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THE DECLINE OF THE LABOR SHARE: NEW EMPIRICAL EVIDENCE*

DRAGO BERGHOLT§, FRANCESCO FURLANETTO† AND NICOLÒ MAFFEI FACCIOLI‡

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Abstract: We estimate a structural vector autoregressive model in order to quantify four main explanations for the decline of the US labor income share: (i) rising market power of firms, (ii) falling market power of workers, (iii) higher investment-specific technology growth, and (iv) the widespread emergence of automation or robotization in production processes. Identification is achieved with theory robust sign restrictions imposed at medium-run horizons. The restrictions are derived from a stylized macroeconomic model of structural change. Across specifications we find that automation is the main driver of the long-run labor share. Firms' rising markups can, however, account for a significant part of the accelerating labor share decline observed in the last 20 years. Our results also point to complementarity between labor and capital, thus ruling out capital deepening as a major force behind declining labor shares. If anything, investment-specific technology growth has contributed to higher labor income shares in our sample.

Keywords: *Labor income share, secular trends, technological progress, market power.*
JEL Classification: *E2, D2, D4, J3, L1.*

1 INTRODUCTION

Labor's share of national income has fallen in many countries in the last decades. In the US, the labor income share has accelerated its decline since the beginning of the

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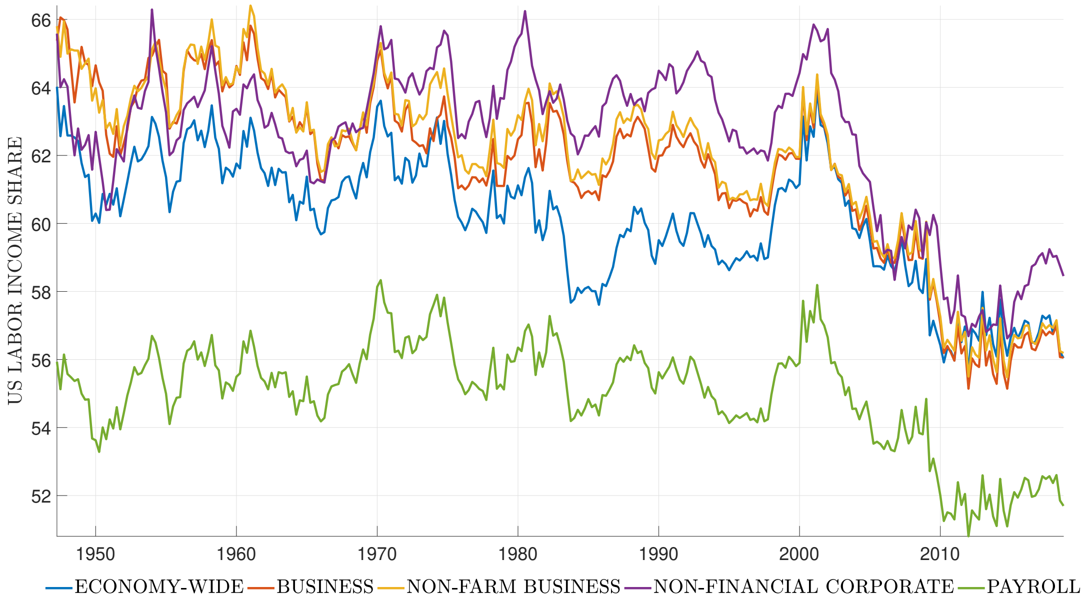
Figure 1: The US labor income share over time



Source: Bureau of Labor Statistics and authors' calculations.

new century, reaching its postwar lowest level in the aftermath of the Great Recession (Elsby, Hobijn, and Sahin, 2013). Figure 1 documents the evolution of five alternative measures of the US labor income share (subsection 5.2 provides a detailed description of the measures). While each series implies a somewhat different trend, they have all gone through a clear fall in the last 20 years. In addition, Gutierrez and Piton (2019) show that, while the evidence for a global decline of the labor share across major economies is weaker, the recent decline in the US is undisputed, with several potential implications for policy and welfare. 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, 2018; De Loecker and Eeckhout, 2017; Eggertsson, Robbins, and Wold, 2018; Gutierrez and Philippon, 2017). These studies find evidence of declining competition and increasing market concentration. The claim is that trends in firms' market power has 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, 2019, 2018; Autor and Salomons, 2018; Leduc and Liu, 2019; Martinez, 2018). Acemoglu and Restrepo (2019), 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 US. 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 á 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 (2018)). We then consider the macroeconomic implications of each candidate explanation under a broad set of model parameterizations. In particular, we show that they can be separately identified by a combination of medium-run sign restrictions that are mutually exclusive and jointly exhaustive. Second, this set of restrictions is used to identify the structural shocks in the empirical model. As a byproduct, 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 inference 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 normally done in the business cycle literature. To the best of our knowledge, this is the first paper using 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) amongst 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 1983Q1-2018Q3. 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. 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.

Our empirical findings help to assess various the explanations of declining labor shares. They are well in line with the view that tasks previously done by human workers have been taken over by robots on a significant scale in recent years (Acemoglu and Restrepo, 2019; Autor and Salomons, 2018; Leduc and Liu, 2019; Martinez, 2018), but also with stories about increased market concentration (Barkai, 2018; De Loecker and Eeckhout, 2017; Eggertsson et al., 2018; Gutierrez and Philippon, 2017). Moreover, while our results confirm that capital deepening in the form of investment-specific technology growth has taken place in the last decades (Karabarbounis and Neiman, 2014), we find that net complementarity between labor and capital has led to a crowding-in of labor rather than the opposite.

Interestingly, we reach our conclusions using a fundamentally different approach than the aforementioned studies. Moreover, our results do not seem to suffer from the timing issue put forward by Elsby et al. (2013), who note that some of the explanations for falling labor shares rely on trends that started decades before the labor share decline. All in all, the 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 (2019). With the labor share defined as total labor income over output, we emphasize that the response to automation of each of these variables 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 between wages and labor productivity. Note, however, that 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 characteristic of economic fluctuations.

The literature on falling labor income shares has exploded in recent years and several explanations have been proposed in addition to those included in our baseline model: Rognlie (2015) focuses on developments in the housing sector and 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 why labor shares are falling within many industries, although the aggregate effects are milder. Glover and Short (2017) formalize a hypothesis linking an aging workforce to the declining labor share. Kaymak and Schott (2018) focus on the manufacturing sector and emphasize the role played by corporate tax cuts. Finally, Elsby et al. (2013) argue that globalization, and the process of off-shoring of intermediate goods production to developing countries in particular, is a promising candidate for the decline in the labor share. In later sections, we discuss how our identification approach and main results might be interpreted in light of some alternative explanations.

An important strand of the literature has focused on issues related to the measurement of labor income. The seminal paper by Elsby et al. (2013), for example, discusses how mis-measurement of income earned by the self-employed may exaggerate the recent decline in the labor income share. More recently, Koh, Santaeulalia-Llopis, and Zheng (2018) argue that the long-run post-war trend in labor income may be driven by the capitalization of intellectual property products (IPP). In fact, the Bureau of Economic Analysis (BEA) has revised the treatment of IPP from an accounting perspective by attributing the entire rents from IPP investment to capital income. This choice affects the long-run trend in the labor share series but not its steep decline in recent years. Finally, disentangling the capital share of income and the profit share of income has proven to be challenging from an empirical point of view. Barkai (2018) argues that pure profits have increased substantially in recent years, while the capital share has decreased. Karabarbounis and Neiman (2018) claim that the residual payments (referred to as "factorless income") obtained after measuring the labor share and the capital share 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 will conduct an extensive sensitivity analysis using alternative measures for those variables.

The rest of the paper is organized as follows: Section 2 describes a theoretical model of structural change. Section 3 derives the set of theory robust sign restrictions, lays out the econometric methodology and discusses identification. Section 4 documents our main empirical results. Section 5 provides a battery of robustness tests and extensions. Finally, Section 6 concludes.

2 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 due to (i) investment-specific technical change, (ii) automation of labor-intensive production tasks, (iii) distortions in labor markets, and (iv) changes in the market power of firms. The resulting framework is, with minor deviations, similar to those used by Karabarbounis and Neiman (2014), Barkai (2018) and Caballero, Farhi, and Gourinchas (2017), amongst 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.

2.1 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 towards 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.

2.2 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 US.

2.3 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:

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

2.4 HOUSEHOLDS

There is a unit mass of optimizing households in the economy. Household $n \in [0,1]$ derives utility from consumption and dis-utility 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 $\mathbb{E}_t \sum_{s=t}^{\infty} \beta^{s-t} \mathcal{U}_{n,s}$, 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, as well as five optimality conditions. We define the gross wage markup as $\mathcal{M}_{w,t} = \frac{W_t}{MRS_t}$, where MRS_t is the marginal rate of substitution between labor and consumption. Optimality conditions are stated below:

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

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

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

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

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

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 (2017), 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.

2.5 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. $\alpha_{k,t}$, in 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 et al. (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 market concentration, segmentation, product specialization, or other factors that affect the degree of competition between firms (Barkai, 2018). 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.

2.6 Aggregation and income accounting

Market clearing in labor and capital markets dictate that:

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

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

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

Income shares in our simple model are defined accordingly:

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

Moreover, $s_{l,t} + s_{k,t} + s_{d,t} = 1$. 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 non-stochastic equilibrium outcome once all shock dynamics have settled down. In the 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- 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 3.

2.7 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:

$$\frac{\mathcal{M}_{p,t}}{\mathcal{M}_{p,t-1}} = 1 + g_{p,t} = (1+g_p)\exp(z_{p,t}) \qquad \frac{\mathcal{M}_{w,t}}{\mathcal{M}_{w,t-1}} = 1 + g_{w,t} = (1+g_w)\exp(z_{w,t})$$
$$\frac{\Upsilon_t}{\Upsilon_{t-1}} = 1 + g_{\Upsilon,t} = (1+g_\Upsilon)\exp(z_{\Upsilon,t}) \qquad \frac{\alpha_{k,t}}{\alpha_{k,t-1}} = 1 + g_{\alpha_k,t} = (1+g_{\alpha_k})\exp(z_{\alpha_k,t})$$

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 $\varepsilon_{p,t}$, $\varepsilon_{w,t}$, $\varepsilon_{\upsilon,t}$ 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.

3 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 et al. (1978), for example, derive non-identification from the sign patterns produced by a fairly general class of neoclassical production functions.[1] More recently, León-Ledesma et al. (2010) claim that the "impossibility theorem" developed by Diamond et al. (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 (2019), 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 which 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.[2]

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 check and show that the main results are robust to additional elasticity

[1] 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).

