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The Decline of the Labor Share: New Empirical Evidence†

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We use time series techniques to estimate the importance of four main explanations for the decline of the US labor income share: rising firm markups, falling bargaining power of workers, higher investment-specific technology growth, and more automated production processes. Identification is achieved with restrictions derived from a stylized model of structural change. Our results point to automation as the main driver of the labor share, although rising markups have played an important role in the last 20 years. We also find evidence of capital-labor complementarity, suggesting that capital deepening may have raised the labor share. (*JEL* D21, D43, E25, J51, L23, O33, O41)

Labor's share of national income has fallen in many countries in the last decades. In the United States, the labor income share has accelerated its decline since the beginning of the new century, reaching its lowest postwar level in the aftermath of the Great Recession (Elsby, Hobijn, and Şahin 2013). Figure 1 documents the evolution of five alternative measures of the US labor income share. (A detailed description of each measure is provided in Section IV.) While estimates of their long-run trends depend heavily on accounting assumptions and, thus, are subject to debate,[1] they have all gone through a clear fall in the last 20 years. This relative decline in labor income has several potential implications for policy and welfare.

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[1] Koh, Santaeulàlia-Llopis, and Zheng (2020) show that the average decline in US labor share figures since 1929 hinges on how the Bureau of Economic Analysis (BEA) defines intellectual capital and property rights in the national accounts. Gutiérrez and Piton (2020) find that labor income shares in major economies except for the United States become relatively stable when self-employment and dwellings from the corporate sector are excluded.

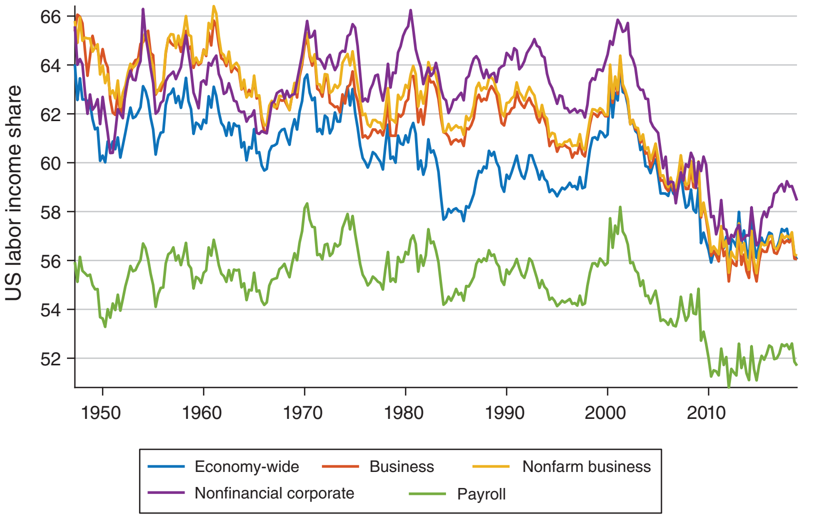

Figure 1. Measures of the US Labor Income Share over Time

Sources: Bureau of Labor Statistics and authors' calculations.

Yet, a consensus view regarding the main structural forces at play is still lacking. The aim of this paper, therefore, is to empirically evaluate and quantify some of the main explanations for observed labor share trends in the US economy. We do this using a combination of economic theory and time series techniques applied to US macroeconomic data.

We consider four explanations with rather broad appeal in the literature: first, a number of recent studies have argued that rising market power among firms has crowded out labor's share of income (Barkai 2020; De Loecker, Eeckhout, and Unger 2020; Eggertsson, Robbins, and Wold 2018; Gutiérrez and Philippon 2017). These studies find evidence of declining competition and increasing market concentration. The claim is that trends in firms' market power have spurred profit growth at the expense of labor income. A second take on the labor share decline concerns technological progress in the form of automation or robotization (Acemoglu and Restrepo 2018, 2020; Autor and Salomons 2018; Leduc and Liu 2021; Martinez 2019). Acemoglu and Restrepo (2020), for example, argue that many tasks previously done by workers are currently being automated on a relatively large scale. They find that automation leads to lower employment and stagnant wages, thus lowering the labor share of income. A third group of arguments focuses on labor market institutions such as unions and minimum wages (Piketty 2014). Along these lines, Blanchard and Giavazzi (2003) and Ciminelli, Duval, and Furceri (2018) find that a decline in the bargaining power of workers—proxied, respectively, by labor market deregulation and by major reforms in employment protection legislation—may be responsible for substantial movements in the labor share. Finally, the fourth explanation we consider puts forward a major role for capital-biased technology growth. Karabarbounis and Neiman (2014), in particular, use the relative price of investment as a proxy for investment-specific technological progress and find that capital deepening measured in this way may account for declining labor shares in a number of countries including the United States. Importantly, cheaper capital should imply lower labor income shares only if labor and capital are net substitutes, which is exactly what Karabarbounis and Neiman (2014) find in their data.

While a large literature has discussed each of these four explanations in isolation, an empirical analysis including all of them in the context of the same model is lacking. Our aim is to fill this gap. To this end, we estimate a structural vector autoregression (SVAR) with permanent shocks. These shocks are interpreted as candidate explanations for low-frequency changes in the labor share. We identify them using theory-robust sign restrictions à la Canova and Paustian (2011), imposed on impulse-response functions at medium-run horizons. "Theory-robust" in this context means that the restrictions hold across a broad set of parameterizations in a benchmark, macroeconomic model. Our approach involves two steps: first, we set up a fairly stylized yet flexible model of structural change. It incorporates the four candidate explanations of interest and nests, as special cases, several of the models used to study declining labor shares (including those used by Karabarbounis and Neiman 2014 and Barkai 2020). We then consider the macroeconomic implications of each candidate explanation under a broad set of model parameterizations. In particular, we show that the explanations can be separately identified by a combination of medium-run sign restrictions that are mutually exclusive and jointly exhaustive. The automation shock, for example, is unique in that none of the other shocks considered generate a medium-run rise in GDP combined with a medium-run decline in real wages and employment. Second, we use the derived set of theory-based sign restrictions to identify structural shocks in the empirical model. Continuing with the automation example: if—after controlling for endogenous dynamics and other shocks in data—one observes a medium-run rise in GDP, combined with a medium-run decline in wages and employment, then the identification scheme attributes these movements to automation.[2] As a byproduct of our empirical approach, we can also obtain indirect empirical evidence on the elasticity of substitution between labor and capital—arguably a key parameter for labor share dynamics. Importantly, we show that our identification scheme holds for about any value of this parameter, and the estimated impulse responses from the SVAR can be used to infer whether the capital-labor substitution elasticity is bigger or smaller than one.

The econometric approach used in this paper differs fundamentally from typical approaches in the existing literature on labor shares: while most studies draw inferences based on cross-sectional variation in microeconomic data (at the firm or sectoral level), we instead exploit the macroeconomic time series implications of permanent but aggregate shocks. Moreover, we use the SVAR framework to study medium-run trends rather than short-run fluctuations, as is normally done in the business-cycle literature. To the best of our knowledge, this is the first paper using

[2] It is important to stress that the labels we assign to shocks are only as good as the underlying theoretical assumptions: other structural forces that cause the same medium-run signs as automation, for example, but which we abstract from in the empirical analysis, will be interpreted as automation shocks in our framework. Identifying many shocks, as we do, naturally helps to reduce this issue.

sign restrictions to identify several permanent shocks. Finally, we stress that our estimation approach addresses a well-known issue in the literature on factor substitution and biased technical change: Diamond, McFadden, and Rodriguez (1978), among others, argue that factor elasticities and technology cannot be jointly identified in a theoretical model like ours. (See León-Ledesma, McAdam, and Willman 2010 for further discussion of this so-called "impossibility theorem.") We confirm that this is likely to be the case if model equations are estimated directly, but that the sign-restriction approach used here can get around the issue.

The empirical model is estimated on data covering the period 1983:I–2018:III. With the estimated model at hand, we set out to shed light on the observed labor share decline in the US economy. Our main results can be summarized as follows: first, we find that the labor income share falls permanently after a rise in automation or a rise in firms' market power but increases permanently in response to higher investment-specific technology growth. The labor share response to a decline in workers' market power is negative in the short run, but unclear and not significantly different from zero in the long run. Importantly, although we cannot pinpoint the exact value of the substitution elasticity between labor and capital, the latter two findings are only consistent with net complementarity. Our second result concerns the main drivers of the labor share. We find that automation accounts for the bulk of labor share fluctuations in our sample. The second most important factor is firms' market power, at least in the medium to long run. Labor markups have some explanatory power in the very short run, while investment-specific technology only plays a minor role. Why do we find an important role for automation? A positive automation shock increases output in the medium run and lowers wages and total hours, as in Acemoglu and Restrepo (2020). With the labor share defined as total labor income over output, we emphasize that all three components of the labor share favor a decline in response to automation. No other shock generates such a negative co-movement between output and the components of labor income, explaining why the automation shock is favored by data.[3] Our third result sheds light on the causes of the accelerating labor share decline observed in the last 20 years. A historical decomposition reveals that this decline is driven both by automation and firms' rising market power, with the latter becoming increasingly important after the Great Recession. Turning to investment-specific or capital-biased technology, we find that this kind of shock, if anything, has led to an increase in the labor share throughout the 2000s.

An important strand of the literature has focused on issues related to the measurement of labor income. The seminal paper by Elsby, Hobijn, and Şahin (2013), for example, discusses how mismeasurement of income earned by the self-employed may exaggerate the recent decline in the labor income share. More recently, Koh, Santaeulàlia-Llopis, and Zheng (2020) show that the average decline in the labor income share since 1929 is explained by the capitalization of intellectual property products (IPP). In fact, the Bureau of Economic Analysis (BEA) has revised

[3] At the same time, the automation shock is redistributive in nature and does not have important aggregate effects on output. This is hardly surprising, since countercyclical wages and hours are not a prominent characteristic of economic fluctuations.

the treatment of IPP by attributing the entire rents from IPP investment to capital income. This choice affects the long-run trend in the labor share series, and Koh, Santaeulàlia-Llopis, and Zheng (2020) argue that at least some of the newly generated income due to IPP should be attributed to labor. Finally, disentangling capital income from pure profit income has proven to be challenging from an empirical point of view. Barkai (2020) argues that pure profits have increased substantially in recent years while the capital share has decreased. Karabarbounis and Neiman (2019) claim that the residual payments (referred to as "factorless income") obtained after measuring labor and capital income cannot be interpreted as pure profits and may reflect measurement error in the capital stock or in the rental rate of capital. In order to reduce the unavoidable issues related to the measurement of the labor share and the profit share, we conduct an extensive sensitivity analysis using alternative measures for those variables.

The literature on labor share trends has exploded in recent years and several explanations have been proposed in addition to those included in our baseline model: Autor et al. (2020), looking at US firm-level data, estimate that rapid technology growth among capital intensive "superstar firms" has led to reallocation of market shares away from labor-intensive companies. Rognlie (2015) finds that more expensive residential investment and increased land scarcity have led to higher (housing) capital shares at the expense of labor income. Giannoni and Mertens (2019) document how outsourcing—firms' contracting of labor-intensive activities to external companies—can explain labor share trends across US industries. Glover and Short (2018) study labor share implications of an aging workforce, while d'Albis, Boubtane, and Coulibaly (2019) estimate the effects of cross-country migration for factor shares in OECD countries. Kaymak and Schott (2019) focus on the manufacturing sector and emphasize the role played by corporate tax cuts. Finally, Elsby, Hobijn, and Şahin (2013) argue that globalization, and in particular the offshoring of intermediate goods production to developing countries, is a promising candidate for the decline in the labor share. Inspired by these studies, we discuss how our identification approach and main results might be interpreted in light of some alternative explanations.

The rest of the paper is organized as follows: Section I describes a theoretical model of structural change. Section II derives the set of theory-robust sign restrictions, lays out the econometric methodology, and discusses identification. Section III documents our main empirical results. Section IV discusses selected extensions, while most of the robustness exercises are included in the online Appendix. Finally, Section V concludes.

I. Theoretical Framework

Our baseline theoretical framework is the standard neoclassical growth model, but we add a few simple extensions that allow us to consider trends in the labor share. Importantly, in our setup the labor share can change—albeit in somewhat reduced form—due to investment-specific technical change, automation of labor-intensive production tasks, distortions in labor markets, and changes in the market power of firms. The resulting framework is, with minor deviations, similar to those used by Karabarbounis and Neiman (2014); Barkai (2020); and Caballero, Farhi, and Gourinchas (2017), among others.

