The U.S. Labor Income Share and Automation Shocks

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May 12, 2019

Abstract

The causes and consequences of the 1964–2016 swings in the U.S. labor income share (LS) are parsed through the lens of a structural model estimated on aggregate and LS series jointly. Where conventional models fall short, the present model yields a counter-cyclical LS unconditionally and in response to demand and monetary policy shocks, as well as a small wage pro-cyclicality, via moderate wage indexation. Shifts in automation, workers' market power, investment efficiency, and the relative price of investment account for 54%, 24%, 6%, and 4% of LS fluctuations, respectively. Automation shocks explain the lion's share of the post-2007 cyclical LS tumble and 11% of output cycles, and generate a distinctive counter-cyclical labor response.

Keywords: Labor Income Share, Automation, Wages, Relative Price of Investment

JEL classification: E32, E25, E52

* Acknowledgments: [TBA] Support from the Alexander S. Onassis Foundation, Scholarship Program, and the UC Irvine, is gratefully acknowledged. Correspondence to: charalan@uci.edu, http://sites.uci.edu/nikolaoscharalampidis/, Department of Economics, 3151 Social Science Plaza, University of California, Irvine, CA 92697-5100.

1 Introduction

It is well known by now that the U.S. labor income share exhibits a downward trend over the past decades. Empirical studies have identified several determinants of that trend, namely production automation or, interchangeably, routine-biased technical change [Goos et al., 2014; Autor and Dorn, 2013; Dao et al., 2017; Abdih and Danninger, 2017; Graetz and Michaels, 2018], the relative price of investment [Karabarbounis and Neiman, 2014], labor market institutions and trade globalization [Abdih and Danninger, 2017], statistical errors and offshoring of labor activities [Elsby et al., 2014], as well as firms' market power [Autor et al., 2017b, 2017a; Dixon and Lim, 2018][1]. Automation, in particular, holds a position so prominent that it has led authors using simulated growth models to make predictions about the future role of machines that paint a bleak picture for labor [Acemoglu and Restrepo, 2017b; Kotlikoff and Sachs, 2012; Nordhaus, 2015; Berg et al., 2018].

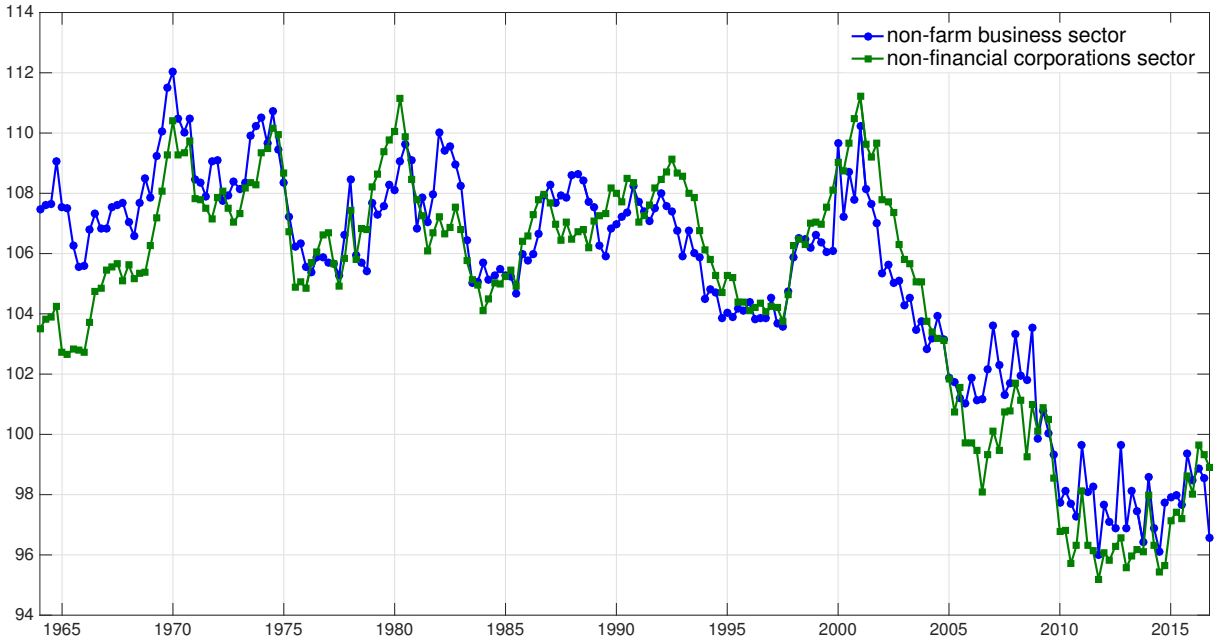
Contrary to the aforementioned studies focusing on the recent trend of the labor share, henceforth "LS", the present paper contributes by examining the origins and macroeconomic implications of the cyclical fluctuations of the LS, since 1964 to 2016. Fig.(1), in fact, gives inklings on beyond garden-variety swings during that period. The fluctuations are parsed in conjunction with U.S. aggregate data through the lens of a structural model, namely the dynamic general equilibrium model of Justiniano et al. (2011), henceforth "JPT", that allows to quantify the relative importance of a variety of factors, such as the relative price of investment, labor market institutions, firms' market power, and measurement errors. Two novelties are considered. The first pertains to the inclusion of LS observables and their joint consideration with aggregate data in a state-of-the-art Bayesian approach. The second pertains to the incorporation of automation shocks.

The examination of the LS fluctuations in estimated structural models is not straightforward because the model-implied LS is uniquely pinned down when series for wages, output, and labor are matched[2]. The present paper overcomes this obstacle. I include LS observables by treating both the LS and wages as latent states that are identified through multiple wage measures and LS observables, displayed in Fig.(1), via a factor approach. The rationale for this choice is that neither a single observed wage measure nor a single LS measure exactly

[1] Blanchard and Giavazzi (2003) argue for shifts in regulation of the European product and labor markets.

[2] Similarly, the FRBNY DSGE model [Del Negro et al., 2013] matches output, labor, and the labor share but does not account for wages, various measures of the labor share, and the trend in the labor share.

Figure 1: Swings in the Labor Share



Notes: Indices. *Data Source:* U.S. Bureau of Labor Statistics

matches the definition of its latent analogue. A factor approach to both wages and the LS alleviates this issue by *jointly* sampling the latent wage and LS as the common components of multiple observables.

Moreover, incorporating multiple LS observables draws insights from the heterogeneous evolution of sectorial labor shares documented in Alvarez-Cuadrado et al. (2018), while a factor approach to wages is examined in studies aiming to strengthen the identification of wage markup shocks [Galí et al., 2012a; Justiniano et al., 2013; Lindé et al., 2016; Charalampidis, 2018]. In addition, the present data-driven examination of the LS swings complements branches of the literature that study the implications of models featuring either labor search [Shao and Silos, 2014] or other deviations from Walrasian markets [Boldrin and Horvath, 1995; Gomme and Greenwood, 1995] for the LS via summary statistics from simulations.

Including observables for the labor share entails profound implications. More specifically, the JPT model yields a *pro-cyclical* model-implied LS that is at odds with the *counter-cyclicality* observed in the data (about -0.4 is the correlation between LS and output growth). I demonstrate that this pro-cyclicality is even amplified in models matching only multiple

wage indicators. The problem is triggered by an overstated wage pro-cyclicality compared to that in the data. In contrast, including the LS in the observation set disciplines the evolution of its model-implied analogue to match the salient features of the data such as the moderate, albeit slowly decreasing since the 1980s, degree of LS counter-cyclicality. This improvement is accomplished mainly via a moderate (0.55) degree of wage indexation that renders wages less responsive to general equilibrium forces. By matching the LS counter-cyclicality and the small wage pro-cyclicality, the model overcomes two notorious labor market puzzles[3].

Moreover, parsing the observed gyrations of the LS over five decades allows the present model to come closer to the data in terms of pinning down the LS response to a plethora of shocks. More specifically, Cantore et al. (2019) find that the LS is counter-cyclical in response to monetary policy innovations in the data, whereas the New Keynesian model features a monetary policy transmission that is based on a pro-cyclical LS. These authors argue that several model modifications fail to alter the latter. In the present model, I show that the LS is counter-cyclical in response to monetary innovations despite being pro-cyclical in the JPT model. Furthermore, the findings demonstrate that although the LS is pro-cyclical in response to demand shocks in the JPT model – a result challenged by the empirical evidence of Nekarda and Ramey (2013)[4] suggesting a pro-cyclical markup in response to those shocks – it becomes counter-cyclical when the model matches the LS data.

The present structural perspective allows to determine the driving forces of the LS. According to the findings, about half of fluctuations in the U.S. LS are explained by persistent automation shocks at any horizon. Wage markup shocks, reflecting changes in workers' market power, maintain a prominent role in the swings of the labor share: they account for 24% and 15% of the short- and long-run swings, respectively. This result is consistent with Abdih and Danninger (2017) who find an influence of changes in unionization on the decline of the labor share. Demand side shocks and, in particular, disturbances associated with the marginal efficiency of investment (MEI) exert limited short-run influence (6%) and moderate long-run influence (20%) on the LS. Contrary to Karabarbounis and Neiman (2014) who find that the decline in the corporate labor share is attributed to the relative investment price, I find that investment-specific technological (IST)[5] disturbances account

[3]According to Koh and Santaeulàlia-Llopis (2017): (i) a low correlation between real wages and output; (ii) the declining pro-cyclicality of productivity; the counter-cyclicality (iii) of the LS and (iv) of labor hours.

[4]They also find a pro-cyclical markup after technology shocks that implies a counter-cyclical LS. Although the present model does not yield the latter, it attenuates the pro-cyclical LS response of the JPT model.

[5]I follow the strategy of Justiniano et al. (2011) to disentangle MEI shocks from IST shocks suggested

for a negligible fraction (4%) of the cyclical fluctuations in the LS.

Furthermore, during the 1960s, the fluctuations of the LS are small and closely tracked by the effect of automation. During the 1970s, the LS overshoots its steady state due to supply side factors. During the 1980s and 1990s, the LS remains above its steady state thanks to (negative) automation shocks. From the early 2000s to about 2007, a temporary decline in the LS is driven by demand shocks. The lion's share of the subsequent tumble in the cyclical part of the LS, however, is explained by automation shocks.Thus, gauging the cyclical effect of automation through structural lenses complements empirical studies [Goos et al., 2014; Autor and Dorn, 2013; Dao et al., 2017; Abdih and Danninger, 2017; Graetz and Michaels, 2018] that attribute a crucial role to automation for the LS's downward trend.

In addition, the information in the LS series alters to some extent the nature of aggregate shocks found in JPT. Although MEI shocks are the main determinant of output and investment cycles as in Justiniano et al. (2011), these shocks are less persistent and lose explanatory power over output in the present model compared to the JPT case (66/63% vs 72/84% in the short/long run). This attenuation happens because MEI shocks trigger a pro-cyclical LS in the JPT model which becomes counter-cyclical in the present paper due to wage indexation that attenuates the pro-cyclicality of wages. A similar result is observed in the case of risk premium shocks. It is worth mentioning that the reduced influence of MEI shocks is similar to that obtained in Kaihatsu and Kurozumi (2014) who introduce a financial accelerator and shocks to net worth and the external finance premium in JPT. Compared to their influence in the JPT model, the present impact of wage markup shocks doubles while that of price markup shocks is reduced by about half since the former shocks yield a counter-cyclical LS favored by the data whereas the latter yield a pro-cyclical LS.

Turning to the second novelty of the present work, the estimation extracts disturbances encapsulating shifts in production automation. These disturbances are modeled as stochastic variations in the output elasticities with respect to the production factors, that is, in the exponents of the individual firm's production function along the lines of Lansing (2015) and Lansing and Markiewicz (2016) who study the asset-pricing and welfare implications of exogenous capital share shifts in a Real Business Cycle (RBC) model, respectively; of Rios-Rull and Santaeulàlia-Llopis (2010) who consider redistribution shocks; and of Young

by Greenwood et al. (1988), examined in Greenwood et al.(1997, 2000) and Fisher (2006), and introduced in an international RBC model in Mandelman et al. (2011). Moura (2018) confirms the sizable role of MEI shocks in a two-sector model but finds a weak link between the relative investment price and IST shocks.

(2004) who incorporates capital share shifts in a RBC model without neutral technology[6]. The present work adds to that strand of studies along two dimensions.

First, given monopolistic competition in goods, automation shocks introduce a wedge between marginal costs and the LS. Thereby, the moderate model-implied LS counter-cyclicality is associated with an a-cyclical price markup (-0.01 is the correlation between the inverse of the real marginal cost and output, both in growth terms) that is compatible with the pro-cyclical or a-cyclical price markup found in the U.S. private sector [Nekarda and Ramey, 2013]. Second, the evolution of automation shifts is disciplined by the information of both aggregate and LS data. This feature adds to (i) the branch of studies examining shifts in factor shares via simulation [Lansing, 2015; Lansing and Markiewicz, 2016; Rios-Rull and Santaeulàlia-Llopis, 2010; Young, 2004; Castanẽda et al. (1998)] or regression analysis [Blanchard, 1997; Bentolila and Saint-Paul, 2003]; and (ii) to DSGE studies featuring capital-augmenting shocks [Cantore et al., 2015; Di Pace and Villa, 2016] identified based on information found only in aggregate data rather than in the LS.

As for the macroeconomic implications of automation shocks, I find that these shocks trigger a counter-cyclical labor response on impact. This response is intuitive since automation shifts, at their core, entail a substitution of labor with capital, as well as a temporary output expansion. This characteristic implies that the present modeling of those disturbances is not susceptible to the critique of Acemoglu and Restrepo (2018) about various modeling ways of automation shocks not being able to generate a fall in labor demand[7]. Automation disturbances account for 11/19% of output cycles in the short/long run, and spur a counter-cyclical LS. Their interaction with sticky prices amplifies the impact and persistence of their effect. The negative correlation between labor and output also appears after technology shocks[8]. Nevertheless, automation and technology shocks differ on two grounds.

