

Identifying Demand Regimes: Pitfalls and a Structural Solution ^{*}

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BCRP

September, 2026

Abstract: A large empirical literature asks whether aggregate demand is profit-led or wage-led. This paper uses a supermultiplier model in which the labor share is determined through Nash bargaining to show that conventional identification strategies are biased towards wage-led results. The model's cross-equation restrictions identify the demand regime and the causal effects of bargaining shocks. An application to U.S. data shows that this bias is severe: the structural estimate of the demand-regime coefficient is over six times larger in magnitude than the conventional estimate. As a result, the effects of bargaining shocks on output are five times larger than traditional estimates.

JEL Codes: C32, E12, E32

Keywords: Demand Regime, Identification, Supermultiplier

^{*}I thank the late Robert Blecker, Peter Skott, Engelbert Stockhammer, Rafael Wildauer, Marwil Dávila-Fernández, Steven Fazzari, Costas Azariadis and Michele Boldrin for comments and suggestions on previous versions of this draft. I also thank participants at the 27th FMM Conference, Berlin, the 2024 Eastern Economic Association conference, the 5th International Workshop on Demand-Led Growth and seminar participants at Washington University in St. Louis, the University of Greenwich, University of Siena and Universidad Complutense de Madrid. A previous version of this paper circulated as 'Bargaining power, demand growth and the decline of the labor share'. The views expressed here are those of the author and do not necessarily reflect those of the Central Reserve Bank of Peru.

1 Introduction

What are the effects of changes in income distribution on aggregate demand? The answer to this question is crucial to assess the aggregate effects of labor market reforms (Lavoie and Stockhammer, 2013) and to understand the causal effects of bargaining shocks on output (Blecker, 2016). Legions of macroeconomists have tried to answer this question in the three decades since the publication of Bowles and Boyer (1995). Hundreds of papers have run regressions of consumption, investment and net exports on the labor share to determine whether an increase in the labor share raises aggregate demand. If this is the case, then demand is said to be ‘wage-led’, while if the opposite is true, then demand is ‘profit-led’. A consensus has not emerged from this empirical literature: demand regimes vary substantially by country and over time (Lavoie and Stockhammer, 2013; Blecker, 2016). Furthermore, exogenous changes in the labor share do not seem to account for a large fraction of the variance of output (Stockhammer, 2017).

These empirical exercises are justified if the labor share is contemporaneously exogenous with respect to the error term, which implies that the labor share must be independent of current output (Stock and Watson, 2018). This is true in partial equilibrium models of the goods market where income distribution is given. However, in general equilibrium, the labor share is an endogenous object: demand shocks that move output also affect the labor share through their effects on the labor market. This has long been recognized in the theoretical (Blecker, 1989; Skott, 2017) and empirical (Stockhammer, Onaran and Ederer, 2009) literature. Even in partial equilibrium models with search and matching frictions, the labor share is jointly determined with unemployment and labor-market tightness (Pissarides, 2000).

This paper argues that allowing the labor share to respond endogenously to aggregate demand is necessary for credible identification of demand regimes. To do so, I develop a Keynesian growth model in which income distribution is determined through Nash bargaining. The resulting wage-setting equation takes the form of a wage curve, relating labor-market slack to the labor share, as in Blanchflower and Oswald (1994). A positive demand shock reduces unemployment, improves workers’ outside options, and raises the labor share. Demand shocks therefore move output and the labor share in the same direction, violating the exogeneity condition imposed by traditional methods. Exogenous shifts in distribution instead arise from innovations to the parameter that reflects the weight of worker preferences in the Nash bargaining model, which defines exogenous bargaining shocks. The response of output to these shocks is the object implicitly targeted by this body of research: the causal

effect of an exogenous shift in income distribution on aggregate demand.

I use my Keynesian growth model as a laboratory to study the identification and estimation of demand regimes. If this model is treated as the data-generating process (DGP), what exactly does a regression of output growth on the labor share recover? My first result is that in the presence of a wage curve and demand shocks, traditional methods bias the demand-regime towards the wage-led case. The size of this bias can be so severe that an econometrician can wrongly conclude that an economy is wage-led when the DGP is profit-led. The intuition for this result is that in the presence of a wage curve and when demand shocks are volatile enough, the unconditional correlation between the labor share and output will be positive. Traditional regression methods would then wrongly conclude that this positive correlation is evidence of a wage-led regime.

An alternative to these single-equation methods has been to estimate a recursive VAR using data on the labor share, unemployment and output, ordering the labor share first to identify the response of output to a ‘labor share shock’ (Stockhammer and Onaran, 2006; Jump and Mendieta-Muñoz, 2017; Carrillo-Maldonado and Nikiforos, 2024). Using my model, however, I show that the ‘labor share shock’ identified by the recursive approach is in fact a linear combination of demand, supply and bargaining shocks. As a consequence, a recursive ‘labor share shock’ that raises the labor share by 1% will produce a short-run output response that is always biased upwards relative to the true response implied by my model. When the model economy is profit-led, this can severely attenuate the output response to a bargaining shock towards 0 or make it slightly positive, which has the potential to explain why a number of papers often find small effects of ‘labor share shocks’ on output.

To address the pitfalls of traditional estimation methods, I show my model economy produces enough cross-equation restrictions to be globally identified. To the best of my knowledge, this is the first constructive identification result in any Post-Keynesian model where the labor share is not contemporaneously exogenous. Armed with this identification result, I estimate the model through maximum likelihood methods using quarterly U.S. data. I estimate jointly the demand regime and the slope of the wage curve, as well as the responses of output and the labor share to bargaining and demand shocks. I then compare my estimates to what an econometrician would find using traditional methods.

My estimation yields two key results. First, the demand regime in the U.S. is very profit-led, much more so than what is implied by a regression of output growth on the labor share: the

slope of aggregate demand with respect to the labor share implied by my structural model is six times larger in absolute value than what is implied by traditional regression methods. Second, shocks to the bargaining power of labor have large effects on output: upon impact, a bargaining shock that increases the labor share by one percentage point lowers output by 6%. Ten years after the shock, output is still 2.4% lower. This long-run effect¹ is over five times larger in absolute value than the recursive estimate of 0.4%.

Related Literature. This paper contributes to three strands of literature. First and foremost, it contributes to the literature on estimating demand regimes. The demand-regime terminology comes from Bhaduri and Marglin (1990). Surveys of traditional approaches, which often rely on regressing different components of aggregate demand on the labor share, can be found in Stockhammer (2017) and Blecker (2016). Some representative studies of this approach are Stockhammer, Onaran and Ederer (2009), Onaran and Galanis (2013) and Stockhammer and Wildauer (2016). In these studies, the effects of the labor share on consumption, investment and exports are separately estimated, and then a weighted sum is reported as the total effect on output. The source of the simultaneous equation bias discussed in this paper applies to this approach, whether these regressions are conducted on separate components of aggregate demand or directly on output itself.

A related approach in the same literature estimates the effects that ‘labor share shocks’ have on output, and it is claimed that the sign of this response can be used to infer the demand regime. Typically, this involves estimating a SVAR that includes the labor share, output, and other control variables and ordering the labor share first, which again assumes that the labor share is contemporaneously exogenous with respect to output (Stockhammer and Onaran, 2004; Jump and Mendieta-Muñoz, 2017; Carrillo-Maldonado and Nikiforos, 2024). Many of these papers explicitly recognize that the structural shock of interest should be interpreted as a bargaining shock but do not present a formal model to support this claim. This paper clarifies the assumptions needed to justify this recursive identification: wage setting must be independent of slack in the labor market. It also characterizes the bias in the transmission of bargaining shocks to output that occurs when the econometrician imposes a recursive structure at odds with the DGP.²

¹In the model, the effects of bargaining shocks on output vanish asymptotically. I use the term long-run in what follows to denote output responses that are well beyond business-cycle frequencies.

²Some papers in the related literature have attempted to correct for simultaneous equation bias using an instrumental variable approach, such as Nikiforos and Foley (2012) and Blecker et al. (2022). They are immune to the issues raised in this paper, as long as one thinks their instruments are credibly exogenous.

Second, the theoretical model in this section also contributes to the literature on demand-led growth. It is part of the supermultiplier approach pioneered by Hicks (1950) and revived by Serrano (1995). In these models, the growth rate of output converges, in the long run, to the growth rate of an exogenous demand component (Allain, 2015; Fazzari et al., 2013; Freitas and Serrano, 2015; Lavoie, 2016). A survey of this rapidly growing literature can be found in Serrano et al. (2023). This paper contributes to the strand of supermultiplier models where technical change is endogenous (Deleidi and Mazzucato, 2019; Fazzari et al., 2020; Nomaler et al., 2021; see Tavani and Zamparelli, 2017, for a survey), by incorporating wage bargaining following a Nash protocol, as well as technology and bargaining shocks. To the best of my knowledge, this is the first paper to estimate a supermultiplier model with multiple structural shocks. The theoretical model closest to the one presented here is in Morlin and Pariboni (2024), who have a reduced-form wage equation almost identical to the one I derive. However, their model is deterministic and is used to study a set of issues very different from the ones raised in this paper.