The model economy is populated by a unit mass of firms and households. For convenience, we also distinguish between retailers, investment producers, and conventional (wholesale) firms. In the labor market, we make a distinction between individual workers and a labor union that rents workers' services in order to provide labor to firms.

A. *Retailers*

A competitive retailer combines individual goods in order to produce an aggregate, final good. The aggregation technology is standard:

$$Y_t = \left(\int_0^1 Y_{j,t}^{\frac{\epsilon_{p,t}-1}{\epsilon_{p,t}}} dj\right)^{\frac{\epsilon_{p,t}}{\epsilon_{p,t}-1}}.$$

$Y_{j,t}$ is output by firm j and $\epsilon_{p,t}$ is a time-varying elasticity of substitution between inputs. The retailer chooses inputs in order to maximize profits. Optimal demand toward firm j's output follows

$$Y_{j,t} = P_{j,t}^{-\epsilon_{p,t}} Y_t.$$

$P_{j,t}$ is the price of good j relative to the aggregate price index specified below. This downward-sloping demand function equips firms with market power and allows them to charge a markup over marginal costs when they set their own prices. The optimal price index is given by

$$1 = \left(\int_0^1 P_{j,t}^{1-\epsilon_{p,t}} dj\right)^{\frac{1}{1-\epsilon_{p,t}}}.$$

Thus, we choose the final good Y_t as the numeraire. It can be used for consumption or investment purposes. Market-clearing dictates that

$$Y_t = C_t + X_t, \tag{1}$$

where C_t denotes consumption and X_t represents raw investments.

B. *Investment Producers*

Following Fisher (2006), we suppose that a competitive investment goods producer transforms raw investments X_t into final investment goods. The production technology for this activity is given by

$$I_t = \Upsilon_t X_t. \tag{2}$$

Changes in Υ_t represent investment-specific technological progress. The final good I_t is sold to households, who accumulate capital. We denote by $P_{I,t}$ the unit price of final investments relative to final consumption. Profit maximization on behalf of the investment producer leads to the optimality condition

$$P_{I,t} = \Upsilon_t^{-1}, \tag{3}$$

which in turn implies the zero profit condition $P_{I,t} I_t = X_t$. Karabarbounis and Neiman (2014) find that falling investment prices can explain a major share of the observed labor share decline in many countries, including the United States.

C. *Labor Union*

A competitive labor union combines hours from individual workers using the technology

$$L_t = \left(\int_0^1 L_{n,t}^{\frac{\epsilon_{w,t}-1}{\epsilon_{w,t}}} dn \right)^{\frac{\epsilon_{w,t}}{\epsilon_{w,t}-1}},$$

where $L_{n,t}$ is hours supplied by worker n. $\epsilon_{w,t}$ is a time-varying elasticity of substitution between labor varieties. Optimal demand for worker n's services follows

$$L_{n,t} = \left(\frac{W_{n,t}}{W_t} \right)^{-\epsilon_{w,t}} L_t.$$

$W_{n,t}$ is the unit cost of worker n while W_t is the optimal, aggregate wage index:

$$W_t = \left(\int_0^1 W_{n,t}^{1-\epsilon_{w,t}} dn \right)^{\frac{1}{1-\epsilon_{w,t}}}.$$

D. *Households*

There is a unit mass of optimizing households in the economy. Household $n \in [0,1]$ derives utility from consumption and disutility from work activities. The period utility is equal to

$$\mathcal{U}_{n,t} = \frac{C_{n,t}^{1-\sigma}}{1-\sigma} \exp\left(-\Psi \frac{(1-\sigma) L_{n,t}^{1+\varphi}}{1+\varphi} \right).$$

These preferences allow for a balanced growth path when the intertemporal substitution elasticity differs from one, as shown by King, Plosser, and Rebelo (1988). Household n maximizes $E_t \sum_{s=t}^{\infty} \beta^{s-t} \mathcal{U}_{n,s}$, where β is a time discount factor. Maximization is subject to two constraints. The first is an intertemporal budget constraint:

$$C_{n,t} + P_{I,t} I_{n,t} + B_{n,t} \leq W_{n,t} L_{n,t} + r_t^k K_{n,t-1} + \mathcal{D}_{n,t} + (1 + r_{t-1}) B_{n,t-1} - T_{n,t}.$$

Labor income, capital income, and profit income are denoted by $W_{n,t} L_{n,t}$, $r_t^k K_{n,t-1}$, and $\mathcal{D}_{n,t}$, respectively. r_t^k is the competitive rental price on the current capital stock in place, $K_{n,t-1}$. $B_{n,t}$ represents the amount of one-period bonds purchased in period t with return r_t. Finally, T_t is a lump-sum tax levied by the government. The second constraint is the law of motion for capital,

$$K_{n,t} \leq (1-\delta) K_{n,t-1} + I_{n,t},$$

where δ is the capital depreciation rate. We assume perfect risk-sharing across households. This allows us to consider a symmetric equilibrium ($W_{n,t} = W_t$, $L_{n,t} = L_t$, etc.) with a representative household. The representative household's behavior can be summarized by the budget constraint, the law of motion for capital, and five optimality conditions. We define the gross wage markup as $\mathcal{M}_{w,t} = W_t / MRS_t$, where MRS_t is the marginal rate of substitution between labor and consumption. Optimality conditions are stated below.

$$\Lambda_t = C_t^{-\sigma} \exp\left(-\Psi \frac{(1-\sigma) L_t^{1+\varphi}}{1+\varphi}\right) \tag{4}$$

$$\Lambda_t = \beta E_t \Lambda_{t+1}(1+r_t) \tag{5}$$

$$W_t = \mathcal{M}_{w,t} \Psi L_t^{\varphi} C_t \tag{6}$$

$$P_{I,t} = \beta E_t \frac{\Lambda_{t+1}}{\Lambda_t}\left[r_{t+1}^k + P_{I,t+1}(1-\delta)\right] \tag{7}$$

$$\mathcal{M}_{w,t} = \frac{\epsilon_{w,t}}{\epsilon_{w,t} - 1} \tag{8}$$

The evolution of $\mathcal{M}_{w,t}$ is exogenous from the household's point of view. It can be triggered by changes in union power but also by leisure preferences, demographics, or other factors that influence the supply side of the labor market. Drautzburg, Fernández-Villaverde, and Guerrón-Quintana (2021), for example, provide narrative evidence of the macroeconomic importance of workers' bargaining power. We do not take a stand on the particular drivers of $\mathcal{M}_{w,t}$, but simply refer to them as wage or labor markup shocks.

E. *Monopolistic Firms*

There is a unit measure of monopolistically competitive firms in the economy. Their output is produced with labor and capital. Firm $j \in [0,1]$ sets its own price in order to maximize profits $\mathcal{D}_{j,t}$:

$$\mathcal{D}_{j,t} = P_{j,t} Y_{j,t} - W_t L_{j,t} - r_t^k K_{j,t-1}.$$

Profit maximization is subject to the downward-sloping demand from retailers, as well as a production technology featuring constant elasticity of substitution:

$$Y_{j,t} = \left[\alpha_{l,t}\left(A_{l,t}L_{j,t}\right)^{\frac{\eta-1}{\eta}} + \alpha_{k,t}\left(A_{k,t}K_{j,t-1}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}.$$

η represents the elasticity of substitution between capital and labor. This production function includes three distinct technological processes: $A_{l,t}$ and $A_{k,t}$, respectively, represent the conventional labor-augmenting and capital-augmenting technology innovations. $\alpha_{k,t}$, by contrast, is interpreted as an automation shock that makes output more capital intensive at the expense of labor. Its microeconomic foundation is derived by Acemoglu and Restrepo (2018) and the references therein. They consider a framework where a continuum of tasks is produced within a production unit such as a firm. Some tasks require labor, but for others, labor and capital are perfect substitutes. Automation in this context is interpreted as a shift in the share of tasks that can be produced with capital. Acemoglu and Restrepo (2018) show how one can aggregate the tasks in order to establish a production function like ours, with time-varying weights $\alpha_{l,t}$ and $\alpha_{k,t}$. Importantly, $\alpha_{l,t}$ and $\alpha_{k,t}$ are decreasing and increasing in the degree of automation, respectively. We follow Caballero, Farhi, and Gourinchas (2017) by restricting attention to a baseline case where automation implies that $\alpha_{l,t} = \bar{\alpha} - \alpha_{k,t}$. As before, we consider a representative firm in the symmetric equilibrium ($P_{j,t} = 1$, $Y_{j,t} = Y_t$, etc.) and define the firm's gross markup as $\mathcal{M}_{p,t} = MC_t^{-1}$ (price over nominal marginal costs). Firm behavior can then be summarized by the production function as well as the following optimality conditions:

$$r_t^k \mathcal{M}_{p,t} = \alpha_{k,t} A_{k,t}^{\frac{\eta-1}{\eta}} \left(\frac{Y_t}{K_{t-1}}\right)^{\frac{1}{\eta}} \tag{9}$$

$$W_t \mathcal{M}_{p,t} = \alpha_{l,t} A_{l,t}^{\frac{\eta-1}{\eta}} \left(\frac{Y_t}{L_t}\right)^{\frac{1}{\eta}} \tag{10}$$

$$\mathcal{M}_{p,t} = \frac{\epsilon_{p,t}}{\epsilon_{p,t} - 1}. \tag{11}$$

The last equation defines the optimal, time-varying markup from firms' point of view. Firm revenues follow:

$$Y_t = \mathcal{M}_{p,t}\left(W_t L_t + r_t^k K_{t-1}\right).$$

Movements in $\mathcal{M}_{p,t}$ can be caused by changes in entry costs, antitrust enforcement, lobbying, product specialization, or other factors that directly affect the degree of competition between firms.[4] We do not take a stand on the particular drivers of $\mathcal{M}_{p,t}$, but simply refer to them as price or firm markup shocks.

[4] This is consistent with the evidence presented by Barkai (2020); De Loecker, Eeckhout, and Unger (2020); Eggertsson, Robbins, and Wold (2018); Gutiérrez and Philippon (2017); and Grullon, Larkin, and Michaely

F. *Aggregation and Income Accounting*

Market clearing in labor and capital markets dictates that

$$L_t = \int_0^1 L_{j,t} dj \quad K_{t-1} = \int_0^1 K_{j,t-1} dj \quad \mathcal{D}_t = \int_0^1 \mathcal{D}_{j,t} dj.$$

We suppose that bonds are in zero net supply and sum up over all households' budget constraints in order to express aggregate income:

$$Y_t = C_t + P_{I,t} I_t = W_t L_t + r_t^k K_{t-1} + \mathcal{D}_t.$$

Income shares in our simple model are defined accordingly:

$$s_{l,t} = \frac{W_t L_t}{Y_t} \quad s_{k,t} = \frac{r_t^k K_{t-1}}{Y_t} \quad s_{d,t} = \frac{\mathcal{D}_t}{Y_t}.$$

Thus, $s_{l,t} + s_{k,t} + s_{d,t} = 1$. At this point, it is useful to evaluate how the labor income share in our simple model reacts to structural shocks at low frequencies. To this end, we define a long-run equilibrium as the nonstochastic equilibrium outcome once all shock dynamics have settled down. In the online Appendix we show that

$$\bar{s}_{l,t} = \frac{1}{\bar{\mathcal{M}}_{p,t}} \left[1 - \bar{\alpha}_{k,t}^{\eta} \left(\frac{\beta^{-1} - (1-\delta)}{\bar{\Upsilon}_t \bar{A}_{k,t}} \bar{\mathcal{M}}_{p,t} \right)^{1-\eta} \right],$$

where long-run equilibrium variables are denoted by a bar. A few remarks are in place: first, the long-run labor share is not affected by labor-augmenting technology or markups in the labor market. Thus, only short-run to medium-run fluctuations in the labor share can be accounted for by these shocks, according to our model. Second, higher firm markups or more automation both imply a decline in the long-run labor share. This is true regardless of the degree of substitutability between capital and labor. Third, the long-run effects of investment-specific and capital-augmenting technology shocks on the labor share are observationally equivalent. For this reason, it is sufficient to consider only one of the two shocks, as long as the focus is on low-frequency dynamics. Finally, whether or not a rise in $\bar{\Upsilon}_t$ (or $\bar{A}_{k,t}$) reduces labor's share of income depends crucially on η: the labor share unambiguously falls if $\eta > 1$, and unambiguously rises if $\eta < 1$. The knife-edge case with Cobb-Douglas production $(\eta = 1)$ implies no change in the long-run labor share in response to factor-augmenting shocks. We further describe the identification challenge associated with η and how we address it in Section II.