[2] See León-Ledesma and Satchi (2018) for an application. When estimating their model, the authors impose restrictions on the elasticity of substitution between labor and capital.

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

Note: Bounds for the uniform distributions. Notation: M $\rightarrow$ median; LB $\rightarrow$ lower bound; UB $\rightarrow$ 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.

restrictions. The rest of this section lays out the details of our empirical strategy.

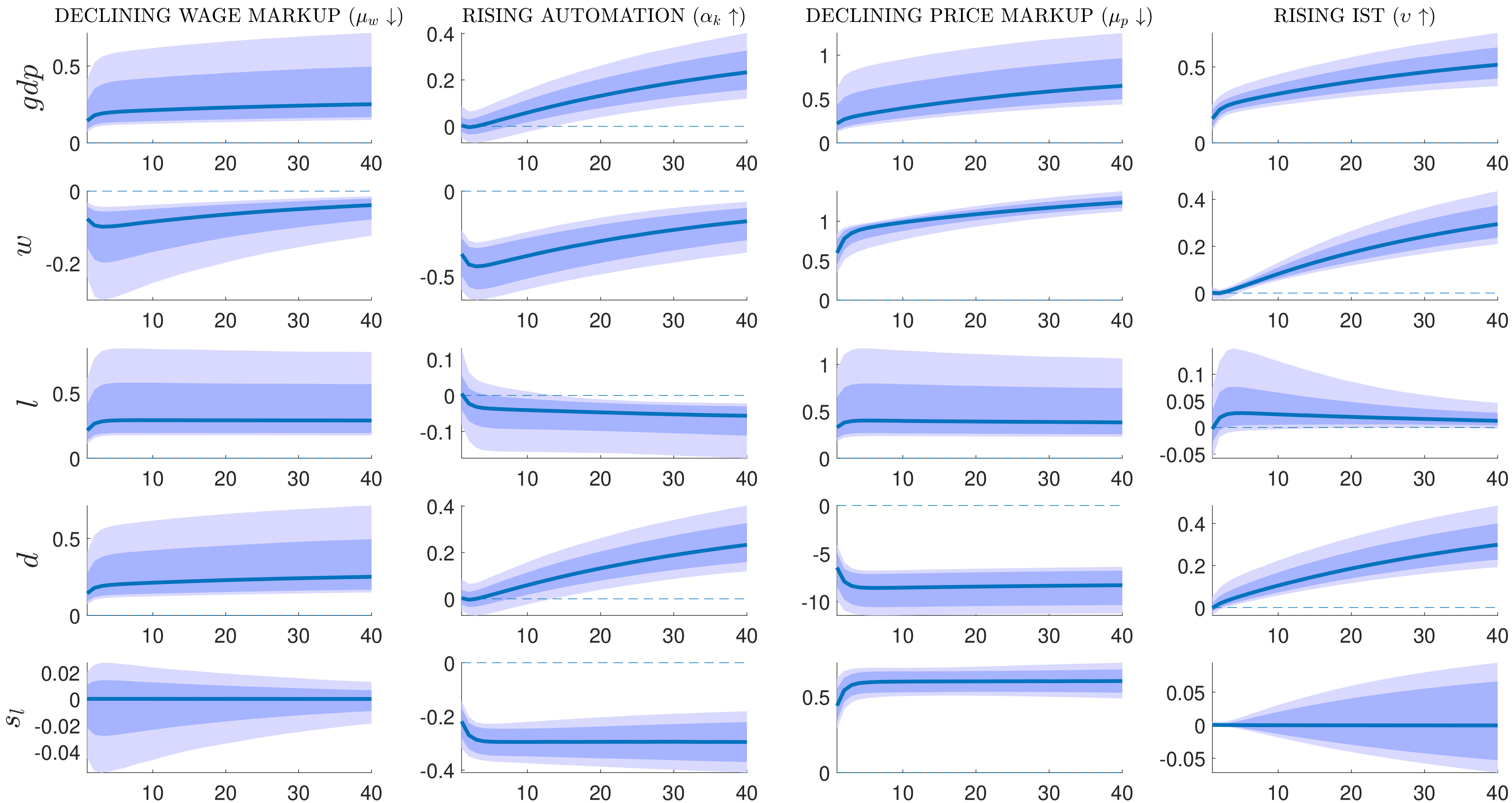
3.1 Step one – Theory robust sign restrictions

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.[3] 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, León-Ledesma, McAdam, and Willman (2014) for discussion of the latter issue). Therefore, for every simulation we draw initial income shares and add them to the

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

Figure 2: Simulation results from the baseline theoretical model



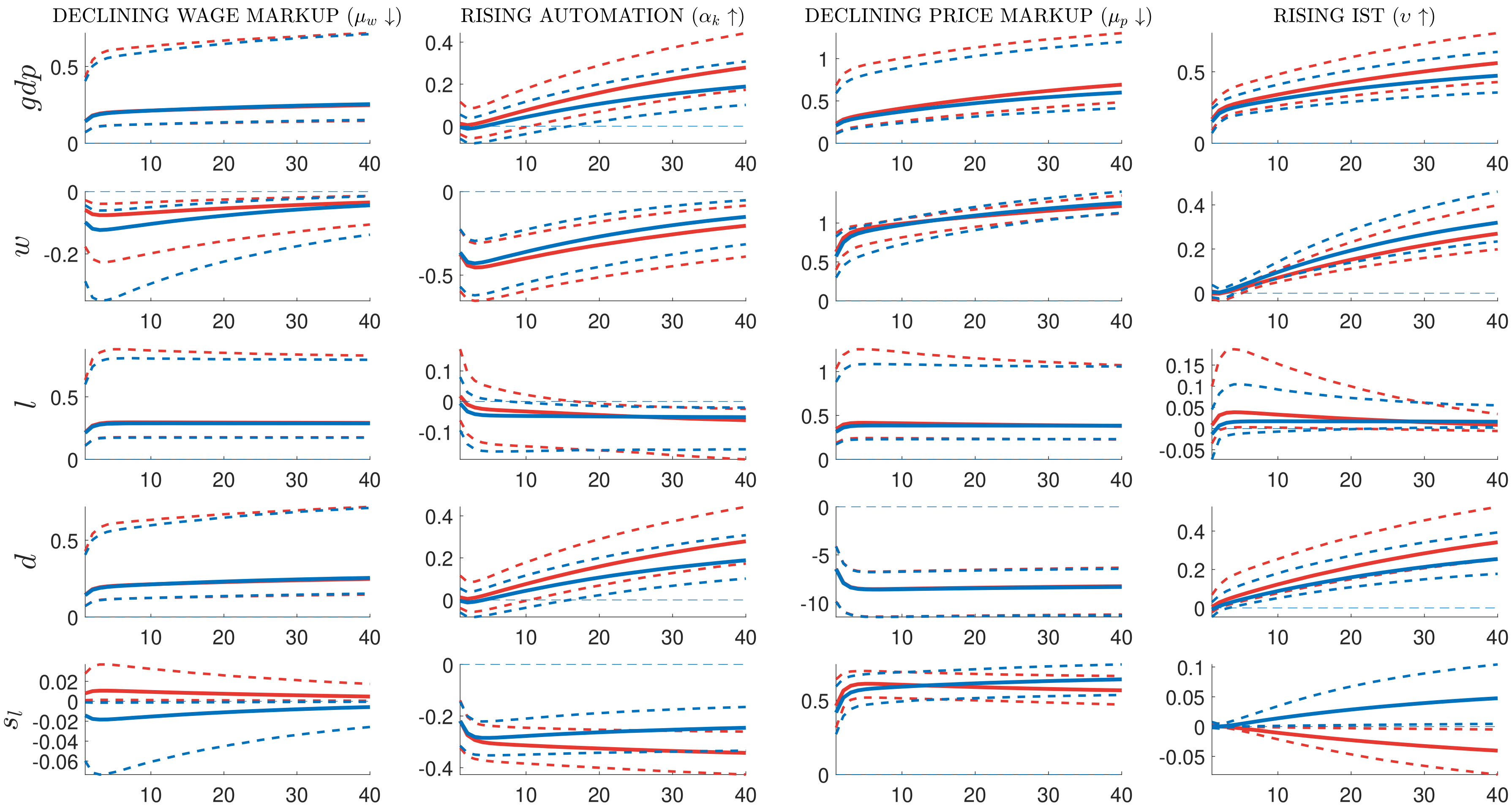
Note: Median (solid line), 90%, and 68% credible bands based on 10,000 draws. Income shares are expressed in percentage point deviations from initial values. Remaining variables are expressed in percentage deviations.

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 $\beta = 0.99$ and $\delta = 0.025$. 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 post-war US economy (see Figure 1). Moreover, also 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 et al., 2010). Karabarbounis and Neiman (2014), in 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 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 un-forecastable, negative co-movement between GDP and wages to labor markups or automation. We further disentangle these two by exploiting their contrasting implications for 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, in contrast, reduces the need for firms to hire workers. As such, automation is a negative labor demand shock. Note that an increase in automation leads to a decline in wages and hours: these are precisely the macroeconomic effects of automation documented both theoretically and empirically by Acemoglu and Restrepo (2019, 2018). We remark that an increase in automation has small aggregate effects on output (in some cases even negative in the short run) but a strong re-distributive effects with large displacement of labor in favor of capital and profits. 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 3: Simulation results from the baseline model: $\eta < 1$ vs. $\eta > 1$



Note: Comparison of Monte Carlo results based on 10,000 draws in i) the model with $\eta < 1$ (blue) and ii) the model with $\eta > 1$ (red). Median (solid line) and 90% credible bands (dotted lines). Income shares are expressed in percentage point deviations from initial values. Remaining variables are expressed in percentage deviations.

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	/	/	-	+

Note: Sign restrictions on impulse responses in the empirical models. The restrictions are imposed at quarter 16 in the baseline specification.

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" by Diamond et al. (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, 2018). However, as shown in Appendix A.3.1, 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 also analyze the role of real and nominal frictions, and find that impulse response signs are unaffected by these from quarter 16 and onwards (see Appendix A.3.2). 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). Next, we lay out the details of the second step in our empirical strategy.

3.2 STEP TWO – EMPIRICAL SPECIFICATION

The simulation results just described allow us to construct theory robust sign restrictions which 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- 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 in the robustness section. The focus on permanent shocks and the use of medium-run restrictions set us apart from the standard use of SVARs to study business cycle fluctuations as in Furlanetto, Ravazzolo, and Sarferaz (2019) among others.

