

# THE DECLINE OF THE LABOR SHARE: NEW EMPIRICAL EVIDENCE\*

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**Abstract:** We estimate a structural, vector autoregressive model in order to quantify four of the 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 to long 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 we find the opposite: investment specific technology growth has led to a mild increase of the labor income share in our sample.

## 1 INTRODUCTION

Labor's share of national income has fallen in many countries 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 (see Figure A.1 in the appendix). These observations have led to renewed interest in the sources of labor market dynamics, but also created significant concerns among policy makers. Secular trends in labor income are important for at least two reasons: first, non-labor income tends to be concentrated among the top of the income distribution, suggesting that challenges associated with inequality will rise when labor income declines. Second, trends in the labor share might be a symptom of rising efficiency wedges (Autor, Dorn, Katz, Patterson, and Van Reenen, 2017a,b; Barkai, 2018). Needless to say, it is crucial to pinpoint the underlying causes in order to understand which policy implications, if any, that should follow. Yet, a consensus view regarding the 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.

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We consider four explanations with rather broad appeal in academia and policy circles:<sup>1</sup> first, a number of recent studies have argued that rising market power among firms has crowded out labor’s share of income (Autor et al., 2017a,b; Barkai, 2018; De Loecker and Eeckhout, 2017). These studies find evidence of declining competition and increasing market concentration. The claim is that trends in firms’ market power, whether being a nationwide phenomenon or driven by a few superstar firms, 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, 2017, 2018; Autor and Salomons, 2018). Acemoglu and Restrepo (2017), for example, argue that many tasks previously done by workers are currently being automated at 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. Blanchard and Giavazzi (2003) and Ciminelli, Duval, and Furceri (2018) among others find that a decline in the bargaining power of workers, proxied, respectively, by labor market deregulation and by major reforms to employment protection legislation (especially in the 1990s and in the 2000s for the latter), is responsible for a substantial fraction of the labor share decline. Finally, the fourth explanation we consider is about capital biased technological growth. Karabarbounis and Neiman (2014) in particular use the relative price of investment as proxy for investment specific technological progress, and find that capital deepening measured in this way can account well for declining labor shares in a number of countries including the US. Importantly, cheaper capital should imply lower labor shares only if labor and capital are net substitutes, which is exactly what Karabarbounis and Neiman (2014) find in their data.

While the strengths and weaknesses of these four explanations have been discussed in depth in the literature, 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 trend shocks. These shocks are interpreted as candidate explanations for permanent changes in the labor share, and we identify them using theory robust restrictions á la Canova and Paustian (2011), imposed at medium to long run horizons. “Theory robust” in this context means that the restrictions hold in a broad set of macroeconomic models, including some benchmark models in the literature on labor share dynamics. In order to derive the restrictions we set up a fairly stylized, yet flexible model of structural change. It nests, as special cases, many of the models used to study declining labor shares (including those used by Karabarbounis and Neiman (2014) and Barkai (2018)). Following Canova and Paustian (2011) we perform an extensive Monte Carlo study to characterize medium to long run effects on macroeconomic variables that are robust across all model specifications. In particular, we show that the explanations under consideration can be separately identified by a combination of low frequency sign restrictions that are mutually exclusive and jointly exhaustive. This set of restrictions is used to identify the structural shocks in the empirical model. As a byproduct, we can also infer how likely it is that the elasticity of substitution between labor and capital—arguably

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<sup>1</sup>The labor share decline has occurred not only in the US but also at the global level within a large number of countries and industries. Elsby, Hobijn, and Sahin (2013) argue that globalization, and the process of offshoring of intermediate goods production in developing countries in particular, is a promising candidate for the decline in the labor share. While it is easy to sympathize with this view, we find it very difficult to separate the role of globalization from de-unionization, automation and other trends in domestic markets. Nevertheless, in the robustness section we offer some attempts to quantify the role of global factors.

a key parameter for labor share dynamics—is greater than one. Our identification scheme holds for about any value of this parameter. At this point it should be clear to informed readers that the econometric approach used here differs fundamentally from typical approaches in 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. This allows us to be rather agnostic about the true data generating process, at the cost of less precise inference about the exact nature of structural change.

The empirical model is estimated on data covering the period 1983Q3-2018Q1. With the estimated model at hand, we set out to shed light on the observed labor share decline in the US. Our main results can be summarized as follows: first, we find that the labor 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 declining market power of workers 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 majority of labor share fluctuations in our sample. The second most important factor is firms' market power, at least at sufficiently low frequencies. 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 rising market power of firms, although the latter has been particularly important after the Great Recession. Thus, our empirical findings are well in line with stories about increased market concentration (Autor et al., 2017a; De Loecker and Eeckhout, 2017), but also with the view that tasks previously done by human workers have been set out to robots at significant scale in the last 20 years (Acemoglu and Restrepo, 2017; Autor and Salomons, 2018). Interestingly, we reach these 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).<sup>2</sup> 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 in our sample. This is consistent with the view that capital deepening in the form of investment specific technology growth has taken place in the last decades, but that net complementarity between labor and capital has led to crowding in of labor rather than the opposite. Thus, our results stand in sharp contrast to Karabarbounis and Neiman (2014) who argue that investment specific technology growth account for a major share of the observed labor share decline.

The rest of the paper is organized as follows: section 2 describes a theoretical model of structural change. Section 3 presents Monte Carlo simulations and the resulting set of theory robust sign restrictions. Section 4 lays out the econometric methodology and discusses identification. Section 5 documents our main empirical results. Section 6 provides a battery of robustness tests and extensions. Finally, section 7 concludes.

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<sup>2</sup>These authors notice that some of the explanations for falling labor shares rely on trends which started decades before the labor decline. Union membership rates, for example, have been on a downward path at least since the 1960s. De-unionization is, therefore, an implausible explanation according to the authors.

## 2 THEORETICAL FRAMEWORK

Our baseline, theoretical framework is a fairly 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. As a result, our framework captures as special cases the views taken by Karabarbounis and Neiman (2014), Acemoglu and Restrepo (2018), Blanchard and Giavazzi (2003), and Barkai (2018), amongst others. As a robustness check we also consider a second model, referred to as the New Keynesian version. This model extends the first with various bells and whistles: nominal wage and price stickiness on the supply side, habit formation, investment adjustment costs, and variable capital utilization on the demand side. These frictions are often introduced in business cycle models in order to obtain a better fit to data, and allow for a more agnostic view on the various theoretical restrictions. Importantly, although the two models differ in terms of short to medium run dynamics, they share the exact same long run properties. In the following we describe the baseline, neoclassical model. The New Keynesian extension is summarized in the appendix. 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 who rents those services in order to provide labor services 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 good producer transforms raw investments  $X_t$  into final investments goods. The production technology for this activity is given by

$$I_t = \Upsilon_t X_t. \quad (2)$$

Changes in  $\Upsilon_t$  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

$$P_{I,t} = \Upsilon_t^{-1}, \quad (3)$$

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  $\beta$  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:

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

$\delta$  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:

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

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

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

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

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

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 as put forward by Blanchard and Giavazzi (2003), but also by leisure preferences, demographics, or other factors that influence the supply side of the labor market. 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:

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

$\eta$  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 restrict 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:

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

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

$$\mathcal{M}_{p,t} = \frac{\epsilon_{p,t}}{\epsilon_{p,t} - 1} \quad (11)$$

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

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

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 (Autor et al., 2017a,b; 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:

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

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

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

Income shares in our simple model are defined accordingly:

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

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 unaffected by labor augmenting technology as well as 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, investment specific and capital augmenting technology shocks affect the labor share in exactly the same way. For this reason it is sufficient to consider only one of the two as long as the focus is on low frequency dynamics. However, whether or not shocks to  $\bar{\Upsilon}_t$  (or  $\bar{A}_{k,t}$ ) reduce labor's share of income depends crucially on  $\eta$ , and herein lies a potential identification problem: an observed fall in the labor share might be caused by the combination of rising  $\bar{\Upsilon}_t$  and  $\eta > 1$ , but also by declining  $\bar{\Upsilon}_t$  and  $\eta < 1$ . Since neither  $\bar{\Upsilon}_t$  nor  $\eta$  are observable, the degree of substitutability between labor and capital remains an open question in the literature.

## 2.7 SHOCK PROCESSES

Dynamics in the model are driven by six stochastic processes:  $A_{l,t}$ ,  $A_{k,t}$ ,  $\mathcal{M}_{p,t}$ ,  $\mathcal{M}_{w,t}$ ,  $\Upsilon_t$ , and  $\alpha_{k,t}$ . Given the preceding discussion we restrict attention to four of them: firm and labor markups, investment specific technology, and automation. Their dynamics are assumed to follow a random walk:

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

The innovations themselves are autoregressive processes:

$$\begin{aligned} z_{p,t} &= \rho_p z_{p,t-1} + \sigma_p \varepsilon_{p,t} & z_{w,t} &= \rho_w z_{w,t-1} + \sigma_w \varepsilon_{w,t} \\ z_{\Upsilon,t} &= \rho_\Upsilon z_{\Upsilon,t-1} + \sigma_\Upsilon \varepsilon_{\Upsilon,t} & z_{\alpha_k,t} &= \rho_{\alpha_k} z_{\alpha_k,t-1} + \sigma_{\alpha_k} \varepsilon_{\alpha_k,t} \end{aligned}$$

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



Table 1: Parameter bounds for the Monte Carlo exercises

		<i>Neoclassical</i>		<i>New Keynesian</i>	
		<i>LB</i>	<i>UB</i>	<i>LB</i>	<i>UB</i>
<i>“Deep” parameters</i>					
$\sigma$	Inverse of intertemporal elasticity	1	5	1	5
$\varphi$	Inverse Frisch elasticity	1	5	1	5
$\eta$	Substitution between $L$ and $K$	0.5	1.5	0.5	1.5
<i>Shocks’ persistence</i>					
$\rho_l$	Labor augmenting technology growth	0	0.75	0	0.75
$\rho_k$	Capital augmenting technology growth	0	0.75	0	0.75
$\rho_p$	Firms’ markup growth	0	0.75	0	0.75
$\rho_w$	Labor’s markup growth	0	0.75	0	0.75
$\rho_v$	Investment specific technology growth	0	0.75	0	0.75
$\rho_{\alpha_k}$	Automation growth	0	0.75	0	0.75
<i>Additional parameters in the New Keynesian model</i>					
$h$	Habit formation	0	0	0	0.9
$\chi$	Investment adjustment cost	0	0	0	10
$\theta_p$	Nominal price stickiness	0	0	0	0.9
$\theta_w$	Nominal wage stickiness	0	0	0	0.9
$\gamma_p$	Degree of price indexation	-	-	0	0.75
$\gamma_w$	Degree of wage indexation	-	-	0	0.75
$\xi_u$	Utilization cost	-	-	0.05	100
$\rho_i$	Interest rate inertia	-	-	0	0.9
$\rho_\pi$	Response to inflation	-	-	1.01	10
$\rho_y$	Response to output	-	-	0	1

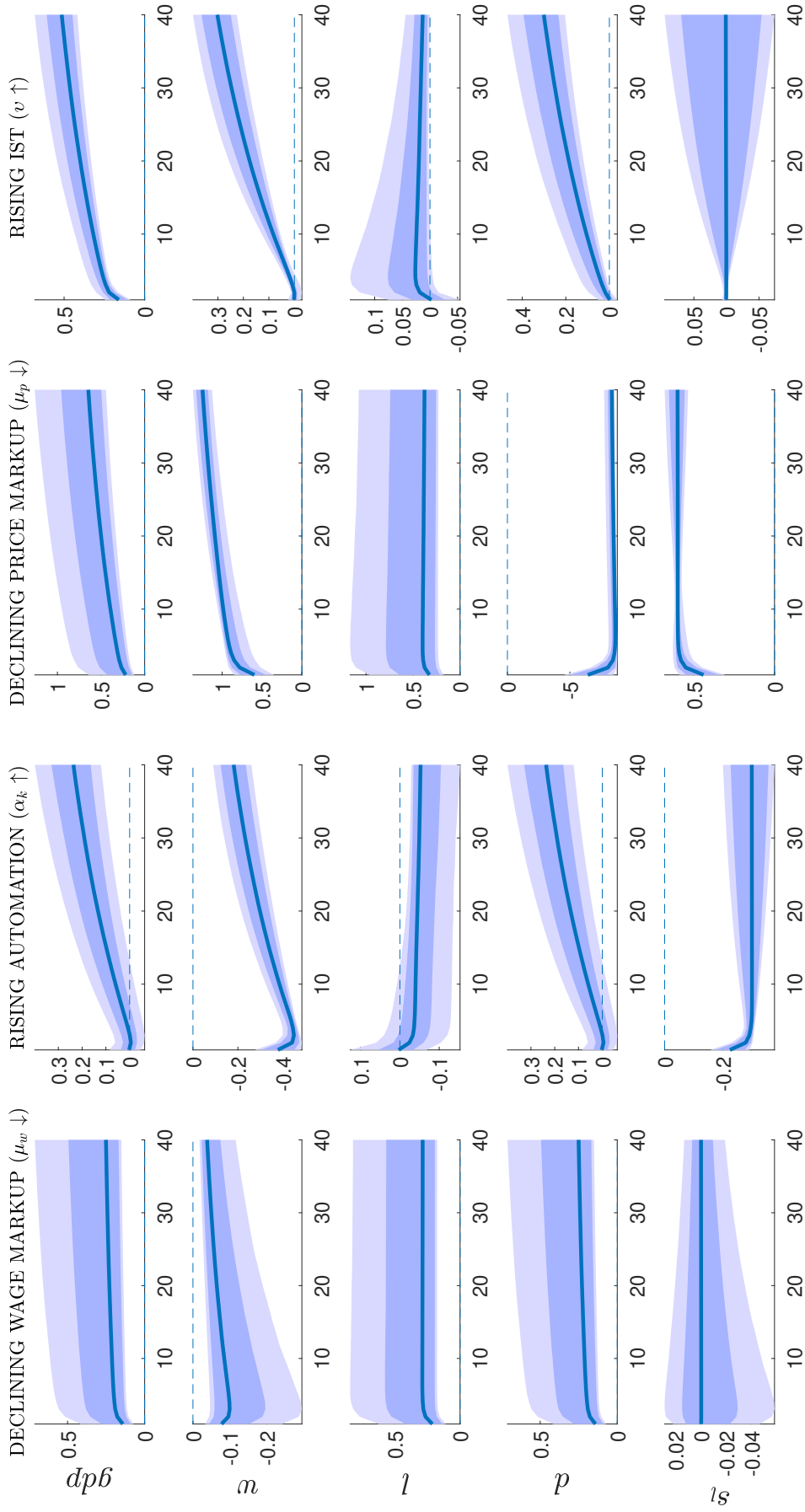
*Note:* LB  $\rightarrow$  lower bound; UB  $\rightarrow$  upper bound. The parameters  $\theta_p$  and  $\theta_w$  represent the probabilities of being stuck with old prices and wages in the Calvo model. They do not appear in our model because we use Rotemberg pricing. However, we exploit the first order equivalence between Calvo and Rotemberg pricing in order to back out  $\xi_p$  and  $\xi_w$ , given  $\theta_p$  and  $\theta_w$ .