(2019). These papers argue that the observed increase in firm concentration is associated with changes in competition rather than improved technological efficiency. Autor et al. (2020) support the latter view, instead.

G. *Shock Processes*

Given the preceding discussion, we restrict attention to four stochastic shock processes: exogenous innovations to firms' price markup $\mathcal{M}_{p,t}$, to labor's wage markup $\mathcal{M}_{w,t}$, to investment-specific technology Υ_t, and to the automation parameter $\alpha_{k,t}$. The processes are assumed to follow a random walk:

$$\frac{\mathcal{M}_{p,t}}{\mathcal{M}_{p,t-1}} = 1 + g_{p,t} = (1 + g_p)\exp(z_{p,t})$$

$$\frac{\mathcal{M}_{w,t}}{\mathcal{M}_{w,t-1}} = 1 + g_{w,t} = (1 + g_w)\exp(z_{w,t})$$

$$\frac{\Upsilon_t}{\Upsilon_{t-1}} = 1 + g_{\Upsilon,t} = (1 + g_{\Upsilon})\exp(z_{\Upsilon,t})$$

$$\frac{\alpha_{k,t}}{\alpha_{k,t-1}} = 1 + g_{\alpha_k,t} = (1 + g_{\alpha_k})\exp(z_{\alpha_k,t})$$

The innovations themselves are autoregressive processes:

$$z_{p,t} = \rho_p z_{p,t-1} + \sigma_p \varepsilon_{p,t} \qquad z_{w,t} = \rho_w z_{w,t-1} + \sigma_w \varepsilon_{w,t}$$

$$z_{\Upsilon,t} = \rho_{\Upsilon} z_{\Upsilon,t-1} + \sigma_{\Upsilon} \varepsilon_{\Upsilon,t} \qquad z_{\alpha_k,t} = \rho_{\alpha_k} z_{\alpha_k,t-1} + \sigma_{\alpha_k} \varepsilon_{\alpha_k,t}$$

It is assumed that $\varepsilon_{p,t}$, $\varepsilon_{w,t}$, $\varepsilon_{v,t}$, and $\varepsilon_{\alpha_k,t}$ are independently drawn from a normal distribution with mean zero and unit variance. We stress that the shock processes specified here in general imply separate stochastic trends for all variables of interest in the model. A common stochastic trend is obtained only in a particular special case: if the automation shock as well as both markup shocks are absent (or if all three shocks are temporary), and at the same time $\eta = 1$, then one is back to the standard, neoclassical growth model with constant long-run income shares.

II. Empirical Strategy

We have already seen how the substitution elasticity η determines the response of labor's income share to factor-augmenting technical change. An observed fall in the labor share, for example, can be attributed to the combination of rising investment-specific technology (Υ_t) and net substitutability between capital and labor $(\eta > 1)$ but equally well to declining investment technology and net complementarity. Herein lies a potentially serious identification problem, as neither Υ_t nor η are observed. This issue is well known in the literature and has led researchers to suggest that one cannot simultaneously identify the capital-labor elasticity and biased technical change. Diamond, McFadden, and Rodriguez (1978), for example, derive nonidentification from the sign patterns produced by a fairly general class of neoclassical production functions.[5] More recently, León-Ledesma, McAdam, and Willman (2010) claim that the "impossibility theorem" developed by Diamond, McFadden, and Rodriguez (1978) represents the received wisdom in the literature.

Faced with this challenge, applied researchers have typically opted for one of two strategies: the first is to obtain a direct measure, or at least a proxy, of technical change. This is the route taken by Karabarbounis and Neiman (2014), who use relative investment prices to measure investment technology, as well as by Acemoglu and Restrepo (2020), who proxy automation by the number of robots per worker. One can then regress the labor share on the obtained measure. Typically, this single-equation approach derives inference from cross-sectional variation in microeconomic data at the firm or sectoral level. The second strategy is to directly estimate the full theoretical model or at least parts of it, either by maximum likelihood (with or without priors) or by moment matching. The idea, then, is to achieve identification from the cross-equation restrictions embedded in the system of model equations. Equipped with the estimated model, one can use the Kalman filter to estimate unobserved drivers of the labor share. While both of these approaches bear some merits, there are important reasons why we prefer a fundamentally different identification strategy: first and foremost, since our goal is to quantify the relative importance of four different labor share drivers—all unobservable—it is not sufficient to exploit proxy variables for only one or two shocks in a single-equation setting. Rather, we need an identification strategy that allows us to identify and quantify all four shocks simultaneously within the same system. Second, as we show later in this section, η has very little influence on macroeconomic variables in the model other than the labor share. System estimation where the model is fitted quantitatively to empirical moments is, therefore, subject to a problem of weak identification unless additional assumptions are made.[6]

These concerns call for an alternative strategy, still heavily guided by economic theory, but in which theoretically consistent sign patterns of impulse-response functions are exploited as a means to sidestep the identification issue. This is exactly the approach we take here. The identification problem is addressed using a two-step procedure: first, we conduct a careful analysis of the theoretical model in order to arrive at identification restrictions—in terms of signs—which are robust to a broad range of values for the model's parameters (including η). Importantly, these theory-robust restrictions do not involve the labor share itself. Second, we impose the derived sign restrictions on a flexible time series model in order to estimate the evolution of shocks and their effects on the labor share. Of course, one could go ahead and estimate an empirical time series model, as we do, and then impose sign restrictions on the labor share itself. However, any sign restriction imposed on the labor share (in response to shocks that move relative factor prices, such as investment-specific technology) would implicitly assume either net complementarity or net substitutability between labor and capital. We nevertheless do this exercise as a sensitivity

[5] Among others, the authors show that the data generated by one particular production function can be perfectly replicated by another production function exhibiting different elasticities and different technical bias. See also the discussions by Kumar and Gapinski (1974) and Thursby (1980).

[6] See León-Ledesma and Satchi (2019) for an application. When estimating their model, the authors impose restrictions on the elasticity of substitution between labor and capital.

check and show that the main results are robust to additional elasticity restrictions. The rest of this section lays out the details of our empirical strategy.

A. *Step One—Theory-Robust Sign Restrictions*

The objective in step one is to establish a set of theory-robust restrictions that we can use to separately identify the potential structural forces at play in the empirical model. The exercise follows along the lines of Canova and Paustian (2011) and involves the following stages: first, we make one independent draw from a uniform distribution specific to each of the model's structural parameters and gather the resulting parameter values in a vector Θ. Second, we solve the model conditional on Θ. Third, we compute and save the impulse responses implied by the model solution. Stages 1–3 are repeated 10,000 times.[7] This exercise leaves us with a distribution of impulse responses that can be used to establish combinations of sign restrictions unique to each shock under consideration.

Further details about the inferred identification scheme are laid out below, but first we make a few comments regarding the numerical approximations involved. We use perturbation methods to solve the model, which means that we must choose an initial point to start simulations from. Two issues arise here: first, the elasticity of labor's income share to various shocks depends on the initial income shares when those shocks are realized, and the model is consistent with a continuum of distinct, initial income shares. Second, $\alpha_{l,t}$ and $\alpha_{k,t}$ are not dimension-free, regardless of which starting point we consider (see Cantore et al. 2014 for discussion of the latter issue). Therefore, for every simulation we draw initial income shares and add them to the parameter vector Θ. In turn, the model is re-parameterized conditional on realized values for initial income shares. The re-parametrization follows along the lines of Cantore and Levine (2012). Initial equilibrium values of certain great ratios are fixed by setting $\beta = 0.99$, $\delta = 0.025$, and $g_p = g_w = g_\Upsilon = g_{\alpha_k} = 0$. Without loss of generality, we also start the simulations at $\bar{A}_{l,t} = \bar{\Upsilon}_t = \bar{L}_t = 1$. Finally, the volatility parameters σ_p, σ_w, σ_v, and σ_{α_k} are normalized so that impulse responses are computed conditional on a long-run change in $\mathcal{M}_{p,t}$, $\mathcal{M}_{w,t}$, Υ_t, and $\alpha_{k,t}$ of 1 percent. Remaining variables follow endogenously. Table 1 reports chosen bounds for the uniform distributions of parameters and initial income shares. We choose relatively wide bands for the latter, so that the initial labor income share can take all values observed in the postwar US economy (see Figure 1). Moreover, the parameter bounds span commonly used values in the literature. The elasticity of substitution between labor and capital, for example, is centered around unity with support between 0.5 and 1.5. Applied work commonly assumes $\eta = 1$ (Cobb-Douglas production), although many empirical estimates are somewhat smaller (León-Ledesma, McAdam, and Willman 2010). Karabarbounis and Neiman (2014), by contrast, find numbers around 1.2 or even higher.

Figure 2 summarizes the distribution of impulse responses derived from the Monte Carlo exercise. In the figure, we have normalized the two markup shocks so

[7] Parameter combinations that violate saddle-path stability are discarded.

TABLE 1—PARAMETER BOUNDS FOR THE MONTE CARLO EXERCISES

		Benchmark model		
		M	*LB*	*UB*
Initial income shares				
s_l	Labor income share	0.6	0.5	0.7
s_k	Capital income share	0.3	0.225	0.375
s_d	Profit income share	0.1	0.075	0.125
"Deep" parameters				
σ	Inverse of intertemporal elasticity	3	1	5
φ	Inverse Frisch elasticity	3	1	5
η	Substitution between labor and capital	1	0.5	1.5
Shocks' persistence				
ρ_p	Firms' markup growth	0.25	0	0.5
ρ_w	Labor's markup growth	0.25	0	0.5
ρ_υ	Investment-specific technology growth	0.25	0	0.5
ρ_{α_k}	Automation growth	0.25	0	0.5

Notes: The table lists bounds for the uniform distributions. *M* indicates median, *LB* indicates lower bound, and *UB* indicates upper bound. The parameters σ_p, σ_w, σ_υ, and σ_{α_k} are normalized so that impulse responses are computed conditional on a long-run change in $\mathcal{M}_{p,t}$, $\mathcal{M}_{w,t}$, Υ_t, and $\alpha_{k,t}$ of 1 percent.

