>36</sup>Such an interpretation requires that the estimated elasticities are not confounded by markups. For  $\eta$ , Section 5.2 addresses this issue. As for preferences, Appendix B.1 provides evidence suggesting that the income effect is indeed driven by differential labor intensities in production, not markups. Finally, the baseline model calibration uses model-generated relative prices—by construction not containing markups—to estimate  $\sigma$ . Thus, the substitution effect in consumer demand, which is rather minor to begin with across specifications (Figure 7), is not confounded by markups either.

<sup>37</sup>Using Compustat data and the production function approach to compute markups, the headline series in De Loecker, Eeckhout, and Unger (2020) shows a much larger increase when using sales weights to aggregate firm markups. The relevant aggregation method to assess the contribution to the labor share decline is cost weighting, as discussed in Edmond, Midrigan, and Xu (2022); using this aggregation, they find an increase of about 10 log points. Hubmer and Restrepo (2021) show that allowing for heterogeneity in technology by firm size in the production function approach to estimate markups implies a smaller increase of at most 5 log points. Such heterogeneity is consistent with the empirical findings in Autor et al. (2020), Kehrig and Vincent (2021). Baqaee and Farhi (2020) report that other methods to estimate markups yield smaller increases: the user cost approach yields an increase in the aggregate markup of 4 log points, and the accounting profit approach yields an increase of 5 log points.

investment, or a rising wedge between realized risk-free interest rates and the effective rate used by firms to make investment decisions (or a combination of these two channels).<sup>38</sup> To understand the logic of the model prediction, observe that if the decline of the labor share were entirely due to rising economic profits, firms' capital demand (relative to output) must not have increased. But since the relative price of capital has been falling, leading to capital deepening in real terms even when taking at face value the observed flat or slightly decreasing nominal investment rates, this could only be the case if (unobserved) capital-augmenting technology has regressed enough to fully counteract the falling equipment price.

## 7. CONCLUDING REMARKS

This paper documents two novel cross-sectional facts about labor shares in the U.S. economy: First, households' consumption labor shares increase in household income. Second, across goods and services, the decline in labor shares since the 1980s can be largely explained by the equipment and software intensity of production. The rest of the paper uses these facts to estimate the key elasticities in a neoclassical framework with multiple sectors and non-homothetic demand. Through the lens of the model, I find that the evolution of the U.S. labor share in the post-war era has been driven by two counteracting forces. On the one hand, capital-labor substitution, driven by investment-specific technical change, has put downward pressure on the labor share. On the other hand, an income effect arising from aggregate economic growth has led to a shift of consumption toward more labor-intensive goods and services. As observed in the data, abstracting from short-run fluctuations, the model generates an aggregate labor share that is relatively stable until the early 1980s, and declining thereafter. With constant substitution and income elasticities, the model identifies an accelerating bias of technological progress toward equipment and software capital—observed in relative prices—as the main culprit for the decline in the labor share of national income.

What does the model predict for the future evolution of the labor share? Figure 9 extends the model calibration to 2019, and performs a scenario analysis until 2040. While plausible variation in GDP growth has only a mild impact on the predicted future evolution of the labor share, the degree of investment-specific technical change (ISTC) is critical. Echoing the model findings for the evolution of the labor share in the past, the model predicts a stable labor share if ISTC returns to the modest levels observed until the early 1980s; on the other hand, if ISTC is as strong as observed in the 1982–2012 period, then the labor share is predicted to drop further by close to five percentage points.

Building on the results of this paper, there are several directions for future work. The first concerns a better understanding of why labor-intensive goods and services tend to be luxuries. One hypothesis is that new goods are more labor-intensive, and high-income households are early adopters. Empirically, investigating this hypothesis requires going beyond the framework in this paper with a fixed set of industries and goods, and to analyze product-level data instead. Furthermore, technological changes are exogenous in this paper. To inform policy, incorporating directed technical change is crucial. In such a setting, the income distribution can be allowed to feed back into the evolution of factor shares through endogenous improvements in technology, in addition to the consumption channel studied in the present paper.

<sup>38</sup> While there is no visible uptick in the measured aggregate investment rate as discussed, using data from the NBER-CES Manufacturing Industry Database, Kaymak and Schott (2020) show that across U.S. manufacturing industries, falling labor shares are indeed associated with significantly higher investment rates.