as well as both markup shocks are absent (or if all three shocks are temporary), and at the same time  $\eta = 1$ , then we are back to the standard growth with a constant labor share. This completes our description of the neoclassical growth model. As a robustness test we also analyze an extended, New Keynesian model with several bells and whistles. That model, while being identical to the one presented here in the long run, differs with respect to short and medium run dynamics. The New Keynesian model is briefly described in the appendix.

### 3 MONTE CARLO SIMULATIONS

This section documents the distribution of impulse responses from our Monte Carlo exercise. The exercise follows along the lines of Canova and Paustian (2011) and involves the following steps: first, we choose a uniform distribution specific to each of the model’s structural parameters. Second, we make an independent draw from each of the distri-

Figure 1: Monte Carlo results from the baseline theoretical model



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

butions and solve the model conditional on that draw. Third, we compute and save the impulse responses. Steps 2-3 are repeated 10,000 times.<sup>3</sup> This exercise leaves us with a distribution of impulse responses which can be used to establish theory robust sign restrictions. Importantly, those restrictions do not require exact knowledge about the data generating process. 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, our model features several different stochastic trends, each implying a continuum of distinct steady states. Second,  $\alpha_{l,t}$  and  $\alpha_{k,t}$  are not dimension free, regardless of which steady state we consider (see Cantore, León-Ledesma, McAdam, and Willman (2014) for discussion of the latter issue). Therefore, across simulations we choose as approximation point an initial reference period where the income shares  $s_l$ ,  $s_k$  and  $s_d$  are known, and re-parameterize the model conditional on those shares. The re-parametrization follows along the lines of Cantore and Levine (2012). The initial long run equilibrium is characterized by  $\bar{s}_{l,t} = 0.60$ ,  $\bar{s}_{k,t} = 0.30$ , and  $\bar{s}_{d,t} = 0.10$ . Initial 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  $\bar{A}_{l,t} = \bar{Y}_t = \bar{L}_t = 1$ . Finally, the volatility parameters  $\sigma_p$ ,  $\sigma_w$ ,  $\sigma_v$ , and  $\sigma_{\alpha_k}$  are normalized so that impulse responses are computed conditional on a long run change in  $\mathcal{M}_{p,t}$ ,  $\mathcal{M}_{w,t}$ ,  $\Upsilon_t$ , and  $\alpha_{k,t}$  of 1 percent. Remaining variables follow endogenously. Table 1 reports chosen bounds for the parameters that are drawn from uniform distributions. These bounds span commonly used parameter values in the literature. The elasticity of substitution between labor and capital, for example, has support between 0.5 and 1.5. Applied work commonly assumes  $\eta = 1$  (Cobb-Douglas production), although many empirical estimates are somewhat smaller (León-Ledesma, McAdam, and Willman, 2010). Karabarbounis and Neiman (2014), in contrast, find numbers around 1.2 or even higher.

Figure 1 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 opposite employment responses: a decline in the wage markup implies more competition among workers and is, therefore, a positive supply shock in the labor market. This stimulates employment. Automation, in contrast, reduces the need for firms to hire workers. As such, automation is a negative labor demand shock. In order to distinguish between price markup shocks and investment specific technology, we note that the former leads to a decline in profits, while the opposite happens after a rise in investment specific technology. The intuition is simple: more competition between firms implies lower margins and, therefore, lower profits. Rising investment productivity, on the other hand, leads to an abundance of capital and higher output. The result is higher profits, even though profit margins might be unchanged. As a robustness test of these theoretical responses, we also redo the Monte Carlo exercise in the extended model with real and nominal frictions. Results are reported

<sup>3</sup>Parameter combinations that violate saddle path stability are discarded.

Table 2: Theory robust sign restrictions

Sign Restrictions				
	Labor's	Automation	Firms'	IST
	$\mu_w \downarrow$	$\alpha_k \uparrow$	$\mu_p \downarrow$	$v \uparrow$
GDP	+	+	+	+
Wages	-	-	+	+
Employment	+	-	NA	NA
Profits	NA	NA	-	+

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

in the appendix. Importantly, after some periods the results are qualitatively similar. Finally, the results are unchanged if we impose restrictions on the elasticity between labor and capital. In the appendix we document that, except for the labor share, the signs of all variables remain the same regardless of whether  $\eta$  is higher or lower than one.

The Monte Carlo 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 VAR model are 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. Finally we stress that the labor share responses to wage markups and investment technology are ambiguous and in general depend on whether  $\eta$  is higher or lower than one. In fact, the median response to both shocks is zero. A zero response at the median occurs because the distribution of  $\eta$  in our Monte Carlo analysis is centered around unity. This further motivates our strategy to infer the size of  $\eta$  indirectly, like we do in the empirical section.