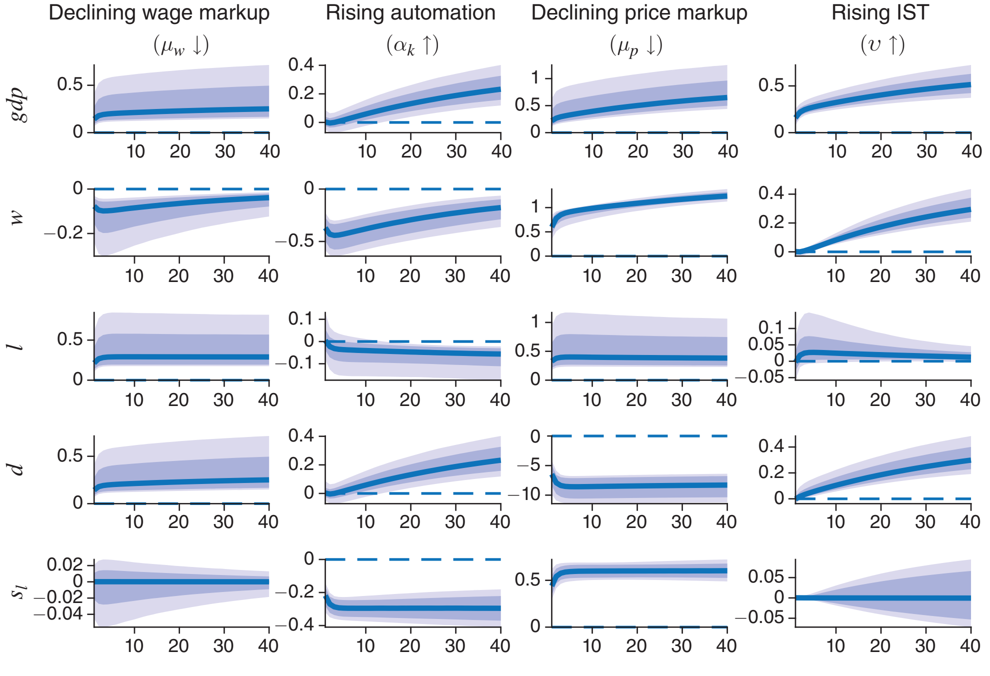

FIGURE 2. SIMULATION RESULTS FROM THE BASELINE THEORETICAL MODEL

Notes: The figure shows median (solid line), 90 percent, and 68 percent credible bands based on 10,000 draws. Income shares are expressed in percentage point deviations from initial values. Remaining variables are expressed in percentage deviations.

that the long-run effect on output is positive. Thus, all shocks considered here will eventually cause a rise in output. Our first part of the identification scheme comes from the observation that wages inevitably decline following labor markup and automation shocks but rise in response to firm markup and investment-specific technology shocks. As such, we will attribute unforecastable, negative co-movement between GDP and wages to labor markups or automation. We further disentangle these two by exploiting their contrasting implications for total hours worked: a decline in the wage markup implies more competition among workers and is, therefore, a positive supply shock in the labor market. Working hours rise as a result. Automation, by contrast, reduces the need for firms to hire workers. As such, automation is a negative labor demand shock that causes wages and hours to decline. These are precisely the macroeconomic effects of automation documented both theoretically and empirically by Acemoglu and Restrepo (2018, 2020). Moreover, while automation tends to imply a relatively strong redistribution of income, with substantial displacement of labor earnings, the expansion of aggregate output is rather small. (Output even declines in the short run under several parametrizations.) In order to distinguish between innovations to firms' markup and investment-specific technology, we note that the former leads to a decline in profits while profits rise in response to an increase in investment-specific technology. The intuition is simple: stronger competition between firms implies lower margins and, therefore, lower profits. Higher investment productivity, on the other hand, leads to an abundance of capital and higher output. This results in more profits, even though profit margins might be unchanged. For completeness, Figure 2 also reports the impulse responses of labor income shares. Consistent with the earlier discussion, wage markup and investment technology shocks can raise or lower the labor share, depending on whether η is higher or lower than one. The median response to both shocks is exactly zero, as the distribution of η is centered around unity.

Figure 3 documents the impulse responses when we redo the simulation exercise but restrict the distribution of η. In the first case, values of η are drawn from a uniform distribution with support $[1, 1.5]$. In the second case, we instead consider values in the range $[0.5, 1]$. The remaining parameter distributions are as before. As seen from the figure, an increase in investment-specific technology, for example, unambiguously lowers the labor share if $\eta > 1$, while the labor share increases if $\eta < 1$. More intriguingly, the labor share is the only variable that depends quantitatively on the parametrization of η. For all other variables, the impulse responses are very similar. This implies an important insight: if we were to estimate the model and its parameters directly, then it would be difficult to obtain a sharp identification of the shocks driving labor income shares from the quantitative responses of GDP, wages, and so on. If anything, the results in Figure 3 suggest that the "impossibility theorem" of Diamond, McFadden, and Rodriguez (1978) applies also in a context where a system of model equations is fitted quantitatively to empirical moments. For this reason, we choose to infer whether or not η is larger than one indirectly.

A potential issue with the analysis so far concerns the measurement of profit income, which in data might be distorted by the inclusion of some unobserved, intangible capital (Karabarbounis and Neiman 2019). However, as shown in online Appendix A.4.1, our sign restrictions hold even if one takes the extreme view that all capital income is counted as profits in data. As an additional robustness test, we

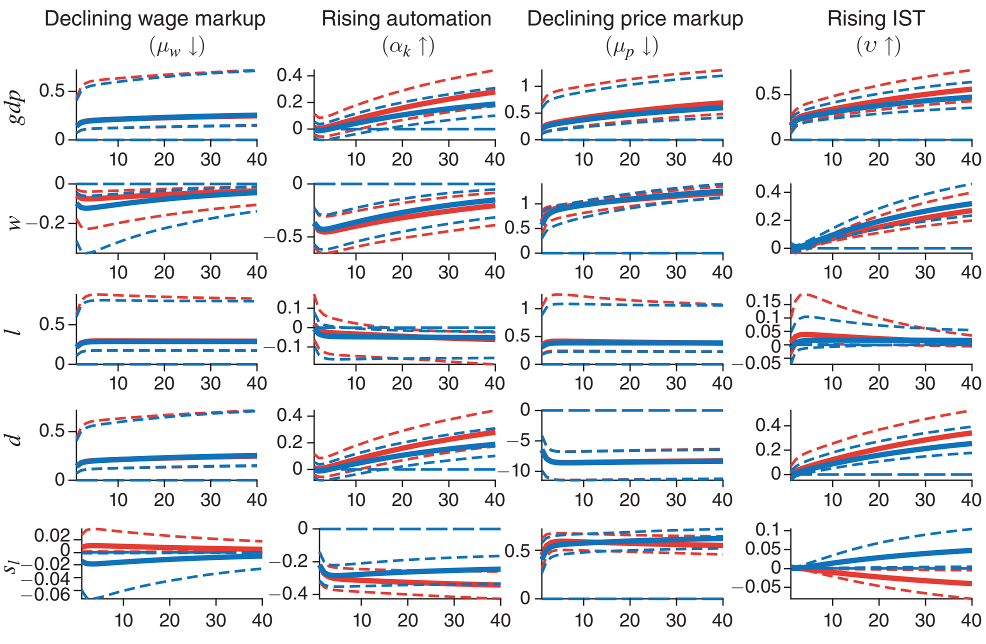

Figure 3. Simulation Results from the Baseline Model: $\eta < 1$ versus $\eta > 1$

Notes: This comparison of Monte Carlo results is based on 10,000 draws in the model with $\eta < 1$ (blue) and the model with $\eta > 1$ (red). The median (solid line) and 90 percent credible bands (dotted lines) are shown. Income shares are expressed in percentage point deviations from initial values. Remaining variables are expressed in percentage deviations.

also analyze the role of real and nominal frictions and find that impulse-response signs are unaffected by these from quarter 16 onward (see online Appendix A.4.2). Our restrictions are satisfied in the medium run, also, in a version of the model with sticky investment prices (results are available upon request), although the impact responses might differ (see Basu, Fernald, and Liu 2012 for further discussion).

Finally, we note that our model also implies certain long-run zero restrictions. For example, a wage markup shock has no long-run effects on the labor share and the automation shock has no long-run effects on real wages, while only the price-markup shock has permanent effects on the profit share. We can, in principle, impose these additional restrictions on the empirical model in order to further sharpen the identification of different shocks. However, some of the long-run effects predicted by our theoretical framework are not as general as the medium-run sign restrictions described above: for example, a wage-bargaining shock affects the labor share permanently in models with labor market frictions and wage bargaining, unlike in our simple framework.[8] We do not, therefore, impose any long-run zero restrictions in

[8] Bentolila and Saint-Paul (2003) show that, in a model with efficient bargaining, the long-run labor share declines in response to a decrease in the bargaining power of workers. Moreover, they find that the effect is ambiguous with "right-to-manage" bargaining, depending on whether or not capital and labor are net substitutes. By contrast, the short-run effect of bargaining power shocks in models with search-and-matching frictions is qualitatively consistent with the sign restrictions derived in our theoretical framework (cf. Foroni, Furlanetto, and Lepetit 2018 and Drautzburg, Fernández-Villaverde, and Guerrón-Quintana 2021).

TABLE 2—BASELINE SIGN RESTRICTIONS

	Labor's $\mathcal{M}_w\downarrow$	Automation $\alpha_k\uparrow$	Firms' $\mathcal{M}_p\downarrow$	IST $\Upsilon\uparrow$
GDP	+	+	+	+
Wages	−	−	+	+
Hours	+	−	/	/
Profits	/	/	−	+

Notes: The table lists sign restrictions on impulse responses in the empirical models. The restrictions are imposed at quarter 16 in the baseline specification.

the baseline but instead consider them as extensions in Section IV. Next, we lay out the details of the second step in our empirical strategy.

B. *Step Two—Empirical Specification*

The simulation results just described allow us to construct theory-robust sign restrictions that separately identify all four shocks under consideration. The sign restrictions used in our baseline SVAR model are derived from Figure 2 (or Figure 3) and summarized in Table 2. Combined, they account for all variation in data. Note, however, that the signs need not hold in the short run. Rather, we use them as medium-run to long-run restrictions in the empirical analysis. Our baseline identification scheme is one where the signs are imposed 16 quarters after shocks are realized, although alternative frequencies are explored as a robustness test. The use of permanent shocks and medium-run restrictions sets us apart from the more common focus on business cycle fluctuations in the SVAR literature (cf. Furlanetto, Ravazzolo, and Sarferaz 2019, among others).

We believe that our restrictions are intuitive and already established in the literature: more than twenty years ago, Blanchard (1997) discussed "labor supply factors," "shifts in the distribution of rents from workers to firms," and "technological bias against labor" as possible drivers of the labor share. In our framework, these drivers are equivalent to shocks to the wage markup, price markup, and automation respectively. Thus, all the economic mechanisms discussed by Blanchard (1997), including the fact that technological bias against labor may lead to a decrease in wages and hours, are consistent with the sign restrictions in Table 2.

For the empirical analysis, we consider the following reduced-form VAR model:

$$Y_t = C + \sum_{j=1}^{p} A_j Y_{t-j} + u_t, \tag{12}$$

where Y_t is a $n \times 1$ vector containing all the endogenous variables, C is a $n \times 1$ vector of constants, $A_1, \ldots, A_p$ are the $n \times n$ matrices of coefficients associated with the p lags of the dependent variable, and $u_t \sim N(0, \Sigma)$ is the $n \times 1$ vector of reduced-form residuals. We estimate the VAR model using Bayesian methods and the variables in first differences. This specification of the empirical model is motivated by our theoretical framework, where all variables follow separate stochastic trends conditional on the four shocks under consideration (wage markup, price markup, automation, and investment-specific technology). Thus, we consider an empirical framework with permanent shocks. We specify flat priors for the reduced-form parameters so that the posterior distribution has the usual Normal-Inverse-Wishart form and the information in the likelihood is dominant. In order to map the economically meaningful structural shocks from the estimated residuals, we need to impose restrictions on the variance-covariance matrix previously estimated. In particular, let $u_t = A\epsilon_t$, where $\epsilon_t \sim N(0, I_n)$ is the $n \times 1$ vector of structural disturbances with unit variance. A is a nonsingular parameter matrix such that $AA' = \Sigma$. In order to identify all the shocks in the system, we need at least $n(n-1)/2$ additional restrictions. The sign restrictions summarized in Table 2, which are mutually exclusive and jointly exhaustive, are sufficient to set apart our four structural shocks of interest. The signs are imposed using the QR decomposition algorithm proposed by Rubio-Ramírez, Waggoner, and Zha (2010).[9]

Our dataset is quarterly and spans the period 1983:I–2018:III. Consistent with the identification scheme summarized in Table 2, the set of endogenous variables Y_t includes four variables for the US economy: real GDP per capita, real hourly wages, hours worked per capita, and real per capita corporate profits after tax with inventory valuation and capital consumption adjustments. The first three variables are taken for the nonfarm business sector so that their combination results in BLS's headline measure of the labor share. The latter variable is taken from the BEA and has been used by De Loecker, Eeckhout, and Unger (2020) to externally validate their measure of profits, although they focus on the nonfinancial corporate sector. We take the log of all variables and then the first difference. The resulting series are multiplied by 100. The baseline model is estimated using four lags. As mentioned in the previous section, we impose our sign restrictions after 16 quarters, since at that horizon they are satisfied for nearly all parameterizations in our theoretical model (cf. in particular the response of output to an automation shock and the response of hours to an investment-specific change). Nonetheless, we checked the robustness of our main results by changing the horizon at which the medium-run restrictions are imposed and the number of lags we include in the system (see the online Appendix). The impulse responses of the labor share are then backed out from the impulse responses of real GDP, real wages, and hours worked. Specifically, as the variables in the system are in natural logarithms, the impulse responses of the labor share can be simply computed as a linear combination of the impulses of its components:

$$IRF_{LS,j} = IRF_{wages,j} + IRF_{hours,j} - IRF_{GDP,j} \quad \text{for } j = 0, \ldots, J$$

The same approach is used when we compute variance decompositions as well as the historical decomposition of the labor share data.