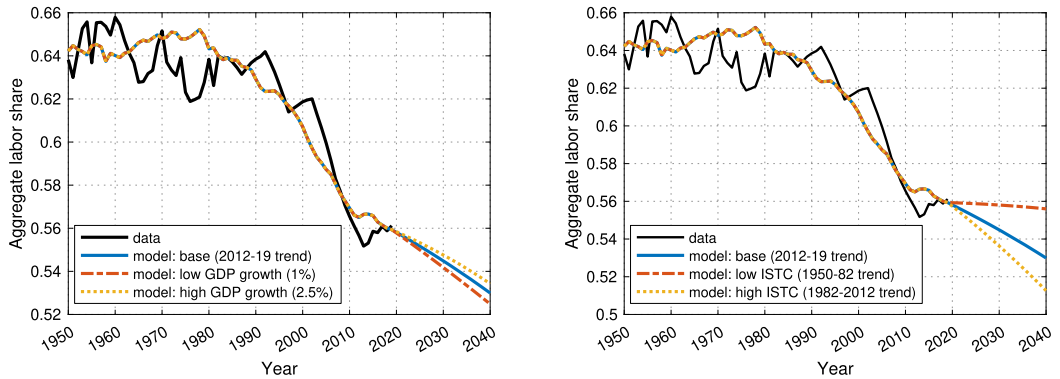


FIGURE 9.—Model predictions for the future evolution of the labor share. Data sources: BLS, BEA I–O Tables, CEX. All model scenarios are based on the model with consumption and investment in Section 6.2. The baseline calibration linearly extrapolates the 2012–2019 trends in GDP growth and relative capital prices until 2040. The left panel displays in addition sensitivity to GDP growth; the right panel displays in addition sensitivity to investment-specific technical change.

## REFERENCES

- ACEMOGLU, DARON, AND PASCUAL RESTREPO (2018): “The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment,” *American Economic Review*, 108, 1488–1542. [231]
- (2020): “Robots and Jobs: Evidence From US Labor Markets,” *Journal of Political Economy*, 128, 2188–2244. [231]
- ACEMOGLU, DARON, ANDREA MANERA, AND PASCUAL RESTREPO (2020): “Does the U.S. Tax Code Favor Automation?” *Brookings Papers on Economic Activity*, 50, 231–285. [253]
- ACKERBERG, DANIEL A., KEVIN CAVES, AND GARTH FRAZER (2015): “Identification Properties of Recent Production Function Estimators,” *Econometrica*, 83, 2411–2451. [248]
- AGUIAR, MARK, AND MARK BILS (2015): “Has Consumption Inequality Mirrored Income Inequality?” *American Economic Review*, 105, 2725–2756. [231,241,244]
- ALONSO, CRISTIAN (2016): “Cutting Back on Labor Intensive Goods? Implications for Fiscal Stimulus,” Technical report, Princeton University. [231]
- ANTRÀS, POL (2004): “Is the U.S. Aggregate Production Function Cobb–Douglas? New Estimates of the Elasticity of Substitution,” *The B.E. Journal of Macroeconomics*, 4, 1–36. [249]
- AUTOR, DAVID, DAVID DORN, LAWRENCE F. KATZ, CHRISTINA PATTERSON, AND JOHN VAN REENEN (2020): “The Fall of the Labor Share and the Rise of Superstar Firms,” *The Quarterly Journal of Economics*, 135, 645–709. [230,238,249,257]
- BAQAEE, DAVID REZZA, AND EMMANUEL FARHI (2020): “Productivity and Misallocation in General Equilibrium,” *The Quarterly Journal of Economics*, 135, 105–163. [257]
- BARKAI, SIMCHA (2020): “Declining Labor and Capital Shares,” *The Journal of Finance*, 75, 2421–2463. [230, 257]
- BASU, SUSANTO (2019): “Are Price–Cost Markups Rising in the United States? A Discussion of the Evidence,” *Journal of Economic Perspectives*, 33, 3–22. [248]
- BECKER, RANDY, WAYNE GRAY, AND JORDAN MARVAKOV (2016): “NBER–CES Manufacturing Industry Database: Technical Notes,” Technical report, National Bureau of Economic Research. [235]
- BOND, STEVE, ARSHIA HASHEMI, GREG KAPLAN, AND PIOTR ZOCH (2021): “Some Unpleasant Markup Arithmetic: Production Function Elasticities and Their Estimation From Production Data,” *Journal of Monetary Economics*, 121, 1–14. [248]
- BOPPART, TIMO (2014): “Structural Change and the Kaldor Facts in a Growth Model With Relative Price Effects and Non–Gorman Preferences,” *Econometrica*, 82, 2167–2196. [231]
- CABALLERO, RICARDO J., EMMANUEL FARHI, AND PIERRE-OLIVIER GOURINCHAS (2017): “Rents, Technical Change, and Risk Premia Accounting for Secular Trends in Interest Rates, Returns on Capital, Earning Yields, and Factor Shares,” *American Economic Review*, 107, 614–620. [256]
- CHIRINKO, ROBERT S. (2008): “ $\sigma$ : The Long and Short of It,” *Journal of Macroeconomics*, 30, 671–686, the CES Production Function in the Theory and Empirics of Economic Growth. [231]