## 4 ECONOMETRIC METHODOLOGY

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

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

$Y_t$  is a  $n \times 1$  vector containing all the  $n$  endogenous variables,  $C$  is a  $n \times 1$  vector of constants,  $A_1, \dots, A_p$  are  $n \times n$  matrices of coefficients associated with the  $p$  lags of the dependent variable and  $u_t \sim N(0, \Sigma)$  is the reduced form residual. 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, conditional on the four shocks under consideration (wage markup, price markup, automation and investment specific technology), all variables follow separate, stochastic trends. We specify flat priors for the reduced form parameters so that the posterior distribution has the usual Normal-Inverse-Wishart form. In order to map the economically meaningful structural shocks from the reduced form estimated shocks, we need to impose restrictions on the variance

covariance matrix previously estimated. In particular, let  $u_t = A\epsilon_t$ , where  $\epsilon_t \sim N(0, I_n)$  and  $A$  is such that  $AA' = \Sigma$ . In what follows, we assume that  $A$  is a Cholesky decomposition of  $\Sigma$ . In order to identify all the shocks in the system, we need at least additional  $\frac{n(n-1)}{2}$  conditions. The additional robust sign restrictions described above are imposed using the QR decomposition algorithm proposed by Rubio-Ramírez, Waggoner, and Zha (2010). It consists of the following steps:

1. Make a draw from a  $MN(0_n, I_n)$  and perform a QR decomposition of the matrix with the diagonal of  $R$  normalized to be positive, where  $QQ' = I_n$ .
2. Compute  $IRF_j = C_jAQ'$ , where  $C_j$  are the reduced form impulse responses, for  $j = 0, \dots, J$ . If the set of IRFs satisfy the sign restriction, store them. If not, discard them.
3. Repeat step 1 and 2 until 25,000 impulse responses are obtained.

## 5 EMPIRICAL RESULTS

This section presents results derived from the baseline VAR model. Our dataset set is quarterly and spans the period 1983Q1-2018Q1. 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. 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 and implementing the restrictions in Table 2 at a medium run horizon. In particular, we impose our restrictions after 16 quarters since at that horizon all sign restrictions 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. The impulse responses of the labor share are backed out from the impulse responses of real GDP, real wages and hours worked. Specifically, as the variables in the system are in natural logarithms, the impulse responses of the labor share can be simply computed as a linear combination of its components:

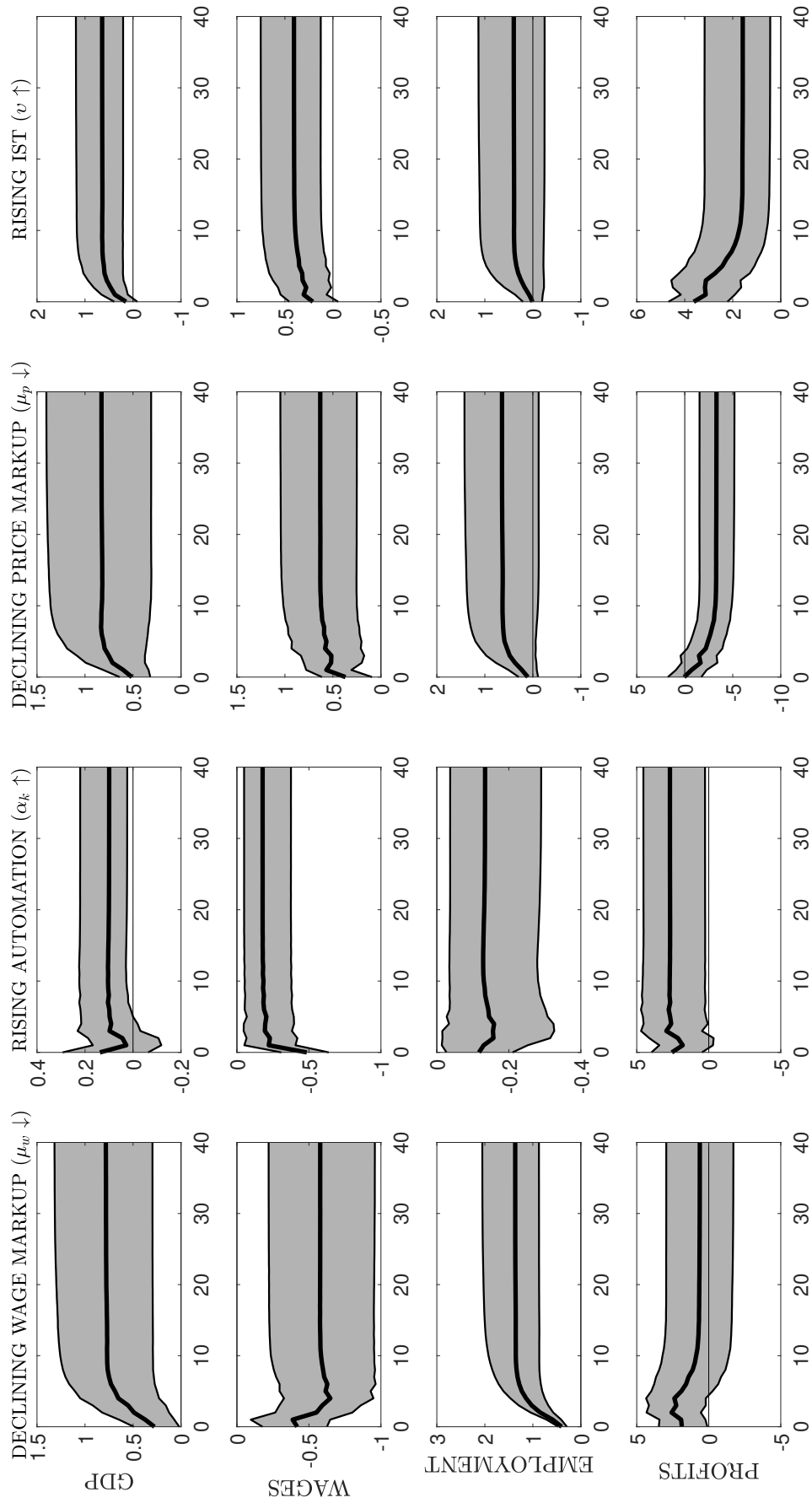
$$IRF_{LS,t} = IRF_{wages,t} + IRF_{hours,t} - IRF_{GDP,t}$$