Finally, the model also contributes to the literature on the transmission of bargaining shocks. My empirical results imply that bargaining shocks can have substantial effects on output. Gali, Smets and Wouters (2012) estimate a DSGE model where shocks to the wage mark-up—which are conceptually similar to bargaining shocks—account for a large fraction of long-run unemployment and output fluctuations. Drautzburg et al. (2021) estimate a DSGE model with stochastic fluctuations in bargaining power and find that bargaining shocks have large, contractionary effects on output at all horizons. Using an SVAR approach with sign restrictions, Foroni et al. (2018) estimate that bargaining shocks have negative, medium-term effects on output and account for 20% of output fluctuations in the long run. In all of these approaches, bargaining shocks are assumed to be contractionary by construction, either due to the structure of the theoretical model or imposed as a sign restriction. Through the lens of my model, this is equivalent to imposing a profit-led regime prior to estimation. González (2025) and Budrys et al. (2026) estimate the effects of bargaining shocks without using this restriction, and exploit narrative information that is incorporated into an SVAR using the methods developed by Antolin-Diaz and Rubio-Ramirez (2018). The first paper exploits variation in the attitudes of U.S. presidents towards capital-labor conflict, while the second one exploits legislated increases in the minimum wage and strike activity in Germany. Both papers find that bargaining shocks contract output at business cycle frequencies, and account for a quarter to a third of output fluctuations at all horizons. Thus, the empirical results from the structural model reproduce the findings of the narrative sign restriction approach.

2 The Model

The starting point of my discussion regarding the identification of demand regimes is the development of a supermultiplier model where the labor share is endogenous. Formally, this is an extension of the model presented in section 2 of Fazzari and González (2025), which is part of the broader supermultiplier tradition started by Serrano (1995). The key feature of this approach is that the growth rate of output converges to the growth rate of an autonomous component of aggregate demand; that is, a component of spending independent of economic activity. For example, military expenditures, which are largely set with reference to political and strategic reasons.³ In this sense, growth is demand-led. Interest in this approach has been revitalized by Allain (2015), Fazzari et al. (2013), Freitas and Serrano (2015), Lavoie (2016) and Fazzari et al. (2020), among others.

To study how demand influences the labor share, and the consequences this has for the identification of demand regimes, I extend the standard supermultiplier approach in two directions. First, I develop a simple theory of the real wage, a key relative price, based on Nash Bargaining. This provides a link from the transmission of demand shocks to income distribution: increases in autonomous demand growth decrease the long-run unemployment rate. As a result of reduced slack in the labor market, workers' outside options improve, which raises their real wage demands, and consequently, the labor share. This creates the potential for demand shocks to increase the labor share. Second, I incorporate stochastic fluctuations in the bargaining power of labor, which is the exponent of the Nash bargaining problem. An increase in workers' bargaining power leads to a higher labor share. Whether this expands or contracts output will depend on the demand regime, as is standard in Post-Keynesian models. This makes both output and the labor share dependent on demand and bargaining shocks, and allows me to study the identification of both of these shocks in my model environment.

2.1 Aggregate Demand

I start by deriving an aggregate demand equation that relates the labor share to output growth. There is a unit mass of workers who earn wages and a unit mass of capitalists that earns profits. Both agents save a fixed fraction of their income. Denoting the marginal and average propensity to save by s_w and s_π for workers and capitalists, respectively, the

³Another prominent example is exports for a small open economy. See Skott (2019) for a critical discussion of the assumption that autonomous demand grows at an exogenous rate.

consumption function is:

$$C_t = (1 - s_w)\omega_t Y_t + (1 - s_\pi)(1 - \omega_t)Y_t,$$

where ω_t is the labor share, C_t is aggregate consumption, and Y_t is output. This consumption function, first derived by Kaldor (1955) and generalized by Pasinetti (1962), is a standard specification in Post-Keynesian models. I assume $s_\pi > s_w$, which makes consumption an increasing function of the labor share.

Investment depends on output and cash flow available to firms. Denoting by $\bar{\omega}$ the long-run level of the labor share:

$$I_t = \lambda Y_t + \gamma Y_t[(1 - \omega_t) - (1 - \bar{\omega})],$$

where I_t is the level of investment. The first term λY_t captures an accelerator effect, which is implied by a fixed-coefficient technology: λ is the investment-output coefficient along the balanced growth path. The second term is a cash-flow term, following Fazzari, Ferri and Greenberg (2008). In the absence of any interest payments, cash flow is just revenues minus the wage bill, which can be written $\Pi_t = Y_t(1 - \omega_t)$. This is equal to total profits in our environment. The sensitivity of investment to cash-flow is parameterized by γ . Empirical evidence that cash flow is important for investment behavior can be found in the survey by Chirinko (1993). Along the balanced growth path, there is no permanent effect of a higher profit share on the investment share: when the labor share ω_t is equal to its long-run value, $\bar{\omega}$, increases in cash flow do not affect the level of investment.

One interpretation of this specification is that higher cash flows allow firms to adjust faster to the long-run level of investment implied by the accelerator, but firm liquidity does not exert any permanent effect on investment. If this were not the case, then firms would find themselves with a level of capital that was higher or lower than the technologically determined capital-output ratio.⁴

Finally, there are autonomous components of demand. Denoting autonomous demand Z_t , I assume that it evolves as a random walk with a drift. Denoting $z_t = \ln Z_t$, this is equivalent to:

$$z_t = g_z + z_{t-1} + \varepsilon_t^z,$$

⁴The reader might be wondering how we should reconcile this investment function with the desired level of capital implied by the fixed-coefficient technology used in the model, as well as the law of motion for capital. Appendix A.1 shows how this reconciliation takes place.

where $\varepsilon_t^z \sim i.i.dN(0, \sigma_z^2)$ is a structural demand shock. The growth rate of autonomous demand in the long run is g_z , the drift of this random walk. Goods market equilibrium implies

$$Y_t = C_t + I_t + Z_t.$$

To derive the relationship between income distribution and aggregate demand, substitute the investment and consumption functions inside goods-market equilibrium to obtain:

$$Y_t = \frac{1}{s_\pi - \lambda - \gamma\bar{\omega} - (s_\pi - s_w - \gamma)\omega_t} Z_t.$$

This is an extension of the old Keynesian multiplier relationship, but where the multiplier depends on the labor share. I assume that the multiplier is positive and bounded, which requires $s_\pi - (s_\pi - s_w)\omega_t > \lambda + \gamma(\bar{\omega} - \omega_t)$. This is known as the Keynesian stability condition in the related literature. Taking logarithms and first differences of the equation above, and using the stochastic process for autonomous demand yields:

$$\Delta y_t = g_z + \Delta f(\omega_t) + \varepsilon_t^z, \tag{AD}$$

where lowercase letters denote natural logarithms, and Δ is the first-difference operator. With some abuse of notation, $\Delta f(\omega_t) \equiv f(\omega_t) - f(\omega_{t-1})$. The function f is nonlinear and equals:

$$f(\omega_t) = -\ln[s_\pi - \lambda - \gamma\bar{\omega} - (s_\pi - s_w - \gamma)\omega_t].$$

A deterministic version of equation (AD) is commonly used in the supermultiplier literature starting with Serrano (1995). If the distribution of income converges to a long-run level, denoted by $\bar{\omega}$, then the labor share cannot exert any permanent influence on the growth rate of the economy. This feature of Keynesian models that incorporate an autonomous demand component has been discussed at length by Freitas and Serrano (2015), Lavoie (2016) and Pariboni (2016), among others, which contain similar aggregate-demand equations to the one discussed above.

2.2 Aggregate Supply

The second block of the model is an aggregate supply equation that will relate the level of unemployment to the growth rate. This equation summarizes the technological constraints of the economy. I follow closely the supply side of Fazzari and González (2025), with two differences. First, I will assume that labor supply is inelastic. There is a unit mass of workers

that can be either employed or unemployed. This is summarized by the resource constraint:

$$1 = L_t + u_t,$$

where L_t is the employment rate, and conversely, u_t is the unemployment rate. Second, I derive a relationship between productivity growth and unemployment from more primitive assumptions about technology. The production function of this economy is Leontief, as in much of the related literature. There are two reasons to use a fixed-coefficient technology. The first one is empirical: as shown by Gechert et al. (2022) in their meta-analysis of the estimation of production functions, the mean elasticity of substitution reported in these studies is 0.3, which is much closer to the Leontief case than to the Cobb-Douglas case. The second one is theoretical. With a fixed-coefficient technology, increases in the real wage induced by bargaining shocks do not decrease capital through factor-substitution channels; the effects are purely transmitted through aggregate demand. Because the conventional channels make bargaining shocks more contractionary (see Gali, Smets and Wouters, 2012), our model environment presents the most optimistic scenario for bargaining shocks to be expansionary. The production function is given by:

$$Y_t = \min\{A_t L_t, \frac{K_t}{v}\},$$

where A_t is average labor productivity, and v is the capital-output ratio. Cost minimization implies the following conditional demand for inputs:

$$Y_t = A_t L_t,$$

$$Y_t = \frac{K_t}{v}.$$

I assume that there is learning-by-doing: as output accumulates over time, the level of knowledge increases, as first outlined by Arrow (1962). However, a portion of this knowledge depreciates over time. Because output is produced with labor, this will create a link between the degree of slack in the economy and the growth rate of productivity. Formally, there is a constant returns to scale technology $e : \mathbb{R}_+^2 \rightarrow \mathbb{R}_+$ that produces knowledge today from inherited knowledge and output, denoted by:

$$A_t = e(Y_{t-1}, A_{t-1}).$$

Since e has constant returns to scale, and using conditional labor demand, re-write the function as:

$$\frac{A_t}{A_{t-1}} = e(L_{t-1}, 1),$$

which states that productivity growth depends on the level of employment. I specialize the discussion to a learning function that is log-linear:

$$e(L_{t-1}, 1) = \exp(\phi_0 + \varepsilon_t^a) L_{t-1}^{\phi_1},$$

where $\phi_0 > 0$ measures the exogenous rate of technical progress, ϕ_1 parametrizes the degree of learning-by-doing, and $\varepsilon_t^a \sim i.i.dN(0, \sigma_a^2)$ is a technology shock. Constant returns to scale imply that $\phi_1 \in [0, 1]$. Specifications of learning-by-doing functions like this have been used by Stadler (1990) and Cooper and Johri (2002). Log-differencing the above expression, and using the resource constraint for labor:

$$\begin{aligned} \Delta a_t &= \phi_0 + \phi_1 \ln L_{t-1} + \varepsilon_t^a \\ &= \phi_0 + \phi_1 \ln(1 - u_{t-1}) + \varepsilon_t^a \\ &\approx \phi_0 - \phi_1 u_{t-1} + \varepsilon_t^a, \end{aligned}$$

where $a_t \equiv \ln A_t$, and hence Δa_t is the growth rate of labor productivity, which is a negative function of lagged unemployment. The approximation $\ln(1 - u_{t-1}) \approx -u_{t-1}$ is very accurate for empirically reasonable unemployment rates. Aggregate productivity growth is a decreasing function of the unemployment rate, which means that transitory demand shocks can have permanent effects on productivity growth. The intuition behind the specification is the following: if we interpret average labor productivity as the stock of knowledge that society possesses, as proposed by Romer (1990) and eloquently discussed in Jones (2019), then the stock of knowledge depreciates at a rate $(1 - \phi_1)$, and current employment increases knowledge tomorrow by ϕ_1 . This increase in knowledge occurs through learning-by-doing: an increase in output today decreases the unemployment rate, which then increases knowledge tomorrow.⁵

We can log-difference the demand for labor and combine it with the law of motion for labor productivity to obtain an aggregate supply relationship that links unemployment with output growth:

$$u_t = \phi_0 - \Delta y_t + (1 - \phi_1)u_{t-1} + \varepsilon_t^a. \quad (\text{AS})$$

⁵Equilibrium relationships between productivity growth and the unemployment rate have been derived from other microfoundations; see for example Aghion and Howitt (1994).

Intuitively, equation (AS) states that unemployment is the gap between the growth of the supply side and the demand side. Whenever the growth rate of output increases, which is determined to a first order by demand, unemployment decreases. In contrast, if the exogenous growth rate of technology accelerates, or there is a sudden technological improvement, then unemployment rises.

2.3 Wage Bargaining

The final block of the model is composed of a wage curve, which determines real wages and the labor share. This block of the model is responsible for the negative identification issues of this paper, since it will create the main transmission channel through which demand shocks influence the labor share. Workers and capitalists bargain *à la* Nash over the real wage; if negotiation breaks down, workers become unemployed. I will follow McDonald and Solow (1992), Blanchard and Giavazzi (2003) and Tavani (2012) and assume that the employment rate influences workers' outside option. This is a shortcut meant to capture that whenever the job-finding rate goes up, this simultaneously decreases the unemployment rate and improves workers' outside option, without having to explicitly model the search frictions that pin down the job-finding rate. However, in a more general model with search frictions, there will still be a link between the labor share and the unemployment rate, which is the key equation responsible for my results.⁶ Because I don't intend to use my model for policy analysis, a semi-structural specification is both more tractable and can illustrate the econometric problems that plague the related literature. This also creates a bridge between search and matching models of the labor market and traditional Post-Keynesian models, which I see as a happy encounter.

Workers have linear preferences over the total wage bill, while capitalists have linear preferences over profits. Production is Leontief. Negotiation takes place after investment decisions are made and capital is installed; there is no second-hand market for capital. This implies that if negotiation breaks down, capitalists will find themselves with unused capital. Hence, their outside option is $-r_t K_t$, where r_t is the cost of capital. Workers' outside option is given by the probability of finding an alternative job, which I assume equal to the employment rate, $1 - u_t$, times an alternative wage, w_a . The workers take the alternative wage as given when bargaining. The wage w_t that solves this Nash Bargaining protocol satisfies:

⁶Naturally, other explanations for the link between demand and the labor share can also exist. For example, a positive demand shock can decrease the mark-up charged by firms, which in turn raises the labor share. This channel is present in the standard three-equation New Keynesian model.

$$\max_w V = [(w_t - w_a)L_t]^{\eta_t} [A_t L_t - w_t L_t]^{1-\eta_t}.$$

The first-order condition is:

$$w_t = \eta_t A_t + (1 - \eta_t)w_a.$$

As discussed above, the alternative wage in equilibrium is $w_a = (1 - u_t)w_t$. Combine these two expressions to obtain the following wage equation:

$$w_t = \frac{\eta_t}{\eta_t + (1 - \eta_t)u_t} A_t,$$

which yields a labor share, $\omega_t = w_t/A_t$, equal to:

$$\frac{w_t}{A_t} = \omega_t = \frac{\eta_t}{\eta_t + (1 - \eta_t)u_t}. \quad (\text{WC})$$

Call the right-hand side of this equation $h(u_t)$. This wage curve depends on two things: the unemployment rate, which summarizes the outside options available to workers, and the parameter η_t , which is the share of the surplus appropriated by workers, and which can therefore be interpreted as the bargaining power of workers. The following Lemma characterizes the wage curve:

Lemma 1: (Wage Curve) The function $h : [0, 1] \rightarrow [0, 1]$ is non-increasing and convex, and satisfies $h(0) = 1$ and $h(1) = \eta_t$.

Proof.

$$h'(u_t) = -\frac{\eta_t(1 - \eta_t)}{(\eta_t + (1 - \eta_t)u_t)^2} \leq 0,$$

$$h''(u_t) = \frac{2\eta_t(1 - \eta_t)^2}{(\eta_t + (1 - \eta_t)u_t)^3} \geq 0,$$

$$\lim_{u_t \rightarrow 1} h(u_t) = \eta_t,$$

$$\lim_{u_t \rightarrow 0} h(u_t) = 1,$$

which completes the proof. □

Note that the lemma holds outside the knife-edge case where $u_t = \eta_t = 0$. This case can be

ruled out by appropriate parameter restrictions along the balanced growth path.

To complete the model, I assume that the bargaining power of labor evolves as follows:

$$\eta_t = (1 - \rho)\bar{\eta} + \rho\eta_{t-1} + \varepsilon_t^\eta, \quad (\text{BP})$$

with $\varepsilon_t^\eta \sim i.i.d N(0, \sigma_\eta^2)$ being the shock to the bargaining power of labor, $\bar{\eta} \in [0, 1]$ the steady-state bargaining weight and $\rho \in [0, 1)$ a persistence parameter on the bargaining shocks. If we interpret fluctuations in the bargaining weight as changes in labor legislation or bargaining institutions, then it seems natural to assume that these changes are persistent. Structural estimates of η_t often show significant persistence (Drautzburg et al., 2021; Mengano, 2022); furthermore, narrative events like changes in the attitude of the executive power towards capital-labor relations (González, 2025), legislated increases in the minimum wage or general strikes (Budrys et al., 2026) are best conceptualized as persistent.

2.4 The Balanced Growth Path

In order to study the transmission of bargaining and demand shocks, we need to log-linearize the model around the balanced growth path. This will also illustrate the long-run, positive relationship that exists between the growth rate of demand and the labor share present in the model. The following proposition proves the existence of a balanced growth path:

Proposition 1: (Balanced Growth Path) Consider the system of equations given by (AD), (AS), (WC) and (BP). There exists a unique, deterministic balanced-growth path solution to the above system, where $x_t = x_{t-1} = \bar{x}$ for $x_t = (\Delta y_t, u_t, \omega_t, \eta_t)$, as long as $\phi_0 \in [g_z, g_z + \phi_1]$, given by:

$$\Delta \bar{y} = g_z, \quad (1)$$

$$\bar{u} = \frac{\phi_0 - g_z}{\phi_1}, \quad (2)$$

$$\bar{\omega} = \frac{\bar{\eta}}{\bar{\eta} + (1 - \bar{\eta})\bar{u}} = h(\bar{u}). \quad (3)$$

Proof. Since we are analyzing the deterministic counterpart of the system, $\varepsilon_t^i = 0, \forall i = z, a, \eta$. We can solve the system recursively. The first equation always has a solution. To ensure

that the unemployment rate is well defined, that is, $\bar{u} \in [0, 1]$, we must have that

$$0 \leq \frac{\phi_0 - g_z}{\phi_1} \leq 1.$$

Since $g_z \in \mathbb{R}^+$, $\phi_0 \in \mathbb{R}^+$ and $\phi_1 \in (0, 1]$, some manipulation of the above inequality reduces to the condition $\phi_0 \in [g_z, g_z + \phi_1]$.