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

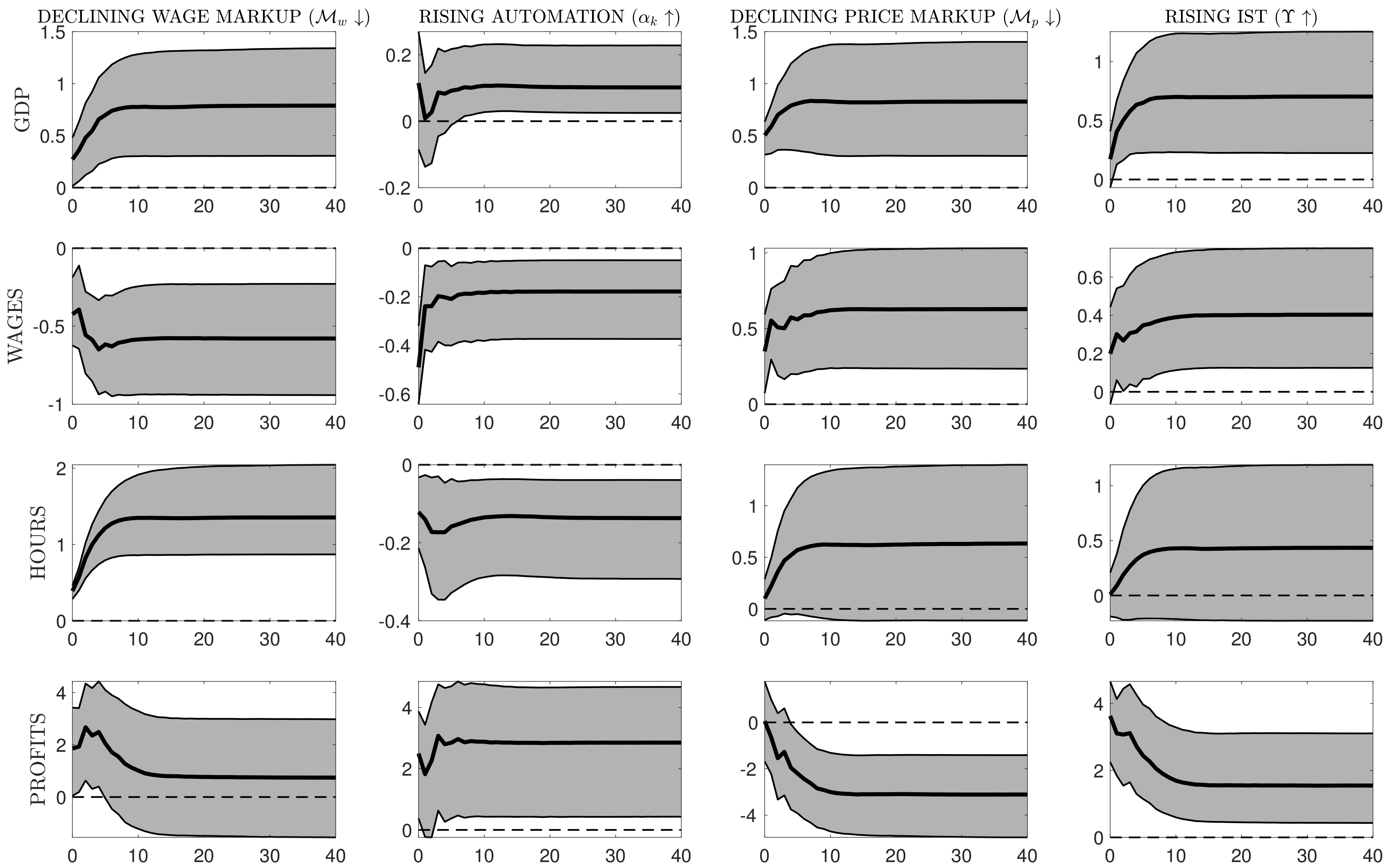
$$Y_t = C + \sum_{j=1}^{p} A_j Y_{t-j} + u_t \tag{12}$$

where Y_t is a nx1 vector containing all the endogenous variables, C is a nx1 vector of constants, $A_1, ..., A_p$ are the nxn matrices of coefficients associated with the p lags of the dependent variable and $u_t \sim N(0, \Sigma)$ is the nx1 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 nx1 vector of structural disturbances with unit variance. A is a non-singular parameter matrix such that $AA' = \Sigma$. In order to identify all the shocks in the system, we need at least $\frac{n(n-1)}{2}$ 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).[4]

Our dataset is quarterly and spans the period 1983Q1-2018Q3. 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 and Eeckhout (2017) to externally validate their measure of profits, although they focus on the non-financial 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 4 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 Section 5). 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

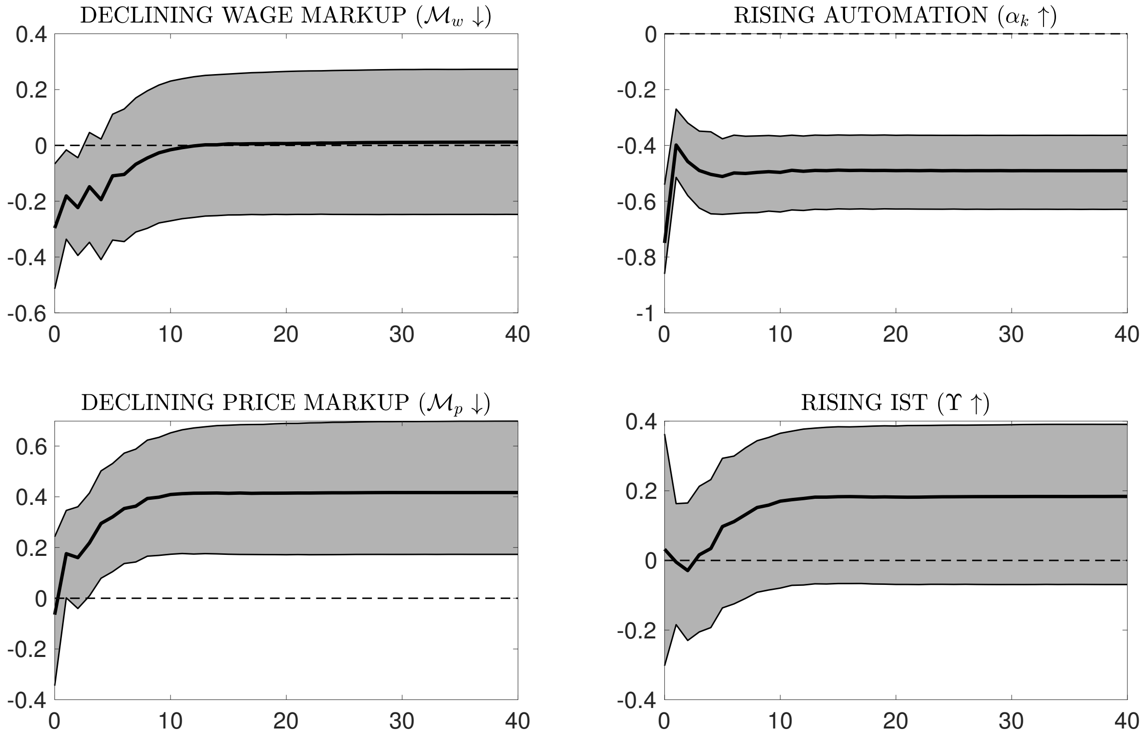
[4]Additional details on the Bayesian estimation of the reduced form VAR model and on the QR algorithm are provided in Appendix B.

Figure 4: Empirical impulse responses from the baseline VAR model



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

Figure 5: Implied labor share responses to structural change



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

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.

4 RESULTS

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

4.1 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 percent.

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 higher GDP and hours, while wages drop. Also, without any restrictions on profits we obtain a persistent rise in the majority of draws. This is consistent with the theoretical framework. The more interesting feature is the labor share response. The median response decreases significantly in the short run but then goes back towards zero. Recall that the theoretical model implies a zero long-run effect on the labor share of shocks to the wage markup. 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.

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, in 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.

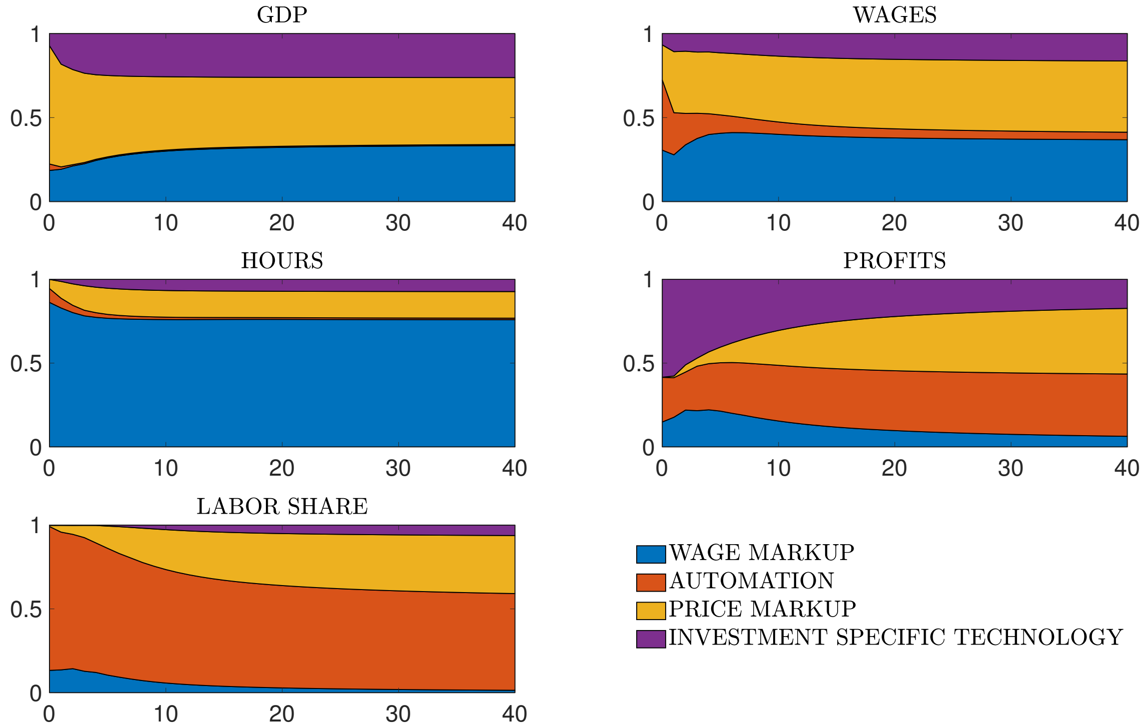
Finally, the last column in Figure 4 documents how an investment-specific technology shock affects the observables in our model. GDP, wages and profits increase by assumption (at quarter 16), but hours tend to rise too. More interestingly, after a few quarters the labor share responds positively in the vast majority of draws. This is shown in Figure 5. Thus, the VAR 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.