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

### 5.1 LABOR SHARE RESPONSES TO STRUCTURAL CHANGE

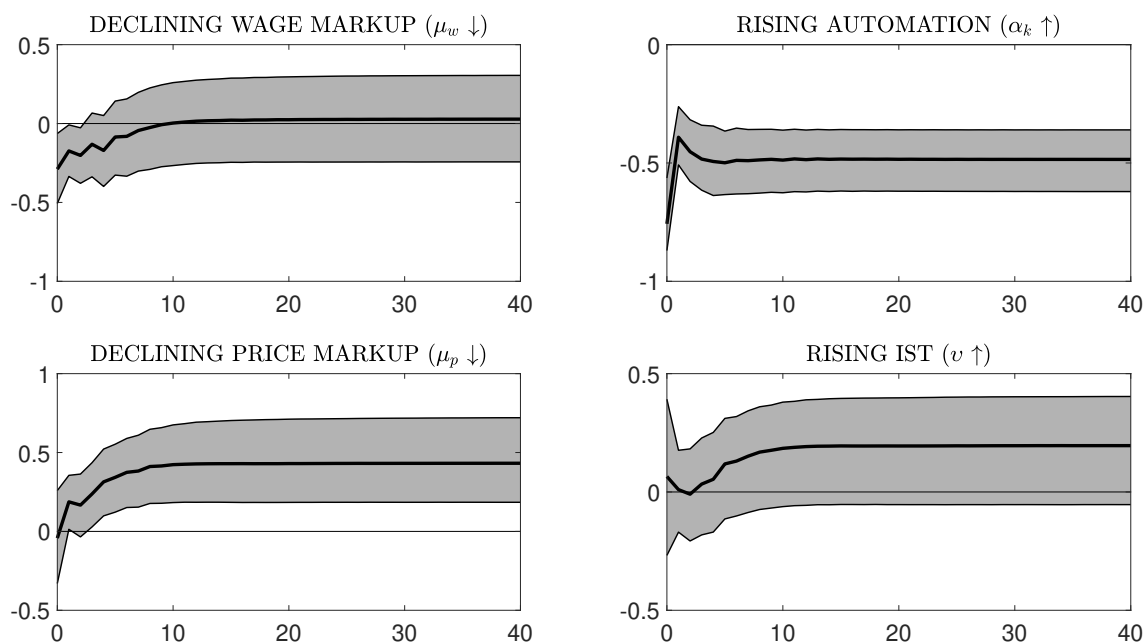
We first use the estimated VAR model to ask the following question: how does the labor income share respond to permanent changes in wage markups, automation, price markups and investment specific technology? Empirical impulse responses for the four variables included in the VAR are reported in Figure 2. The implied labor share responses are documented in Figure 3. In both figures the horizontal axis measures time in quarters

Figure 2: Empirical impulse responses from the baseline VAR model



Note: Posterior impulse response distributions to an estimated shock of one standard deviation. Median (solid line) and 68% probability density intervals (shaded area) based on 25,000 draws. The median is defined at each point in time.

Figure 3: Implied labor share responses to structural change



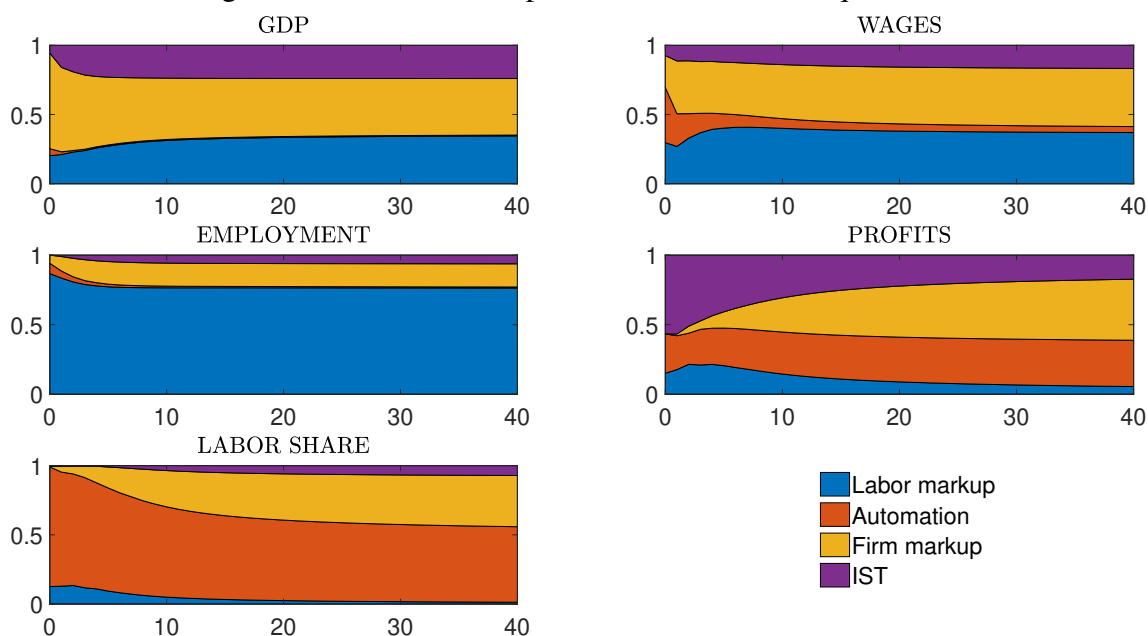
*Note:* Posterior impulse response distributions of the labor income share to an estimated shock of one standard deviation. Median (solid line) and 68% probability density intervals (shaded area) based on 1,000 draws. The median is defined at each point in time.

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 employment while the wage drops. These effects are imposed at quarter 16, but qualitatively the responses remain the same both at short and long horizons. 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  $\eta$ .

Next we consider the responses to a positive automation shock, identified by a rise in GDP at quarter 16, combined with negative wage and employment responses in that period. These results hold qualitatively even after 10 years. 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. This is comforting since the theoretical framework unambiguously predicts a labor share decline after this type of shock.

Figure 4: Variance decompositions at different frequencies



Note: TBA

The macroeconomic responses to an expansionary price markup shock are reported in the third column in Figure 2. This shock is assumed to raise output and wages, while at the same time lowering profits at quarter 16. We note that employment, which is left unrestricted, increase for the bulk of draws. More importantly, the labor income share which is plotted in Figure 3 rises unambiguously as in the theoretical model, at least we consider responses beyond the very short run. At lower frequencies the median labor share response is sizeable.

Finally, the last column in Figure 2 documents how an investment specific technology shock affects the observables in our model. GDP, wages and profits increase by assumption (at quarter 16), but also employment tends to rise. More interestingly, at lower frequencies even the labor share responds positively in the vast majority of cases. This is shown in Figure 3. Thus, the VAR is informative about the sign of the labor share response even without restrictions 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 on net labor-capital complementarity.