Finally, by lemma 1, $h : [0, 1] \rightarrow [\bar{\eta}, 1]$ is continuous and strictly decreasing in $\bar{u}$. Therefore, $\bar{\omega} = h(\bar{u})$ exists and satisfies $\bar{\omega} \in [\bar{\eta}, 1]$. A light manipulation of the stochastic process for η_t shows that $\eta_t = \eta_{t-1} = \bar{\eta}$. $\square$

As discussed above, the growth rate of output converges to the growth rate of autonomous demand in the long run, which is the defining feature of supermultiplier models. Changes in income distribution do not have permanent effects on the growth rate. The long-run unemployment rate is identical to that of Fazzari et al. (2020): it reflects the gap between demand growth, given by g_z , and the growth rate of potential output, given by ϕ_0 , scaled by the learning-by-doing parameter.

To the uninitiated, this balanced growth path can look a bit strange. On the one hand, the growth rate of output is exogenous, but unlike the neoclassical growth model, it is not given by the forces of technology and demography, but rather by the exogenously given level of demand. In this sense, it flips the logic of the Solow-Swan growth model on its head. On the other hand, making productivity growth endogenous does not make the growth rate endogenous, but rather, ensures that the unemployment rate is well defined. In the absence of learning-by-doing, productivity and output drift apart eternally like estranged lovers. Learning-by-doing, however small, gently reconciles them, and keeps unemployment bounded.

The model provides a simple and rich theory of the labor share, which is an endogenous object influenced by changes in aggregate demand, even in the long run. This can be appreciated by differentiating equation (3) with respect to g_z :

$$\frac{\partial \bar{\omega}}{\partial g_z} = h'(\bar{u}) \cdot \frac{\partial \bar{u}}{\partial g_z} = h'(\bar{u}) \cdot -\frac{1}{\phi_1} > 0. \quad (4)$$

Thus, the effect of growth on the labor share is the product of $h'(\bar{u})$, which is the slope of the wage curve around the long-run unemployment rate, times the inverse of the learning-by-doing parameter. This effect is positive as long as workers have some bargaining power,

since $\bar{\eta} > 0$ guarantees $h'(\bar{u}) < 0$ by Lemma 1. Fazzari and González (2025) estimate that $1/\phi_1$ is equal to 1 at the yearly level. If the slope of the wage curve is big enough in absolute value, changes in the growth rate can have a quantitatively large impact on the labor share.⁷ The result that changes in demand growth can lead to endogenous changes in the labor share has also been emphasized by Morlin and Pariboni (2024) in a supermultiplier model similar to the one presented here, and Setterfield (2026) in a Marx-Keynes-Schumpeter model.

This long-run relationship between the labor share and the growth rate should also invite caution when interpreting a positive correlation between the labor share and the growth rate as evidence for wage-led growth, as done by Barrales-Ruiz et al. (2025). It is clear from the derivations alone that this positive relationship is independent of the demand regime.

2.5 Linearization

To study the transmission of structural shocks and the identification of demand regimes, I linearize the model around the balanced growth path. I carry this out in Appendix A.3. The model becomes:

$$\Delta y_t = g_z + \alpha \Delta \omega_t + \varepsilon_t^z, \quad (\text{LL-AD})$$

$$u_t = \phi_0 - \Delta y_t + (1 - \phi_1)u_{t-1} + \varepsilon_t^a, \quad (\text{AS})$$

$$\omega_t = \bar{\omega} + \Psi_u(u_t - \bar{u}) + \Psi_\eta(\eta_t - \bar{\eta}), \quad (\text{LL-WC})$$

$$\eta_t = (1 - \rho)\bar{\eta} + \rho\eta_{t-1} + \varepsilon_t^\eta. \quad (\text{BP})$$

Equation (LL-AD) relates changes in the labor share to changes in the growth rate. The sign of α is one of the key parameters of interest, as this determines the demand regime. The sign of α depends on the sign of $s_\pi - s_w - \gamma$, which is the gap between the marginal propensities to save out of capital and labor income, minus the effect of cash flows on firm investment. The bigger the gap in the marginal propensities to consume of each class, and the smaller the cash-flow sensitivity of firms, the more likely demand is to be wage-led.

Isn't there enough microeconomic evidence on marginal propensities to consume and cash-flow effects on firm investment to pin down α ? Unfortunately, estimates of these parameters vary widely: Kumar et al. (2018) estimate a savings rate out of capital income between 0.64 and 0.81, while they assume a savings rate out of wages is close to 0. Cantore and

⁷Naturally, any parameter that influences the long-run unemployment rate, including changes in technology, will influence the labor share as well. In Appendix A.2 I discuss other comparative statics implied by the model.

Freund (2021) estimate short-run marginal propensities to save of 0.98 and 0.74 for workers and capitalists, respectively. Fazzari et al. (2008) report a value of γ between 0.27 and 0.49. If $\gamma = 0.45$ and $s_\pi - s_w = 0.3$, then α would be negative. However, with $\gamma = 0.3$ and $s_\pi - s_w = 0.8$ the economy would be wage-led. This implies that macroeconomists need to rely on time-series evidence to pin down this parameter.

Equation (AS) was already linear. Equation (LL-WC) is the linearized wage curve, which describes a negative relationship between unemployment and the labor share. The slope of the wage curve around the steady-state is given by Ψ_u , while Ψ_η is the sensitivity of the wage curve with respect to the bargaining power of labor. By direct application of lemma 1, $\Psi_u \leq 0$ and $\Psi_\eta \geq 0$ for all parameter values, as shown in Appendix A.3. The evolution of bargaining power is tracked by (BP), which is the only state variable of the model. The slope of the wage curve will be a key determinant of simultaneity bias.

To use the model as a DGP to study the identification of demand regimes, we have to make sure that we restrict the structural parameters to ensure stability. The next proposition characterizes the stable parameter region.

Proposition 2: (Stability) Consider the linearized dynamical system given by (LL-AD), (AS), (LL-WC) and (BP). The system is globally stable if $\alpha \leq 0$. If $\alpha > 0$, then the system is stable as long as:

$$(1 + \alpha\Psi_u) > \frac{\phi_1}{2}, \quad (5)$$

which implies that $(1 + \alpha\Psi_u) \equiv m > 0$.

Proof. See Appendix A.4.

In other words, the model is always locally stable in the profit-led case, and to ensure stability in the wage-led case, the effects of distribution on aggregate demand cannot be too strong relative to the wage curve. The intuition for this result is that if aggregate demand is too wage-led, any shock that raises output increases the labor share through the wage curve. This then stimulates aggregate demand further, since the economy is wage-led, increasing production, which further increases the labor share the next period, and so on. If either the wage curve is too steep or demand is too sensitive to income distribution, the economy diverges. The term $(1 + \alpha\Psi_u) \equiv m$ summarizes the interaction of these two effects. In the profit-led case, the labor market stabilizes movements in the goods market: an increase in

output increases the labor share, which depresses demand, which then reduces output next period.⁸ In what follows, I will assume that the economy is stable, summarized in the next assumption:

Assumption 1: (*Stab*) The parameter restriction $(1 + \alpha\Psi_u) \equiv m > \frac{\phi_1}{2} > 0$ holds.

3 Identification Pitfalls

The first negative identification result concerns the demand regime summarized by α . Suppose that we treat our model as the DGP, and an econometrician runs a regression of output growth on the change in the labor share.⁹ Does this regression recover α , which is the demand regime? The answer to this question is negative: the following proposition shows that when the economy is subject to demand shocks and the slope of the wage curve is negative, *this regression coefficient is biased, and the size of the bias is always positive* - which means that the econometrician always finds the demand regime to be more wage-led than it actually is.

Proposition 3: (Simultaneous equations bias) Suppose that the DGP is given by (LL-AD), (AS), (LL-WC) and (BP). Assume that *Stab* holds. Without loss of generality, if the econometrician demeans the variables $(\Delta y_t, \omega_t)$ and runs the regression

$$(\Delta y_t - g_z) = \beta \Delta(\omega_t - \bar{\omega}) + e_t,$$

where $E[e_t \Delta(\omega_t - \bar{\omega})] = 0$ by construction. The population regression coefficient is:

$$\beta_{OLS} = \alpha - \frac{\Psi_u \sigma_z^2}{1 + \alpha \Psi_u} \cdot \frac{1}{\sigma_{\Delta\omega}^2}. \quad (6)$$

Where $\sigma_{\Delta\omega}^2 \equiv \text{Var}[\Delta\omega_t]$, the variance of first-differenced labor share. Furthermore, the bias between β_{OLS} and α is non-negative:

$$\beta_{OLS} - \alpha = -\frac{\Psi_u \sigma_z^2}{1 + \alpha \Psi_u} \cdot \frac{1}{\sigma_{\Delta\omega}^2} > 0. \quad (7)$$

⁸The fact that profit-led demand stabilizes the economy through the labor market echoes the discussion in Skott (2017, 2019).