- COMIN, DIEGO A., DANIAL LASHKARI, AND MARTÍ MESTIERI (2021): “Structural Change With Long-Run Income and Price Effects,” *Econometrica*, 89, 311–374. [231]
- CUMMINS, JASON G., AND GIOVANNI L. VIOLANTE (2002): “Investment-Specific Technical Change in the US (1947–2000): Measurement and Macroeconomic Consequences,” *Review of Economic Dynamics*, 5, 243–284. [229]
- DE LOECKER, JAN, JAN EECKHOUT, AND GABRIEL UNGER (2020): “The Rise of Market Power and the Macroeconomic Implications,” *The Quarterly Journal of Economics*, 135, 561–644. [230,247,248,257]
- DICECIO, RICCARDO (2009): “Sticky Wages and Sectoral Labor Comovement,” *Journal of Economic Dynamics and Control*, 33, 538–553. [228,229,239]
- EDEN, MAYA, AND PAUL GAGGL (2018): “On the Welfare Implications of Automation,” *Review of Economic Dynamics*, 29, 15–43. [231,238]
- EDMOND, CHRIS, VIRGILIU MIDRIGAN, AND DANIEL YI XU (2022): “How Costly Are Markups?” *Journal of Political Economy* (forthcoming). <https://doi.org/10.1086/722986>. [257]
- ELSBY, MICHAEL, BART HOBIJN, AND AYSEFUL SAHIN (2013): “The Decline of the U.S. Labor Share,” *Brookings Papers on Economic Activity*, 44, 1–63. [227,230]
- FABER, BENJAMIN, AND THIBAUT FALLY (2021): “Firm Heterogeneity in Consumption Baskets: Evidence From Home and Store Scanner Data,” *The Review of Economic Studies*, 89, 1420–1459. [234]
- FLYNN, ZACH, AMIT GANDHI, AND JAMES TRAINA (2019): “Identifying Market Power in Production Data,” Working paper. [248]
- GOLLIN, DOUGLAS (2002): “Getting Income Shares Right,” *Journal of Political Economy*, 110, 458–474. [230, 232]
- GORDON, ROBERT J. (1990): *The Measurement of Durable Goods Prices*. Chicago, IL: University of Chicago Press. [229]
- GREENWOOD, JEREMY, ZVI HERCOWITZ, AND PER KRUSELL (1997): “Long-Run Implications of Investment-Specific Technological Change,” *The American Economic Review*, 87, 342–362. [229]
- HALL, ROBERT E. (2018): “Using Empirical Marginal Cost to Measure Market Power in the US Economy,” Working Paper 25251, National Bureau of Economic Research. [247,248]
- HALL, ROBERT E., AND DALE W. JORGENSON (1967): “Tax Policy and Investment Behavior,” *The American Economic Review*, 57, 391–414. [235]
- HÉMOUS, DAVID, AND MORTEN OLSEN (2022): “The Rise of the Machines: Automation, Horizontal Innovation, and Income Inequality,” *American Economic Journal: Macroeconomics*, 14, 179–223. [230,231]
- HERRENDORF, BERTHOLD, RICHARD ROGERSON, AND ÁKOS VALENTINYI (2013): “Two Perspectives on Preferences and Structural Transformation,” *American Economic Review*, 103, 2752–2789. [232]
- HUBMER, JOACHIM (2023): “Supplement to ‘The Race Between Preferences and Technology’,” *Econometrica Supplemental Material*, 91, <https://doi.org/10.3982/ECTA18580>. [230]
- HUBMER, JOACHIM, AND PASCUAL RESTREPO (2021): “Not a Typical Firm: The Joint Dynamics of Firms, Labor Shares, and Capital–Labor Substitution,” Working Paper 28579, National Bureau of Economic Research. [238,248,249,257]
- HULTEN, CHARLES R. (1992): “Growth Accounting When Technical Change Is Embodied in Capital,” *The American Economic Review*, 82, 964–980. [229]
- JAIMOVICH, NIR, SERGIO REBELO, AND ARLENE WONG (2019): “Trading Down and the Business Cycle,” *Journal of Monetary Economics*, 102, 96–121. [231,234]
- KALDOR, NICHOLAS (1961): “Capital Accumulation and Economic Growth,” in *The Theory of Capital: Proceedings of a Conference Held by the International Economic Association*, ed. by Douglas C. Hague. London: Palgrave Macmillan UK, 177–222. [227]
- KARABARBOUNIS, LOUKAS, AND BRENT NEIMAN (2014): “The Global Decline of the Labor Share,” *The Quarterly Journal of Economics*, 129, 61–103. [227,230,231,243,248,249]
- (2019): “Accounting for Factorless Income,” *NBER Macroeconomics Annual*, 33, 167–228. [231,256, 257]
- KAYMAK, BARIS, AND IMMO SCHOTT (2020): “Corporate Tax Cuts and the Decline of the Labor Share,” Working paper. [258]
- KEHRIG, MATTHIAS, AND NICOLAS VINCENT (2021): “The Micro-Level Anatomy of the Labor Share Decline,” *The Quarterly Journal of Economics*, 136, 1031–1087. [238,249,257]
- KEYNES, JOHN M. (1939): “Relative Movements of Real Wages and Output,” *The Economic Journal*, 49, 34–51. [253]
- KOH, DONGYA, RAÛL SANTAEULÀLIA-LLOPIS, AND YU ZHENG (2020): “Labor Share Decline and Intellectual Property Products Capital,” *Econometrica*, 88, 2609–2628. [230]
- LASHKARI, DANIAL, ARTHUR BAUER, AND JOCELYN BOUSSARD (2019): “Information Technology and Returns to Scale,” Technical report, Boston College. [238]