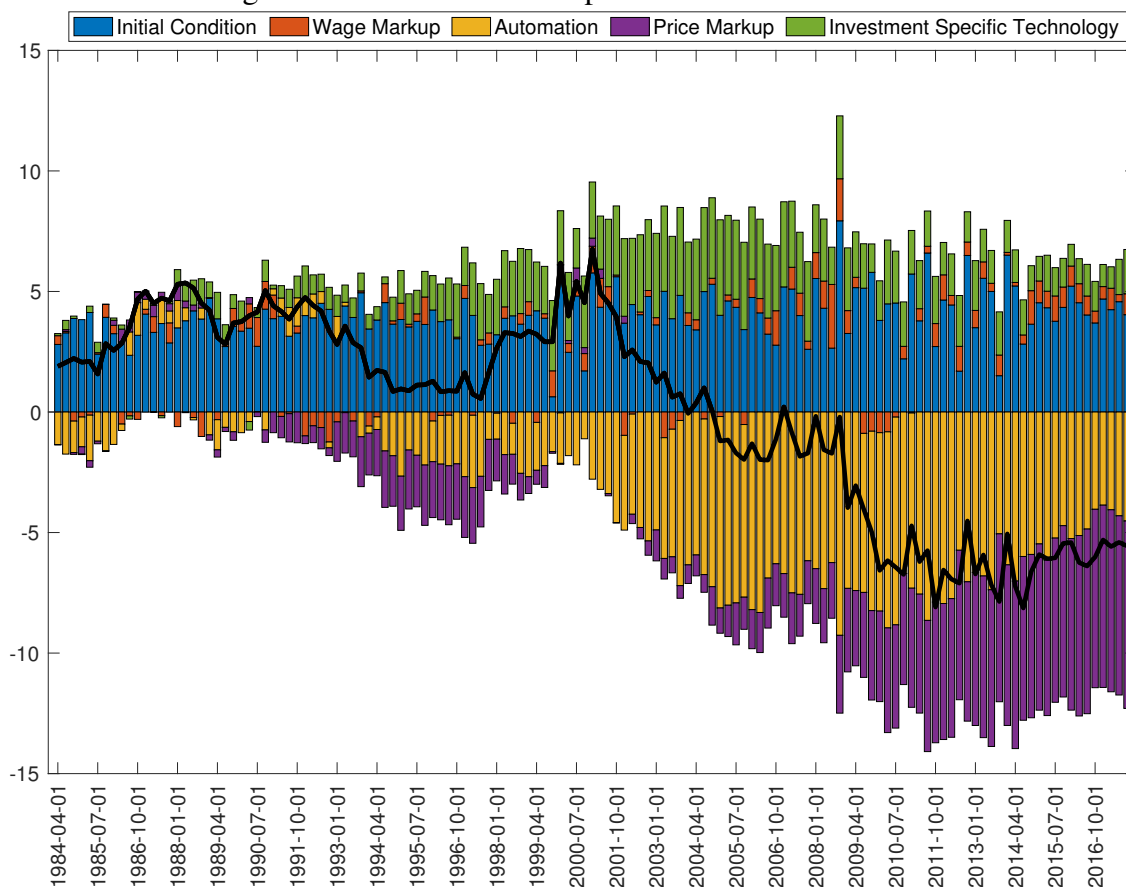
## 5.2 WHAT ARE THE MAIN DRIVERS OF THE LABOR SHARE?

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 1 to 40 quarters ahead.

Figure 4 shows the results. A couple of remarks are in place: first, investment specific technology as well as wage and price markup shocks explain the bulk of variation in GDP



Figure 5: A historical decomposition of the labor share



Note: TBA

and wages. Employment fluctuations, in contrast, are mainly driven by wage markups and to some extent by price markups. Turning to profits, they are well explained by investment specific technology in the short to medium run, while also 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 DSGE models where these shocks are quantified. Note, however, our departure from that literature by focusing on permanent shocks rather than business cycle fluctuations. This difference implies limited scope for comparison. If anything, we document that the importance of certain macroeconomic shocks holds even in a context where these shocks are treated as permanent.

Second and more importantly, we find that at least half of the variation in labor income shares is due to automation. At first glance this might seem surprising given the limited role of automation for the individual components of the labor share. Note, however, that the variation in macroeconomic variables such as GDP is of a different order of magnitude compared with the labor share. The fraction of labor share fluctuations not accounted for by automation is mostly attributed to price markup shocks while investment specific technology plays only a very minor role. Wage markups have some explanatory power in the short run but their importance become negligible at lower frequencies. This latter results is consistent with our theoretical model where wage markups are irrelevant for the long run labor share. In total, our estimated VAR model confirms the findings

from the impulse response analysis: automation and firms' markups are important drivers of the labor share in our sample, while investment or capital biased technology is not. This motivates further work on the microeconomic origins automation á la Acemoglu and Restrepo (2018), but also lends support to explanations about rising market power (De Loecker and Eeckhout, 2017) and superstar firms (Autor et al., 2017b).

### 5.3 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 do a historical shock decomposition of the labor share.

Figure 5 displays the labor share decomposition in deviations from its mean. A brief remark about the deterministic components (initial conditions) is warranted. These component can be interpreted as our model based forecast of the labor share in the very beginning of the sample. That forecast entails an evolution of the labor share broadly in line with its initial observation. That is, the deterministic components do not play a big role in explaining the secular labor share decline. Rather, according to our model it is clear that automation and rising market power of firms are key for understanding the post 2000 labor share evolution. Automation has become an increasingly more important factor since the early 90s, while firm markups started to contribute around the year 2000. 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. Regarding investment specific or capital biased technology, we find that this kind of shock, if anything, has led to a mild increase in the labor share. This is consistent with the view that investment specific technology growth has taken place in the last 25 years, but that net complementarity between labor and capital has led to crowding in of labor rather than the opposite. Our results stand in sharp contrast to Karabarbounis and Neiman (2014), who argue that investment specific technology growth account for a major share of the labor share decline.

## 6 ROBUSTNESS AND EXTENSIONS

Exercises that we have done, are currently doing or at least plan to do, but which remain to be added in the text:

- Longer sample and annual data
- Alternative labor market variables, in particular alternative measures of the labor share
- Restrictions at different horizons
- Alternative priors
- More variables: investment, routine employment, inequality measures from the CEX data, the natural rate of interest
- More shocks: outsourcing, offshoring, labor augmenting technology, demographics
- Long-run restrictions with focus on the permanent vs. temporary changes in the labor share

## 7 CONCLUSIONS

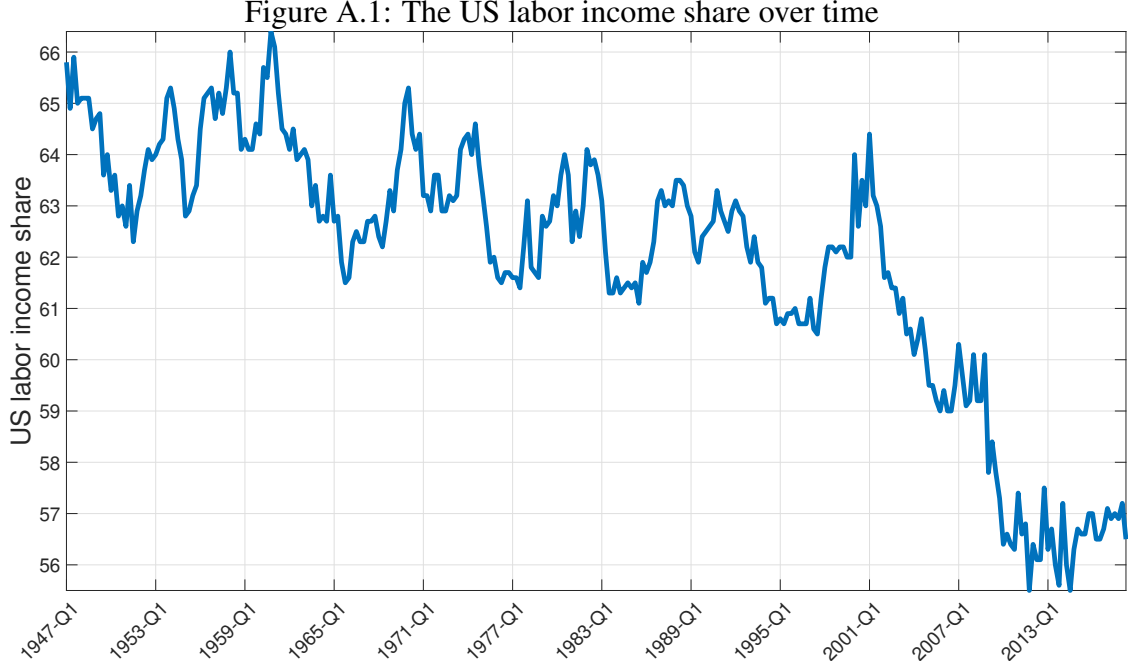
This paper sheds new light on the factors driving the decline of the US labor share in the last decades. We estimate a VAR model with shocks identified by theory robust sign restrictions. These restrictions are derived from a stylized, macroeconomic model of structural change. We document that the labor share decline, to a large extent, is accounted for by automation and rising profit margins among firms. Changes in the bargaining power workers have some relevance for short-run fluctuations while investment or capital biased technology never plays a major role. As a byproduct of our identification approach we are also able to say something about the elasticity of substitution between capital and labor. In particular, the results presented here provide evidence of an elasticity of substitution smaller than one, ruling out capital deepening as a main explanation for the observed labor share decline. If anything we find the opposite: investment specific technology growth has on average led to a mild increase in the labor share in our sample.