4.2 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

Figure 6: Variance decompositions at different frequencies

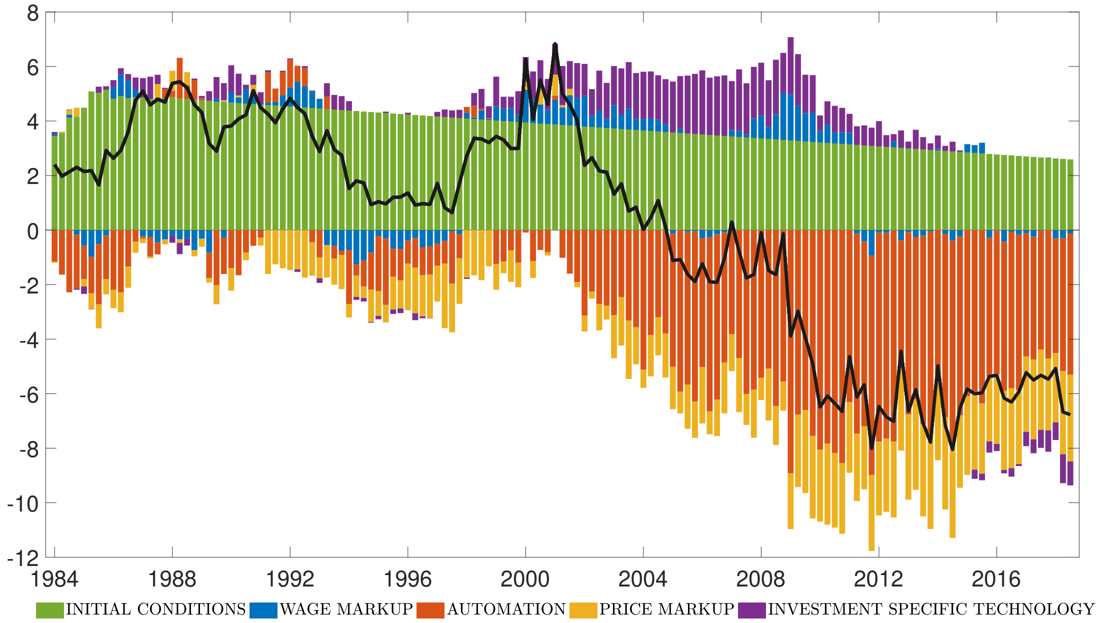


Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance of each variable (in levels) at horizons $j = 0, 1, \ldots, 40$ using the baseline identifying restrictions.

accounts for over 80% 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. This latter results is consistent with our theoretical model where wage markups are irrelevant for the labor share in the long run.

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 (2019). 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 increase wages, a decline in the bargaining power of workers increases total hours worked and, finally, an increase in markups generates a decline in output. Each of these effects in isolation pushes for an increase of the labor share. Of course, the response of the other variables may overturn the sign of the labor share response (as is the case for price markup and wage markup shocks). Nevertheless, only the automation shock generates the right movements in all components of the labor share, so that its decline becomes quantitatively important.

Figure 7: A historical decomposition of the labor share



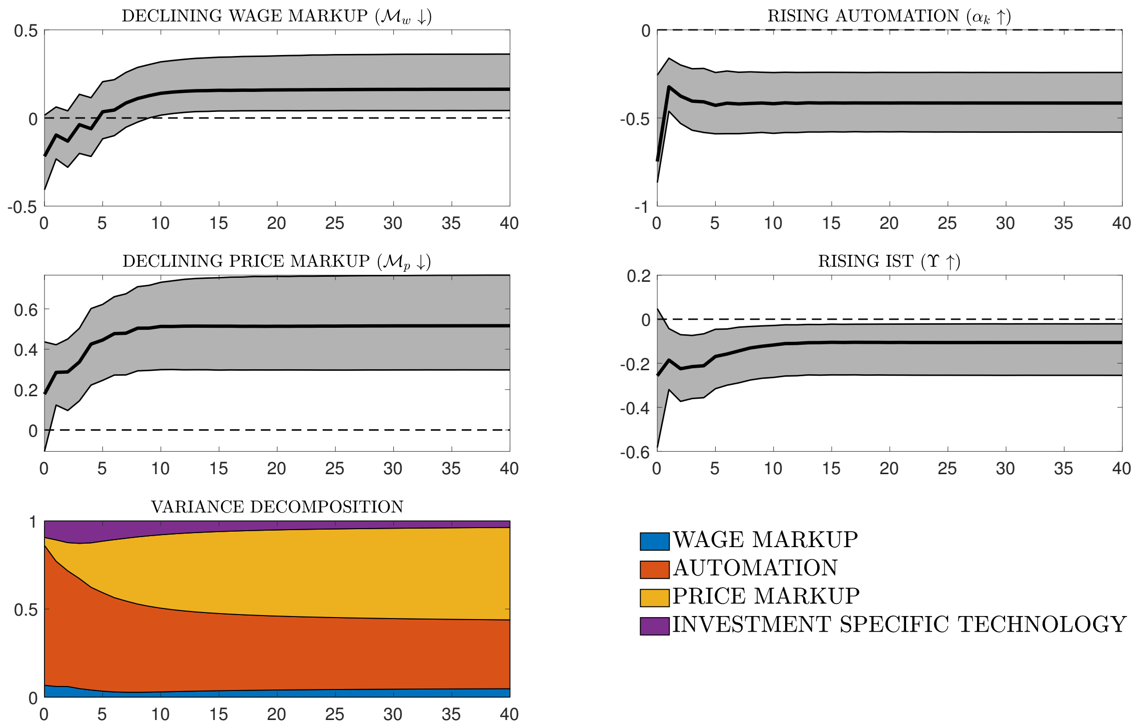
Note: The colored bars present the evolution of the labor share, in deviations from its mean, attributable to the deterministic components (initial conditions) of the VAR and to each structural shock, based on the median-target model of Fry and Pagan (2011).

Next we discuss the role of the four identified shocks for 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, in 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 re-distributive 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.

4.3 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 conditions) is warranted. This component can be interpreted as our model-based forecast of the labor share in the very

Figure 8: A thought experiment



Note: 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. Median (solid line) and 68% probability density intervals (shaded area) 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 $j = 0, 1, \ldots, 40$.

beginning of the sample, given the estimated VAR 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 (2018) 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 mark-up 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 et al. (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 phenomenons whose timing correlates well with the sharp decline of the labor share. In contrast, investment-specific technological progress and the decline in unionization, which could proxy a decline in wage mark-ups, 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), in contrast, argue that labor and capital may be net substitutes. Given the debate on the degree of labor-capital substitutability, we now consider the following thought experiment: for the sake of argument, we suppose for a second that capital and labor are net substitutes and we restrict the labor share accordingly in the SVAR. We thus impose that the labor share is procyclical in response to price and wage mark-up shocks and countercyclical in response to automation and investment-specific shocks (at a horizon of 16 quarters ahead). The impulse responses presented in Figure 8 reflect the identification assumptions and are thus not particularly informative. However, the variance decomposition obtained from this non-agnostic exercise is far more interesting. In fact, although we impose that positive investment-specific shocks must lower the labor share, these shocks turn out to be quantitatively unimportant. We see in Figure 8 that automation and price mark-up shocks are still the dominant drivers of the labor share decline, as in our baseline model. This exercise constitutes, we believe, an important validation for the main results of our paper.

5 Robustness and extensions

In this section we check the robustness of our baseline results to a battery of sensitivity checks and perform a number of extensions to the baseline specification. We include all the figures related to this section in Appendix C.

5.1 Alternative horizons, lag specifications, samples and priors

The baseline SVAR model presented in the previous section is estimated using 4 lags, imposing the sign restrictions of Table 2 at a horizon of 16 quarters ahead, using the variables in differences with a flat prior and on a quarterly sample that spans 1983Q1-2018Q3. We check the robustness of our results to changes in all of these specifications. For the sake of exposition, we present only the variance decompositions of the labor share corresponding to the different sensitivity checks, but the complete set of results is available upon request. The first two rows of Figure C.1 present the variance decompositions of the labor share using, respectively, different horizons and lag specifications. Changing the horizon at which the sign restrictions are imposed does not seem to affect the results presented in the previous section. The same is true if we use a different lag specification, although the role of price markups in explaining labor share fluctuations becomes slightly higher at long-run horizons when we include more feedback in the system. In the first two panels of the third row, we first expand the sample to go back to 1948Q1 and then restrict it from 1990Q1 onwards. Interestingly, price markups seem to have significantly less explanatory power in the first decades after the second World War. This evidence supports the view that firms' market power started to rise in the beginning of the 1980s and then accelerated in the 1990s and 2000s. The third panel, instead, presents the variance decomposition of the labor share using annual data in the estimation of the baseline model. The three panels of the fourth row refer to three different exercises. In the previous two, we use two different prior specifications: we estimate the VAR in levels using the dummy observation prior proposed by Sims and Zha (1998) and the priors for the long run (PLR) of Giannone et al. (2018), which resemble our baseline specification in differences when infinitely tight. Differently from our baseline empirical framework, in these cases shocks do not necessarily have permanent effects. In the latter, we consider the median-target impulse responses proposed by Fry and Pagan (2011). Overall, the results are in line with our baseline, although price markups seem slightly less relevant when we use the VAR in levels with the sum of coefficients prior or PLR.

5.2 Alternative measures of the labor share

In this subsection we present the robustness of our baseline results to different measures of the labor share. A first step in this direction is to focus on the business sector, which includes the farm sector and therefore covers a larger share of the economy compared with our baseline specification. We adjust the other variables in the system (real GDP, real hourly wages and hours) accordingly.

As discussed in depth in the literature, BLS's headline measure of the labor share suffers from measurement issues related to the treatment of self-employment (proprietors') income. This income component is ambiguous in that it reflects returns on both work effort and investment, and thus there is no straightforward way to isolate which part accrues to labor and which to capital. The way that the BLS tackles this problem is by assuming that the self-employed pay themselves the average hourly wage of workers on payroll. Therefore, the part of self-employment income accruing to labor is obtained by multiplying the average hourly wage by the hours worked by the self-employed. The remaining part of proprietors' income accrues to capital. The headline measure of the labor share is then constructed as follows:

$$s_{l,t} = \frac{W_t L_t}{Y_t} = \frac{W_t^p L_t^p}{Y_t} + \frac{W_t^s L_t^s}{Y_t}$$

$W_t = W_t^p = W_t^s$ denotes the average hourly wage of workers on payroll, L_t^p is hours of payroll workers and L_t^s is hours of self-employed. As noted by Elsby et al. (2013), this assumption results in an overstatement of the overall decline of the labor share and implies a negative capital share in the proprietors' sector in the 1980s, which is clearly an implausible outcome and casts doubts on the reliability of this measure.