[6] In a similar spirit, Goldin and Katz (2007) model shifts in the shares of a CES production function to study the premium between skilled and unskilled workers.

[7] For example, the aforementioned capital-augmenting shocks generate a labor increase in the RBC model, as well as in the New Keynesian model for an elasticity smaller than one; see Cantore et al. (2014).

[8] Galí (1999) first obtains a negative response of hours to technology that was read in favor of sticky prices. Francis and Ramey (2005), Basu et al. (2006), Fernald (2007), and Canova et al. (2010) confirm the negative correlation and emphasize factors such as identification schemes, productivity measures, trend breaks, and subsample estimations. In contrast, Christiano et al. (2003) and Chari et al. (2008) challenge it on the grounds of detrending choices and a lag truncation bias in the VAR, respectively. Alexopoulos (2011) and Holly and Petrella (2012) find a positive relationship using newly-constructed technology indices and sectorial interactions in VARs, respectively. Cantore et al. (2014) argue that the hours' response depends on the production function. Cantore et al. (2017) find that the hours' response has increased over time.

First, under flexible prices, technology shocks generate an increase in labor that later falls below its steady state confirming the results of Francis and Ramey (2005) that with habit and investment adjustments costs, hours can fall in response to technology shocks[9]. In contrast, automation shocks generate a decline in labor hours even under flexible prices. Second, under sticky prices, automation shocks generate counter-cyclical responses in inflation, marginal costs, and the labor share that contradict the pro-cyclical responses generated after technology shocks. Additionally, the counter-cyclical inflation response distinguishes these shocks from all demand side shocks generating pro-cyclical inflation.

Furthermore, the present data-driven examination of the historical swings in the U.S. labor share complements branches of the literature that study shifts in factor shares via production with constant elasticity of substitution (CES) between capital and labor in a DSGE context but without matching data on the labor share [Cantore et al., 2015]. Considering CES production and LS series in the estimation, raises the impact of automation shocks on the LS, and does not diminish their impact on output cycles and labor. The estimation yields a higher degree of wage inertia than in the Cobb-Douglas specification, and an elasticity of substitution between capital and labor above one. The latter is more in line with the empirical findings of Karabarbounis and Neiman (2014) placing that elasticity around 1.25, of Piketty (2014) and of Duffy and Papageorgiou (2000), than with the low estimates (0.15-0.18) of Cantore et al. (2015) in a DSGE model, and of León-Ledesma et al. (2010) and Chirinko (2008) (0.4-0.7) using single-equation first-order conditions. Finally, the present findings suggest a pro-cyclical response of the rental rate of capital to automation shocks that is opposite to the responses obtained after shocks to the labor-augmenting and capital-augmenting technological processes.

Section 2 outlines the structural model. Section 3 develops the estimation and identification strategy. Section 4 presents the results. Section 5 concludes.

2 Full-fledged Model

This section outlines the model which builds on Justiniano et al. (2011) who include the relative price of investment and non-stationary technology in the environment of Christiano et al. (2005) and Smets and Wouters (2007).

[9]Rotemberg (2003) and Lindé (2009) provide an alternative argument for the fall of hours in the absence of sticky prices that is based on technological changes that manifest only gradually.

A representative firm converts units of the final good to investment purchased by a capital producer. The latter produces capital that is channeled to a continuum of monopolistically competitive firms. The firms combine capital and labor to produce intermediate goods, and choose prices in a staggered fashion. Households invest in one-period nominal bonds priced at a rate determined by monetary policy, consume the final good, and supply labor. Perfect risk sharing holds. Each household consists of a continuum of agents with different labor types. The differentiated labor is uniformly distributed, supplied along the intensive margin, and priced in a staggered fashion by monopolistically competitive unions.

2.1 Final Good.

A perfectly competitive final good producer purchases and aggregates intermediate goods $Y_t(i), \forall i \in [0,1]$, to output Y_t that is sold to consumers at price P_t. The producer maximizes period-t profits, $P_t Y_t - \int P_t(i) Y_t(i) di$, subject to technology

$$Y_t = \left[\int Y_t(i)^{(\lambda_{p,t}-1)/\lambda_{p,t}} di\right]^{\lambda_{p,t}/(\lambda_{p,t}-1)} \tag{2.1}$$

where $\lambda_{p,t}$ is the time-varying elasticity of substitution across product varieties, with the gross price markup $\lambda_{p,t}/(\lambda_{p,t}-1)$ following an AR(1) process with parameters $\{\rho_p, \sigma_p\}$. The resulting demand for good "i" and the aggregate price index are given by

$$Y_t(i) = (P_t(i)/P_t)^{-\lambda_{p,t}} Y_t \qquad \text{and} \qquad P_t = \left(\int P_t(i)^{1-\lambda_{p,t}} di\right)^{1/(1-\lambda_{p,t})} \tag{2.2}$$

2.2 Intermediate Good.

Monopolistically competitive intermediate good producers, indexed by "i" and situated in the unit interval, hire labor $L_t(i)$ from a labor aggregator defined below, and capital $K_t(i)$ from the capital producing sector while taking as given factor prices (W_t, R_t^k), in order to produce output $Y_t(i)$ according to the production function:

$$Y_t(i) = K_t(i)^{\alpha_t} \left(Z_t L_t(i)\right)^{1-\alpha_t} - A_t \Phi_y \tag{2.3}$$

The labor-augmenting technological process exhibits a unit root, $ln(Z_t/Z_{t-1}) = \gamma_z + \widehat{z}_t$. $\widehat{z}_t$ follows an AR(1) process with associated parameters $\{\rho_z, \sigma_z\}$. A_t is a composite technological factor pinned down by $Z_t \Omega_t^{\frac{\alpha_t}{1-\alpha_t}}$. Ω_t is the investment-specific technological factor – to be explained below. Fixed costs, Φ_y, guarantee zero steady state profits.

α_t and $1-\alpha_t$ stand for the time-varying output elasticities with respect to capital and labor, respectively. Stationary stochastic variations in α_t aim to reflect shifts in automa-

tion – such as those related to routine-biased technological change – because they alter the responsiveness of output to the capital-labor mix in the production line[10]. α_t follows

$$\alpha_t = \alpha^{1-\rho_\alpha} \alpha_{t-1}^{\rho_\alpha} e^{\epsilon_t^\alpha} \quad , \quad \epsilon_t^\alpha \sim N(0, \sigma_\alpha^2) \tag{2.4}$$

Such variations are recently considered in Lansing (2015), Lansing and Markiewicz (2016), and Rios-Rull and Santaeulàlia-Llopis (2010), and differ from the modeling of automation as a capital-augmenting process [Kotlikoff and Sachs, 2012; Nordhaus, 2015; Graetz and Michaels, 2018]. The model-based labor share is given by $LS_t^m = (W_t^r L_t)/(Y_t + \Phi_y A_t)$, where W_t^r and L_t stand for the real wage and labor, respectively. Cost minimization yields

$$LS_t^m = (1 - \alpha_t) MC_t^r \tag{2.5}$$

A constant α implies that movements in LS_t^m and the (real) marginal cost, MC_t^r, are proportional. In contrast, a time-varying automation disturbance, α_t, introduces a wedge between LS_t^m and MC_t^r that allows for different degrees of cyclicality between the labor share and the marginal cost. Furthermore, α_t generates cross-equation influence in the model by appearing in the equations for the capital-to-labor ratio and marginal cost given by

$$K_t(i)/L_t(i) = [\alpha_t/(1-\alpha_t)](W_t/R_t^k) \tag{2.6}$$

$$MC_t = (\alpha_t)^{-\alpha_t}(1-\alpha_t)^{-(1-\alpha_t)}(W_t)^{(1-\alpha_t)}(R_t^k)^{\alpha_t} Z_t^{-(1-\alpha_t)} \tag{2.7}$$

where R_t^k is the rental rate of capital.

Each firm chooses price $P_t^\circ(i)$ with probability ζ_p in order to maximize the present discounted value of future profits subject to output demand (2.2). In periods in which the price cannot be optimally chosen, it is updated according to a convex combination of the one-period-lagged (gross) inflation and steady-state (gross) inflation according to the indexation parameter ι_p; thus, the period-$(t+s)$ price of a firm that last chose its price in period t is given by $P_{t+s|t}(i) = P_t^\circ(i) X_{t,s}^p$, where $X_{t,s}^p \equiv \prod_{l=1}^s \Pi_{t+l-1}^{\iota_p} \Pi^{1-\iota_p}$ for $s > 0$ and $= 1$ for $s = 0$[11]. The present discounted value of current and future profits is given by

$$E_t \sum_{s=0}^{+\infty} (\beta\zeta_p)^s \left[(\Xi_{t+s} P_t)/(\Xi_t P_{t+s})\right] \left[P_{t+s|t}(i) - MC_{t+s}\right] Y_{t+s|t}(i) \tag{2.8}$$

[10]Rewriting (2.3) as $Y_t(i) = (K_t(i)/Z_t L_t)^{\alpha_t} (Z_t L_t(i)) - A_t \Phi_y$ suggests that output depends on labor and the capital-labor mix. α_t regulates the importance of that mix. Automation in this setup implies that the same output can be produced with fewer labor hours insofar as the influence of capital-per-labor-unit rises.

[11]This indexation scheme is proposed in Smets and Wouters (2007). Ascari and Ropele (2007) study the effects of a positive trend inflation that arise in cases that do not adopt the previous indexation scheme.

2.3 Investment.

A representative firm purchases Y_t^I units of the final good, and converts them to I_t units of the investment good according to: $I_t = \Omega_t Y_t^I$. The latter is sold to a capital producing firm at price P_t^I. Ω_t is the investment-specific technological factor (IST) capturing shifts in the price of investment goods over the price of consumption goods. Its evolution is described by: $ln(\Omega_t/\Omega_{t-1}) = \gamma_\omega + \widehat{\upsilon}_t^\omega$, where $\widehat{\upsilon}_t^\omega$ follows an AR(1) process with parameters $\{\rho_\omega, \sigma_\omega\}$. The growth rate along the balanced growth path, therefore, is given by $\gamma = \gamma_z + \frac{\alpha}{1-\alpha}\gamma_\omega$. Profit maximization balances the value of marginal product $(P_t^I \Omega_t)$ and marginal cost (P_t), thus:

$$P_t^I/P_t = 1/\Omega_t \tag{2.9}$$

2.4 Capital Production.

A representative firm invests (I_t) in raw capital $(\bar{K}_t)$ subject to adjustment costs $S(I_t/I_{t-1})$. It chooses the utilization rate u_t that determines the effective capital, $K_t \equiv u_t \bar{K}_{t-1}$, subject to costs that are proportional to the last period's raw capital $(a(u_t)\bar{K}_{t-1}/\Omega_t)$ scaled by Ω_t to ensure a balanced growth path. Capital is sold to intermediate good producers at the rental rate R_t^k. The firm maximizes the present discounted value of future dividends,

$$E_t \sum_{s=0}^{\infty} \frac{(\beta^s \Xi_{t+s} P_t)}{(\Xi_t P_{t+s})} \left[R_{t+s}^k K_{t+s} - \frac{P_{t+s} a(u_{t+s}) \bar{K}_{t+s-1}}{\Omega_{t+s}} - P_{t+s}^I I_{t+s} - A_{t+s} P_{t+s} \Phi_k \right] \tag{2.10}$$

subject to the law of capital accumulation,

$$\bar{K}_t = (1-\delta)\bar{K}_{t-1} + \upsilon_t^i \left(1 - S(I_t/I_{t-1})\right) I_t \tag{2.11}$$

υ_t^i is the marginal efficiency of investment (MEI) shock affecting the transformation of investment goods to capital. $ln(\upsilon_t^i)$ follows an AR(1) process with associated parameters $\{\rho_i, \sigma_i\}$.

Investment in units of the final good reads as $\widetilde{I}_t = (P_t^I/P_t)I_t$. The steady state full utilization is associated with zero cost: $a(1) = 0$. As in Smets and Wouters (2007), the properties of the cost functions for utilization and investment are defined so that $a(1)''/a(1)' = \psi/(1-\psi)$, $S(\cdot) = S(\cdot)' = 0$, and $S(\cdot)'' \equiv S > 0$. δ is the depreciation rate. Fixed costs (Φ_k) ensure zero steady state dividends. Ξ_{t+s}/Ξ_t is the stochastic discount factor.