III. Results

This section documents our main empirical results, obtained from the estimated SVAR model.

[9] Additional details on the Bayesian estimation of the reduced-form VAR model and on the QR algorithm are provided in online Appendix B.

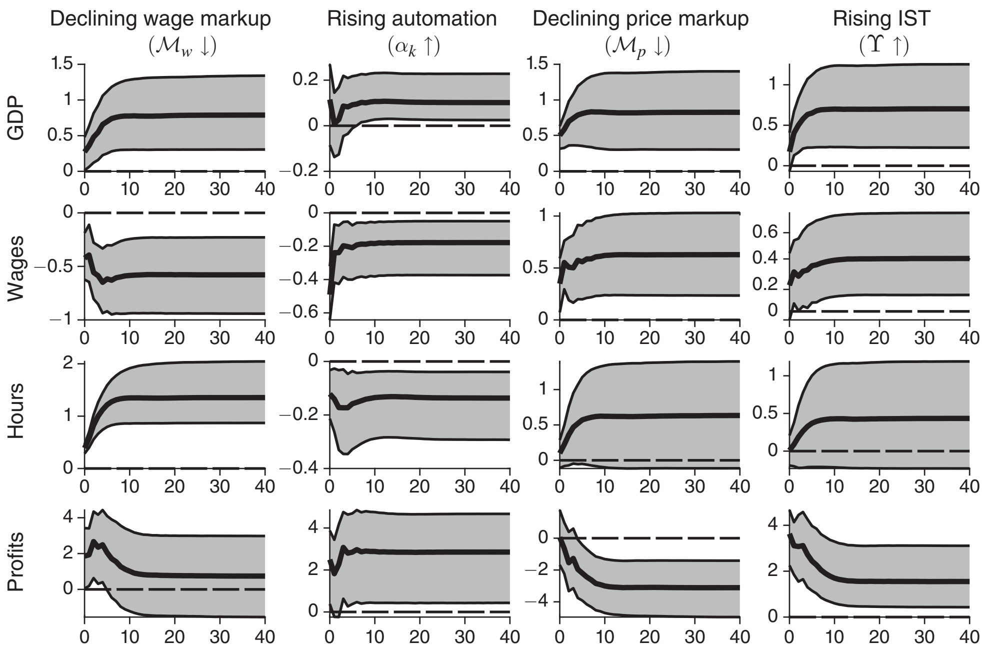

Figure 4. Empirical Impulse Responses from the Baseline SVAR Model

Notes: The figure shows posterior distributions of cumulated impulse responses to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68 percent probability density intervals (shaded area) are based on 10,000 draws. The median and the percentiles are defined at each point in time.

A. *Labor Share Responses to Structural Change*

We first use the estimated model to ask the following question: how does the labor income share respond to permanent changes in wage markups, automation, price markups, and investment-specific technology? Empirical cumulated impulse responses for the four variables included in the SVAR are reported in Figure 4. The implied labor share responses are documented in Figure 5. In both figures the horizontal axis measures time in quarters from impact to 40 quarters after innovations have occurred. The vertical axis represents the responses in percentages.

We start by considering a negative wage markup shock. This shock can be interpreted, for example, as a decrease in the bargaining power of workers. It leads to a higher GDP and increased hours, while wages drop. Without any restrictions on profits, we also obtain a persistent rise in the majority of draws. This is consistent with the theoretical framework. The more interesting response is that of the labor share, which declines significantly on impact. Intriguingly, a short-run decline in the labor share after falling wage markups is only consistent with complementarity between labor and capital. This is our first piece of indicative evidence about the likely size of η. Moreover, the median labor share response goes back toward zero after a few periods. Recall that the theoretical model implies a zero long-run effect on the labor share of shocks to the wage markup. Our empirical estimates recover that feature, but without any restrictions on the labor share response.

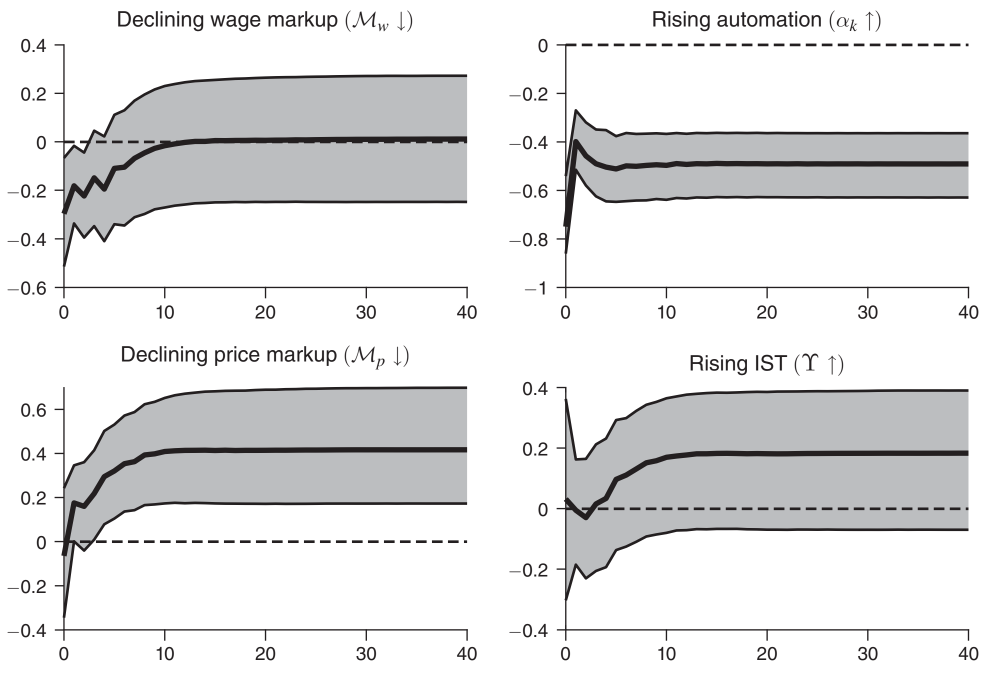

Figure 5. Implied Labor Share Responses to Structural Change

Note: The figure shows posterior distributions of cumulated impulse responses of the labor income share to an estimated shock of one standard deviation using the baseline identifying restrictions. The median (solid line) and 68 percent probability density intervals (shaded area) are based on 10,000 draws. The median and the percentiles are defined at each point in time.

Next, we consider the responses to a positive automation shock, identified by a rise in GDP at quarter 16, combined with negative wage and hours responses in that period. While the long-run dynamics of these variables are in line with the identification scheme, the very short-run effect on GDP is ambiguous. This is consistent with findings by Acemoglu and Restrepo (2018), who argue that automation might reduce economic activity in a transition period as firms and workers prepare for more automated production technologies. Without restricting profits, we also obtain a positive response as in the theoretical framework. The labor share, by contrast, decreases substantially and on a permanent basis.

The macroeconomic responses to an expansionary price-markup shock are reported in the third column in Figure 4. This shock is assumed to raise output and wages while at the same time lowering profits at quarter 16. We note that hours, which are left unrestricted, increase for the bulk of draws. More importantly, the labor income share that is plotted in Figure 5 rises unambiguously, as in the theoretical model, at least when we consider responses beyond the very short run. At lower frequencies, the median labor share response is sizeable.

Finally, the last column in Figure 4 documents how an investment-specific technology shock affects the observables in our model. GDP, wages, and profits increase by assumption (at quarter 16), but hours tend to rise too. More interestingly, after a few quarters the labor share responds positively in the vast majority

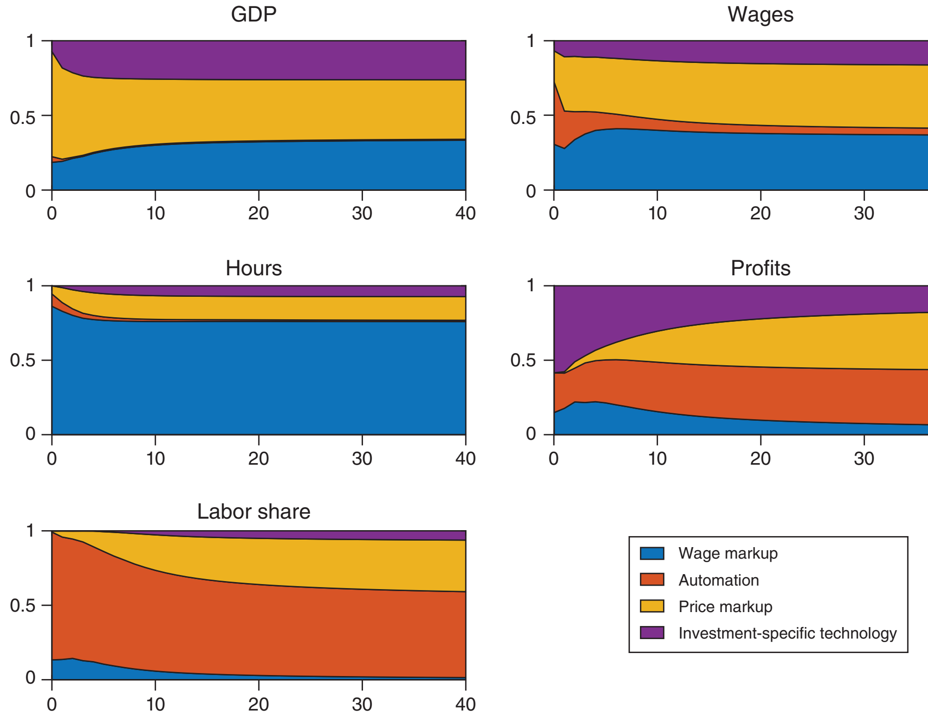

Figure 6. Variance Decompositions at Different Frequencies

Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance of each variable (in levels) at horizons $j = 0, 1, \ldots, 40$ using the baseline identifying restrictions.

of draws. This is shown in Figure 5. Thus, the SVAR is informative about the sign of the labor share response despite not imposing any restriction on this variable. From a theoretical point of view, the investment shock implies rising productivity of capital relative to labor. A positive labor share response in our empirical model is, therefore, consistent with an elasticity of substitution between labor and capital smaller than one. This is our second piece of evidence in favor of net capital-labor complementarity.

B. *What Are the Main Drivers of the Labor Share?*

Next, we ask the model to quantify the relative importance of the four structural shocks under consideration. To this end, we compute the share of the variance of a given variable attributable to each shock in the system. This is done at different frequencies from impact to 40 quarters ahead. Figure 6 shows the results.

Importantly, we find that at least half of the variation in the labor income share is due to automation. The role of automation is even more prominent in the short run, where it accounts for over 80 percent of fluctuations. At longer horizons, the remaining fraction of labor share fluctuations is mostly attributable to price-markup shocks, while investment-specific technology only plays a very minor role.

Wage markups have some explanatory power in the short run, but their importance becomes negligible at longer horizons.

All in all, automation and firms' markups are dominant drivers of the US labor income share, while investment or capital-biased technology are not. Such an important role for automation emerging from the SVAR can be explained on intuitive grounds: a positive automation shock increases output in the medium run and lowers wages and total hours, in keeping with the effects discussed in Acemoglu and Restrepo (2020). With the labor share defined as total labor income over output, we remark that the response of each variable favors a decline of the labor share. Put simply, the numerator of the labor share decreases, while the denominator increases. No other shock generates such a negative co-movement: investment-specific technology shocks stimulate output but also increase wages. A decline in the bargaining power of workers lowers wages but increases total hours worked. Finally, an increase in markups reduces labor income but at the same time generates a decline in output. Thus, all disturbances except the automation shock come with counteracting forces that effectively dampen the labor share response. This makes it harder for these other shocks to explain the large labor share decline of the last twenty years without the support of counterfactual implications. We note, however, that price markups still play a significant role. They imply negative co-movement between the growth rates of output and profits, suggesting that periods in which such negative co-movement takes place coincide with significant changes in the labor share.