One way to address the measurement issues related to the self-employed is to focus on the payroll share, $s_{l,t}^p = \frac{W_t^p L_t^p}{Y_t}$, thus taking proprietors' income out of the picture and considering a measure which unambiguously reflects payments to labor only. This can be conveniently implemented in our baseline empirical framework by simply substituting, in our set of endogenous variables, hours in the nonfarm business sector L_t with hours of payroll workers in the nonfarm business sector L_t^p, which are available on the website of the BLS. Then the responses of the payroll share to the different shocks for the nonfarm business sector are constructed exactly as in the previous section.

Another alternative to bypass this problem is to consider the labor share for the nonfinancial corporate sector, as proposed by Karabarbounis and Neiman (2014). This measure does not suffer from the issues related to proprietors' income as 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 US economy. In our empirical framework, we can restrict our interest to real GDP per capita, real wages, hours per capita and real profits per capita for the nonfinancial corporate sector. The labor share for the nonfinancial corporate sector is then obtained by combining the first three variables, as shown in the previous section.

Finally, we can also consider the economy-wide measure proposed by Kravis (1959) and used by Gomme and Rupert (2004). The assumption underlying this measure is that the self-employment labor share is the same as that of the overall economy. Specifically, the economy-wide measure is defined as follows:

$$s_{l,t}^{ew} = \frac{W_t^p L_t^p}{Y_t - Y_t^s}$$

where Y_t^s is proprietors' income without consumption allowances and inventory valuation adjustment. This is effectively performed in our baseline empirical framework by including in the system $Y_t - Y_t^s$ instead of GDP and hours of payroll workers instead of L_t.

We present the results of different measures of the labor share (business sector, payroll, non-financial corporate and economy-wide) using our baseline restrictions of Table 2 in Figure C.2. Our baseline results are robust across different definitions of the labor share. In particular, the responses of the labor share to investment-specific technology shocks are positive for the bulk of the draws and negative on impact in response to wage markups regardless of the measure used, confirming the evidence in favor of capital-labor complementarity. Price markups become slightly more important for low frequency fluctuations in the labor share when we restrict our analysis to the non-financial corporate sector. This result is not too surprising given a relatively large increase in the profits-to-GDP ratio for the non-financial corporate sector compared with the overall economy.

5.3 ADDITIONAL RESTRICTIONS

In our baseline specification of Table 2, we have shown a minimum set of identifying restrictions that are sufficient to set apart the four economically meaningful structural shocks under consideration. Our theoretical model, however, gives us additional sign restrictions that we could potentially exploit to sharpen the identification of the structural shocks. Figure C.3 shows the impulse responses and variance decompositions of BLS's headline measure of the labor share to the different structural shocks adding additional restrictions to the minimal set of Table 2. In the first row, we add the restriction that hours increase at horizon 16 in response to a negative price markup shock. In the second, we impose the restriction that hours increase at horizon 16 in response to a positive investment-specific technology shock. In the third, we restrict all the variables in the system: hours increase in response to both price markup and investment-specific technology shocks at horizon 16, and profits increase in response to wage markups and automation at horizon 16. Our baseline results are largely confirmed by adding additional restrictions. If anything, the evidence in favor of capital-labor complementarity becomes stronger once we restrict hours to increase in response to investment technology.

5.4 More variables

To externally validate our empirical methodology and, generally, the identification of the different shocks in the system, we can include additional variables in the VAR and analyze the behavior of these in response to the different shocks in the system. In what follows, we add, one by one, the following *unrestricted* variables to the system: relative price of investment, real investment per capita, routine and non-routine employment. We then estimate the augmented SVAR with the same baseline restrictions exposed in Table 2. The results are reported in Figure C.4. The first row presents the impulse responses and the variance decomposition of the relative price of investment. In line with the theoretical model, movements in the price of investment are explained mainly by investment-specific technology shocks, which lead to a permanent decrease in this variable. This is reassuring because we would expect the investment-specific shock to lead to a long-run decrease in the relative price of investment, if correctly identified. The second row presents the results for real investment. Investment 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 Gutierrez 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 4. The third and fourth rows show the responses of routine and non-routine per capita employment to the different structural disturbances using the series by Zhang (2019), which in turn updates the data constructed by Jaimovich and Siu (2019). Interestingly, while wage markups are important drivers of both routine and non-routine employment, automation has a much stronger negative effect on routine employment at short horizons. Moreover, price markups are also more important for routine than non-routine employment. When compared to the variance decomposition of hours in Figure 6, non-routine employment has an extremely similar behavior to hours, whereas routine employment features a much larger role, on impact, for automation and, over the entire horizon, for price markups.

5.5 Taking stock—how to interpret our identified shocks

In this section we further discuss the interpretation of the two main drivers of the labor share according to our empirical model, i.e. automation and rising price markups. When interpreted literally, the price markup shock captures a decline in domestic competition in US industries—for example driven by increasing entry costs, lax antitrust enforcement or lobbying.[5] This interpretation is perhaps the most widespread and consistent with the evidence presented by Barkai (2018), De Loecker and Eeckhout (2017), Eggertsson et al. (2018), Gutierrez and Philippon (2017), and Grullon, Larkin, and Michaely (2019). All these papers argue that the observed increase in market concentration is associated with higher firm profitability, mainly because of rising profit margins rather than improved technological efficiency.

However, a more benign interpretation of the increase in market concentration points to technical change, perhaps in combination with barriers to entry. Autor, Dorn, Katz, Pat-

[5]Similar stories would also fit well, such as a rise in firms' monopsony power in labor markets, as studied by Alpanda (2019).

terson, and Van Reenen (2017) find that the increase in concentration in several industries reflects changes in the economic environment, favoring a few very productive "superstar" firms. Kehrig and Vincent (2018) obtain similar results but with a focus on the manufacturing sector. These results may, at least in part, reflect better search technologies which favor certain firms or industries. For example, the rise in concentration could come about due to the emergence of platform competition or advances in information technology, as argued by Aghion, Bergeaud, Li, Klenow, and Boppart (2019). It is not clear where such a technology driven rise in market concentration and profit income would show up in our framework. This depends to a large extent on the associated productivity effects: on the one hand, a rise in market concentration is likely to hamper economic activity and thereby reduce aggregate output, consistent with our identified markup shock. But simultaneous productivity improvements (e.g. due to the scale effects of advances in platform technologies), on the other hand, are likely to work the opposite way. Indeed, aggregate output may even rise if the productivity effects are sufficiently powerful, implying a positive conditional correlation between output and profits (but still with contractionary effects on the labor market). If the productivity effect dominates, then a rise in profit revenues will necessarily be interpreted as an automation shock in our model.

Finally, it is important to stress that this paper is rather silent regarding the role of globalization. An automation shock, for example, could also capture the effects of globalization, import competition or offshoring out of the US economy, as originally proposed by Elsby et al. (2013). These shocks may indeed 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. We remark, however, that recent analysis of the labor share at the industry or establishment level downplay the importance of open economy factors for labor share dynamics (Giannoni and Mertens, 2019; Autor et al., 2017). Nevertheless, we acknowledge that disentangling the automation narrative from globalization narratives is an important topic for future research.

6 CONCLUSIONS

The labor share of national income has fallen in many countries in the last decades. In the US, the labor income share has accelerated its decline since the beginning of the new century, reaching its postwar lowest level in the aftermath of the Great Recession. While this observation has led to substantial interest, both 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 inference 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, in 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 pre-crisis decline can be attributed to automation, while firms' rising market power has been the main source of lower 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. This latter finding is consistent with the view that investment-specific technology growth has indeed taken place in recent decades, but that this has stimulated labor's income share because of complementarity between labor and capital. Finally, we document that our empirical results are robust to a large battery of robustness tests, including various identification assumptions and the use of different measures of labor's income share.

While this paper offers a benchmark account of the evolution of labor shares in the post-war US economy, we ignore 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 topic for our future research.

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APPENDIX

A ADDITIONAL DETAILS ON THE THEORETICAL MODEL

A.1 THE INITIAL STEADY STATE USED FOR SIMULATIONS

The steady state in the baseline, theoretical model follows recursively given an initialization of s_l, s_k, s_d, A_l, Υ and L:

$$
\begin{aligned}
r &= \beta^{-1} - 1 \\
P_I &= \Upsilon^{-1} \\
r^k &= P_I \left(r + \delta\right) \\
\alpha_l &= \frac{s_l}{1 - s_d} \\
\alpha_k &= \frac{s_k}{1 - s_d} \\
\mathcal{M}_p &= \frac{1}{1 - s_d} \\
A_k &= r^k s_k^{\frac{1}{\eta-1}} \left(\frac{\mathcal{M}_p}{\alpha_k}\right)^{\frac{\eta}{\eta-1}} \\
Y &= \left(\frac{\alpha_l}{\mathcal{M}_p s_l}\right)^{\frac{\eta}{\eta-1}} A_l L \\
W &= s_l \frac{Y}{L} \\
K &= \frac{s_k Y}{r^k} \\
I &= \delta K \\
X &= P_I I \\
C &= Y - X \\
\mathcal{D} &= s_d Y \\
\epsilon_p &= \frac{\mathcal{M}_p}{\mathcal{M}_p - 1} \\
\mathcal{M}_w &= \mathcal{M}_p \\
\epsilon_w &= \frac{\mathcal{M}_w}{\mathcal{M}_w - 1} \\
\Psi &= \frac{W}{\mathcal{M}_w L^{\varphi} C} \\
\Lambda &= C^{-\sigma} \exp\left(-\Psi \frac{\left(1 - \sigma\right) L^{1+\varphi}}{1 + \varphi}\right)
\end{aligned}
$$

The steady state of the New Keynesian model (see Appendix A.3.2) is identical, except that we also have to solve for nominal variables: given a choice of gross inflation Π (we set $\Pi = 1$), we have $i_p = \frac{\Pi}{\beta} - 1$ and $\Pi_w = \Pi$.