2.5 Labor Demand.

Individuals of the same labor type "j" form a union that operates in a monopolistically competitive environment and sets wages in a staggered fashion. The unions sell differentiated

labor to a labor agency that aggregates it according to technology

$$L_t = \left[\int L_t(j)^{(\lambda_{w,t}-1)/\lambda_{w,t}} dj\right]^{\lambda_{w,t}/(\lambda_{w,t}-1)} \quad , \quad \forall j \in [0,1] \tag{2.12}$$

where $\lambda_{w,t}$ is the time varying elasticity of substitution across labor varieties, with the gross wage markup, $\lambda_{w,t}/(\lambda_{w,t}-1)$, following an AR(1) process with parameters $\{\rho_w, \sigma_w\}$ and encapsulating stochastic variations in workers' market power and, thereby, in labor market competitiveness[12] as argued in Blanchard and Giavazzi (2003), Justiniano et al. (2013), and Galí et al. (2012b). Profit maximization yields the following labor demand and wage

$$L_t(j) = (W_t(j)/W_t)^{-\lambda_{w,t}} L_t \ , \ \forall j \in [0,1] \quad \text{and} \quad W_t = \left(\int W_t(j)^{1-\lambda_{w,t}} dj\right)^{1/(1-\lambda_{w,t})} \tag{2.13}$$

Each union chooses wage $W_t^\circ(j)$ in a staggered way [Erceg et al., 2000] subject to labor demand (2.13) in order to maximize the present discounted value of future wages net of the type-j labor disutility expressed in terms of the final good, $W_t^{h,r}(j)$. In periods in which the wage is not reset, it is updated according to the weighted product of one-period-lagged and steady-state price inflation rates, with the weight given by the indexation parameter ι_w: $W_{t+s|t}(j) = W_t^\circ(j) X_{t,s}^w$, where $X_{t,s}^w = \prod_{l=1}^{s} (e^{\gamma+\widehat{z}_{t+l-1}+(\alpha_{t+l-1}/[1-\alpha_{t+l-1}])\widehat{\upsilon}_{t+l-1}^{\omega}} \Pi_{t+l-1})^{\iota_w} (e^\gamma \Pi)^{1-\iota_w}$ for $s > 0$ and $= 1$ for $s = 0$. The union's objective function is:

$$E_t \sum_{s=0}^{+\infty} (\beta\zeta_w)^s \left[(\Xi_{t+s}P_t)/(\Xi_t P_{t+s})\right] \left[W_{t+s|t}(j) - W_{t+s}^{h,r}(j) P_{t+s}\right] L_{t+s}(j) \tag{2.14}$$

2.6 Demand Side.

The household chooses an infinite sequence of consumption and bonds $\{C_t, B_t\}_{t=0}^{\infty}$, to maximize the present discounted value of future expected utility:

$$E_t \sum_{s=0}^{+\infty} \beta^s \left[ln\left(C_{t+s} - \eta C_{t+s-1}\right) - \theta \int_0^1 \frac{L_{t+s}(j)^{1+\chi}}{1+\chi} dj\right] \tag{2.15}$$

Preferences are log-separable. η mirrors external habit formation, and χ is the inverse Frisch elasticity. The budget constraint is given by

$$C_t - B_t/(\upsilon_t^b R_t P_t) + T_t/P_t = \int W_t^{h,r}(j) L_t(j) dj + F_t - B_{t-1}/(P_{t-1}\Pi_t) + V_t \tag{2.16}$$

$ln(\upsilon_t^b)$ is a risk premium shock following an AR(1) process with parameters $\{\rho_b, \sigma_b\}$. T_t and V_t denote taxes and economy wide profits, respectively. The marginal labor disutility

[12] The model does not feature labor disutility shocks capturing shifts in labor supply, such as the women's participation in the labor force or changes in immigration. As a result, such changes are likely reflected in the wage markup shock. I thank the referee for pointing out this issue.

expressed in terms of the consumption good, $\theta L_t(j)^{\chi}/\Xi_t$, is equal to the type-j real wage that would prevail in the absence of rigidities: $W_t^{h,r}(j)$. F_t stands for transfers by the unions.

2.7 Policy.

Monetary policy is determined according to a stylized policy rule,

$$R_t/R = (R_{t-1}/R)^{\rho_r}\left[(\Pi_t/\Pi)^{\psi_\pi}\left(Y_t/Y_t^f\right)^{\psi_y}\left((Y_t/Y_{t-1})/(Y_t^f/Y_{t-1}^f)\right)^{\psi_{\Delta y}}\right]^{1-\rho_r} e^{\epsilon_t^{mp}} \tag{2.17}$$

where $R = \Pi e^{\gamma}/\beta$; $\rho_r \in (0,1)$ captures interest rate smoothing; $\psi_\pi > 1$, $\psi_y, \psi_{\Delta y} \geq 0$; and $\epsilon_t^{mp} \sim N(0, \sigma_{mp}^2)$ is a white noise disturbance. Fiscal policy follows a balanced budget, with spending given by $ln(G_t/A_t/G) = \rho_g ln(G_{t-1}/A_{t-1}/G) + \rho_{gz}\epsilon_t^z + \epsilon_t^g$, with $\epsilon_t^g \sim N(0, \sigma_g^2)$. Y_t^f denotes output under flexible prices and wages. Automation shocks shift that equilibrium.

2.8 Aggregation.

Combining (2.3) and (2.6) across firms yields aggregate production: $Y_t D_t = K_t^{\alpha_t}(Z_t L_t)^{1-\alpha_t} - A_t \Phi_y$, where $D_t \equiv \int_0^1 (P_t(i)/P_t)^{-\lambda_{p,t}} di$ is a measure of price dispersion. Firms' profits and dividends read as: $\Pi_t^{int} \equiv P_t Y_t - W_t L_t - R_t^k K_t$ and $Div_t \equiv R_t^k K_t - P_t a(u_t)\bar{K}_{t-1}/\Omega_t - P_t \widetilde{I}_t - P_t A_t \Phi_k$, respectively. Thus, economy wide profits are: $V_t = \Pi_t^{int} + Div_t$. Combining (2.16), government's balanced budget, and profits, yields the following resource constraint:

$$C_t + \widetilde{I}_t + G_t + a(u_t)\bar{K}_{t-1}/\Omega_t + \Phi_k A_t = Y_t \tag{2.18}$$

2.9 Equilibrium.

The stationary equilibrium and the log-linearized equilibrium conditions are reported in the Appendix. The model features 9 structural shocks in total. Eight of them appear in Justiniano et al. (2011): risk premium, technology, wage and price markup, spending, IST, MEI, and monetary policy shocks. An automation shock is the additional disturbance.

3 Estimation

I conduct Bayesian estimation starting in 1964Q1 and stoping in 2016Q4. The data, the measurement equations, the state space approach, and the priors are discussed below.

3.1 Data And Observation Equations.

The span of the sample is denoted by $t = \{1, 2, \ldots, n_q\} \mapsto \{1964Q1, \ldots, 2016Q4\}$. Eleven (o_q) series are used. Nominal GDP, consumption, and investment are divided by a price

deflator and population. As in Justiniano et al. (2011), consumption corresponds to the sum of expenditures on non-durable goods and services, while investment corresponds to the sum of consumption expenditures on durable goods and gross private domestic investment. Inflation is matched to the log-difference of the implicit deflator of consumption. The relative price of investment is defined as the ratio of consumption and investment implicit price deflators. Labor hours are constructed as in Smets and Wouters (2007). Measurement error, $\epsilon_t^j \sim N(0, \mu_j^2)$, is incorporated in each j series. No detrending is applied prior to estimation[13].

The model's policy rate is matched to the Federal Funds Rate during normal times. In contrast, during the turbulent times of the binding ZLB (2009Q1–15Q4), it is linked to the shadow rate of Wu and Xia (2016) that is extracted from the underlying term structure[14].

I include two series for wage inflation as in Galí et al. (2012a), Justiniano et al. (2013), and Lindé et al. (2016). Wage multiplicity strengthens the identification of wage markup shocks by allowing to extract the latent wage from multiple series.Compensation in the private non-farm businesses (W_t^c) is used as in Smets and Wouters (2007), along with the survey-based weekly earnings of production and nonsupervisory employees (W_t^e) – both series are deflated with the aforementioned deflator. The loading on compensation is Ψ_w. The observation equation is reported below. Δ is the first-difference operator, $\bar{\gamma} = 100\gamma$.

$$\begin{bmatrix} \Delta lnW_t^e \\ \Delta lnW_t^c \end{bmatrix} = \begin{bmatrix} \bar{\gamma}^e \\ \bar{\gamma} \end{bmatrix} + \begin{bmatrix} 1 \\ \Psi_w \end{bmatrix} [\Delta \widehat{w}_t^r + \widehat{z}_t + (\alpha/[1-\alpha])\widehat{\upsilon}_t^\omega] + \begin{bmatrix} \epsilon_t^e \\ \epsilon_t^c \end{bmatrix} \tag{3.1}$$

Wage multiplicity has an additional role in the present paper: it allows to match data for the LS. Consider the labor share given by $LS_t = W_t^r L_t / Y_t$[15]. Log-linearization yields

$$\widehat{ls}_t = \widehat{w}_t^r + \widehat{l}_t - \widehat{y}_t \tag{3.2}$$

Had we used a single measure for wages, the right-hand-side of (3.2) and, in turn, the labor share would uniquely be pinned down rendering impossible to match data series for

[13] Since the logarithm of the labor hours series is demeaned, θ is appropriately parameterized. All data series are compiled by the U.S. Bureau of Labor Statistics (BLS) and retrieved from FRED.

[14] Alternatives to deal with the ZLB in DSGE models include non-linear solutions that are difficult to implement given the model size, perfect foresight approaches as in Chen et al. (2012), Del Negro et al. (2015), and Lindé et al. (2016), that postulate agents' knowledge of the absorbing state and the ZLB duration, and the approach of anticipated structural changes [Cagliarini and Kulish, 2013; Kulish et al., 2017].

[15] This data-driven definition of the labor share that abstracts from fixed costs is usually employed in the literature since it is aligned with the construction of the labor share in the data. It is worth pointing out that the link between LS_t and LS_t^m depends on fixed costs and, in turn, on the net steady state price markup; in log-linear terms, it is given by: $\widehat{ls}_t^m = \widehat{ls}_t + [\Phi_y/(y+\Phi_y)]\widehat{y}_t = \widehat{ls}_t + [\upsilon_p/(1+\upsilon_p)]\widehat{y}_t$.

the latter. Nonetheless, matching data for the labor share is viable because the wage is a latent state. More specifically, I extract the labor share from two measures compiled by the BLS[16] and shown in Fig.(1): the first pertains to non-farm businesses (LS_t^{nf}); the second pertains to non-financial corporations (LS_t^c). The loading on the latter is Ψ_α. Both series include a disperse measurement error. The associated observation equations are

$$\begin{bmatrix} dlnLS_t^{nf} \\ dlnLS_t^c \end{bmatrix} = \begin{bmatrix} \bar{\gamma}_{ls}^{nf} \\ \bar{\gamma}_{ls}^c \end{bmatrix} + \begin{bmatrix} 1 \\ \Psi_\alpha \end{bmatrix} \Delta\widehat{ls}_t + \begin{bmatrix} \epsilon_t^{nf} \\ \epsilon_t^c \end{bmatrix} \tag{3.3}$$

In this approach, the evolution of the extracted labor share influences the wage sampled from the data. In other words, the labor share series provide discipline to the whole model – a discipline that incarnates the idea of *jointly* examining U.S. aggregate and LS series. It is in a similar spirit to the motivation of Justiniano et al. (2011) about using the relative price of investment goods to provide discipline in the estimation.

It is worth pointing out that I opt for an empirically oriented approach and include trends for both labor share series ($\bar{\gamma}_{ls}^{nf}, \bar{\gamma}_{ls}^c$) and both wages ($\bar{\gamma}, \bar{\gamma}_e$) to avoid spurious correlations. Compensation growth is more or less consistent with the balanced growth path rate (0.27%) whereas earnings growth is not (0.02%). Galí et al. (2012b) include different trends in wages too. Similarly, the growth rates of the labor share series, although stationary in theory, are not zero within the sample: the mean growth rates for LS_t^{nf} and LS_t^c are about zero during 1964–2003, and -0.15% and -0.13%, respectively, after 2003. Thus, the estimation uses different trends across the two windows: $\bar{\gamma}_{ls}^{nf,1}, \bar{\gamma}_{ls}^{nf,2}, \bar{\gamma}_{ls}^{c,1}, \bar{\gamma}_{ls}^{c,2}$. As in Justiniano et al. (2011), I include different trends for the growth of composite technology and of the relative investment price before and after 1982 given the break in the latter: $\bar{\gamma}^1, \bar{\gamma}^2, \bar{\gamma}_\omega^1, \bar{\gamma}_\omega^2$.

3.2 State Space and Likelihood.

I apply the state space approach of Chan and Jeliazkov (2009), along the lines of Charalampidis (2018), that leads to computational gains by exploiting the sparse and block-banded nature of the precision matrices. Stacking all measurement equations vertically, yields

$$\Upsilon_t = \Gamma_q + H_0\zeta_t + H_1\zeta_{t-1} + M_t \quad , \quad M_t \sim N(0, \Sigma_q) \tag{3.4}$$

where Υ_t and Γ_q are $(o_q \times 1)$ vectors of observables and intercepts, respectively. $\{H_0, H_1\}$ denote the $(o_q \times n_\zeta)$ selection matrices and include the slope coefficients of the measurement

[16]For the construction of these series, see Giandrea and Sprague (2017).

equations. ζ_t is the period-t $(n_\zeta \times 1)$ state vector. M_t collects the measurement errors. Σ_q is the diagonal covariance matrix of measurement errors. Stacking (3.4) over time yields:

$$\begin{bmatrix} \Upsilon_{t=1} \\ \Upsilon_{t=2} \\ \Upsilon_{t=3} \\ \vdots \end{bmatrix} = \begin{bmatrix} \Gamma_q \\ \Gamma_q \\ \Gamma_q \\ \vdots \end{bmatrix} + \begin{bmatrix} H_0 & \dots & \dots & \dots \\ H_1 & H_0 & \dots & \dots \\ \dots & H_1 & H_0 & \dots \\ \dots & \ddots & \ddots & \ddots \end{bmatrix} \begin{bmatrix} \zeta_{t=1} \\ \zeta_{t=2} \\ \zeta_{t=3} \\ \vdots \end{bmatrix} + \begin{bmatrix} M_{t=1} \\ M_{t=2} \\ M_{t=3} \\ \vdots \end{bmatrix} \tag{3.5}$$

The matrix representation of (3.5) is given by

$$\Upsilon = \Gamma + H\zeta + M \quad , \quad M \sim N\left(0_o, \Sigma_M \equiv I_{n_q} \otimes \Sigma_q\right) \tag{3.6}$$

where 0_o is $(o_q n_q) \times 1$. $\Upsilon \equiv [\Upsilon'_{t=1}, \Upsilon'_{t=2}, \dots]'$ is the observation vector. $\Gamma \equiv [\Gamma'_q, \Gamma'_q, \dots]'$ is a vector of intercepts. $\zeta \equiv [\zeta'_1, \zeta'_2, \dots]'$ is the $(n_\zeta n_q) \times 1$ state vector. $M \equiv [M'_{t=1}, M'_{t=2}, \dots]'$ collects the measurement errors. H is a sparse and block-banded matrix. According to (3.6), the likelihood of the data given the parameter vector Θ and the states ζ is $P(\Upsilon - \Gamma|\Theta, \zeta)$, where $(\Upsilon - \Gamma)|\Theta, \zeta \ \sim \ N(H\zeta, \Sigma_M)$.