Next, we discuss the role of the four identified shocks for the remaining variables in the system. A couple of remarks are warranted. First, investment-specific technology as well as wage and price-markup shocks explain the bulk of variations in GDP and wages. Fluctuations in hours, by contrast, are mainly driven by wage markups and to some extent by price markups. At first glance it might seem surprising that automation, while being important for the labor share, plays such a minor role for the macroeconomy. Note, however, that automation shocks are redistributive by nature: they shift the composition of factor use but do not necessarily lead to large changes in aggregate activity (see Acemoglu and Restrepo 2018 for further discussion). In addition, they generate countercyclical wages and hours that are not standard features of economic fluctuations, despite being very useful to generate the labor share decline. Turning to profits, they are well explained by investment-specific technology in the short to medium run, while price markups and automation have significant explanatory power in the long run. Our results are broadly in line with common findings in the literature on estimated macroeconomic models where these shocks are quantified. Note, however, our departure from that literature by focusing on permanent rather than temporary shocks.

C. *What Caused the Observed Labor Share Decline?*

Our final result concerns the relative importance of different explanations for the labor share decline observed in data. To this end, we carry out a historical decomposition of the labor share. Figure 7 displays the labor share decomposition in deviations from its mean. A brief remark about the deterministic component (initial

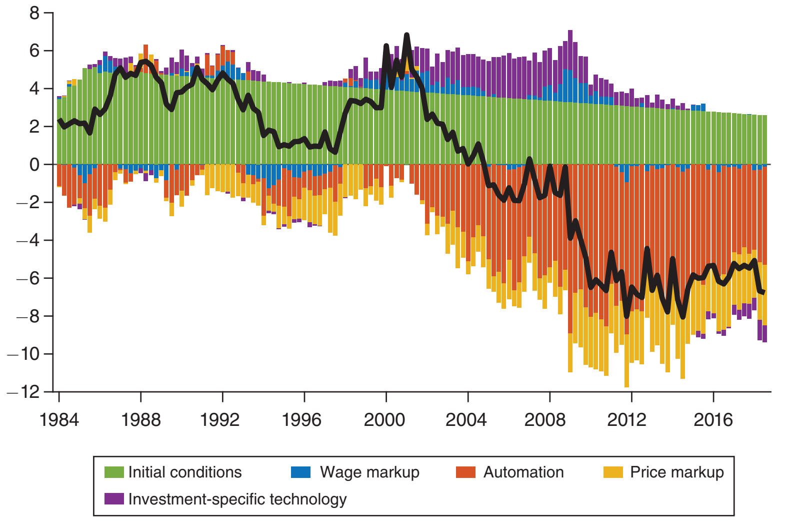

Figure 7. A Historical Decomposition of the Labor Share

Note: The colored bars present the evolution of the labor share, in deviations from its mean, attributable to the deterministic components (initial conditions) of the SVAR and to each structural shock, based on the median-target model of Fry and Pagan (2011).

conditions) is warranted. This component can be interpreted as our model-based forecast of the labor share in the very beginning of the sample, given the estimated SVAR coefficients and the initially discarded observations. That forecast entails an evolution of the labor share broadly in line with its initial observations. That is, the deterministic component does not play a big role in explaining the secular labor-share decline (see Giannone, Lenza, and Primiceri 2019 for a discussion on the pathological behavior of initial conditions in VAR models).

Turning to the structural shocks of interest, it is clear that, according to our model, automation and firms' rising market power are key for understanding the post-2000 labor share evolution. Automation has become an increasingly important factor since the early 2000s, while the role of price markup shocks is particularly important after 2009, in keeping with the decomposition presented in Giannoni and Mertens (2019). These results corroborate well with the view put forward by Elsby, Hobijn, and Şahin (2013): reasonable explanations for the labor share decline should be consistent with the timing of this decline. Automation and the large increase in profits are recent phenomena whose timing correlates well with the sharp decline of the labor share. By contrast, investment-specific technological progress and the decline in unionization, which could proxy a decline in wage markups, started long before the beginning of the new century.

Finally, we find that investment-specific shocks, if anything, have led to a mild increase in the labor share. This is particularly true during most of the 2000s. Again, the conditional labor share increase following rising investment-specific technology suggests net complementarity between labor and capital. Karabarbounis and Neiman (2014), by contrast, find that labor and capital are net substitutes. Given the debate

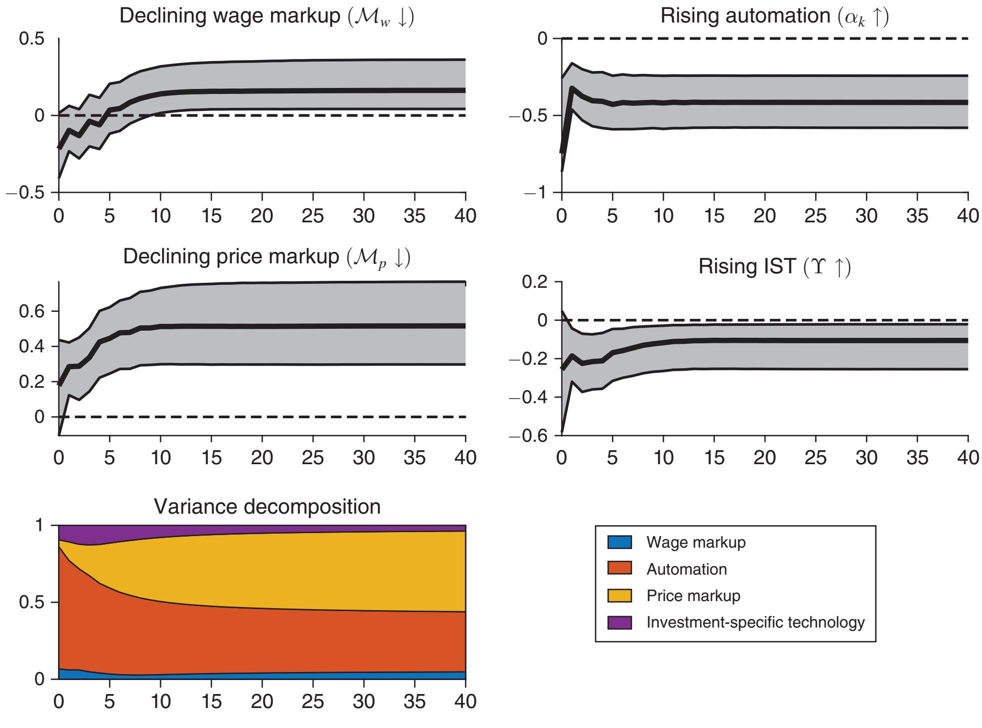

Figure 8. A Thought Experiment

Notes: The figure shows posterior distributions of cumulated impulse responses of the labor income share to an estimated shock of one standard deviation using the baseline identifying restrictions and imposing net substitution between capital and labor. The median (solid line) and 68 percent probability density intervals (shaded area) are based on 10,000 draws. The median and the percentiles are defined at each point in time. The colored areas represent the point-wise median contributions of each identified shock to the forecast-error variance of the labor share at horizons $j = 0, 1, \ldots, 40$.

on the degree of labor-capital substitutability, we now consider the following thought experiment: for the sake of argument, we suppose for a moment that capital and labor are net substitutes and restrict the SVAR model accordingly. We thus impose that the labor share is procyclical in response to price and wage markup shocks and countercyclical in response to automation and investment-specific shocks (sign restrictions are still imposed 16 quarters ahead). The resulting impulse responses, presented in Figure 8, merely reflect these identification assumptions. More interestingly, the variance decomposition obtained from this nonagnostic exercise reveals that although we impose a labor share decline in response to investment-specific innovations, these shocks turn out to be quantitatively unimportant. Shocks to automation and price markups remain the dominant drivers of the labor share, with the latter now explaining about 50 percent of the variance at the ten-year horizon. Thus, our baseline findings to do not depend on net complementarity between factors of production. This exercise constitutes, we believe, an important validation for the main results of our paper.

D. *Taking Stock—How to Interpret our Identified Shocks*

This paper shows that, from an empirical point of view, disturbances that generate a negative correlation between wages and GDP and, at the same time, a positive correlation between wages and total hours worked account relatively well for the labor income share in the postwar US economy. The most natural interpretation of these disturbances, in our view, is that they may capture automation of production processes in certain firms or industries. We note that the negative effects on both wages and hours worked set our estimated disturbances apart from most explanations about conventional, factor-augmenting technologies. Moreover, since the disturbances tend to cause co-movement between output and profits (or, alternatively, between output and nonlabor income), we find a pure markup explanation less likely. Although automation may come in different forms, we have in mind the kind described by Acemoglu and Restrepo (2018, 2020), where production processes are automated in such a way and at such a large scale that the importance of labor as a factor in production diminishes in aggregated data. It is on this basis that we label the estimated disturbances as "automation shocks."[10]

Nevertheless, additional explanations may still be consistent with the empirical patterns documented in this paper. One alternative is trends in globalization, import competition, or offshoring out of the US economy, as originally proposed by Elsby, Hobijn, and Şahin (2013). To this end, the relevant question for our purpose is how such trends would affect the taxonomy of shocks in Table 2. We acknowledge the possibility that globalization patterns may imply an increase in output and a decline in wages and hours worked, although there is no agreement in the literature on the magnitude of such displacement effects of globalization on the US labor market. However, we also note that recent analyses of industry-level and establishment-level data downplay the importance of open economy factors for labor share dynamics in the US economy (Giannoni and Mertens 2019; Autor et al. 2020).

Another possible explanation concerns changes in monopsony power. Again, the relevant question for our purpose is how monopsony power would affect the taxonomy of shocks. In a market with monopsony power, reductions in minimum wages (a classic example of reduction in the bargaining power of workers) are likely to result in lower hours and output, as shown in the seminal paper by Card and Krueger (2000). Alpanda (2018) adds monopsony power in the labor market into an otherwise standard New Keynesian model and also finds that a reduction in the bargaining power of worker leads to lower hours and output, unlike in our baseline model with monopolistic competition in the labor market.[11] In such a scenario, bargaining power shocks would satisfy the restrictions that we impose to identify investment-specific technology shocks, and the two shocks would be commingled. However, bargaining power shocks would not be mixed with automation.

[10] Some microfounded models of automation imply that TFP depends on the level of automation. In such a case, one may get a long-run rise in the real wage in response to an automation shock. However, as illustrated by Acemoglu and Restrepo (2018) in their Figure 6, the real wage still declines in the short to medium run unless the productivity effects are too large. We further discuss such productivity effects of automation in the online Appendix.

[11] Interestingly, Alpanda (2018) shows that the bargaining-power shock is the only shock whose transmission mechanism is qualitatively different in presence of monopsony power.

Finally, we emphasize the potential role played by so-called superstar firms, as proposed by Autor et al. (2020). They document rising concentration levels in several industries in the US economy, with significant reallocation of market shares toward certain large and capital-intensive "superstars." This between-firm reallocation of market shares, rather than a broad-based labor share decline within firms, is found to be the reason why one observes falling labor shares in aggregated data. Kehrig and Vincent (2020) obtain similar results but with a focus on the manufacturing sector. These results may, at least in part, reflect the emergence of platform competition or advances in information technology, as argued by Aghion et al. (2022). Baqaee and Farhi (2020) find that the reallocation of market shares has led to a large increase in TFP and thus to an increase in output. Taken together, therefore, it seems reasonable that the emergence of superstar firms led to a rise in aggregate output and a decline in total hours. It is not obvious where such technology-driven reallocation would show up in our framework. Given the taxonomy in Table 2, the behavior of real wages becomes crucial: if the emergence of superstar firms is associated with lower wages, then this event would be bundled together with our automation shock. If it is associated with a wage increase, by contrast, then we obtain a new set of sign patterns that have not been considered so far: a disturbance causing positive co-movement between output and wages and negative co-movement between wages and hours. While neither of the two cases can be ruled out, we believe that the available evidence favors a wage increase as a response to a "superstar firm shock." In fact, both Autor et al. (2020) and Kehrig and Vincent (2020) find that fast-growing establishments featuring a low labor share tend, if anything, to pay somewhat higher wages than their peers. Therefore, as a sensitivity check, we extend our baseline empirical model to include a superstar firm shock. This shock is defined in Table 3. We also introduce a new observable variable, the utilization-adjusted TFP series provided by Fernald (2014). In order to be consistent with microeconomic evidence suggesting a cross-sectional reallocation mainly in terms of output per worker (and not in terms of wages), we impose the conservative assumption that the labor share has to decrease in response to a superstar firm shock. This assumption is well in line with the narrative of how superstar firms affect the labor share. The estimated variance decompositions of TFP and the labor share are shown in Figure 9. Consistent with microeconomic findings, our superstar firm shock turns out to be a major source of fluctuations in TFP. However, this shock plays a rather limited role for the labor share, despite our restriction that the labor share should decline.[12] Automation and price markups, instead, remain the main drivers in this respect.