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## APPENDIX

### A ADDITIONAL TABLES AND FIGURES



*Note:* Labor income as share of total income in the US non-farm business sector (Bureau of Labor Statistics).

### B ADDITIONAL SIMULATION RESULTS

#### B.1 THE NEW KEYNESIAN EXTENSION

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. The gains of having these frictions are twofold: first, the bells and whistles allow us to derive credible short run restrictions, without having to sacrifice any identification coming from the model’s long run properties. Second, we can explore data on the nominal interest rate, as well as on nominal price or wage inflation. To this end we extend the model in the following ways:

*External habit formation:* The period utility is changed to

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

*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  $\xi_u \rightarrow \infty$ ).

## B.2 THE INITIAL STEADY STATE USED FOR SIMULATIONS

The steady state in the neoclassical model follows recursively given an initialization of  $s_l$ ,  $s_k$ ,  $s_d$ ,  $A_l$ ,  $\Upsilon$  and  $L$ :

$$\begin{aligned} r &= \beta^{-1} - 1 \\ P_I &= \Upsilon^{-1} \\ r^k &= P_I (r + \delta) \\ \alpha_l &= \frac{s_l}{1 - s_d} \\ \alpha_k &= \frac{s_k}{1 - s_d} \\ \mathcal{M}_p &= \frac{1}{1 - s_d} \end{aligned}$$

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

The steady state of the New Keynesian model is identical, except that we also have to solve for nominal variables: given a choice of gross inflation  $\Pi$  (we set  $\Pi = 1$ ), we have:

$$\begin{aligned}
i_p &= \frac{\Pi}{\beta} - 1 \\
\Pi_w &= \Pi
\end{aligned}$$

### B.3 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:

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

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

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

in the long run. The expressions for firms' optimal capital demand can then be used to show that

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

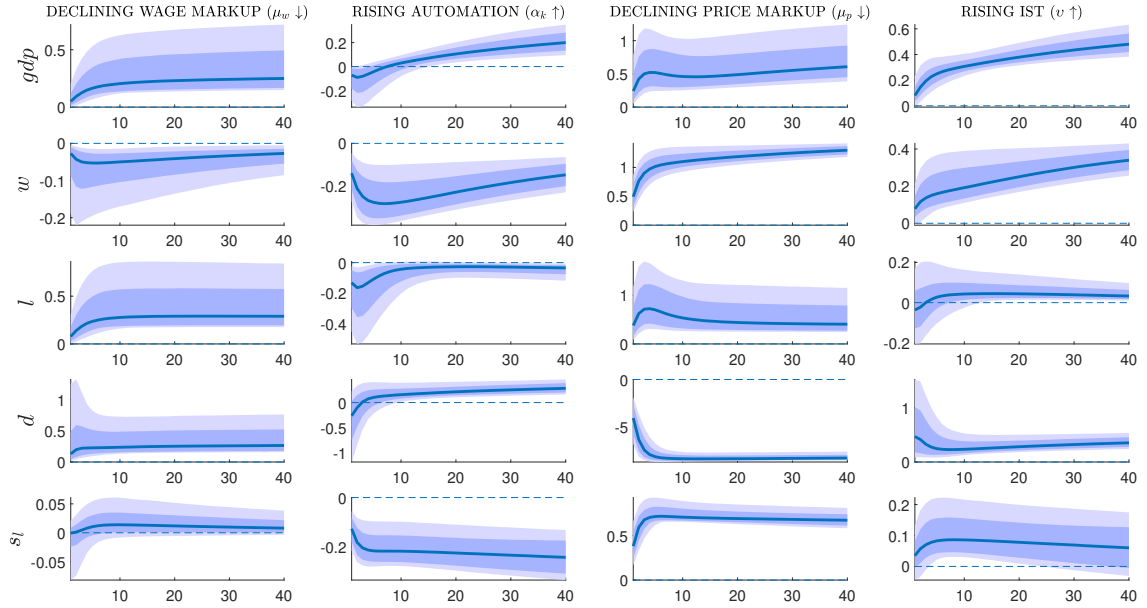
This expressions shows that automation (firms' markup) raises (lower) the capital income share. The effects of investment specific or capital biased technologies depend qualitatively on whether or not  $\eta$  is higher than one. Labor augmenting technology and labor markups have no long run effects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

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

This is the equation used in the text.

## B.4 MONTE CARLO RESULTS IN ALTERNATIVE MODELS

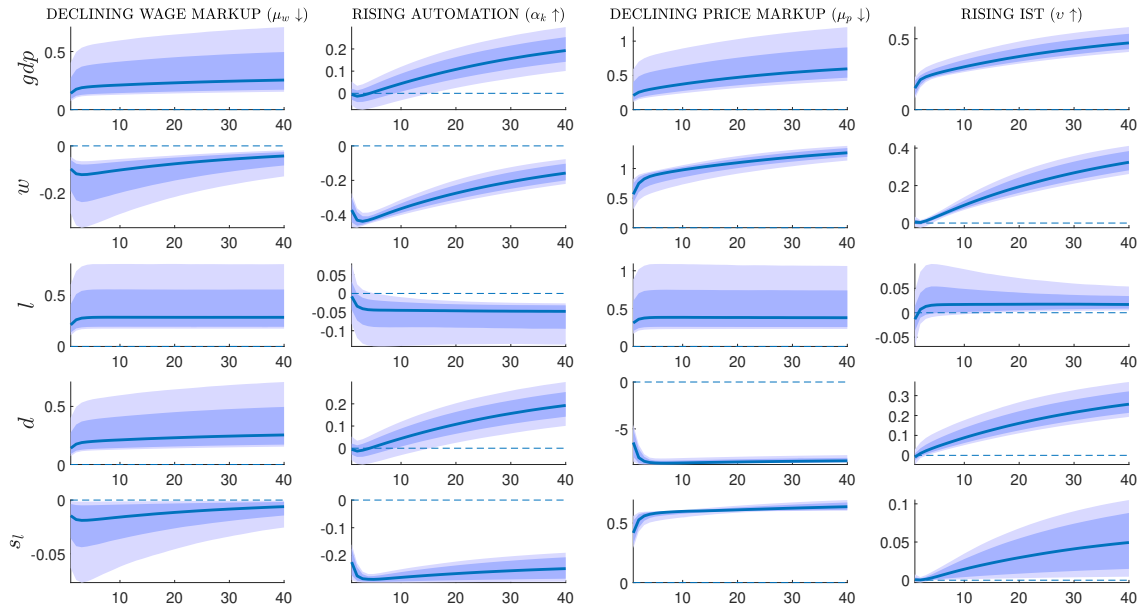
Figure B.1: Monte Carlo results from the New Keynesian model with additional bells and whistles



*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.