A.2 Long-run income shares

Given the definition of a long-run equilibrium in the main text, we set out to derive expressions of long-run income shares. We start with the profit income share. It follows from the definition of profits and optimal price-setting behavior:

$$\bar{s}_{d,t} = \frac{\bar{\mathcal{D}}_t}{\bar{Y}_t} = 1 - \frac{1}{\bar{\mathcal{M}}_{p,t}}$$

Thus, the long-run profit income share depends only on firms' markup, which is assumed exogenous in the baseline model. In order to derive the long-run capital income share we note that

$$\bar{r}_t^k = \bar{\Upsilon}_t^{-1}\left[\beta^{-1} - (1-\delta)\right]$$

The expression for firms' optimal capital demand can then be used to arrive at the following long-run capital share:

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

This expression shows that automation (firms' markup) raises (lowers) the capital income share. The effects of investment-specific or capital-biased technologies depend qualitatively on whether or not η is higher than one. Labor-augmenting technology and labor markups have no long-run effects on the capital share. Finally, the labor income share is found by substituting the two expressions derived above into the identity $\bar{s}_{l,t} + \bar{s}_{k,t} + \bar{s}_{d,t} = 1$:

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

This is the equation used in the main text.

A.3 Alternative theoretical assumptions

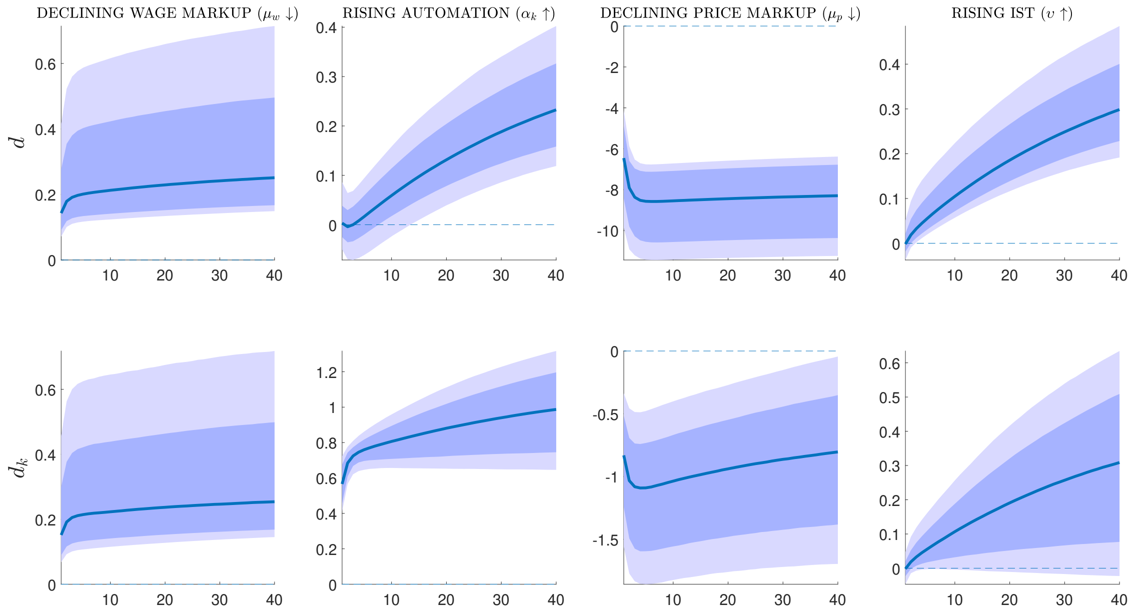
This section documents how robust our identifying sign restrictions are to (i) mis-measurement of profit income, and (ii) the inclusion of various real and nominal frictions.

A.3.1 Measurement of profits

A potential issue with the analysis in Section 3.1 in the main text concerns our measurement of profit income. The profit variable displayed in Figure 2 and Figure 3 is model-consistent and interpreted as sales net of factor payments. However, empirical measurements of profits might be distorted by the inclusion of some unobserved, intangible capital income (Karabarbounis and Neiman, 2018). Therefore, as a robustness check we now take the extreme view that *all capital income* is counted as profits in data, and simply refer to profit revenues $D_{k,t}$ as non-labor income:

$$D_{k,t} = D_t + r_t^k K_{t-1} = Y_t - W_t L_t$$

Figure A.1: Monte Carlo results: pure profits vs. non-labor income in the baseline model



Note: Median (solid line), 90%, and 68% credible bands based on 10000 draws. Pure profits (d) and non-labor income (d_k) are both expressed in percentage deviations from initial values.

Given this new measure, we re-evaluate the model's implied sign restrictions. Figure A.1 compares impulse responses of pure profits, D_t, with those of non-labor income $D_{k,t}$. The medium- to long-run signs of either variable are largely identical for all shocks. Our only disclaimer in this regard is that, conditional on investment-specific technology shocks, about 6% of the models imply a decline in $D_{k,t}$ at horizons relevant for our sign restrictions.

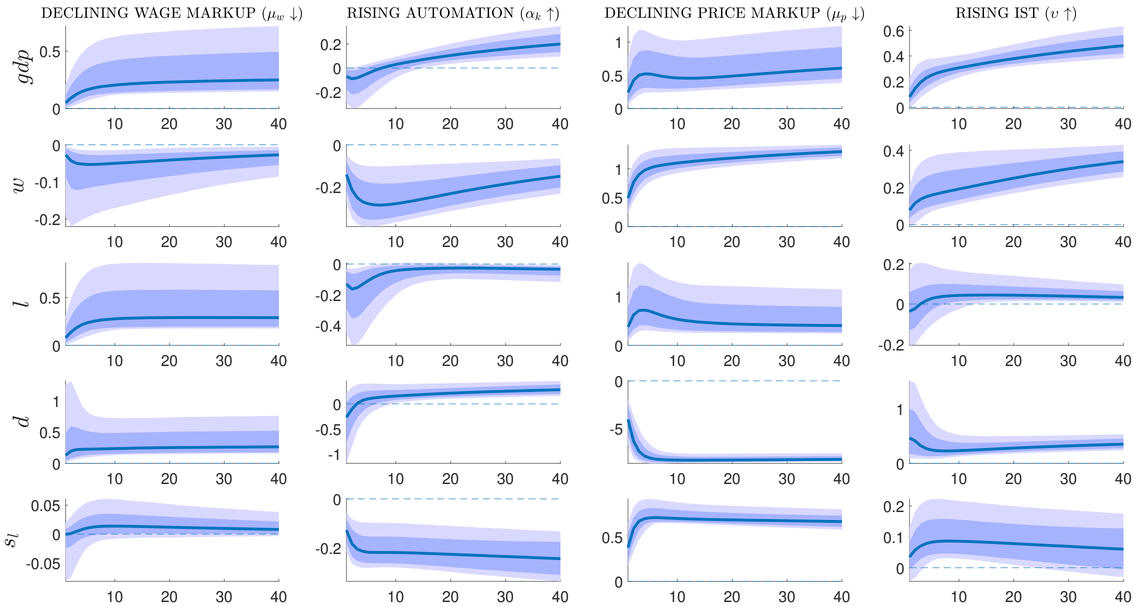
A.3.2 Real and nominal frictions

The theoretical model presented in the main text abstracts from a number of commonly used real and nominal frictions. One potential concern, therefore, is that our sign restrictions might be violated at certain frequencies if these frictions are included. This section incorporates a few "bells and whistles" into the baseline, theoretical model. We add (i) habit formation in consumption, (ii) adjustment costs in investments, (iii) variable capital utilization, (iv) nominal price stickiness, and (v) nominal wage stickiness. We also allow for partial indexation to past inflation in price and wage setting. Finally, we specify (vi) a Taylor-type rule for monetary policy. While the two models share identical long-run properties, the extended version implies different dynamics in the short to medium run. A brief summary of the additions to our baseline model follows:

External habit formation: The period utility is changed to

$$\mathcal{U}_t = \frac{(C_t - hC_{t-1})^{1-\sigma}}{1-\sigma} \exp\left(-\Psi \frac{(1-\sigma)\, L_t^{1+\varphi}}{1+\varphi}\right).$$

Figure A.2: Monte Carlo results: New Keynesian model with additional bells and whistles



Note: Median (solid line), 90%, and 68% credible bands based on 10000 draws. Income shares are expressed in percentage point deviations from initial values. Remaining variables are expressed in percentage deviations.

Investment adjustment costs: We assume a convex investment adjustment cost, so that

$$K_t = (1-\delta) K_{t-1} + \left[1 - \frac{\chi}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2\right] I_t.$$

Variable capital utilization: Wholesale firms rent effective capital services $\bar{K}_t = U_t K_{t-1}$, where U_t is the utilization rate of capital. Higher utilization comes at a cost $AC_{u,t}$ paid by households who own the capital, where

$$AC_{u,t} = \xi_u' (U_t - 1) + \frac{\xi_u \xi_u'}{2} (U_t - 1)^2 .$$

Nominal price stickiness: We incorporate price stickiness á la Rotemberg (1982). Nominal price adjustments are costly for wholesale firms. We also allow for partial indexation to past inflation and specify the cost function as

$$AC_{p,t} = \frac{\xi_p}{2}\left(\frac{\Pi_{jp,t}}{\Pi_{p,t-1}^{\gamma_p} \Pi_p^{1-\gamma_p}} - 1\right)^2 Y_t.$$

Nominal wage stickiness: Wage stickiness á la Rotemberg (1982) is the final extension. Nominal wage adjustments come at a cost paid by households:

$$AC_{w,t} = \frac{\xi_w}{2}\left(\frac{\Pi_{nw,t}}{\Pi_{p,t-1}^{\gamma_w} \Pi_p^{1-\gamma_w}} - 1\right)^2 L_t.$$

Monetary policy: Nominal rigidities imply the need to specify a nominal anchor. To this end we assume a Taylor type rule for the policy rate $i_{p,t}$:

$$1 + i_{p,t} = (1 + i_{p,t-1})^{\rho_i} \left[(1 + i_p) \left(\frac{\Pi_{p,t}}{\Pi_p} \right)^{\rho_\pi} \left(\frac{GDP_t}{GDP_{t-1}} \right)^{\rho_y} \right]^{1-\rho_i}$$

The Fisher equation $(1 + i_{p,t}) = (1 + r_t)\,\Pi_{t+1}$ links nominal to real outcomes. We also note that wage adjustment costs enter $s_{l,t}$, utilization adjustment costs enter $s_{k,t}$, while price adjustment costs enter $s_{d,t}$. However, these shares still sum to one, and the long run properties of the model are unaffected. Finally, we note that the New Keynesian model captures the neoclassical setup as a special case ($h = \chi = \xi_p = \xi_w = 0$ and $\xi_u \to \infty$).

Figure A.2 documents the distributions of theoretical impulse responses when we also draw parameters from the extended model. Importantly, the impulse responses are qualitatively similar across models even after a few periods, and the signs are identical from quarter 16 and onwards. We conclude, therefore, that the sign restrictions used in the main text are robust to the inclusion of real and nominal frictions.