⁹The regression that follows uses the *change* in the labor share as a regressor. If the econometrician instead uses the *level* of the labor share, the coefficient contains the same source of simultaneity bias and an additional term arising from dynamic misspecification. Using the correct dynamic specification isolates the identification problem caused by contemporaneous feedback between output and the labor share.

So that the regression is always biased towards finding a demand regime that is more wage-led.

Proof. Recall that the formula for β_{OLS} is:

$$\beta_{OLS} = \frac{Cov[\Delta(\omega_t - \bar{\omega}), (\Delta y_t - g_z)]}{Var(\Delta\omega_t)}.$$

Replace inside the expression $(\Delta y_t - g_z) = \alpha\Delta\omega_t + \varepsilon_t^z$ from our (LL-AD) equation. We obtain:

$$\beta_{OLS} = \alpha + \frac{Cov[\Delta(\omega_t - \bar{\omega}), \varepsilon_t^z]}{Var[\Delta\omega_t]}.$$

Given that the structural shocks are white noise, we have that $Cov[(\omega_{t-1} - \bar{\omega}), \varepsilon_t^z] = 0$. Additionally, given that we are working with demeaned variables, $Cov[(\omega_t - \bar{\omega}), \varepsilon_t^z] = E[\omega_t \varepsilon_t^z]$ and hence, we only need to compute:

$$\begin{aligned} E[\omega_t \varepsilon_t^z] &= E[(\bar{\omega} + \Psi_u(u_t - \bar{u}) + \Psi_\eta \eta_t) \varepsilon_t^z] \\ &= \Psi_u E[u_t \varepsilon_t^z] \\ &= \Psi_u E[(\phi_0 - \Delta y_t + (1 - \phi_1)u_{t-1} + \varepsilon_t^a) \varepsilon_t^z] \\ &= \Psi_u E[-(g_z + \alpha\Delta\omega_t + \varepsilon_t^z) \varepsilon_t^z] \\ &= -\Psi_u E[\alpha\omega_t \varepsilon_t^z] - \Psi_u E[(\varepsilon_t^z)^2] \\ E[\omega_t \varepsilon_t^z] &= -\frac{\Psi_u \sigma_z^2}{1 + \alpha\Psi_u}. \end{aligned}$$

The first equality uses the definition of the wage curve; the third one, the aggregate supply relation; and the fourth one, the aggregate demand relationship. Simplifications exploit the fact that the structural shocks are mutually uncorrelated and uncorrelated with the lagged values of endogenous variables. Finally, replacing this expression into β_{OLS} , we arrive at

$$\beta_{OLS} = \alpha - \frac{\Psi_u \sigma_z^2}{1 + \alpha\Psi_u} \cdot \frac{1}{\sigma_{\Delta\omega}^2}.$$

This is the expression stated in proposition 3. To prove that

$$\beta_{OLS} - \alpha = -\frac{\Psi_u \sigma_z^2}{1 + \alpha\Psi_u} \cdot \frac{1}{\sigma_{\Delta\omega}^2} > 0.$$

To see that this expression is positive, it suffices to note that $\Psi_u < 0$ and $\sigma_z^2 > 0$ by assumption, and $1 + \alpha\Psi_u > 0$ by the *Stab* assumption. $\square$

This proposition confirms the ‘folk’ theorem that conventional OLS regressions are biased

to find wage-led results, as discussed by Lavoie (2017). The intuition for this bias is that the wage curve induces a positive correlation between the labor share and output: a positive demand shock raises output, which lowers unemployment and raises the labor share. How severe is this bias in practice? The following corollary explores two special, but important cases. First, when aggregate demand is independent of distribution, the bias is positive. Hence, the econometrician wrongly concludes that the economy is wage-led *even when aggregate demand is independent from the labor share*. This stark result should caution us greatly when evaluating the large literature on demand regime estimation. Second, the bias disappears when the slope of the wage curve is 0 - which is equivalent to the exclusion restriction that the labor share is not affected contemporaneously by output.

Corollary 1: Consider the special cases where $\alpha = 0$ and $\Psi_u = 0$. Then, the size of the bias given by equation 7 is given by:

$$\beta_{OLS} - \alpha = -\frac{\Psi_u \sigma_z^2}{\sigma_{\Delta\omega}^2} > 0,$$

and

$$\beta_{OLS} - \alpha = 0.$$

respectively.

Proof. These expressions follow directly from substituting $\alpha = 0$ and $\Psi_u = 0$ in the right-hand side of equation (7). $\square$

The result in Corollary 1 shows that if wage bargaining is independent of the state of the labor market, the model generates the exclusion restriction that output growth does not affect the labor share contemporaneously, and hence, running a single regression of output growth on the change of the labor share would allow the econometrician to pin down the demand regime. However, this restriction does not seem supported by the data: ever since Blanchflower and Oswald (1994), there is substantial evidence that workers' outside options affect wage bargaining (Mengano, 2022; Caldwell and Oehlsen, 2026). It seems reasonable to say that the empirical results of a large part of the demand-regime literature depend on an incredible assumption.

A natural question to ask is how severe this bias is, at the population level, and how it varies as a function of the slope of the wage-curve. Visual inspection of equation (7) would suggest that the bias is monotonically increasing in the slope of the wage curve. This suggestion, however, is erroneous, as the variance of the first-differenced labor share, which appears in

the denominator, is a function of all structural parameters, including Ψ_u .

To explore numerically the size of the bias, I set $(\phi_1, \Psi_\eta \sigma_\eta, \sigma_z, \sigma_a, \rho) = (0.25, 0.005, 0.01, 0.01, 0)$. Since (g_z, ϕ_0) only affect the bias through their effects on Ψ_u , I leave them unrestricted. I pick the value of the learning-by-doing parameter to be within the median estimates obtained by Fazzari and Gonzalez (2025) for U.S. data; this value is close to the one estimated by Watson and Tervala (2026) and slightly higher than the one reported by Cooper and Johri (2002). The standard deviations of the structural shocks are picked to match closely the standard deviation of the labor share, the growth rate of output, and the unemployment rate over U.S. data for the period 1948Q1 - 2019Q4. The persistence parameter is set to 0 for convenience, as it only affects the bias formulas through the variance of the labor share, increasing it is equivalent to using a higher variance.

I consider values of Ψ_u ranging from 0 to -4 and examine all demand regimes: a wage-led case where $\alpha = 0.2$, a case where demand is independent from distribution, and a profit-led case where $\alpha = -0.5$.¹⁰ Figure 1 plots the behavior of the bias as a function of Ψ_u .

Three results stand out: first, the behavior of the bias is non-monotonic in all three cases: it peaks when Ψ_u takes on values between -0.2 and -0.5 , and then decreases monotonically after. Second, the magnitude of the bias can be severe in all three cases: for a wide range of values of Ψ_u , an econometrician would infer a wage-led regime twice as strong as present in the data in the case $\alpha = 0.2$, and would mitigate substantially how profit-led the demand regime is in the $\alpha = -0.5$ case, for all values of Ψ_u . Finally, inferring erroneously that there is a wage-led regime can happen both in the case where $\alpha = 0$, where the econometrician wrongly finds strong, positive effects of income distribution on demand, and in the case where $\alpha = -0.5$, where the red-dashed line marks the size of the bias necessary to estimate a wage-led regime when in fact the DGP features profit-led demand. This can occur for a wide enough range of parameter values that the econometrician should be severely worried in practice about simultaneous equation bias.

3.1 The Transmission of Structural Shocks

A reader unfamiliar with the demand-regime literature might wonder what the fuss is all about: so what if α is biased? It turns out that in a broad family of Post-Keynesian models, α plays a key role in the transmission of shocks to fundamentals and changes in policy. In

¹⁰Setting steady-state unemployment at 6%, I vary the value of $\bar{\eta}$ from 0 to 1. The slope of the wage curve takes on a minimum value a little below -4 with this calibration.