The Rational Expectations solution of the system of log-linearized equilibrium conditions [Sims, 2002] can be represented as[17]

$$\zeta_t = \Phi_1(\Theta)\zeta_{t-1} + \Phi_2(\Theta)\epsilon_t \tag{3.7}$$

where the system matrices $\{\Phi_1, \Phi_2\}$ depend on Θ. The structural shocks are grouped in the $(n_\epsilon \times 1)$ vector $\epsilon_t \sim N(0_{n_\epsilon}, I_{n_\epsilon})$, and are fewer than the observables $(n_\epsilon < o_q)$. Defining the reduced-form errors as $\tilde{\epsilon}_t = \Phi_2\epsilon_t$ for $t > 1$ and $\tilde{\epsilon}_1 = \epsilon_1$, and stacking (3.7) across time yields:

$$\begin{bmatrix} I_{n_\zeta} & \dots & \dots & \dots \\ -\Phi_1 & I_{n_\zeta} & \dots & \dots \\ \dots & \ddots & \ddots & \dots \\ \dots & \dots & -\Phi_1 & I_{n_\zeta} \end{bmatrix} \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \vdots \\ \zeta_T \end{bmatrix} = \begin{bmatrix} \tilde{\epsilon}_1 \\ \tilde{\epsilon}_2 \\ \vdots \\ \tilde{\epsilon}_T \end{bmatrix}, \quad \begin{bmatrix} \tilde{\epsilon}_1 \\ \tilde{\epsilon}_2 \\ \vdots \\ \tilde{\epsilon}_T \end{bmatrix} \sim N\left(0_{n_\zeta n_q}, \begin{bmatrix} D & \dots \\ \vdots & (\Phi_2\Phi'_2) \otimes I_{T-1} \end{bmatrix}\right) \tag{3.8}$$

where D is the steady state covariance of the state vector evaluated at the prior mean of Θ. In matrix notation, the above equation reads as

$$Z\zeta = \tilde{\epsilon} \qquad , \qquad \tilde{\epsilon} \sim N(0_{n_\zeta n_q}, K_{\tilde{\epsilon}}^{-1}) \tag{3.9}$$

[17] This approach assumes that the agents possess more information than the econometrician since they observe the latent shocks whereas the econometrician does not. Following Levine et al. (2012), Cantore et al. (2015) study the implications of CES production under imperfect information that renders the agents' information set the same as that of the researcher. I thank a referee for bringing up this point.

where $\tilde{\epsilon} \equiv [\tilde{\epsilon}_1', \tilde{\epsilon}_2' \ldots]'$ is the $(n_\zeta n_q) \times 1$ vector of errors, and $K_{\tilde{\epsilon}}$ is the sparse and block-banded precision of the latter. A change of variable transformation yields the prior state distribution, $P(\zeta|\Theta)$, with $\zeta|\Theta \sim N(\zeta_0, K^{-1})$ and $\zeta_0 = 0_{n_\zeta n_q}$. The precision $K = Z'K_{\tilde{\epsilon}}Z$ is also sparse and block-banded [Chan and Jeliazkov, 2009].

Bayesian updating yields the block-banded posterior precision: $P = K + H'\Sigma_M^{-1}H$. The posterior mean state vector $(\widehat{\zeta})$ is computed based on the efficient simulation of Chan and Jeliazkov who use forward and backward substitution in (3.10) exploiting the nature of P:

$$P\widehat{\zeta} = K\zeta_0 + H'\Sigma_M^{-1}(\Upsilon - \Gamma) \tag{3.10}$$

The log-likelihood of the data given the parameters but marginally of the states is evaluated at a high density point along the lines of Chib (1995) and, in particular, at the posterior mean of the states: $lnP(\Upsilon|\Theta) = lnP(\Upsilon|\Theta, \widehat{\zeta}) + lnP(\widehat{\zeta}|\Theta) - lnP(\widehat{\zeta}|\Upsilon, \Theta)$.

3.3 Priors And Estimated Models.

The priors are conventional and reported in Table (1)[18]. The persistence of automation shocks is drawn from Beta centered at 0.5 with a 0.2 standard deviation (std). The std of the associated innovations is drawn from the Inverse Gamma centered at 0.15 (1 std). The loadings (Ψ_w, Ψ_α) are sampled from a Normal around 1 (0.5 std). The prior means for all trends are set to the sample averages. The std of the measurement errors in the multiple indicators (for wages and the labor share) are as loose as the std of the stochastic shocks (Inverse Gamma around 0.15 with 1 std). It is worth clarifying that the state space approach described above requires including measurement error to all observables in equation (3.4). This requirement differs from DSGE models estimated with the Kalman Filter that do not include such errors. To preserve comparability between the current approach and conventional methods, the std of measurement errors associated with series other than wages and the labor share is drawn from the Inverse Gamma distribution centered at a small value (0.01) with a tight distribution around it (0.001 std). The Random Walk Metropolis-Hastings algorithm is used to simulate draws from the non-tractable posterior.

It is important to state that moving from Justiniano et al. (2011) to the Benchmark model involves the incorporation of (i) multiple wages and (ii) multiple LS series along with an automation disturbance. To identify the contribution of each new component to

[18] δ and g are set at the values chosen in Smets and Wouters (2007). β is fixed at 0.998. I thank a referee for pointing out that fixing α (at 0.3) can facilitate estimation and comparison across models.

the findings, I also estimate JPT[19] on the sample span of the paper, as well as a model configuration, called "No LS", that only imposes (i). In the robustness analysis, I examine additional model configurations explained therein.

4 Findings

4.1 Parameter Estimates.

Table (1) displays the posterior parameter distribution[20]. Several parameters in the Benchmark configuration are aligned with what is found in Justiniano et al. (2011) and the literature. Nonetheless, others are influenced by the information found in the labor share.

First, automation disturbances are persistent (0.96) and moderately volatile (0.51). The loading Ψ_α (0.54) implies that the model weighs more LS fluctuations in non-farm businesses than LS fluctuations in non-financial corporations; a finding corroborated by the higher measurement error (0.64) of the latter compared to the former (0.45).

Second, a labor market parameter changes profoundly across models: wage indexation (ι_w) is higher in the Benchmark specification than in JPT (0.55 vs 0.2). In addition, the inverse Frisch elasticity (χ) is a tad lower in the Benchmark model than in JPT (4.8 vs 5.11).

Third, inflation and wage dynamics are influenced by the wage and LS series. Mechanisms of endogenous persistence (price, ζ_p, and wage, ζ_w, stickiness) are attenuated (from 0.91 to 0.75 and from 0.79 to 0.75, respectively). Mechanisms of exogenous persistence (price, ρ_p, and wage, ρ_w, markup shocks) are weakened (from 0.67 to 0.53 and from 0.26 to 0.12, respectively) too. In contrast, price indexation (ι_p) rises a tad from 0.14 to 0.21.

Fourth, the following shifts in the stochastic structure are noteworthy. The persistence of risk premium disturbances (ρ_b) sharply falls from 0.87 to 0.76. The persistence of MEI shocks (ρ_i) drops from 0.92 to 0.81 too. In contrast, technology shocks are more persistent (0.54 vs 0.12) and less volatile (0.43 vs 1.17) in the Benchmark model than in JPT.

Column "No LS" only imposes multiple wages in JPT and, thereby, helps identify the origin of the above parameter differences. Judging from the loading of compensation and the measurement errors associated with the wage series (μ_w^c, μ_w^e), the Benchmark model and the

[19]To be precise, compared to Justiniano et al. (2011) the estimation of the present JPT specification features small and tightly estimated measurement errors in all observables required by the state space approach. These errors are negligible in size (see Appx.) and have no consequences for the results.

[20]Estimates for the std of measurement errors for variables with a single observable, the trends that are fully informed by the data, steady state inflation and price and wage markups are relegated to the Appx.

Table 1: Posterior Distribution

		Prior	**Posterior** Mean [5-95%]		
			Benchmark	**JPT**	**No LS**
habit	η	B (0.70, 0.10)	0.83 [0.79, 0.88]	0.84 [0.80, 0.87]	0.83 [0.79, 0.87]
inv. Frisch elast.	χ	N (2.00, 1.00)	4.80 [3.72, 6.05]	5.11 [4.02, 6.26]	3.82 [2.72, 5.21]
util. cost elast.	ψ	B (0.50, 0.10)	0.82 [0.74, 0.90]	0.67 [0.54, 0.79]	0.81 [0.72, 0.88]
adj. cost elast.	S	N (4.00, 1.00)	4.24 [2.83, 5.56]	4.60 [3.35, 6.00]	3.47 [2.27, 4.83]
wage stickiness	ζ_w	B (0.60, 0.10)	0.75 [0.61, 0.84]	0.79 [0.69, 0.89]	0.61 [0.51, 0.69]
price stickiness	ζ_p	B (0.60, 0.10)	0.75 [0.70, 0.80]	0.91 [0.86, 0.95]	0.69 [0.64, 0.74]
price indexation	ι_p	B (0.50, 0.15)	0.21 [0.07, 0.43]	0.14 [0.05, 0.29]	0.09 [0.04, 0.17]
wage indexation	ι_w	B (0.50, 0.15)	0.55 [0.41, 0.70]	0.20 [0.13, 0.27]	0.05 [0.03, 0.08]
MP resp. to int.rate	ρ_r	B (0.75, 0.10)	0.84 [0.82, 0.87]	0.83 [0.80, 0.86]	0.83 [0.80, 0.85]
MP resp. to inflation	ψ_π	N (1.70, 0.25)	1.88 [1.59, 2.16]	1.65 [1.40, 1.93]	2.09 [1.87, 2.33]
MP resp. to gap	ψ_y	N (0.12, 0.05)	0.13 [0.09, 0.17]	0.14 [0.10, 0.18]	0.14 [0.10, 0.18]
MP resp. to growth	$\psi_{\Delta y}$	N (0.12, 0.05)	0.25 [0.18, 0.34]	0.26 [0.18, 0.34]	0.24 [0.17, 0.32]
AR risk premium	ρ_b	B (0.50, 0.20)	0.76 [0.62, 0.86]	0.87 [0.82, 0.92]	0.75 [0.64, 0.85]
std risk premium	σ_b	IG (0.15, 1.00)	0.07 [0.05, 0.09]	0.05 [0.04, 0.06]	0.07 [0.05, 0.09]
AR technology	ρ_z	B (0.40, 0.20)	0.54 [0.29, 0.77]	0.12 [0.04, 0.21]	0.10 [0.04, 0.18]
std technology	σ_z	IG (0.50, 1.00)	0.43 [0.30, 0.57]	1.17 [1.07, 1.28]	1.11 [1.02, 1.22]
AR MEI	ρ_i	B (0.50, 0.20)	0.81 [0.68, 0.91]	0.92 [0.84, 0.97]	0.85 [0.78, 0.91]
std MEI	σ_i	IG (0.50, 1.00)	7.11 [5.26, 9.59]	7.23 [5.88, 8.76]	6.14 [4.74, 8.14]
AR price markup	ρ_p	B (0.50, 0.20)	0.53 [0.15, 0.82]	0.67 [0.48, 0.85]	0.97 [0.91, 0.99]
std price markup	σ_p	IG (0.15, 1.00)	0.19 [0.14, 0.25]	0.14 [0.10, 0.18]	0.16 [0.13, 0.21]
AR wage markup	ρ_w	B (0.50, 0.20)	0.12 [0.03, 0.24]	0.26 [0.14, 0.38]	0.99 [0.97, 1.00]
std wage markup	σ_w	IG (0.15, 1.00)	0.62 [0.51, 0.72]	0.69 [0.58, 0.81]	0.02 [0.02, 0.03]
std MP	σ_{mp}	IG (0.15, 1.00)	0.24 [0.22, 0.26]	0.23 [0.21, 0.25]	0.23 [0.21, 0.26]
AR govt spending	ρ_g	B (0.50, 0.20)	0.99 [0.99, 1.00]	0.99 [0.98, 1.00]	0.98 [0.97, 0.99]
std govt spending	σ_g	IG (0.15, 1.00)	0.36 [0.30, 0.42]	0.47 [0.43, 0.52]	0.48 [0.44, 0.52]
tech. resp. to govt	ρ_{gz}	B (0.50, 0.20)	0.17 [0.08, 0.26]	0.02 [0.01, 0.04]	0.02 [0.01, 0.05]
factor for wages	Ψ_w	N (1.00, 0.50)	1.14 [1.03, 1.24]	[,]	0.77 [0.61, 0.93]
std m.e. earnings	μ_w^e	IG (0.15, 1.00)	0.73 [0.66, 0.81]	[,]	0.32 [0.29, 0.35]
std m.e. compensation	μ_w^c	IG (0.15, 1.00)	0.27 [0.21, 0.34]	0.01 [0.01, 0.01]	0.78 [0.72, 0.84]
AR IST	ρ_ω	B (0.20, 0.10)	0.15 [0.06, 0.24]	0.13 [0.06, 0.23]	0.14 [0.06, 0.22]
std IST	σ_ω	IG (0.50, 1.00)	0.68 [0.63, 0.74]	0.68 [0.63, 0.74]	0.68 [0.62, 0.74]
factor for labor share	Ψ_α	N (1.00, 0.50)	0.54 [0.45, 0.64]	[,]	[,]
AR labor share	ρ_α	B (0.50, 0.20)	0.96 [0.93, 0.98]	[,]	[,]
std labor share	σ_α	IG (0.15, 1.00)	0.51 [0.46, 0.57]	[,]	[,]
std m.e. non farm ls	μ_{ls}^{nf}	IG (0.15, 1.00)	0.45 [0.40, 0.50]	[,]	[,]
std m.e. corporate ls	μ_{ls}^c	IG (0.15, 1.00)	0.64 [0.59, 0.70]	[,]	[,]
Marginal Likelihood			-2331	-1766	-1818

Notes: "Benchmark": this paper. "JPT": Justiniano et al. (2011). "No LS": JPT with multiple wages.