B Bayesian Estimation of the VAR model

Consider the reduced form VAR model presented in Section 3.2:

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

The process above can be stacked in a more compact form as follows:

$$\mathbf{Y} = \mathbf{X}B + \mathbf{U}$$

where:
1) $\mathbf{Y} = (Y_{p+1}, ..., Y_T)'$ is a $(T-p)$ x n matrix, with $Y_t = (Y_{1,t}, ..., Y_{n,t})'$.
2) $\mathbf{X} = (\mathbf{1}, \mathbf{Y}_{-1}, ..., \mathbf{Y}_{-p})$ is a $(T-p)$ x $(np+1)$ matrix, where $\mathbf{1}$ is a $(T-p)$ x 1 matrix of ones and $\mathbf{Y}_{-k} = (Y_{p+1-k}, ..., Y_{T-k})'$ is a $(T-p)$ x n matrix.
3) $\mathbf{U} = (u_{p+1}, ..., u_T)'$ is a $(T-p)$ x n matrix.
4) $B = (C, A_1, ..., A_p)'$ is a $(np+1)$ x n matrix of coefficients.
Vectorizing the equation above, we obtain:

$$\mathbf{y} = (I_n \otimes \mathbf{X})\beta + \mathbf{u}$$

where $\mathbf{y} = vec(\mathbf{Y})$, $\beta = vec(B)$, $\mathbf{u} = vec(\mathbf{U})$ and $\mathbf{u} \sim N(0, \Sigma \otimes I_{T-p})$.
Given the assumption of normality of the reduced-form errors, $u_t \sim N(0, \Sigma)$, we can express the likelihood of the sample, conditional on the parameters of the model and the set of regressors $\mathbf{X}$, as follows:

$$L(\mathbf{y}|\mathbf{X}, \beta, \Sigma) \propto |\Sigma \otimes I_{T-p}|^{-\frac{T-p}{2}} exp\left\{ \frac{1}{2}(\mathbf{y} - I_n \otimes \mathbf{X}\beta)'(\Sigma \otimes I_{T-p})^{-1}(\mathbf{y} - I_n \otimes \mathbf{X}\beta) \right\}$$

Denote $\hat{\beta} = vec(\hat{B})$, where $\hat{B} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$ is the OLS estimate, and let $S = (\mathbf{Y} -$

$\mathbf{X}\hat{B})'(\mathbf{Y} - \mathbf{X}\hat{B})$ be the sum of squared errors. Then we can rewrite the likelihood as follows:

$$L(\mathbf{y}|\mathbf{X}, \beta, \Sigma) \propto |\Sigma \otimes I_{T-p}|^{-\frac{T-p}{2}} exp\left\{\frac{1}{2}(\beta - \hat{\beta})'(\Sigma^{-1} \otimes \mathbf{X}'\mathbf{X})(\beta - \hat{\beta})\right\}$$
$$exp\left\{-\frac{1}{2}tr(\Sigma^{-1}S)\right\}$$

By choosing a non-informative (flat) prior for B and Σ that is proportional to $|\Sigma|^{-\frac{n+1}{2}}$, namely:

$$p(B|\Sigma) \propto 1$$
$$p(\Sigma) \propto |\Sigma|^{-\frac{n+1}{2}}$$

We can compute the posterior of the parameters given the data at hand using Bayes rule, as follows:

$$P(B, \Sigma|\mathbf{y}, \mathbf{X}) \propto L(\mathbf{y}|\mathbf{X}, \beta, \Sigma)p(B|\Sigma)p(\Sigma)$$
$$= |\Sigma|^{-\frac{T-p+n+1}{2}} exp\left\{\frac{1}{2}(\beta - \hat{\beta})'(\Sigma^{-1} \otimes \mathbf{X}'\mathbf{X})(\beta - \hat{\beta})\right\} exp\left\{-\frac{1}{2}tr(\Sigma^{-1}S)\right\}$$

This posterior distribution is the product of a normal distribution for β conditional on Σ and an inverted Wishart distribution for Σ. Thus, we draw β conditional on Σ from:

$$\beta|\Sigma, \mathbf{y}, \mathbf{X} \sim N(\hat{\beta}, \Sigma \otimes (\mathbf{X}'\mathbf{X})^{-1})$$

and Σ from:

$$\Sigma|\mathbf{y}, \mathbf{X} \sim IW(S, v)$$

through Gibbs sampling, where $v = T - p - np - 1$.

The identification procedure described in subsection 3.2 is performed using the algorithm of Rubio-Ramírez et al. (2010), which consists of the following steps, for each given draw from the posterior of the reduced-form parameters:

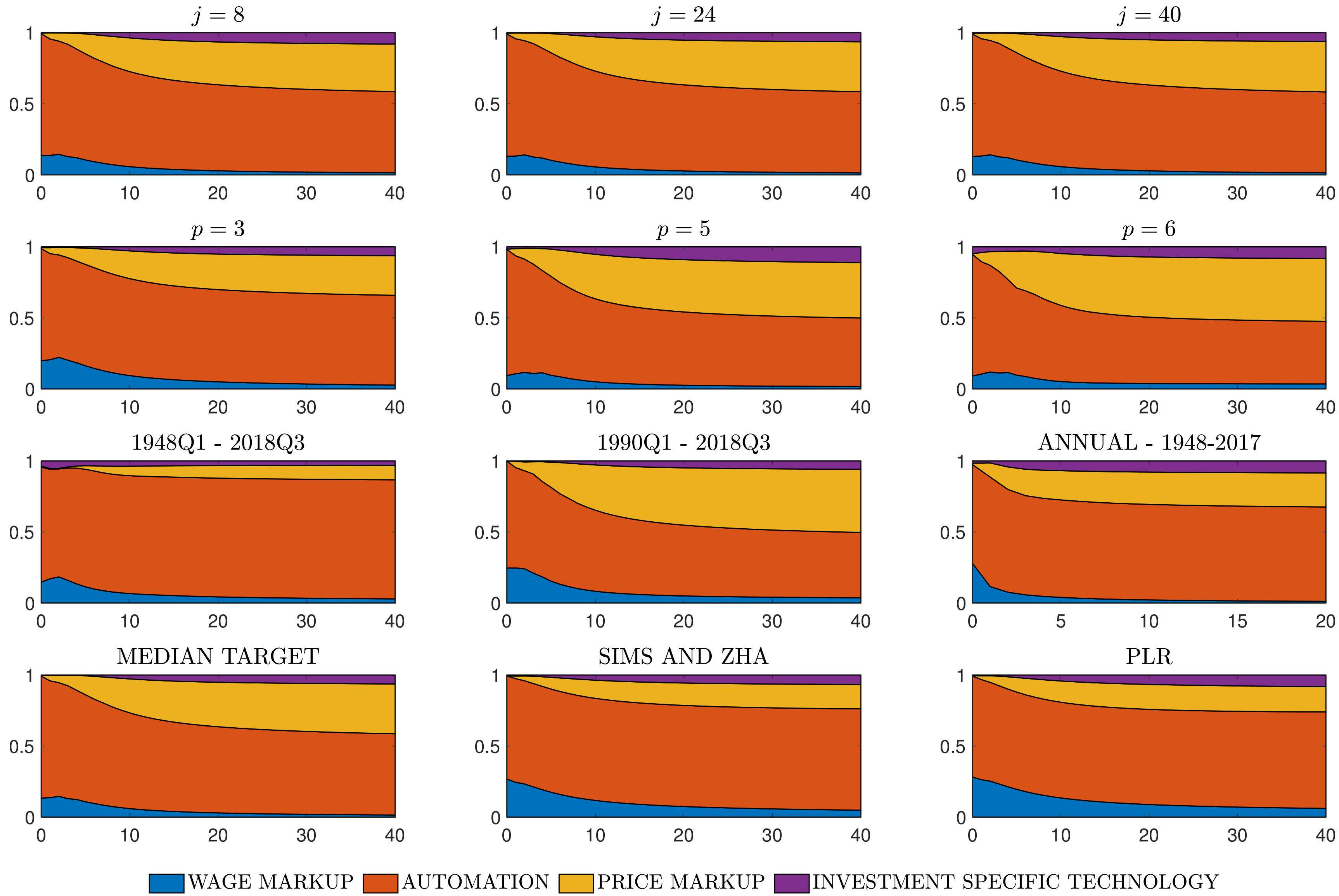
1. Draw a nxn matrix W from $N(0_n, I_n)$ and perform a QR decomposition of W, with the diagonal of R normalized to be positive and $QQ' = I_n$.

2. Let S be the lower triangular Cholesky decomposition of Σ and define $A = SQ'$. Compute the candidate impulse responses as $IRF_j = C_jA$, where C_j are the reduced form impulse responses from the Wold representation, for $j = 0, ..., J$. If the set of impulse responses satisfies all the sign restrictions, store them. If not, discard them and go back to the first step.

3. Repeat steps 1 and 2 until M impulse responses that satisfy the sign restrictions are obtained. The resulting set A, together with the reduced-form estimates, characterizes the set of structural VAR models that satisfy the sign restrictions.