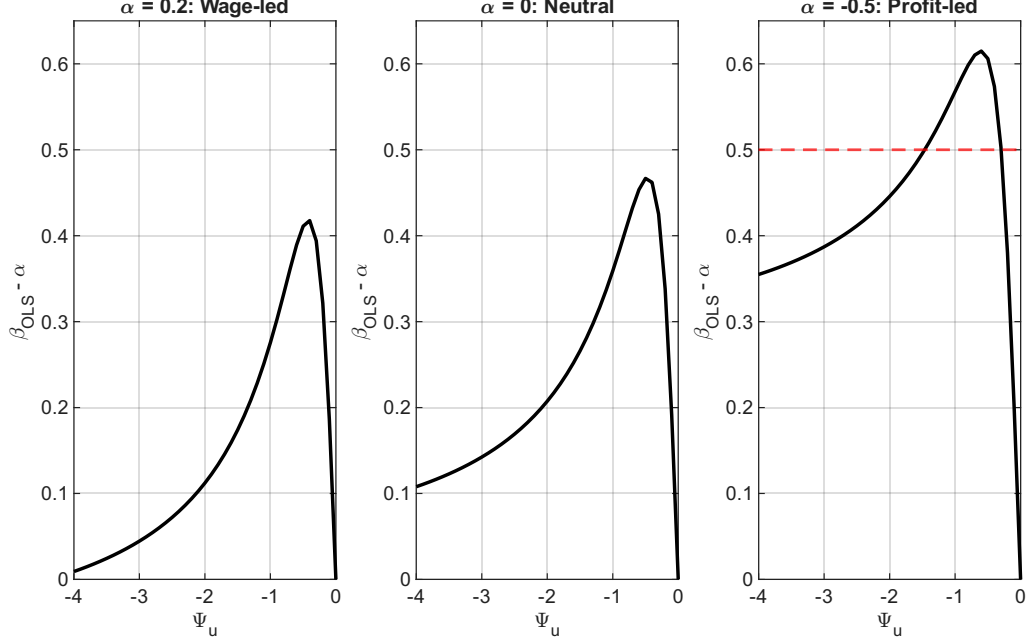


Figure 1: Population OLS bias as a function of the wage-curve slope. The red dashed line in the profit-led case marks the threshold at which the simultaneity bias is large enough for the econometrician to recover a wage-led estimate even though the true economy is profit-led.

particular, whether bargaining shocks are expansionary or contractionary depends on the sign of α . In what follows, I derive the reduced-form VAR representation of our model and use it to study the transmission of structural shocks. This will also illustrate how recursive identification of bargaining shocks will be biased in the presence of a wage curve.

Start by substituting the evolution of bargaining power, (BP), inside the wage curve (LL-WC). Then, write the resulting equation alongside (LL-AD) and (AS) in matrix form:

$$\begin{bmatrix} 1 & 0 & -\Psi_u \\ -\alpha & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} \omega_t \\ \Delta y_t \\ u_t \end{bmatrix} = \begin{bmatrix} (\bar{\omega} - \Psi_u \bar{u})(1 - \rho) \\ g_z \\ \phi_0 \end{bmatrix} + \begin{bmatrix} \rho & 0 & -\rho\Psi_u \\ -\alpha & 0 & 0 \\ 0 & 0 & (1 - \phi_1) \end{bmatrix} \begin{bmatrix} \omega_{t-1} \\ \Delta y_{t-1} \\ u_{t-1} \end{bmatrix} + \begin{bmatrix} \Psi_\eta & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^\eta \\ \varepsilon_t^z \\ \varepsilon_t^a \end{bmatrix}.$$

Or, more compactly, denoting $X_t \equiv (\omega_t, \Delta y_t, u_t)$:

$$BX_t = C + AX_{t-1} + D\varepsilon_t.$$

Consequently, the model has a SVAR representation. To derive the effects of structural shocks on the endogenous variables, I compute B^{-1} , the impact multiplier matrix. This takes the value:

$$B^{-1} = \frac{1}{1 + \alpha\Psi_u} \begin{bmatrix} 1 & -\Psi_u & \Psi_u \\ \alpha & 1 & \alpha\Psi_u \\ -\alpha & -1 & 1 \end{bmatrix}.$$

This matrix is invertible as long as its determinant is not 0, or $\alpha\Psi_u \neq -1$. Notice that invertibility is guaranteed by the *Stab* assumption, as this ensures $1 + \alpha\Psi_u \equiv m$, which acts as a multiplier of the structural shocks, is positive. Premultiplying both sides by B^{-1} , and omitting the uninteresting constants for the moment, this yields:

$$\begin{bmatrix} \omega_t \\ \Delta y_t \\ u_t \end{bmatrix} = \frac{1}{m} \begin{bmatrix} \rho + \alpha\Psi_u & 0 & \Psi_u(1 - \phi_1 - \rho) \\ -\alpha(1 - \rho) & 0 & \alpha\Psi_u(1 - \phi_1 - \rho) \\ \alpha(1 - \rho) & 0 & \rho\alpha\Psi_u + (1 - \phi_1) \end{bmatrix} \begin{bmatrix} \omega_{t-1} \\ \Delta y_{t-1} \\ u_{t-1} \end{bmatrix} + \frac{1}{m} \begin{bmatrix} \Psi_\eta & -\Psi_u & \Psi_u \\ \alpha\Psi_\eta & 1 & \alpha\Psi_u \\ -\alpha\Psi_\eta & -1 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^\eta \\ \varepsilon_t^z \\ \varepsilon_t^a \end{bmatrix}.$$

Or, in matrix form:

$$X_t = \tilde{C} + FX_{t-1} + v_t, \quad (8)$$

where $\tilde{C} = B^{-1}C$, $F = B^{-1}A$ and $v_t = B^{-1}D\varepsilon_t$. This expression allows us to compute the contemporaneous effects of a unit change in the bargaining shock. The following Lemma summarizes the effects of bargaining shocks on the economy.

Lemma 2: (Bargaining Shocks) Assume that *Stab* holds. Then, there exists an invertible SVAR representation of (8). The contemporaneous effects of a bargaining shock are given by:

$$\begin{aligned} \frac{\partial X_t}{\partial \varepsilon_t^\eta} &= \begin{bmatrix} \frac{\partial \omega_t}{\partial \varepsilon_t^\eta} & \frac{\partial \Delta y_t}{\partial \varepsilon_t^\eta} & \frac{\partial u_t}{\partial \varepsilon_t^\eta} \end{bmatrix} \\ &= [B^{-1}D]_{1,*} \\ &= \frac{\Psi_\eta}{1 + \alpha\Psi_u} \begin{bmatrix} 1 & \alpha & -\alpha \end{bmatrix} \end{aligned} \quad (9)$$

This lemma establishes that a bargaining shock always increases the labor share; however, its effects on output and unemployment will depend crucially on the sign of α , the demand regime. This is a common result in much of the related literature, and it emphasizes that estimating this parameter is crucial to understand the transmission of bargaining shocks.

The lemma also establishes that the effects of bargaining shocks on output and unemployment are amplified or mitigated through the labor market: whenever $\Psi_u = 0$, which implies

that wage bargaining does not respond to outside options, the impact response is simply given by $\Psi_\eta\alpha$. Whenever $\Psi_u < 0$, however, this general equilibrium channel amplifies the effects of bargaining shocks when the economy is wage-led ($\alpha > 0$) and mitigates them when it is profit-led ($\alpha < 0$). The intuition behind this economic mechanism is simple: an initial bargaining shock increases output in the wage-led case. This increase in production diminishes unemployment, which then improves workers' outside options and raises the labor share above its initial increase. This amplifies the effects of bargaining shocks. In the profit-led case, a decrease in output raises unemployment, which then worsens workers' outside options, mitigating some of the initial increase in the labor share.

This discussion illustrates that bargaining shocks are not just propagated by their direct effect on aggregate demand, but also by the influence that the unemployment rate exerts on the wage demands by workers. As recognized by Lavoie (2017), an important part of the theoretical literature ignores this mechanism, and to the best of my knowledge, it has been neglected in virtually all of the empirical work.

It should be clear that if an econometrician used β_{OLS} to calibrate the effects of bargaining shocks on economic activity, he would be at risk of concluding that bargaining shocks are expansionary when in reality they could have negative or nil effects on economic activity, as shown by the results in the previous subsection. Instead of trying to directly estimate the demand regime, however, he could try to estimate the effects of bargaining shocks directly on output, and infer the demand regime from the output response. Examples of this approach can be found in Stockhammer and Onaran (2004), Jump and Mendieta-Muñoz (2017), Cauvel (2023) and Carrillo-Maldonado and Nikiforos (2024). This is typically done by using a standard Cholesky decomposition and ordering the labor share first. These empirical SVARs usually include a measure of economic activity, such as output or capacity utilization, and a measure of labor market slack.

Unfortunately, the following proposition shows that these recursive procedures do not identify bargaining shocks and distort the transmission of bargaining shocks on output. In particular, *recursive procedures always bias the impact response of output to a bargaining shock upwards*, leading the econometrician to conclude that the economy is more wage-led than it actually is.

Proposition 4: (Recursive Identification). Assume (8) is the DGP, and *Stab* holds. The econometrician tries to recover the causal effects of bargaining shocks on output by using

the identifying assumption

$$v_t = P\varepsilon_t^{chol}, \quad (10)$$

where the matrix P is the lower-triangular Cholesky factorization of Σ_v . The econometrician orders the labor share first, output growth second, and unemployment third. The structural shocks obtained from this procedure are denoted ε_t^{chol} . He recovers the following bargaining shock:

$$\varepsilon_t^{\eta, chol} = \frac{\Psi_\eta \varepsilon_t^\eta - \Psi_u(\varepsilon_t^z - \varepsilon_t^a)}{\sqrt{\Psi_\eta^2 \sigma_\eta^2 + \Psi_u^2(\sigma_z^2 + \sigma_a^2)}} \neq \frac{\varepsilon_t^\eta}{\sigma_\eta}. \quad (11)$$

Furthermore, suppose that the true structural shock, ε_t^η , increases the labor share by one percentage point. The corresponding log-output response upon impact is $y_t(0) = \alpha$, while the recursive log-output response upon impact is $y_t^{chol}(0) = \alpha - \frac{m\Psi_u\sigma_z^2}{\Psi_\eta^2\sigma_\eta^2 + \Psi_u^2(\sigma_z^2 + \sigma_a^2)}$. Hence, the contemporaneous output response has a bias of size

$$y_t^{chol}(0) - y_t(0) = -\frac{m\Psi_u\sigma_z^2}{\Psi_\eta^2\sigma_\eta^2 + \Psi_u^2(\sigma_z^2 + \sigma_a^2)} \geq 0. \quad (12)$$

The inequality follows from $m > 0$ and $\Psi_u \leq 0$, and is strict when $\Psi_u < 0$ and $\sigma_z^2 > 0$.