All in all, we stress that disturbances generating negative co-movement between wages and GDP and positive co-movement between wages and hours are found to be important for the US labor share. While we interpret these disturbances as automation shocks, it is certainly possible to entertain the idea that other structural factors produce the same type of co-movements in the data. But for this to be the case, these other factors need to operate through channels that are more sophisticated than the conventional ones emphasized by our simple, theoretical framework.

[12] The superstar firm shock becomes even less important for the labor share if we leave it unrestricted.

Table 3—Sign Restrictions with TFP and an Identified Superstar Firm Shock

	Labor's $\mathcal{M}_w\downarrow$	Automation $\alpha_k\uparrow$	Firms' $\mathcal{M}_p\downarrow$	IST $\Upsilon\uparrow$	Rising superstar firms
GDP	+	+	+	+	+
Wages	−	−	+	+	+
Hours	+	−	/	+	−
Profits	/	/	−	+	+
TFP	/	/	/	/	/

Note: The restrictions are imposed at quarter 16.

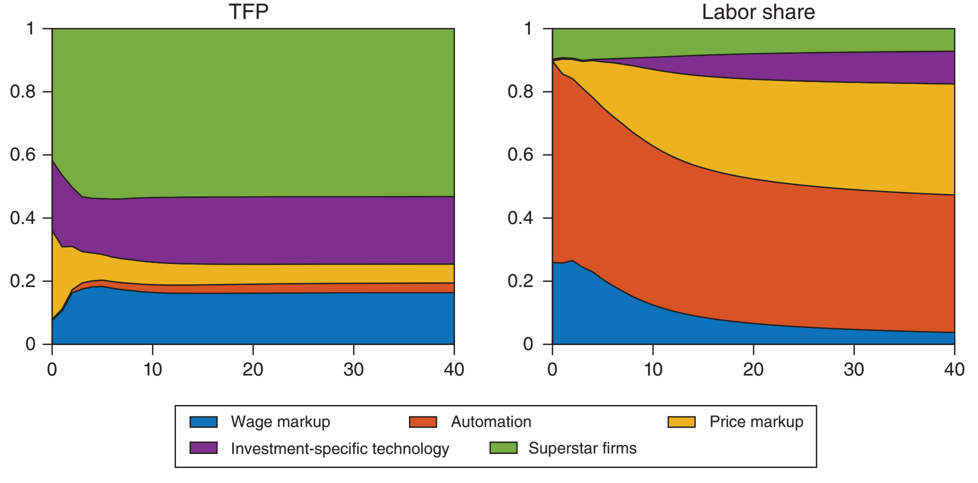

Figure 9. An Assessment of Technical Change Due to Superstar Firms

Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance of each variable (in levels) at horizons $j = 0, 1, \ldots, 40$.

IV. Robustness and Extensions

We have conducted an extensive battery of robustness tests in order to evaluate how sensitive our main results are to perturbations to the baseline setup. These robustness tests are discussed in detail in the online Appendix and we only summarize them briefly here. First, we perform a Monte Carlo study in order to assess whether the sign restriction scheme is able to identify the main drivers of the labor income share. Second, we inspect the role of the horizon in which sign restrictions are imposed as well as lag specifications in the SVAR, samples, and priors. Third, we investigate whether the measurement of profits and other nonlabor income affects the results. Fourth, we exploit additional medium-run and long-run (overidentifying) restrictions implied by the theoretical framework. Finally, we dig deeper into selected labor market effects, including the responses of routine and nonroutine employment. This rather broad set of exercises documents that our main results are remarkably robust to changes in the baseline setup. Automation and price markups, in particular, explain the bulk of labor share fluctuations across all sensitivity checks. Interested readers are invited to consult online Appendix C for further details. In the remainder of this section, we document a few extensions and sensitivity checks of special interest.

A. *Capitalization of IPP*

In a recent paper, Koh, Santaeulàlia-Llopis, and Zheng (2020) investigate implications for the labor share of a change in how the Bureau of Economic Analysis (BEA) treats intellectual property products (IPP) in the national accounts. The authors note that IPP, which used to be defined as intermediate expenditure, has been revised so that it now enters in the product accounts as investment. By construction, the movement of IPP from intermediate expenditure to investment implies an increase in GDP. In order to preserve the accounting identity between product and income accounts, this GDP increase must then be matched by an equal rise in one or several posts in the income accounts. How this newly recognized income affects the measured labor share depends crucially on how it is distributed between labor and capital, as emphasized by Koh, Santaeulàlia-Llopis, and Zheng (2020). The BEA attributes the entire contribution of IPP to gross operating surplus, i.e., to nonlabor income. This naturally implies a mechanical downward shift in the measured labor income share. Moreover, since IPP has grown at a faster rate than GDP since 1929, the labor share trend is also affected. Interestingly, Koh, Santaeulàlia-Llopis, and Zheng (2020) find that the entire secular decline of the labor income share during the last 90 years disappears if they "de-capitalize" IPP by following the same accounting rules as the BEA did before 1999. The question, then, is how much of the IPP income—if any—should be treated as labor income, and how this in turn affects secular trends in the labor share. Koh, Santaeulàlia-Llopis, and Zheng (2020) argue that the split chosen by the BEA is too extreme.

We do not take a stand on this question, but ask instead if our main results are affected by the BEA's revision of accounting standards. To this end, we decapitalize IPP following the procedure in Koh, Santaeulàlia-Llopis, and Zheng (2020), where IPP is subtracted from GDP. Our measure of the resulting labor share with decapitalized IPP is shown in Figure 10, panel A.[13] Consistent with Koh, Santaeulàlia-Llopis, and Zheng (2020), we obtain an IPP-adjusted labor share, which is both higher at any given point in time and displays less of a downward trend than its counterpart based on the current BEA revision standard.[14] Since the data on IPP are yearly, we next estimate two annual versions of the baseline SVAR model: one with and one without IPP adjustments. The first is our annual baseline; the second is consistent with the BEA accounting standards before 1999. The variables in the system are as before, but now for the total economy and deflated with the GDP deflator as well

[13] The IPP-adjusted labor share series in Koh, Santaeulàlia-Llopis, and Zheng (2020) starts in 1929, but we only plot it from 1948 and onward. This is because the decomposition of labor income into wages and hours worked goes back to 1948, and our identification scheme requires us to observe that decomposition.

[14] The linear trend for the IPP-adjusted labor share has a slope coefficient of -0.03, while the BEA labor share has a slope of -0.07. Compared with Koh, Santaeulàlia-Llopis, and Zheng (2020), we obtain a slightly negative slope for the IPP-adjusted labor share because our sample starts in 1948. The slope in Koh, Santaeulàlia-Llopis, and Zheng (2020) is instead affected by a historically low labor share in 1929, at 62 percent.

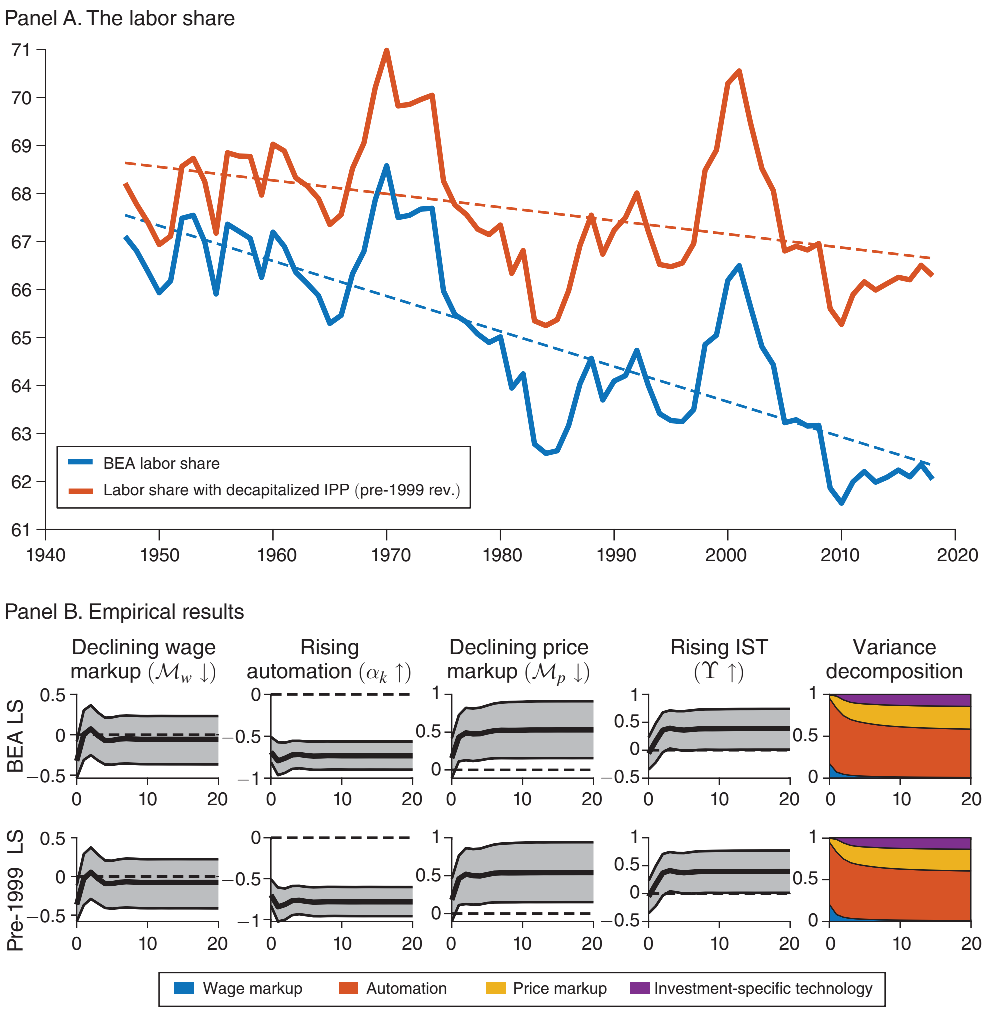

FIGURE 10. THE ROLE OF IPP CAPITALIZATION

as the civilian population.[15] Real wages are computed by summing the compensation of employees to the share of ambiguous labor income and then dividing by hours of all persons and employees from the BEA. The sample covers the period 1948–2018. Our SVAR model is estimated with one lag, and we impose the baseline sign restrictions from Table 2 at horizon 4. Results are shown in Figure 10, panel B. Interestingly, the main results from Section III are robust to both the use of annual data (first row) and to our decapitalization of IPP (second row). Automation remains the main driver of the labor share, although investment-specific technology becomes

[15] Here we use the total economy in order to match exactly the data in Koh, Santaeulàlia-Llopis, and Zheng (2020). Results are almost identical if we instead consider the nonfarm business sector. These results are available upon request.

somewhat more important compared with the baseline in Figure 6. However, we still find that the investment-specific shock leads to a persistent rise in the labor share after a few years. All in all, the important role for automation and price-markup shocks is also confirmed when using the labor share series with decapitalized IPP.

B. *Measurement of Labor Income*

The seminal paper by Elsby, Hobijn, and Şahin (2013) documents challenges associated with the measurement of labor income. From an accounting perspective, total labor income $W_t L_t$ is the sum of labor income for payroll workers, $W_t^p L_t^p$, and labor income for self-employed workers, $W_t^s L_t^s$. The statistical treatment of the latter group is subject to substantial debate because measured income for the self-employed, or so-called "proprietors' income," reflects returns on both work effort and investment. Thus, there is no straightforward way to disentangle labor payments from revenues that accrue to capital. The BLS assumes that self-employed workers pay themselves the average hourly wage of workers on payroll, so that

$$s_{l,t} = \frac{W_t^p L_t^p}{Y_t} + \frac{W_t^p L_t^s}{Y_t} = \left(1 + \frac{L_t^s}{L_t^p}\right)\frac{W_t^p L_t^p}{Y_t}.$$

As noted by Elsby, Hobijn, and Şahin (2013), this assumption likely results in an overstatement of the overall decline of the labor share and even implies a negative capital share in the proprietors' sector in the 1980s.