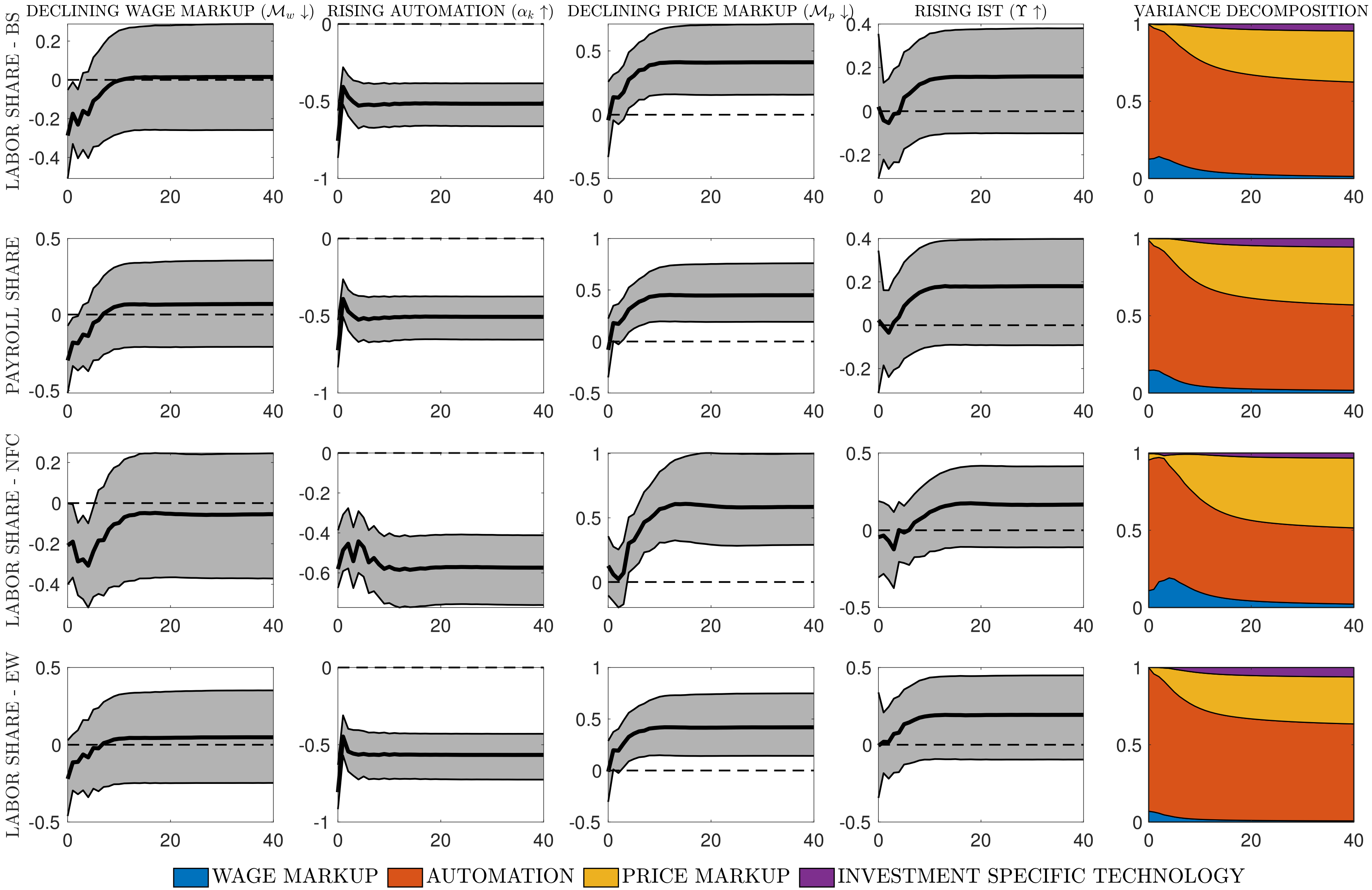
C Additional results

Figure C.1: Empirical impulse responses from the baseline VAR model - Sensitivity checks



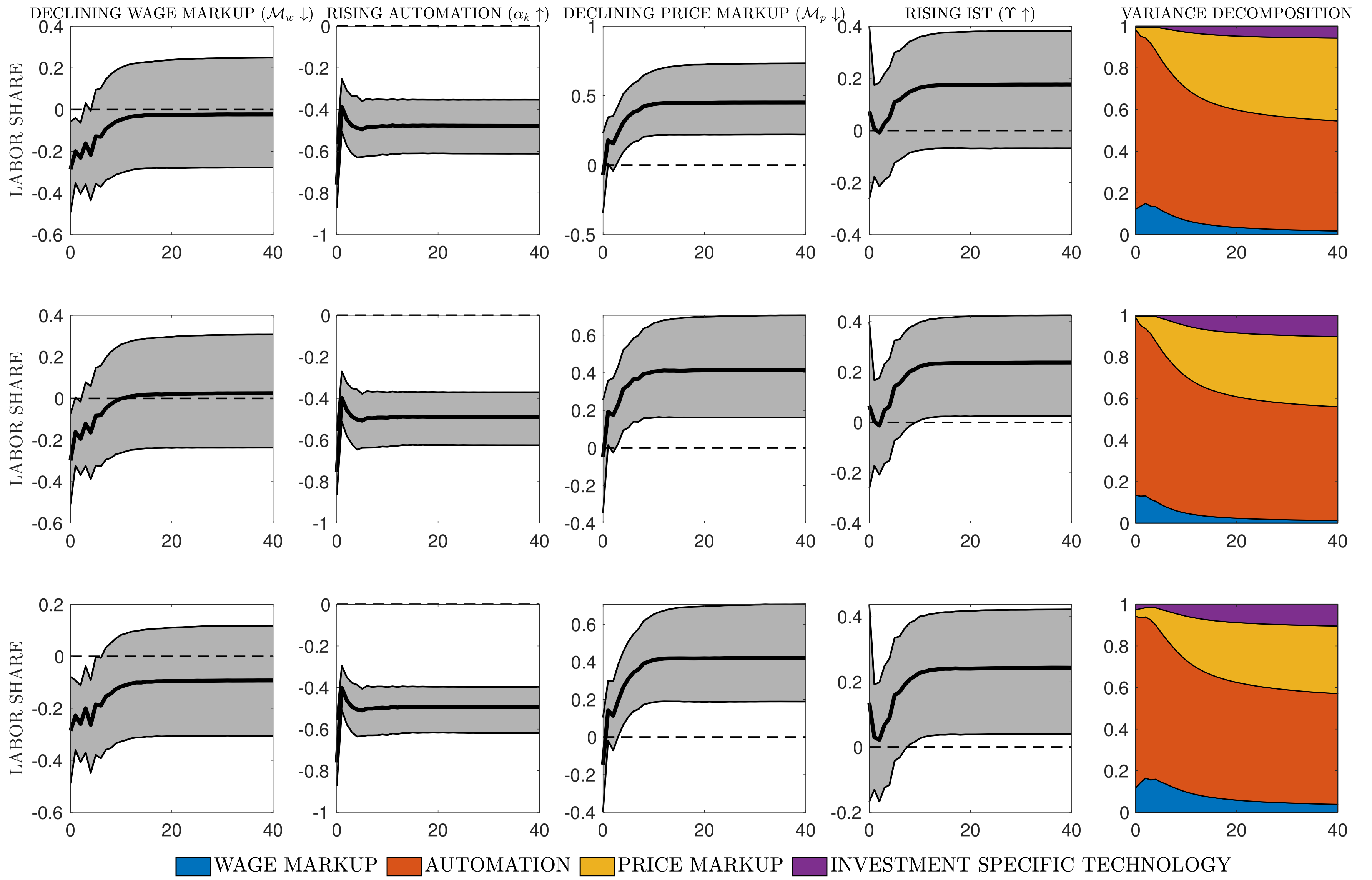
Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance of the labor share (in levels) at horizons $j = 0, 1, \ldots, 40$ using the baseline identifying restrictions.

Figure C.2: Empirical impulse responses from the baseline VAR model - Alternative measures



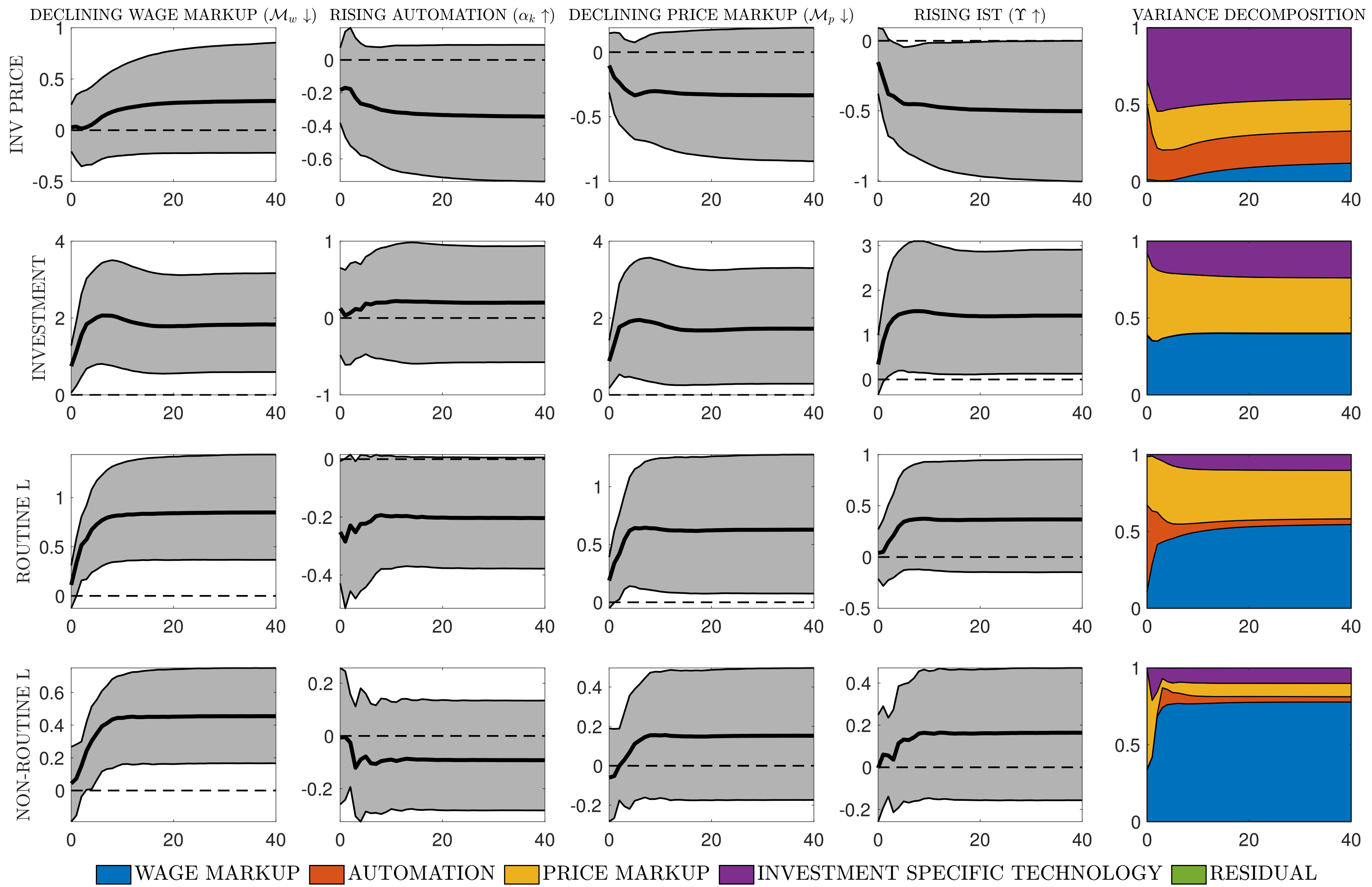
Note: Posterior distributions of cumulated impulse responses to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point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

Figure C.3: Empirical impulse responses from the baseline VAR model - Alternative identification



Note: Posterior distributions of cumulated impulse responses to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) 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 (in levels) at horizons $j = 0, 1, \ldots, 40$ using the alternative identifying restrictions.

Figure C.4: Empirical impulse responses from the baseline VAR model - More variables



Note: Posterior distributions of cumulated impulse responses to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) 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 each variable (in levels) at horizons $j = 0, 1, \ldots, 40$ using the alternative identifying restrictions.