Proof. See Appendix A.5. □

The first part of the proposition establishes that if the econometrician uses short-run restrictions of the type commonly applied in empirical work, the identified ‘labor share shock’ is a mix of bargaining, demand and supply shocks. The weight that demand and supply shocks receive is an increasing function of the slope of the wage curve. The second part establishes that, conditional on an identified ‘labor share shock’ that raises the labor share by 1%, the output response implied by this shock is biased upwards. This distortion is explained due to the fact that demand shocks raise the output and the labor share: since a Cholesky identification scheme mixes both types of disturbances, output must increase if the labor share has increased as a result of a demand shock.

To gain a sense of how large the bias is, we can compute formula 12 for a profit-led case where $\alpha = -1$. Then, normalize the variances of the structural shocks such that $\sigma_z = \sigma_a = \Psi_\eta\sigma_\eta$, which we can interpret as a case where all structural shocks are equally volatile. If $\Psi_u = -3$, which is empirically reasonable, then the size of the bias is 0.63, and the Cholesky response is -0.37. In other words, the bias cuts the response of a bargaining shock that depresses output by one percent by almost two-thirds. This indicates that this bias can be quantitatively important, and the output responses to recursively identified ‘labor share shocks’ are

misleading indicators of the true demand regime on the economy.¹¹

Is there any justification, then, for using a recursive procedure where the labor share is ordered first and treated as weakly exogenous? The following corollary establishes that this is only the case when $\Psi_u = 0$, that is, when the labor share does not respond to the unemployment rate, and therefore, output fluctuations. This is equivalent to asserting that output growth does not affect contemporaneously the labor share. In this case, a recursive procedure identifies shocks to the bargaining power of labor and does not bias the IRF of output to a bargaining shock.

Corollary 2: Consider the economy described by equation (8). If $\Psi_u = 0$, then there exists a Cholesky factorization with the labor share ordered first, growth ordered second and unemployment ordered third that identifies the bargaining shock.

Proof. Substitute this restriction inside of the structural VAR. Omitting the uninteresting constants, the system reduces to:

$$\begin{bmatrix} \omega_t \\ \Delta y_t \\ u_t \end{bmatrix} = \begin{bmatrix} \rho & 0 & 0 \\ -\alpha(1-\rho) & 0 & 0 \\ \alpha(1-\rho) & 0 & (1-\phi_1) \end{bmatrix} \cdot \begin{bmatrix} \omega_{t-1} \\ \Delta y_{t-1} \\ u_{t-1} \end{bmatrix} + \begin{bmatrix} \Psi_\eta & 0 & 0 \\ \alpha\Psi_\eta & 1 & 0 \\ -\alpha\Psi_\eta & -1 & 1 \end{bmatrix} \cdot \begin{bmatrix} \varepsilon_t^\eta \\ \varepsilon_t^z \\ \varepsilon_t^a \end{bmatrix}. \quad (13)$$

By direct substitution in formulas (11) and (12), $\varepsilon_t^{\eta, chol} = \frac{\varepsilon_t^\eta}{\sigma_\eta}$ and $y_t(0) = y_t(0)^{chol}$. $\square$

Propositions 3 and 4 establish an important result: the economic assumption that is needed to properly identify the demand regime when using regression methods is the *same* assumption an econometrician needs to identify the output effects of bargaining shocks using a recursive procedure. Structural VARs identified through short-run restrictions suffer the same shortcomings as approaches that use systems of equations methods in the tradition of the Cowles Commission. As emphasized before, this is the strong assumption that wage bargaining is insensitive to the unemployment rate, and hence, output does not affect contemporaneously the labor share. The fact that this single assumption underlies the validity of both approaches is important, because it has been implied in influential reviews of the literature that both approaches to identification have different strengths and shortcomings (Blecker, 2016).

Before discussing an alternative framework to identify the demand regime and the effects of bargaining shocks, I note that the model implies that demand shocks can strongly influence

¹¹Analogous expressions can be derived for longer horizons. Analytical results are available upon request.

the distribution of income between capital and labor in the short-run. Indeed, inspection of equation (8) shows that the impact response of the labor share to a unit demand shock is $-\Psi_u/m > 0$; which is an increasing function of $-\Psi_u$ in the profit-led case. This result is the cyclical counterpart to the steady-state result that the labor share can be strongly influenced by the growth rate of demand, as long as the slope of the wage curve is steep enough around the steady-state unemployment rate. With enough sensitivity of wage bargaining to unemployment fluctuations, changes in demand can play a central role to explain the secular and cyclical movements of the labor share.

3.2 A Structural Approach to Identification

The negative results of the previous section regarding the identification of demand regimes and bargaining shocks beg a natural question: how can the econometrician recover unbiased estimates of these objects? The structural model developed in this paper provides one path to identification by exploiting the cross-equation restrictions typical of dynamic stochastic economic models.

Formally, call the vector of structural parameters $\theta = (\alpha, \bar{\eta}, \rho, \phi_0, \phi_1, g_z, \sigma_z^2, \sigma_a^2, \sigma_\eta^2)$. The model admits the restricted VAR(1) representation

$$X_t = \tilde{C}(\theta) + F(\theta)X_{t-1} + v_t. \quad (14)$$

The following proposition shows that the model's conditional first and second moments, along with the autoregressive matrix, globally identify the structural parameters.

Proposition 5: (*Identification*) Consider the economic model described by (14), and assume *Stab* holds. The unconditional mean, autoregressive matrix and variance matrix of the innovations $(E[X_t], F(\theta), \Sigma_v)$ are sufficient to globally identify the vector of structural parameters θ .

Proof. I start by noting that we can recover (α, ϕ_1) directly from $F(\theta)$. The entries of this matrix are:

$$F(\theta) = \frac{1}{m} \begin{bmatrix} \rho + \alpha\Psi_u & 0 & \Psi_u(1 - \phi_1 - \rho) \\ -\alpha(1 - \rho) & 0 & \alpha\Psi_u(1 - \phi_1 - \rho) \\ \alpha(1 - \rho) & 0 & \rho\alpha\Psi_u + (1 - \phi_1) \end{bmatrix}.$$

Call a generic entry of this matrix f_{ij} . This object can always be recovered from an unre-

stricted VAR(1). It follows directly that we can identify α from:

$$\alpha = \frac{f_{31}}{1 - f_{11}}. \quad (15)$$

Note that the denominator cannot vanish, as $1 - f_{11} = \frac{1-\rho}{m}$ is always positive by the *Stab* assumption and the constraint $\rho < 1$. Hence, this equation holds generically. Next, note that

$$f_{33} + \alpha f_{13} = \frac{\rho \alpha \Psi_u + (1 - \phi_1) + \alpha \Psi_u (1 - \phi_1 - \rho)}{m}.$$

After simplifying and collecting terms, we get:

$$\phi_1 = 1 - f_{33} - \alpha f_{13}, \quad (16)$$

which identifies ϕ_1 . Next, I show that the steady-state conditions and the first moments of the data allow us to recover $(g_z, \phi_0, \bar{\eta})$. Because the system is stationary and the structural innovations have zero mean, $E[X_t] = \bar{X}$. Consequently, the balanced-growth conditions can be applied directly to the unconditional means of the linearized model. The long-run version of the AD curve yields

$$g_z = E[\Delta y_t]. \quad (17)$$

By the same logic, the steady-state unemployment rate implies:

$$\phi_0 = g_z + \phi_1 E[u_t]. \quad (18)$$

Therefore, given g_z and ϕ_1 , the mean unemployment rate suffices to identify ϕ_0 . Finally, the steady-state condition for the labor share is:

$$E[\omega] = \frac{\bar{\eta}}{\bar{\eta} + (1 - \bar{\eta})E[u_t]},$$

some simple algebraic manipulations show that:

$$\bar{\eta} = \frac{E[u_t]E[\omega_t]}{1 - E[\omega_t] + E[u_t]E[\omega_t]}, \quad (19)$$

which proves that the average value of the bargaining power of labor is identified. To identify ρ , it will be useful to show that the slope of the wage curve, Ψ_u , along with Ψ_η can also be recovered from the first moments in the data. Indeed, from the linearization in Appendix A.3, we have that:

$$\Psi_u = -\frac{\bar{\eta}(1 - \bar{\eta})}{[\bar{\eta} + (1 - \bar{\eta})E[u_t]]^2},$$