- LEÓN-LEDESMA, MIGUEL A., PETER MCADAM, AND ALPO WILLMAN (2010): “Identifying the Elasticity of Substitution With Biased Technical Change,” *American Economic Review*, 100, 1330–1357. [231]
- LEVINSON, ARIK, AND JAMES O’BRIEN (2019): “Environmental Engel Curves: Indirect Emissions of Common Air Pollutants,” *Review of Economics and Statistics*, 101, 121–133. [233]
- MOLL, BENJAMIN, LUKASZ RACHEL, AND PASCUAL RESTREPO (2022): “Uneven Growth: Automation’s Impact on Income and Wealth Inequality,” *Econometrica*, 90, 2645–2683. [256]
- OBERFIELD, EZRA, AND DEVESH RAVAL (2021): “Micro Data and Macro Technology,” *Econometrica*, 89, 703–732. [242,243,249]
- OLLEY, G. STEVEN, AND ARIEL PAKES (1996): “The Dynamics of Productivity in the Telecommunications Equipment Industry,” *Econometrica*, 64, 1263–1297. [248]
- PIKETTY, THOMAS (2014): *Capital in the Twenty-First Century*, Translated by Arthur Goldhammer. Cambridge, MA: Belknap. [231]
- ROGNLIE, MATTHEW (2015): “Deciphering the Fall and Rise in the Net Capital Share: Accumulation or Scarcity?” *Brookings Papers on Economic Activity*, 46, 1–69. [230]
- RUGGLES, STEVEN, SARAH FLOOD, RONALD GOEKEN, JOSIAH GROVER, ERIN MEYER, JOSE PACAS, AND MATTHEW SOBEK (2019): “IPUMS USA: Version 9.0 [Dataset],” IPUMS, Minneapolis, MN. [247]
- VALENTINYI, AKOS, AND BERTHOLD HERRENDORF (2008): “Measuring Factor Income Shares at the Sector Level,” *Review of Economic Dynamics*, 11, 820–835. [232]

---

*Co-editor Charles I. Jones handled this manuscript.*

*Manuscript received 11 June, 2020; final version accepted 14 October, 2022; available online 26 October, 2022.*