"No LS" specification extract different wages from the same wage data: the former favors the properties of compensation ($\Psi_w > 1$) whereas the latter favors the dynamics of survey-based earnings ($\Psi_w < 1$). Jointly sampling LS and wages, therefore, disciplines the extracted wage.

In addition, it is the inclusion of the labor share, not of multiple wages, in the observation set that drives wage and price indexation up and alters features of price markup, wage

markup, and technology shocks. The attenuation in the importance of MEI shocks, of price and wage stickiness, of the inverse Frisch elasticity, and of investment costs (S) are influenced by the introduction of both multiple wages and multiple LS series, with the former exerting the largest contribution. In contrast, the reduction in the persistence of risk shocks and the rise in utilization costs (ψ) are attributed entirely to the introduction of multiple wages.

4.2 Labor Share Cyclicality.

What is the merit of including series for the labor share in the estimation? The answer lies in the counter-cyclicality of the LS that is puzzling for macroeconomic models [Koh and Santaeulàlia-Llopis, 2017][21]. Table (2) displays several correlations found in the 1964–2016 U.S. data. According to this evidence, the LS is (unconditionally) counter-cyclical; -0.4 and -0.3 are the correlations between output growth[22] and the growth of the LS in non-farm businesses and non-financial corporations, respectively. Table (3), though, reveals that the workhorse JPT model implies a pro-cyclical LS (0.5) that is at odds with the data. The first panel of Fig.(2) corroborates the pro-cyclicality of the JPT model across time.

The pro-cyclicality in JPT is associated with a strong correlation between the LS and the real wage (0.9) compared to the moderate observed correlations (-0.1/-0.1 between earnings and the LS in non-farm businesses/non-financial corporations, and 0.6/0.4 between compensation and the LS in non-farm businesses/non-financial corporations). It ultimately emanates from the strong pro-cyclicality of wages (0.6)[23] that is at is at odds with the data (0.1 for compensation and 0.5 for earnings), and constitutes a labor market puzzle according to Koh and Santaeulàlia-Llopis (2017). This LS pro-cyclicality is associated with the fact that the NK model features counter-cyclical price markups that are criticized by Nekarda and Ramey (2013). Worth pointing out is the fact that when the model is estimated only on multiple wage indicators, the pro-cyclicality of the LS is further amplified (0.7) since the extracted wage is heavily influenced by the earnings series which is more pro-cyclical than compensation. The present paper, therefore, demonstrates that including multiple wage

[21] In fact, models need to resort to particular modifications [Young, 2004; Boldrin and Horvath, 1995; Gomme and Greenwood, 1995] to achieve the counter-cyclicality of the labor share.

[22] In assessing the cyclicality, I look at the growth rate since this is matched in the estimation.

[23] To clarify, the high wage pro-cyclicality emerges in JPT where the wage is matched to a single observable (compensation) with low pro-cyclicality (0.1) because the disturbances of the non-stationary labor-augmenting technology and IST processes appear in the observation equation for wages and, thereby, raise the degrees of freedom in the cyclical wage extracted from compensation. That pro-cyclicality, however, does not emerge in Smets and Wouters (2007) where all stochastic processes are stationary, cyclical wage growth is matched one-to-one to demeaned compensation growth, and the model-implied LS is counter-cyclical.

indicators – an approach undertaken in several papers [Galí et al., 2012a; Justiniano et al., 2013; Lindé et al., 2016; Charalampidis, 2018] aiming to strengthen the identification of wage markup shocks – might entail implications that are at odds with the data.

In contrast, when the Benchmark estimation features observables for the labor share, on top of multiple wage indicators, the model-implied cyclicality of the labor share and of wages are disciplined to follow those in the data. Table (3) reveals a counter-cyclical LS (-0.4), as well as a small wage pro-cyclicality (0.1). Fig.(2) further illustrates how the inclusion of LS data helps the model match the sizable, albeit slowly decreasing since the 1980s, degree of LS counter-cyclicality – something that is absent from the alternative specifications. The correlation of the LS with the interest rate and inflation, as well as the pro-cyclicality of labor, are aligned with the data in all models. Altogether, including information reflecting salient features of the LS entails an improvement in the model along the above dimensions.

Table 2: Observed Correlations

	Δoutput	Δearnings	Δcompens.	Δlabor	inflation	int. rate
Δnon farm LS	-0.4	-0.1	0.6	0.0	0.0	0.1
Δnon fin. corp. LS	-0.3	-0.1	0.4	-0.1	-0.0	0.1
Δearnings	0.5	-	0.2	0.3	-0.6	-0.3
Δcompensation	0.1	-	-	-0.1	-0.2	0.0
Δlabor	0.6	-	-	-	-0.0	-0.0

Notes: Quarterly raw data, 1964–2016. ΔX stands for the first difference of the logarithm of X.

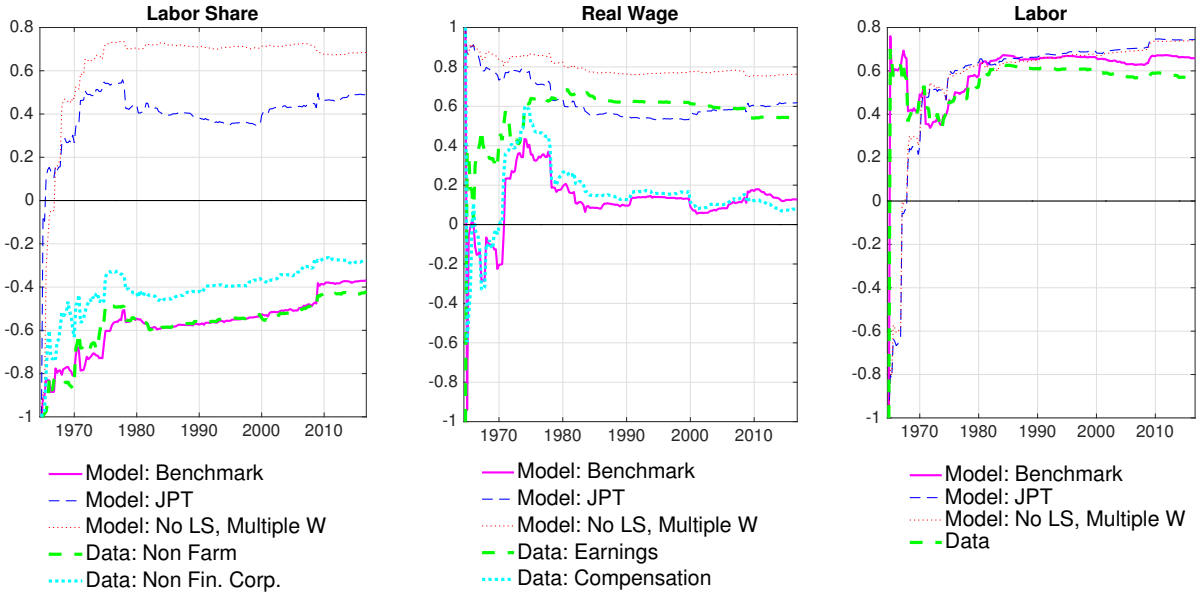
Table 3: Model-Implied Correlations

	$\Delta ls_t, \Delta y_t$	$\Delta w_t^r, \Delta y_t$	$\Delta l_t, \Delta y_t$	$\Delta ls_t, \Delta w_t^r$	$\Delta ls_t, \pi_t$	$\Delta ls_t, r_t$
JPT	0.5	0.6	0.7	0.9	0.0	0.1
No LS, Multiple W	0.7	0.8	0.7	0.9	-0.2	-0.2
Benchmark	-0.4	0.1	0.7	0.7	0.1	0.1

Notes: Cyclical variables extracted from the estimation. ΔX stands for the first difference of the logarithm of variable X. Computations at the posterior mean of the states.

It is worth mentioning that the obtained LS counter-cyclicality (-0.4) is associated with an a-cyclical model-implied price markup (-0.01 is the correlation between the inverse of the real marginal cost and output, both in growth terms) that is consistent with the pro-cyclical or a-cyclical price markup found in the U.S. private sector [Nekarda and Ramey, 2013]. In the present model, the different degrees of cyclicality in the LS and the marginal cost emanate from automation shocks introducing a wedge between the two as seen in (2.5).

Figure 2: Time-Varying Correlations



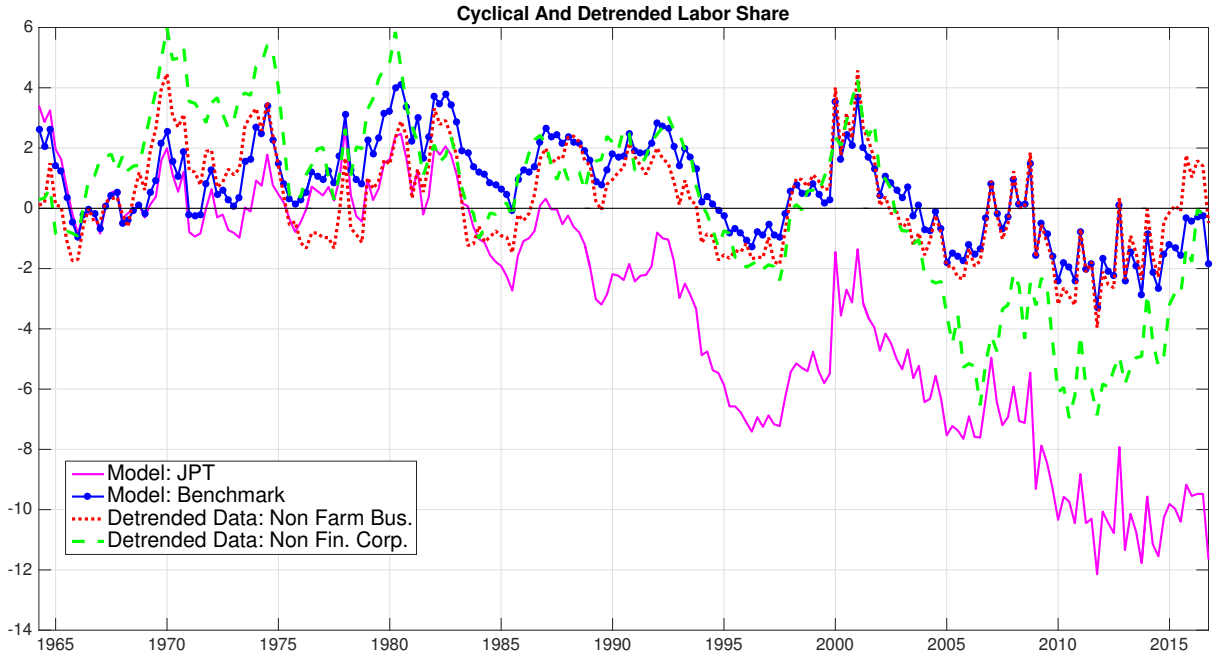
Notes: Cumulative correlation between the growth rate of the variable shown in the panel title and output growth, all computed at the posterior mean of the cyclical states extracted from the estimation.

To shed further light on the findings, I plot the smooth cyclical labor share in Fig.(3) and overlap it with its analogue in JPT in order to assess the role of matching LS data, and with the detrended data series in order to visualize the measurement errors in the observation equations. The figure demonstrates how, especially after the early 1980s, the model-implied LS in the Benchmark model follows the data much more closely than the model-implied LS in the JPT specification does. This divergent behavior between the two LS series suggests that the inclusion of both multiple wages and LS series in the estimation brings in additional information that helps the model come closer to the data.

4.3 Business Cycles.

Table (4) reports the forecast error variance decomposition (FEVD) 8/40 quarters ahead. About half (54%) of the fluctuations in the labor share (ls_t) stem from automaton shocks at any horizon. Supply disturbances account for 40/26% of the LS swings in the short/long run, with about half of this effect emanating from variations in labor market competitiveness and with price markup shocks having mainly a short-run influence. Demand shocks and, in particular, MEI shocks have small/sizable (6/20%) short-/long-run influence on the LS.

Figure 3: Labor Share In The Data And The Model



Notes: Detrended labor share in non-farm businesses and in non-financial corporations, along with the model-implied cyclical labor share in Justiniano et al. (2011) and in the Benchmark model.

The above FEVD differs from that implied by the JPT model (Table 5), and reveals that LS data are informative for the determinants of the labor share. In the absence of LS data in the estimation, almost the entire fluctuations of LS stem from supply side shocks, with wage and price markup shocks explaining about half and a third of them, respectively.