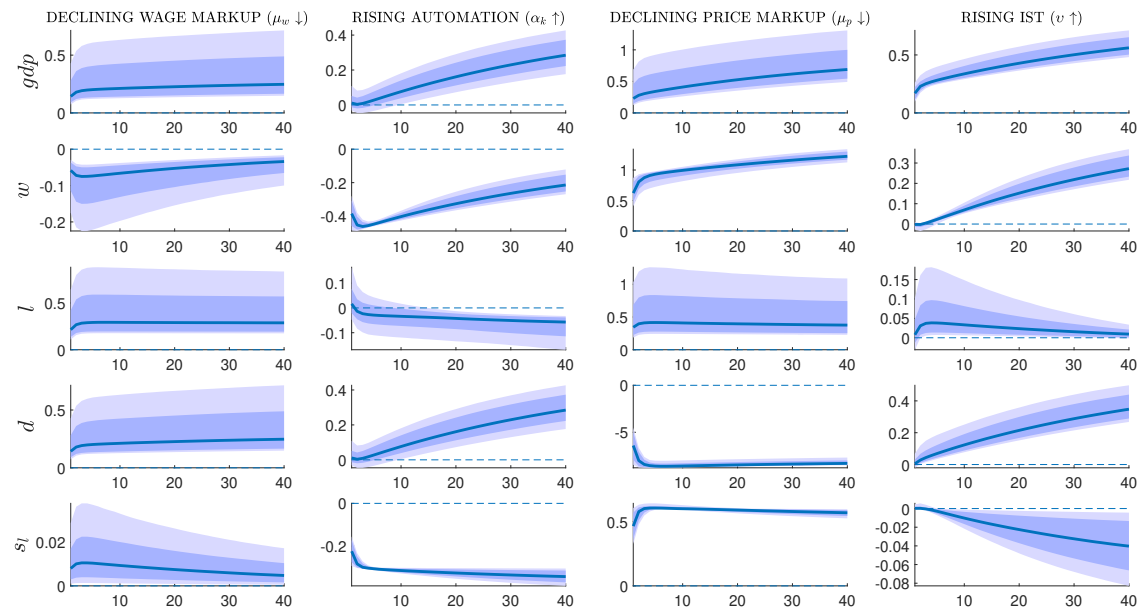


Figure B.2: Restricted Neoclassical:  $\eta < 1$



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.

Figure B.3: Restricted Neoclassical:  $\eta > 1$



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.

## C ADDITIONAL RESULTS FROM THE VAR MODEL

### C.1 SANITY CHECK: IST AND THE INVESTMENT PRICE

Our results: IST shocks

- ... play a significant role for GDP in our sample
- ... but have, if anything, led to higher labor share

Theory suggest that (i) a rise in IST should cause a decline in the relative price of investments, and (ii) that IST is major driver of investment price fluctuations

**Q:** Are these views supported by our framework?

**A1:** Figure C.1 shows that the investment price falls permanently in response to a rise in IST

**A2:** Figure C.2 shows that IST shocks are the most important source of movements in investment prices

Identification scheme, but now with the investment price:

	Sign Restrictions			
	Labor's $\mu_w \downarrow$	Automation $\alpha_k \uparrow$	Firms' $\mu_p \downarrow$	IST $v \uparrow$
Real GDP	+	+	+	+
Real Wages	-	-	+	+
Employment	+	-	NA	NA
Real Profits	NA	NA	-	+
Real inv. price	NA	NA	NA	NA

Remarks:

- All sign restrictions as before
- Investment price is left completely unrestricted

Figure C.1: Permanent IST shock with investment price

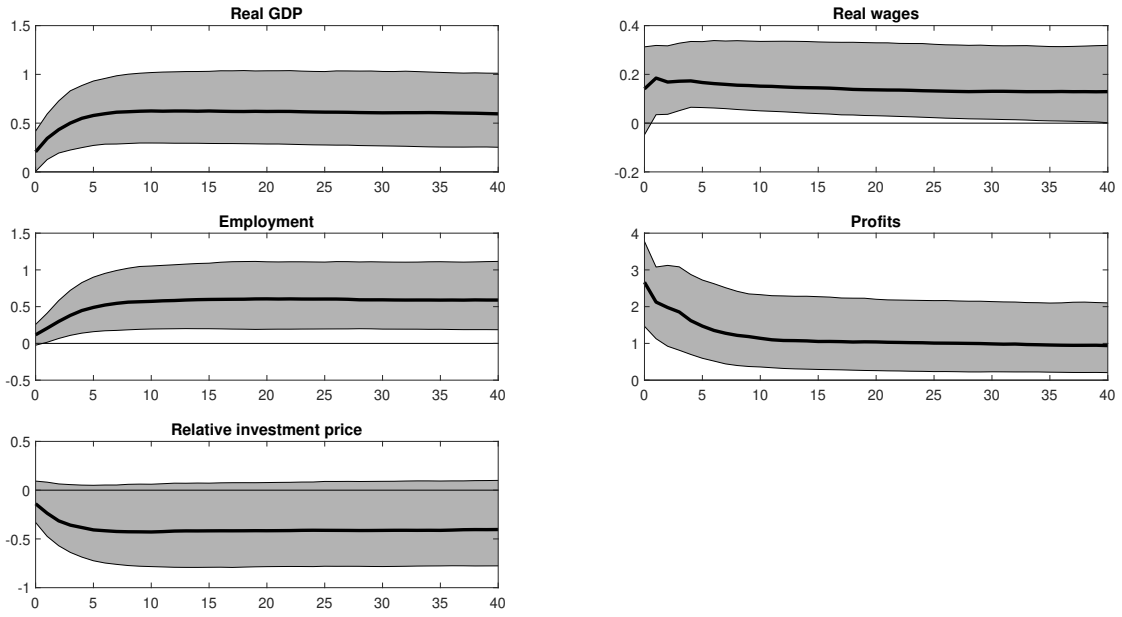


Figure C.2: Variance decompositions with relative investment price