We address this measurement issue in four different ways: first, by focusing solely on $\frac{W_t^p L_t^p}{Y_t}$, which Elsby, Hobijn, and Şahin (2013) refer to as the nonfarm payroll share. This measure unambiguously reflects payments to labor since it takes self-employment income out of the picture. Second, we consider the labor share for the nonfinancial corporate sector, as proposed by Karabarbounis and Neiman (2014). Corporations must declare payrolls and profits separately for fiscal purposes. Thus, there is no ambiguity in the way income is treated and how it accrues to labor or capital. However, this comes at the cost of focusing on a smaller share of the economy. Third, we consider the measure referred to by Kravis (1959) and Gomme and Rupert (2004) as the "economy-wide" labor share. The assumption underlying this measure is that the self-employment labor share is the same as that of the overall economy. This assumption allows us to restrict attention to $\frac{W_t^p L_t^p}{Y_t - Y_t^s}$, where Y_t^s is proprietors' income without consumption allowances and inventory valuation adjustment. Finally, we consider the labor share in manufacturing using annual data, which is of interest in its own respect. Throughout, we adjust the other variables in the SVAR model so that they correspond to the labor share measure used.

Results with the four alternative measures (payroll, nonfinancial corporate, economy-wide and manufacturing) are summarized in Figure 11. In sum, our baseline results are robust across different definitions of the labor share, with price markup shocks and automation accounting for the bulk of variation in labor share

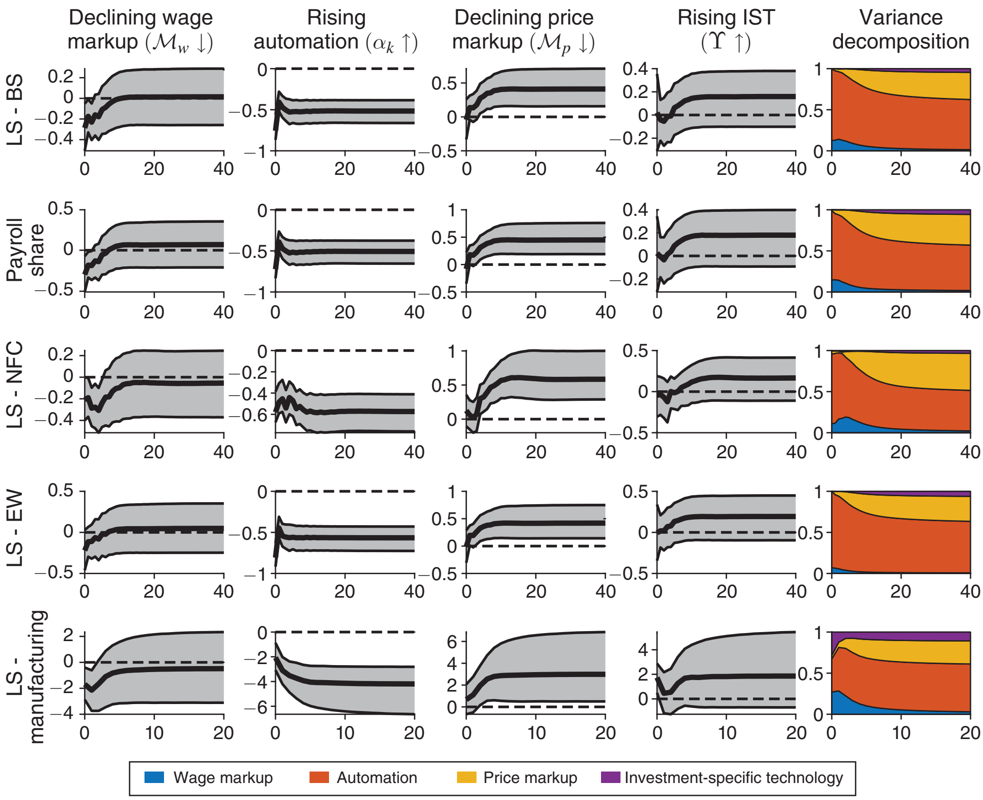

Figure 11. Empirical Impulse Responses with Alternative Labor Share Measures

Notes: The figure shows posterior impulse responses and variance decompositions. The horizontal axes with manufacturing data present periods in years. See Figure 4 and Figure 6 for further details.

data. Price markups become slightly more important for low-frequency fluctuations in the labor share when we restrict our analysis to the nonfinancial corporate sector. This result is not too surprising given a relatively large increase in the profits-to-GDP ratio for the nonfinancial corporate sector compared with the overall economy. Finally, the labor share responses to investment-specific technology shocks are mostly positive, while they are negative on impact in response to wage markups regardless of the measure used. Thus, our indicative evidence of labor-capital complementarity is confirmed across all measures of the labor income share.

C. *Introducing the Relative Price of Investment*

Finally, in order to assess the external validity of our empirical approach, we investigate how our identified shocks relate to the relative price of investment, an economic variable of particular interest. Up until now the investment price, which is readily observable in the national accounts, has not been used at all to inform our estimates. Yet, the theoretical framework in Section I offers rather broadly accepted predictions, which can be used to gauge the main results. The investment-specific

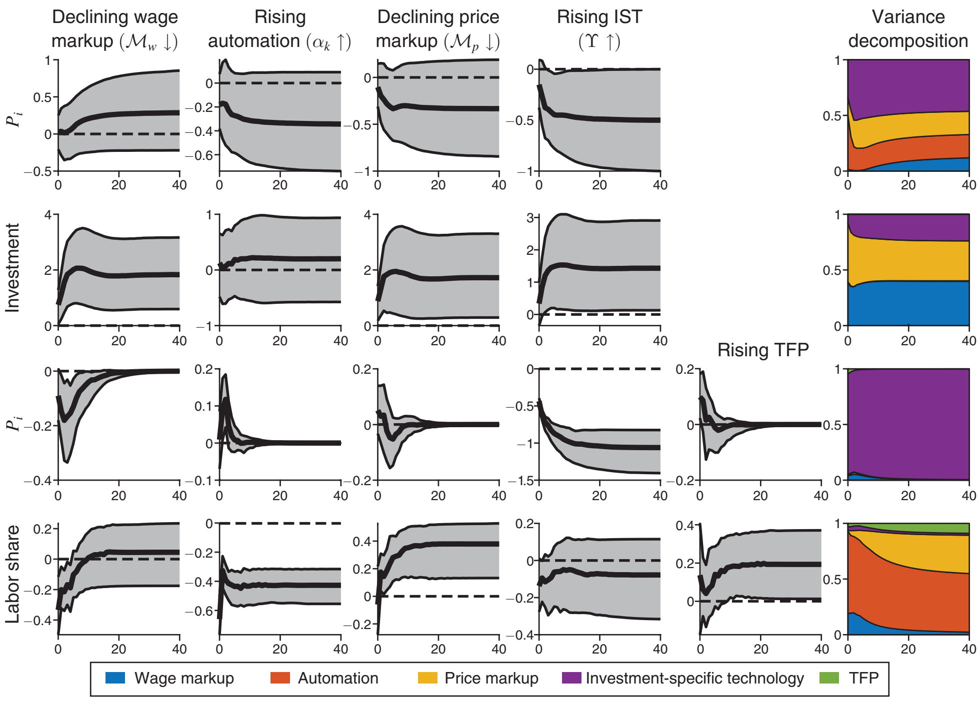

Figure 12. Empirical Results with the Relative Price of Investment

Notes: The figure shows posterior impulse responses and variance decompositions. See Figure 4 and Figure 6 for further details.

technology shock, in particular, should reduce the relative investment price, stimulate real investments, and be a major driver of investment prices in the long run (Fisher 2006). Karabarbounis and Neiman (2014) even use the relative price of investment as a proxy for investment-specific technology shocks. To this end, one can check whether such theoretical predictions hold up when the investment price is included in the SVAR without any restrictions. In what follows we add, one by one, the relative price of investment and real investments per capita. We then estimate the augmented SVAR with the baseline restrictions shown in Table 2.

The results are reported in the first two rows in Figure 12. The first row presents the impulse responses and the variance decomposition of the relative price of investment. Remarkably, a rise in investment-specific technology causes the relative investment price to decline permanently. Moreover, this shock is also its main driver. We find these results reassuring since none of them were imposed. The second row in Figure 12 presents the results for real per capita investment. The investment variable increases significantly and permanently in response to wage markup, price markup, and investment-specific technology shocks. Two results stand out: first, in line with the work of Gutiérrez and Philippon (2017), price markups are important drivers of investment and thus might help to explain its recent slowdown. Second, automation does not seem to affect this variable at all, in line with its small effect on aggregate variables observed in Section III.

As a final exercise involving the investment price, we exploit the theoretical prediction that only the investment-specific technology shock can affect it permanently, as in Fisher (2006). The motivation is twofold: first, this restriction allows us to disentangle investment-specific technology shocks from TFP and other technological innovations. This is useful since TFP, for example, may be confounded in the signs currently used to identify investment-specific technology. Second, the use of long-run zero restrictions may help to sharpen our identification of other shocks in the system as well. To this end, we (i) separate TFP and investment-specific technology from the other driving forces by imposing the sign restrictions in Table 2, where the last column now applies also to TFP, and (ii) separate TFP from investment-specific shocks by adding a long-run zero restriction on the response of investment prices to all shocks except those to investment-specific technology. In order to appropriately combine the zero and sign restrictions, we use the "state-of-the-art" algorithm recently introduced by Arias, Rubio-Ramírez, and Waggoner (2018).

The third and fourth rows in Figure 12 summarize the results when we add the relative investment price as an observable and disentangle TFP from investment-specific technology in the way described above. Interestingly, we find a decline in the investment price in response to investment-specific shocks that is tightly estimated compared with the case where we do not impose any long-run restrictions (Figure 12, first row). Naturally, the long-run zero restrictions force investment-specific technology to explain virtually all the fluctuations in investment prices, at least at low frequencies. Moreover, while TFP now accounts for most of the labor share fluctuations previously interpreted as being driven by investment-specific technology, we keep the conclusion that automation and price markup shocks explain the lion's share.

V. Conclusions

The labor share of national income has fallen in many countries in the last decades. In the United States, the labor income share has accelerated its decline since the beginning of the new century, reaching its lowest postwar level in the aftermath of the Great Recession. While this observation has led to substantial interest among policy makers and in the popular press, a consensus view regarding the structural forces at play is still lacking. In this paper, we quantify and interpret four main explanations for the secular decline of the US labor income share. To this end, we estimate a time series model with permanent shocks, identified with theory-robust sign restrictions. To the best of our knowledge, this is the first paper to quantify the relative importance of these forces within a unified framework. Moreover, our econometric approach to achieve identification differs fundamentally from previous literature: while most studies draw inferences based on cross-sectional variation in microeconomic data (at the firm or sectoral level), we instead exploit the time series properties of macroeconomic data, thus providing a potentially useful complement to the existing literature.

Our main empirical results can be summarized as follows: first, in the postwar US economy, automation and firms' rising market power unambiguously lower the labor income share, while capital deepening in the form of higher investment-specific technology growth tends to raise it. The latter result suggests that labor and capital are net complements as factors of production. Second, the estimated model assigns a major role for automation and firm markups as drivers of labor's income share, especially at lower frequencies. The labor share implications of shocks to labor's markup and investment efficiency, by contrast, are not supported by aggregate time series data on labor income. Third, we decompose the historical evolution of the US labor income share and find that most of the precrisis decline can be attributed to automation, while firms' rising market power has been an increasingly important source of low labor shares since the Great Recession. Interestingly, our historical decomposition suggests that investment-specific technology has tended to raise the US labor income share, at least in the 2000s.

While this paper offers a benchmark account of the evolution of labor shares in the postwar US economy, we acknowledge that more work needs to be done on the precise transmission mechanisms involved. Disentangling the automation narrative from globalization, for example, seems a fruitful area for future research. Moreover, we have ignored distributional aspects such as those studied by Moll, Rachel, and Restrepo (2019). Extending our setup to study questions related to the cross-sectional effects of automation and market power will likely be an important research topic going forward.

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