Moreover, the above suggest that MEI and IST disturbances, that are tightly linked to the evolution of the relative investment price, account for a moderate share of the LS swings (6/20% and 4/4%, respectively). The magnitude of the interaction between the relative investment price and the LS over the business cycle differs from the evidence of Karabarbounis and Neiman (2014) suggesting a strong connection between the two.

On top of their autonomous effect on the labor share, automation disturbances account for 11/19% of short/long-run output cycles. Their influence on other macroeconomic variables (investment, inflation, the interest rate, and wages) is similar, though a tad smaller.

Two shifts in the influence of aggregate shocks caused by the introduction of multiple wage and LS observables take place. First, the impact of demand shocks and, in particular, MEI and risk premium shocks is attenuated and reflects the attenuation in the persistence

Table 4: Business Cycles – Benchmark

	variable						
shock	y_t	i_t	π_t	r_t	L_t	w_t^r	ls_t
technology	0/1	0/0	1/1	0/1	1/2	25/11	2/1
price markup	1/1	0/0	41/33	8/6	2/2	14/3	11/6
wage markup	4/4	2/2	28/24	10/10	6/8	28/6	24/15
IST	4/5	1/1	3/3	1/3	0/0	18/13	4/4
supply side	10/10	3/4	72/61	20/20	8/13	84/34	40/26
risk premium	10/5	3/2	5/5	17/15	14/12	0/0	0/0
MEI	66/63	87/83	13/26	40/45	70/67	6/49	6/20
govt spending	1/1	0/0	0/0	0/0	1/2	0/0	0/0
policy	3/2	1/1	2/2	19/15	4/4	0/0	0/0
demand side	79/70	91/86	21/34	76/75	89/85	6/50	6/20
automation	11/19	5/10	7/6	5/4	2/3	10/16	54/54

Table 5: Business Cycles – JPT

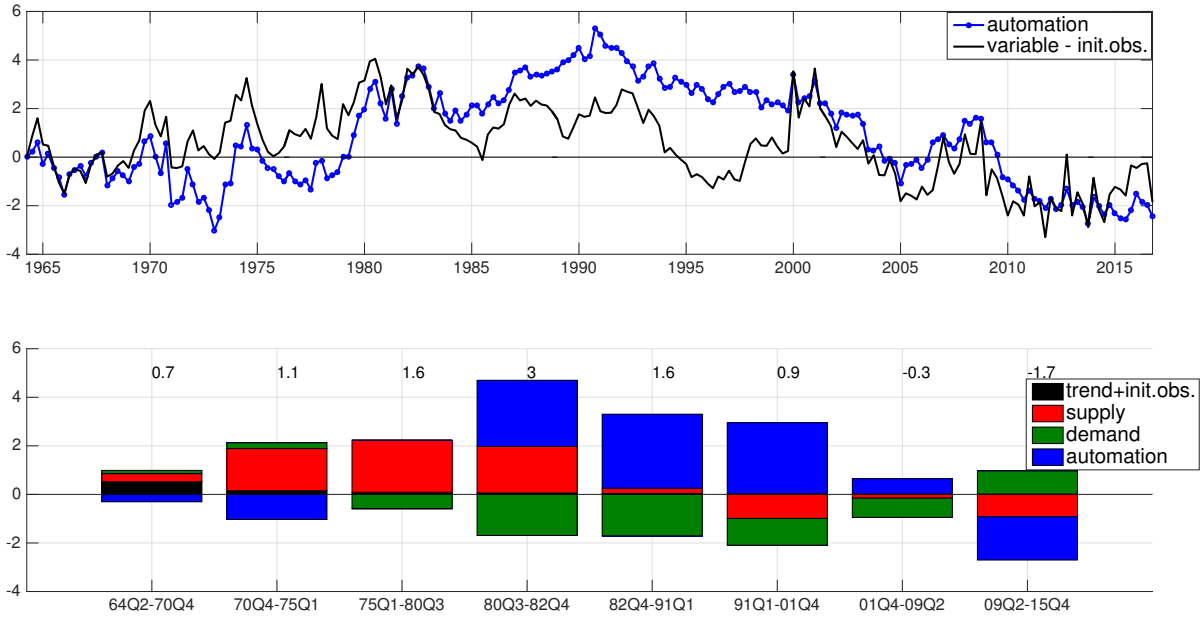
	variable						
shock	y_t	i_t	π_t	r_t	L_t	w_t^r	ls_t
technology	3/1	0/0	3/3	3/2	1/2	34/17	17/12
price markup	4/2	1/1	83/67	17/11	3/3	24/14	34/32
wage markup	0/1	0/0	12/12	5/5	1/2	31/13	48/38
IST	1/1	0/0	0/0	0/1	0/0	3/3	0/1
supply side	8/5	2/2	99/82	25/18	5/8	92/47	99/82
risk premium	16/9	6/3	1/1	23/24	20/16	1/1	0/0
MEI	72/84	92/95	0/16	31/44	71/73	7/51	0/17
govt spending	1/1	0/0	0/0	0/1	1/1	0/0	0/0
policy	2/1	1/0	0/0	21/13	2/2	0/0	0/0
demand side	92/95	98/98	1/18	75/82	95/92	8/53	1/18

Notes: Forecast error variance decmposition at the posterior mean 8/40 quarters ahead. "Benchmark": this paper's model. "JPT": Justiniano et al. (2011) model.

of those shocks; demand shocks explain 92/95% and 79/70% of output cycles in the JPT and Benchmark models, respectively, while the influence of MEI shocks on output falls from 72/84% to 66/63%. MEI shocks, though, retain a large influence on investment (87/83%), since they are investment demand shocks as argued in Moura (2018). Therefore, although MEI shocks are the main driver of the business cycle as in Justiniano et al. (2011), their influence declines when wages and the LS are sampled jointly. The second shift observed in the Benchmark model pertains to the elevated impact of wage markup shocks and the attenuated impact of price markup shocks on output, inflation, and the interest rate. The impact of the former shocks doubles while that of the latter is reduced by about half.

Furthermore, the present structural perspective allows to examine whether the forces behind the evolution of the LS have varied over time. Fig.(4) gives an affirmative answer by displaying the historical decomposition of LS fluctuations across U.S. business cycles. During the 1960s, the fluctuations are small and closely tracked by the effect of automation. During the 1970s, the effect of automation weakens while the LS overshoots its steady state thanks to supply disturbances. During the 1980s and 1990s, the cyclical component of the LS remains above its steady state due to (negative) automation shocks and despite demand shocks exerting downward pressure. From the early 2000s to about 2007, a temporary decline in the LS is driven by demand shocks. From then on, however, the lion's share of the subsequent cyclical tumble of the LS is explained by automation favoring capital over labor in production. This finding is compatible with the evidence of Dao et al. (2017) and Abdih and Danninger (2017) on the effect of automation on the downward trend of the LS.

Figure 4: The Cyclical Component Of The U.S. Labor Income Share



Notes: Historical Decomposition. Deviation of Labor Share from its steady state. *Top Panel:* labor share (cyclical component minus the effect of the initial observation) and its share explained by automation. *Bottom Panel:* historical decomposition of (quarterly average) cyclical labor share (shown on top of each column) across U.S. business cycles (trough to trough). The categorization of shocks follows Table (4).

4.4 Automation Shocks, Labor, And The Labor Share.

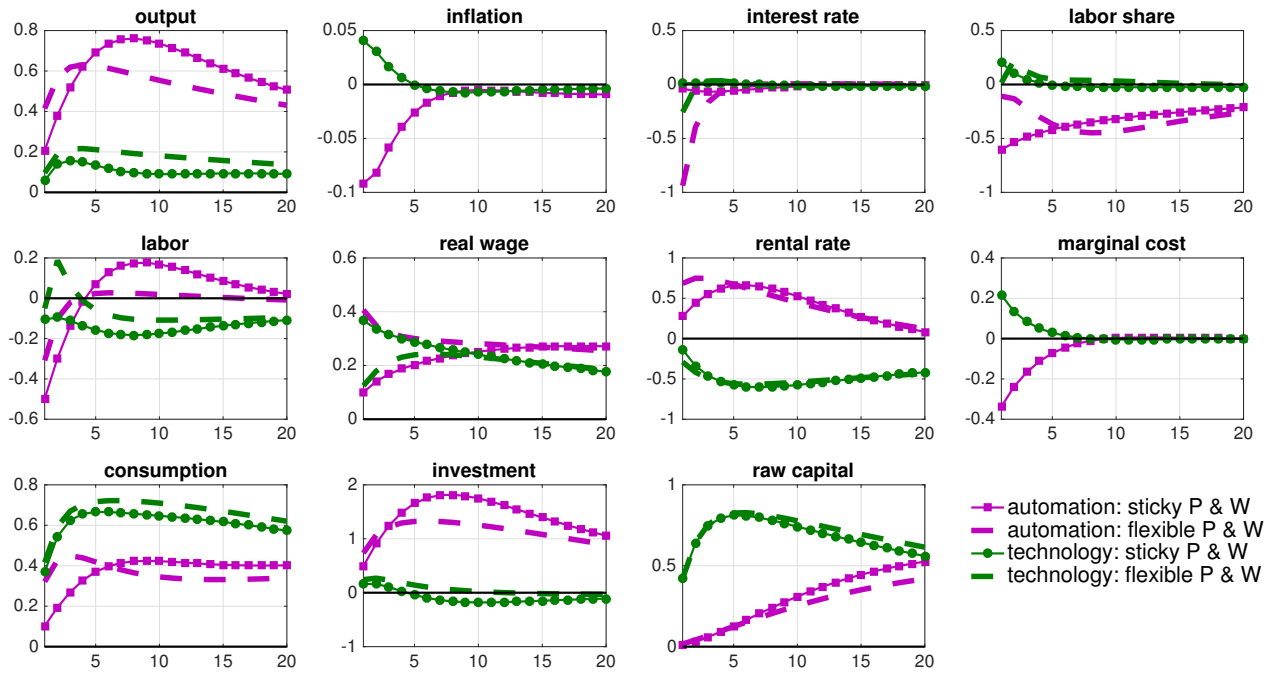
How are, though, automation disturbances diffused in the economy? What are their economy wide effects? I tackle those questions in Fig.(5). In response to automation shocks, output

and capital gradually rise, whereas labor and the labor share fall. Therefore, automation shocks trigger both an output rise and a substitution of labor with capital. Labor falls on impact but over time it overshoots its steady state and demonstrates a pro-cyclicality – albeit a quantitatively small one compared to its initial drop. The LS responds counter-cyclically (decreases) since the wage increase associated with the economic stimulus is small and cannot compensate the combined effect of the employment decline and output expansion. Furthermore, marginal cost falls despite the increase in both the real wage and the rental rate of capital, and generates a pro-cyclical price markup and downward pressure to inflation and, in turn, to the interest rate through the policy rule. Consumption and investment follow paths similar to that of output. The effect of automation shocks persists for several quarters.

Comparing the transmission of automation disturbances under sticky prices and wages to that under flexible prices and wages reveals that the two setups feature quantitative but not qualitative differences. In particular, the interaction of automation shocks and nominal rigidities results in an impact of those shocks that is more persistent and higher in magnitude. For instance, compared to flexible prices and wages, under sticky prices and wages the employment fall is more pronounced, the wage response is more sluggish, the LS response is amplified, and output and investment exhibit more persistent dynamics.

Similarly to automation shocks, technology shocks raise output, capital, consumption, and investment but decrease labor under sticky prices. These changes, though, are smaller in size than those after automation shocks. Furthermore, contrary to the labor fall observed after automation shocks, labor rises on impact after technology shocks under flexible prices and wages. That response is consistent with RBC models (though, when the persistent effects of habit formation and investment costs kick in, labor undershoots its steady state along the lines of Francis and Ramey, 2005). In addition, under sticky prices and wages, technology shocks raise marginal cost and inflation, and generate a pro-cyclical LS since they feature a large wage response. These responses, therefore, disentangle technology from automation shocks conditionally on sticky prices and wages. It is worth pointing out that although technology shocks generate a pro-cyclical LS and, thereby, a counter-cyclical markup that is at odds with the data [Nekarda and Ramey, 2013], the LS pro-cyclicality is attenuated in the Benchmark specification compared to the JPT case (fig.7). Finally, although labor-augmenting technology shocks raise the real wage while reducing the rental rate of capital, automation shocks raise wages to a smaller extent and push the rental rate of capital upwards.

Figure 5: Technology And Automation Shocks



Notes: Impulse responses to technology and automation shocks evaluated at the posterior mean. Stationary % deviations from steady state. "flexible/sticky P & W" stands for flexible/sticky prices and wages.

Neither automation nor technology shocks in the present DSGE context generate the overshooting of the LS in response to productivity shocks found by Rios-Rull and Santaeulàlia-Llopis (2010) in a bivariate VAR. Additionally, the equilibrium drop of labor shows that the model is not susceptible to the critique of Acemoglu and Restrepo (2018) according to which automation generates a drop in labor demand that cannot be matched by models featuring various capital-augmenting technology processes. Moreover, the labor fall cannot be obtained by exotic shocks affecting capital, namely utilization and depreciation shocks – Furlanetto and Seneca (2014) show that those shocks spur a pro-cyclical labor response.

4.5 Aggregate Shocks And The Labor Share.

I pin down the effect of all aggregate shocks on the labor share in Figures (6, 7). It is interesting to start from monetary policy disturbances. According to Cantore et al. (2019), empirical evidence suggests that the LS is counter-cyclical in response to such disturbances but theoretical DSGE models predict a pro-cyclical LS. Based on the impulse response functions (IRFs) displayed in Fig.(6), the LS in the JPT model is indeed pro-cyclical. Nevertheless, when LS data are introduced in the estimation (Benchmark model), the LS becomes counter-cyclical.

The counter-cyclicality is achieved through a sluggish real wage response (top right panel) that rests on the elevated degrees of wage and price indexation (0.55 and 0.21, respectively; Table 1) in the present model compared to the JPT model (0.2 and 0.14, respectively). Due to indexation, wage inflation becomes tightly linked to price inflation and less responsive to general equilibrium forces. This evidence suggests that the wage response plays a catalytic role in shaping the response of the LS. Thus, with moderate indexation the model can match another dimension of the data.

Moreover, in the JPT specification all demand shocks generate a pro-cyclical LS (an a-cyclical LS in the case of government spending shocks) and, thus, a counter-cyclical markup that is at odds with the evidence of Nekarda and Ramey (2013). In contrast, when the estimation matches the LS series, all demand shocks spur a counter-cyclical LS aligned with the data. The influence of MEI shocks on the real economy, in particular, is a tad weakened in the Benchmark model compared to the JPT specification. Those disturbances generate a pro-cyclical LS response on impact in the JPT model but a persistent counter-cyclical response in the Benchmark case. The latter is the reason behind their small (6%) and moderate (20%) influence on LS cycles in the short and long run, respectively. Risk premium and government spending shocks generate only a negligible LS counter-cyclicality and, thus, do not influence a sizable part of LS cycles. Important to mention is that automation innovations are disentangled from demand side innovations on an additional ground, namely the inflation response. Automation shocks trigger counter-cyclical inflation (fig.5) through their effect on production cost, whereas all demand side disturbances spur pro-cyclical inflation (fig.6).

As for supply shocks, the reduced influence of price markup shocks seen in Tables (4, 5) appears here as well: for instance, the output trough is smaller than that observed in the JPT model. The reason behind that attenuated influence (manifested in a decreased persistence, ρ_p, compared to JPT) is that these shocks trigger a highly pro-cyclical LS that is at odds with the observed LS counter-cyclicality. In contrast, wage markup shocks spur a counter-cyclical LS and, thus, their influence in the Benchmark model doubles (though, it still is small in magnitude) compared to their influence in JPT (Tables 4, 5): the output and labor troughs, as well as the inflation spike, are more pronounced in the former than in the latter model. Wage markup shocks differ from automation shocks on the following dimensions: the former shocks generate a well-known counter-cyclical (pro-cyclical) response in the wage (labor), but the latter shocks generate a pro-cyclical (counter-cyclical) wage (labor) response. Finally, the

influence of IST shocks is similar to that of price markup shocks, but IST shocks, contrary to price markup shocks, trigger a counter-cyclical, albeit negligible in size, LS response (fig.7).

Figure 6: Demand Side Disturbances

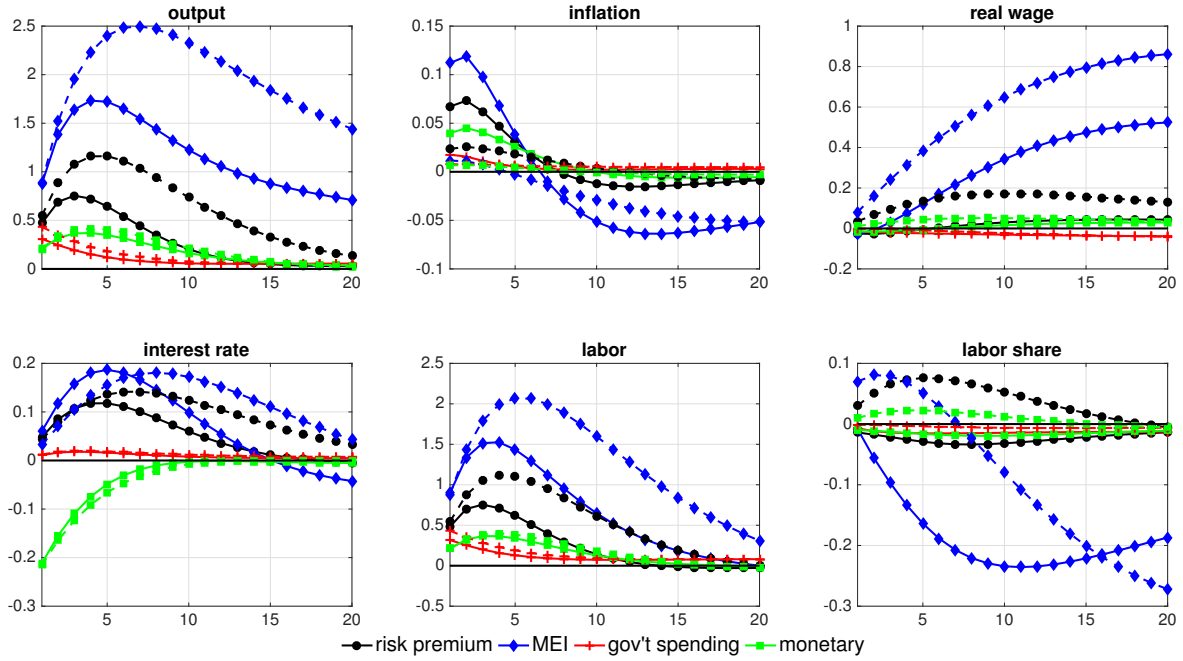
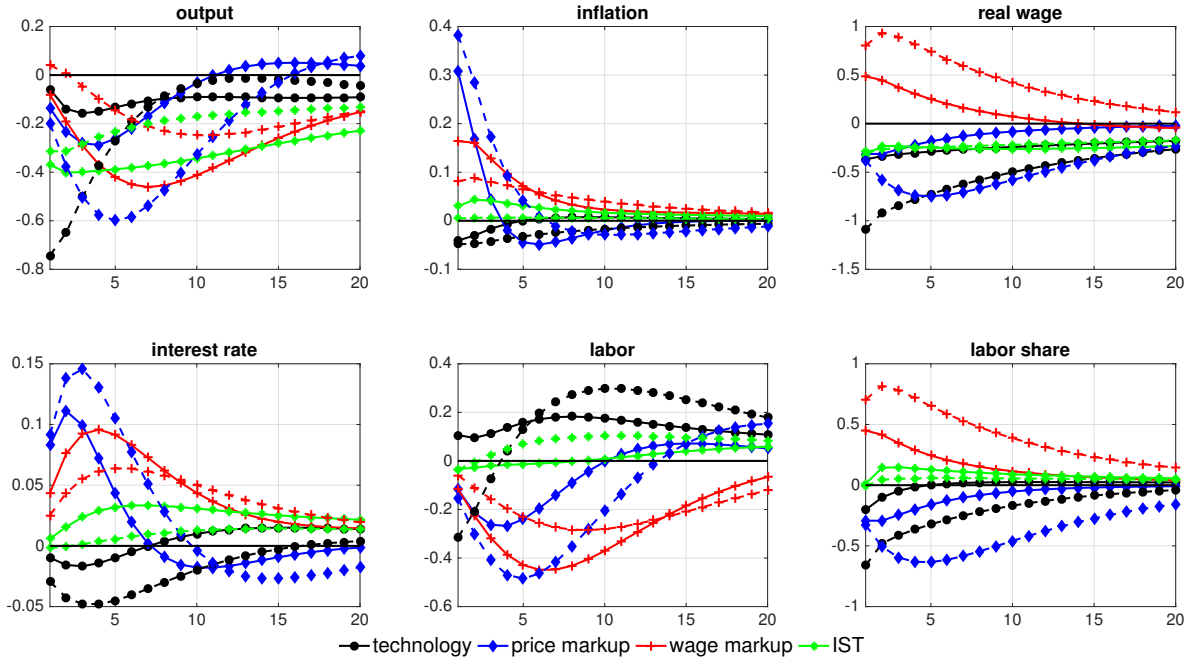


Figure 7: Supply Side Disturbances



Notes: IRFs at the posterior mean. Solid lines: Benchmark model. Dotted lines: JPT specification.

4.6 Robustness Checks.

4.6.1 Prior. In spite of considering a prior specification that is in line with the literature, I investigate the robustness of the results to it. The FEVD at the prior mean shows a substantially smaller influence of automation shocks than that obtained at the posterior: these shocks account for 1% of output fluctuations and 17% of the LS swings (Table 7). Moreover, prior and posterior imply a considerably different influence of supply shocks on the LS. At the prior, technology, price markup, and wage markup shocks explain 20%, 45%, and 16% of the LS cycles demonstrating that technology and price markup shocks are favored more, and wage markup are favored less, at the prior than at the posterior. In addition, the zero prior influence of demand shocks on the LS differs from the 6% (Table 4) posterior influence of MEI shocks. Altogether, these results show that the prior is not dogmatic.

4.6.2 Automation And The Relative Price Of Investment. I consider the case in which shifts in the relative price of investment spur shifts in production automation. To this end, I include the following specification for automation shocks in the estimation:

$$\widehat{\alpha}_t = \rho_\alpha \widehat{\alpha}_{t-1} + \nu_\alpha \epsilon_t^\omega + \sigma_\alpha \epsilon_t^\alpha \tag{4.1}$$

where a Normal prior centered around zero (0.2 std) is assumed for ν_α. The data do not favor this specification; the posterior mean of ν_α is 0.09 (Table 6). According to Table (7), the influence of automation shocks on output (10%) and the LS (54%) is similar to that in the Benchmark case (11% and 54%, respectively). So is the short-run influence of MEI and IST shocks on the LS (7% and 1% vs 6% and 4% in the Benchmark).

4.6.3 Non-Unitary Elasticity Of Substitution. This section delves into the role of the production function in understanding the cyclical fluctuations of the LS, and considers production with non-unitary constant elasticity of substitution (CES) between capital and labor. I adopt the following CES function which draws from Cantore et al. (2015), with the difference being the time variation in the distribution parameters $(\alpha_t, 1-\alpha_t)$,

$$Y_t(i) = \left[\alpha_t(\Lambda_t K_t(i))^{(\sigma-1)/\sigma} + (1-\alpha_t)(Z_t L_t(i))^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)} - \Phi_y A_t \tag{4.2}$$

where $\sigma \in (0, +\infty)$ is the elasticity of substitution between capital and labor. (4.2) boils down to (2.3) for $\sigma \to 1$ and $\Lambda_t = 1$. Λ_t stands for a stationary AR(1) capital-augmenting technological shock with parameters $\{\rho_l, \sigma_l\}$. I estimate the model first without capital-augmenting shocks ($\Lambda_t = 1$) so that the alternative production function is the only change

compared to the Benchmark case, and then I estimate the model with those shocks. In the latter case, the estimation features more sources of stochastic variation than observables.

According to Uzawa (1961), balanced growth is achieved either when technological progress is labor augmenting or when the production function is Cobb-Douglas. Thus, in (4.2), long-run growth stems only from labor-augmenting technology ($A_t = Z_t$), while the IST process (Ω_t) follows an AR(1) process[24]. Automation shocks are still defined as in (2.4). The distribution parameters are not dimension free though [Cantore and Levine, 2012; Klump et al., 2012]. Hence, they are normalized at the stationary steady state according to: $\widetilde{\alpha} \equiv \frac{R^{k,r}k}{mc(y+\Phi_y)} = \alpha\left(k/(y+\Phi_y)\right)^{(\sigma-1)/\sigma}$ and $(1-\widetilde{\alpha}) \equiv \frac{w^r L}{mc(y+\Phi_y)} = (1-\alpha)\left(L/(y+\Phi_y)\right)^{(\sigma-1)/\sigma}$.

The capital-to-labor ratio and the (real) marginal cost are now pinned down by the following expressions that converge to their Cobb-Douglas analogues for $\sigma \to 1$:

$$\frac{W_t^r/Z_t}{R_t^{k,r}/\Lambda_t} = \frac{1-\alpha_t}{\alpha_t}\left(\frac{Z_t L_t(i)}{\Lambda_t K_t(i)}\right)^{-1/\sigma} \tag{4.3}$$

$$MC_t^r = \left[\alpha_t^\sigma (R_t^{k,r}/\Lambda_t)^{1-\sigma} + (1-\alpha_t)^\sigma (W_t^r/Z_t)^{1-\sigma}\right]^{1/(1-\sigma)} \tag{4.4}$$

Including LS series in the estimation influences the elasticity of substitution. σ is estimated above one (1.63 and 2.77; Table 6). Such values differ from the DSGE evidence of Cantore et al. (2015) who find a small elasticity of 0.15-0.18 without using data on the LS, and the estimates of León-Ledesma et al. (2010) and Chirinko (2008) that are in the range of 0.4-0.7, and are derived from single-equation first-order conditions. They are, however, consistent with the empirical evidence of Karabarbounis and Neiman (2014) who find an elasticity of 1.25, of Piketty (2014), and of Duffy and Papageorgiou (2000).

Despite the introduction of CES production, the Benchmark estimates are preserved to a large extent. Wage indexation rises (to 0.78 and 0.72) compared to the Benchmark case (0.55). The persistence of automation shocks is comparable to that in the Benchmark case, but their volatility (σ_α) is higher (1.07 and 1.03 vs 0.51 in the Benchmark). The estimation still favors the LS fluctuations in non-farm businesses over those in non-financial corporations. The properties of wage markup shocks (ρ_w, σ_w) remain similar to those in the Benchmark case[25], and the loading of wage compensation (Ψ_w) suggests that fluctuations in compensation are favored a tad more under CES than under Cobb-Douglas production. Altogether, these results suggest that the model still requires a moderate degree of wage

[24] I remove the trend of the relative price of investment outside of the model

[25] Measurement errors in wages and the LS have similar characteristics across the various specifications.

inertia in order to match the counter-cyclicality of the LS, and extracts properties from the wage data that are similar to those extracted in the Benchmark model.

The introduction of CES production brings in some changes. The persistence of MEI and price markup shocks as well as the volatility of technology shocks are attenuated. Price indexation and the persistence of risk premium shocks rise a tad compared to their Benchmark levels. In the "CES, $\Lambda_t \neq 1$" specification, capital-augmenting shocks are as persistent and volatile as the automation shocks. In that specification, however, more shocks than observables are included and, as a result, identification is a tad more challenging: estimates for the volatility of MEI and government spending shocks, the inverse Frisch elasticity, and the persistence of technology shocks depend considerably on the inclusion or not of Λ_t.

Overall, under CES production, the influence of automation shocks on output eight quarters ahead remains similar to that in the Benchmark case (14% and 9% vs 11%), whereas their influence on the LS rises considerably from 54% in the Benchmark case to 78%. The influence of demand shocks on output, and that of supply shocks on the LS, are a tad attenuated. The former attenuation stems from a reduction in the effect of MEI shocks despite a small amplification in the effect of risk premium shocks. The latter attenuation stems from both price and wage markup shocks. Capital-augmenting technological shocks have moderate impact on output fluctuations (16%) and do not account for LS cycles (2%).

Finally, Fig.(8) illustrates the impact of automation shocks across alternative production functions, and compares it to that of capital-augmenting technological disturbances. Moving from Cobb-Douglas to CES production does not alter the sign and magnitude of the effect of automation shocks on the pro-cyclical responses of output and investment, and on the counter-cyclical response of labor. The response of the LS is stronger under CES production than under Cobb-Douglas production. Nevertheless, under CES production, the responses of marginal cost and inflation are attenuated, and they even change sign under CES production with Λ_t shocks[26]. Capital-augmenting technological shocks trigger effects on the economy and the LS that are similar to, though less persistent than, those of automation shocks. Interestingly, these shocks generate a counter-cyclical response in the rental rate of capital that differs from the pro-cyclical response observed after automation disturbances[27].

[26]In the Appendix, I show that as the elasticity of substitution between capital and labor rises, the effect of automation on the marginal cost gradually goes from negative to positive.

[27]The counter-cyclical response is also obtained in Cantore et al. (2014) for both Cobb-Douglas and CES (with either $\sigma > 1$ or $\sigma < 1$) production.

Automation raises the importance of capital in production and, thereby, capital demand and the rental rate of capital. In contrast, capital-augmenting technology shocks raise the efficiency of the installed capital. As a result, their effect on the capital price is not only attenuated compared to the effect of automation, but also of the opposite sign.

Table 6: Posterior Distribution – Alternative Specifications

		Prior	**Posterior** Mean [5-95%]		
			$\nu_\alpha \neq 0$	**CES**	**CES,** $\Lambda_t \neq 1$
inv. Frisch elast.	χ	N (2.00, 1.00)	4.80 [3.67, 5.99]	4.33 [3.16, 5.56]	3.80 [2.63, 4.93]
price indexation	ι_p	B (0.50, 0.15)	0.22 [0.08, 0.43]	0.38 [0.21, 0.56]	0.31 [0.15, 0.48]
wage indexation	ι_w	B (0.50, 0.15)	0.55 [0.41, 0.68]	0.78 [0.60, 0.90]	0.72 [0.52, 0.89]
MP resp. to infl.	ψ_π	N (1.70, 0.25)	1.88 [1.62, 2.17]	1.93 [1.65, 2.22]	1.77 [1.47, 2.06]
AR risk premium	ρ_b	B (0.50, 0.20)	0.76 [0.62, 0.86]	0.80 [0.67, 0.91]	0.81 [0.70, 0.90]
AR technology	ρ_z	B (0.40, 0.20)	0.47 [0.24, 0.68]	0.75 [0.51, 0.95]	0.40 [0.12, 0.70]
std technology	σ_z	IG (0.50, 1.00)	0.50 [0.34, 0.67]	0.26 [0.16, 0.39]	0.18 [0.10, 0.34]
AR MEI	ρ_i	B (0.50, 0.20)	0.81 [0.70, 0.91]	0.72 [0.39, 0.87]	0.74 [0.48, 0.91]
std MEI	σ_i	IG (0.50, 1.00)	7.25 [5.40, 9.63]	7.42 [5.27, 10.29]	6.51 [4.38, 9.65]
AR price mkp	ρ_p	B (0.50, 0.20)	0.51 [0.18, 0.80]	0.13 [0.03, 0.28]	0.15 [0.04, 0.31]
AR wage mkp	ρ_w	B (0.50, 0.20)	0.12 [0.04, 0.23]	0.08 [0.02, 0.16]	0.08 [0.02, 0.15]
std wage mkp	σ_w	IG (0.15, 1.00)	0.61 [0.52, 0.70]	0.55 [0.46, 0.65]	0.55 [0.45, 0.65]
AR govt spending	ρ_g	B (0.50, 0.20)	0.99 [0.99, 1.00]	0.99 [0.99, 1.00]	0.99 [0.98, 0.99]
std govt spending	σ_g	IG (0.15, 1.00)	0.36 [0.31, 0.41]	0.40 [0.36, 0.44]	0.20 [0.04, 0.39]
tech. resp. to govt	ρ_{gz}	B (0.50, 0.20)	0.15 [0.08, 0.23]	0.12 [0.04, 0.20]	0.31 [0.12, 0.42]
factor for wages	Ψ_w	N (1.00, 0.50)	1.13 [1.04, 1.22]	1.26 [1.09, 1.45]	1.24 [1.08, 1.42]
std m.e. earnings	μ_w^e	IG (0.15, 1.00)	0.74 [0.67, 0.82]	0.69 [0.61, 0.77]	0.68 [0.60, 0.76]
std m.e. compens.	μ_w^c	IG (0.15, 1.00)	0.28 [0.21, 0.34]	0.30 [0.21, 0.38]	0.33 [0.25, 0.40]
AR IST	ρ_ω	B (0.20, 0.10)	0.17 [0.08, 0.26]	0.88 [0.83, 0.92]	0.87 [0.83, 0.91]
std IST	σ_ω	IG (0.50, 1.00)	0.69 [0.63, 0.74]	0.67 [0.62, 0.73]	0.67 [0.62, 0.73]
factor for LS	Ψ_α	N (1.00, 0.50)	0.55 [0.45, 0.64]	0.56 [0.46, 0.65]	0.57 [0.47, 0.67]
AR labor share	ρ_α	B (0.50, 0.20)	0.96 [0.93, 0.98]	0.97 [0.94, 0.99]	0.99 [0.96, 1.00]
std labor share	σ_α	IG (0.15, 1.00)	0.51 [0.45, 0.56]	1.07 [0.90, 1.28]	1.03 [0.86, 1.23]
std m.e. NonFarm	μ_{ls}^{nf}	IG (0.15, 1.00)	0.45 [0.40, 0.50]	0.48 [0.42, 0.55]	0.48 [0.42, 0.55]
std m.e. Corp.	μ_{ls}^c	IG (0.15, 1.00)	0.64 [0.59, 0.70]	0.65 [0.60, 0.71]	0.65 [0.60, 0.71]
CES elasticity	σ	G (0.95, 1.00)	[,]	1.63 [1.24, 2.26]	2.77 [1.76, 4.48]
AR capital augment.	ρ_l	B (0.50, 0.20)	[,]	[,]	0.98 [0.97, 0.99]
std capital augment.	σ_l	IG (0.15, 1.00)	[,]	[,]	1.18 [0.96, 1.42]
α resp. to IST	ν_α	N (0.00, 0.20)	0.09 [0.03, 0.16]	[,]	[,]
Marginal Likelihood			-2331	-2313	-2300

Notes: Selective estimates in alternative specifications; for the full list, see Appx. "$\nu_\alpha \neq 0$": Benchmark model with IST innovations influencing automation shocks. "CES": Benchmark model with CES production. "CES, $\Lambda_t \neq 1$": Benchmark model with CES production and capital-augmenting technological shocks.

5 Concluding Remarks

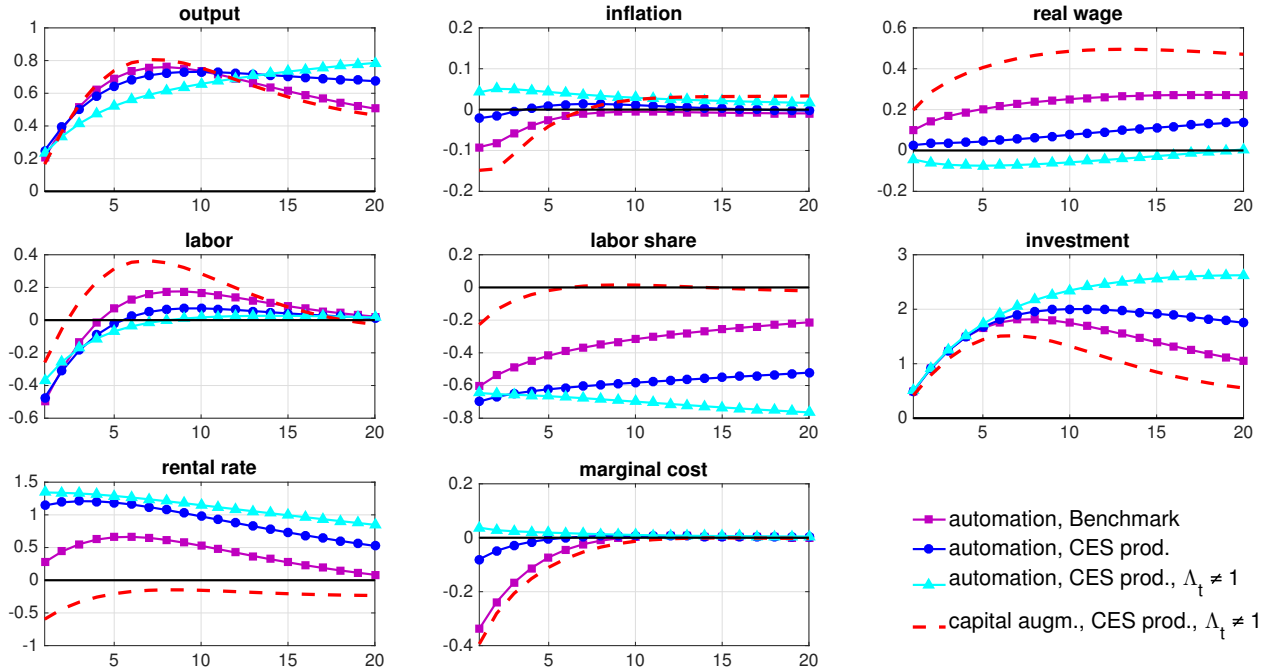
The present paper is the first that brings observables for the labor share into the workhorse medium-scale DSGE model through a latent factor approach, and examines their drivers

Table 7: Business Cycles – Alternative Specifications

	Prior		$\nu_\alpha \neq 0$		**CES**		**CES**, $\Lambda_t \neq 1$	
shock	y_t	ls_t	y_t	ls_t	y_t	ls_t	y_t	ls_t
technology	11	20	1	3	0	2	0	1
price markup	11	45	1	11	1	2	0	2
wage markup	19	16	4	24	10	8	5	7
IST	13	2	3	1	0	2	0	3
supply side	55	83	8	39	11	14	5	13
risk premium	35	0	10	0	16	0	15	0
MEI	1	0	68	7	55	8	52	8
govt spending	3	0	1	0	2	0	0	0
policy	6	0	3	0	3	0	3	0
demand side	44	0	81	7	76	8	70	8
automation	1	17	10	54	14	78	9	78
capital augmenting							16	2

Notes: FEVD at the posterior mean eight quarters ahead. "$\nu_\alpha \neq 0$": Benchmark model with IST innovations influencing automation shocks. "CES": Benchmark model with CES production. "CES, $\Lambda_t \neq 1$": Benchmark model with CES production and capital-augmenting technological shocks.

Figure 8: Automation And Capital Augmenting Shocks



Notes: Impulse responses to automation and capital-augmenting technological shocks evaluated at the posterior mean. % deviations from steady state. "CES": Benchmark model with CES production. "CES, $\Lambda_t \neq 1$": Benchmark model with CES production and capital-augmenting technological shocks.

and implications. Compared to the JPT model, the present framework comes closer to some dimensions of the data and matches the observed LS counter-cyclicality, the small wage pro-cyclicality, and the counter-cyclical LS response to demand and monetary policy shocks that are challenging for structural models, while preserving conventional results such as the importance of MEI shocks in driving output cycles. One of the key factors behind the above success is moderate wage indexation. Interestingly, the importance of wage inertia echoes Nekarda and Ramey (2013): *"... a return to this traditional focus of Keynesian models on sticky wages might render these models more consistent with the microeconomic evidence."*. The contribution of matching LS data sets the stage for further explorations. It can be informative for the underlying mechanisms in papers featuring heterogeneous workers [Krusell et al., 2000; Silos and Polgreen, 2008], or alternative production functions, such a CES [Cantore et al., 2015; Di Pace and Villa, 2016], task-based approaches [Acemoglu and Restrepo, 2018, 2017a, 2017b], and functions with different short-run and long-run elasticities of substitution [León-Ledesma and Satchi, 2019; Koh and Santaeulàlia-Llopis, 2017].

In addition, the present work suggested a way of modeling automation shocks and found that those shocks explain about half of the LS fluctuations and about 10% of output cycles, and generate a counter-cyclical labor response. Admittedly, the debate on how to model automation is still in its infancy [Acemoglu and Restrepo, 2018]. Alternative modeling choices for automation could shed additional light on its macroeconomic effects.

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