and

$$\Psi_\eta = \frac{E[u_t]}{[\bar{\eta} + (1 - \bar{\eta})E[u_t]]^2}.$$

Given (α, Ψ_u, ϕ_1) , an entry of $F(\theta)$ can be used to identify ρ . Pick f_{11} , as this will avoid any knife-edge cases that break global identification:

$$f_{11} = \frac{\rho + \alpha\Psi_u}{m}.$$

We can write:

$$\rho = (1 + \alpha\Psi_u)f_{11} - \alpha\Psi_u, \quad (20)$$

which allows us to recover ρ conditional on any values of (α, Ψ_u) . The only remaining task is to identify the variances of the structural shocks. Recall that the link between the reduced-form and the structural shocks is

$$v_t = B^{-1}D\varepsilon_t.$$

From this, it follows that:

$$\Sigma_v = B^{-1}D\Omega D^\top (B^{-1})^\top.$$

Given that we have identified all structural parameters but the variances of the innovations, the econometrician can always recover B^{-1} . Therefore, premultiplying by B and postmultiplying by $B^\top$:

$$B\Sigma_v B^\top = D\Omega D^\top,$$

with

$$D\Omega D^\top = \begin{bmatrix} \Psi_\eta & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \sigma_\eta^2 & 0 & 0 \\ 0 & \sigma_z^2 & 0 \\ 0 & 0 & \sigma_a^2 \end{bmatrix} \begin{bmatrix} \Psi_\eta & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} \Psi_\eta^2 \sigma_\eta^2 & 0 & 0 \\ 0 & \sigma_z^2 & 0 \\ 0 & 0 & \sigma_a^2 \end{bmatrix}.$$

This allows us to recover the variance of the structural shocks by computing:

$$\sigma_\eta^2 = \frac{(B\Sigma_v B')_{11}}{\Psi_\eta^2}, \quad (21)$$

$$\sigma_z^2 = (B\Sigma_v B')_{22}, \quad (22)$$

$$\sigma_a^2 = (B\Sigma_v B')_{33}. \quad (23)$$

These correspond to the diagonal entries of the matrix $B\Sigma_v B'$. As shown in Appendix A.3, $\Psi_\eta > 0$ as long as $E[u_t] > 0$, which guarantees division by Ψ_η is well defined generically. This completes the proof. $\square$

Intuitively, identification stems from the following sources: the long-run restrictions embodied in the balanced growth path are enough to identify $(g_z, \phi_0, \bar{\eta})$, as well as the slope of the wage curve. The propagation of the structural shocks, which is contained in the matrix $F(\theta)$, helps identify (α, ϕ_1, ρ) . Finally, the variance of the reduced form shocks is enough to identify the variance of the structural shocks.

4 Estimation

4.1 Estimator and Data

The constructive identification proof contained in proposition 5 can be exploited to estimate the structural parameters, including the demand regime and the slope of the wage curve. To do so, I write down the likelihood function of this model which takes the form of a VAR(1) model with a set of cross-equation restrictions. The likelihood function is equal to:

$$\ell_T(\theta) = -\frac{Tk}{2} \log(2\pi) - \frac{T}{2} \log |\Sigma(\theta)| - \frac{1}{2} \sum_{t=1}^T [X_t - \tilde{C}(\theta) - F(\theta)X_{t-1}]' \Sigma(\theta)^{-1} [X_t - \tilde{C}(\theta) - F(\theta)X_{t-1}]. \quad (24)$$

The maximum likelihood estimator is obtained numerically as

$$\hat{\theta} = \arg \max_{\theta \in \Theta} \ell_T(\theta), \quad (25)$$

subject to the constraint that

$$\Theta = \{\theta : \rho \in [0, 1), \phi_1 \in (0, 1], \sigma_\eta^2 > 0, \sigma_z^2 > 0, \sigma_a^2 > 0, 1 + \alpha\Psi_u > \phi_1/2\}.$$

Where Θ is the relevant parameter space. After obtaining this set of structural parameters, we can compare α with β_{OLS} , to assess how severe the bias is implicit in the traditional empirical literature. I also compute the impulse response functions of bargaining and demand shocks implied by the model estimates, and compare these with what an econometrician using a recursive procedure will find. This can give us a sense of how severe the distortions from erroneously imposing the short-run restriction that the labor share does not react to output are for the transmission of bargaining shocks.

Since the score of the likelihood is highly non-linear and does not admit an analytical solution, I maximize the log-likelihood using numerical methods. I use MATLAB's `fmincon` interior-point algorithm to conduct the maximization. I randomize the starting value of

parameters and conduct 40 different maximization runs, and keep the parameter estimates that maximize the log-likelihood across all runs. Comparing the top 5 runs reveals that parameter estimates are remarkably close, which reassures that I am converging to the same maximum. Further details on the maximization routine are available in the online replication code.

I use quarterly data on the labor share, output growth and unemployment for the period 1948:Q1 - 2019:Q4. I restrict the sample to before the COVID pandemic to avoid modeling stochastic volatility or outliers. Given that this sample period contains a wide range of monetary policy rules and substantial structural transformations in the economy, we should interpret the estimates as an average across macroeconomic and policy regimes. Data on all variables is obtained through the FRED website.

My measure of the labor share is the WASCUR series (wages and salaries of employees) divided by nominal GDP. This excludes income from the self-employed, as well as supplements to wages and salaries such as pensions and other benefits. There are a number of open issues regarding how to measure the labor share, which are discussed carefully in Karabarbounis (2024), including how severe the recent decline in the labor share has been. Since we are interested in assessing the performance of two estimators for a given data set, it is likely that these measurement issues are less important in our empirical application.

4.2 Results

Table 1 shows estimates of the structural parameters, along with other objects of interest, such as Ψ_u , the slope of the wage curve. I report asymptotic standard errors and confidence intervals based on the Hessian matrix of the log-likelihood.

The first row of Table 1 shows that α , the response of output growth to changes in income distribution, is negative, economically and statistically significant. The estimate of -5.96 implies that the U.S. economy is strongly profit-led, and much more than what is implied by traditional methods: as shown in Table 2, β_{OLS} is only -0.910, which would lead an econometrician to conclude that the U.S. economy is only slightly profit-led. The structural estimate is more than six times the magnitude of the conventional OLS estimate.

As shown in Proposition 3, a key determinant of the bias $\beta_{OLS} - \alpha$ is the slope of the wage curve. The value of this parameter, Ψ_u , is large and statistically significant: a decrease in the

Table 1: Parameter Estimates from the Structural Model

Symbol	Coef.	Std. Error	95% C.I.
α	-5.963	0.8292	(-7.588,-4.337)
$\bar{\eta}$	0.046	0.0064	(0.033,0.058)
ρ	0.974	0.0146	(0.945,1.002)
g_z	0.008	0.0004	(0.007,0.008)
ϕ_0	0.008	0.0016	(0.005,0.011)
ϕ_1	0.002	0.0269	(-0.050,0.055)
σ_η	0.003	0.0006	(0.001,0.004)
σ_z	0.020	0.0028	(0.015,0.026)
σ_a	0.007	0.0003	(0.007,0.008)

Ψ_u	-3.782	1.0185	(-5.779,-1.786)

Table 2: Bias in the Conventional OLS Estimate

β_{OLS}	$ \beta_{OLS} - \alpha $	$\frac{\alpha}{\beta_{OLS}}$
-0.910	5.052	6.551

unemployment rate of one percentage point relative to its steady-state value raises the labor share by 3.8 percentage points. This illustrates that demand shocks, which produce positive comovements between output and the labor share through this labor-market mechanism, generate substantial bias in traditional estimates of the demand regime. Taken together, these findings cast doubt on studies that have characterized the U.S. economy as slightly wage-led (Hein and Vogel, 2008; Onaran, Stockhammer and Grafl, 2011; Stockhammer and Stehrer, 2011) using traditional regression methods.

The estimate of the steady-state bargaining power of labor, $\bar{\eta}$, is on the lower end of the literature; Mengano (2022) estimates a value of $\bar{\eta} = 0.17$ using a panel of U.S. manufacturing firms. Cahuc et al. (2006) also find very low estimates of bargaining power using French manufacturing firms, with many professions having 0 bargaining power. Therefore, a low aggregate estimate of bargaining power from time-series data need not signal misspecification. The estimates also illustrate that a low average bargaining weight is compatible with a steep wage curve.

Given the strong estimated response of aggregate demand to the labor share, the model implies sizable effects of bargaining shocks on output and unemployment. Figure 2 below plots two sets of IRFs: the solid red line shows the IRFs obtained from the restricted VAR(1)

representation of the model, at the estimated parameter values, while the dashed blue line shows the IRFs obtained from a recursive VAR(5) where the labor share is ordered first, output growth is ordered second, and the unemployment rate is ordered third. The shaded grey area represents 68% confidence intervals obtained through bootstrapping. In order to make both sets of impulse responses comparable, I normalize the bargaining shock to raise the labor share by one percentage point and the demand shock to raise output by 1 percent.¹² The responses of log output in levels are obtained by accumulating the responses of output growth. The recursive specification is more richly parameterized than the structural model: 48 parameters govern its dynamics, compared with only 7 parameters entering the IRFs implied by the structural model. Thus, the recursive VAR is given substantially greater dynamic flexibility in this comparison.¹³

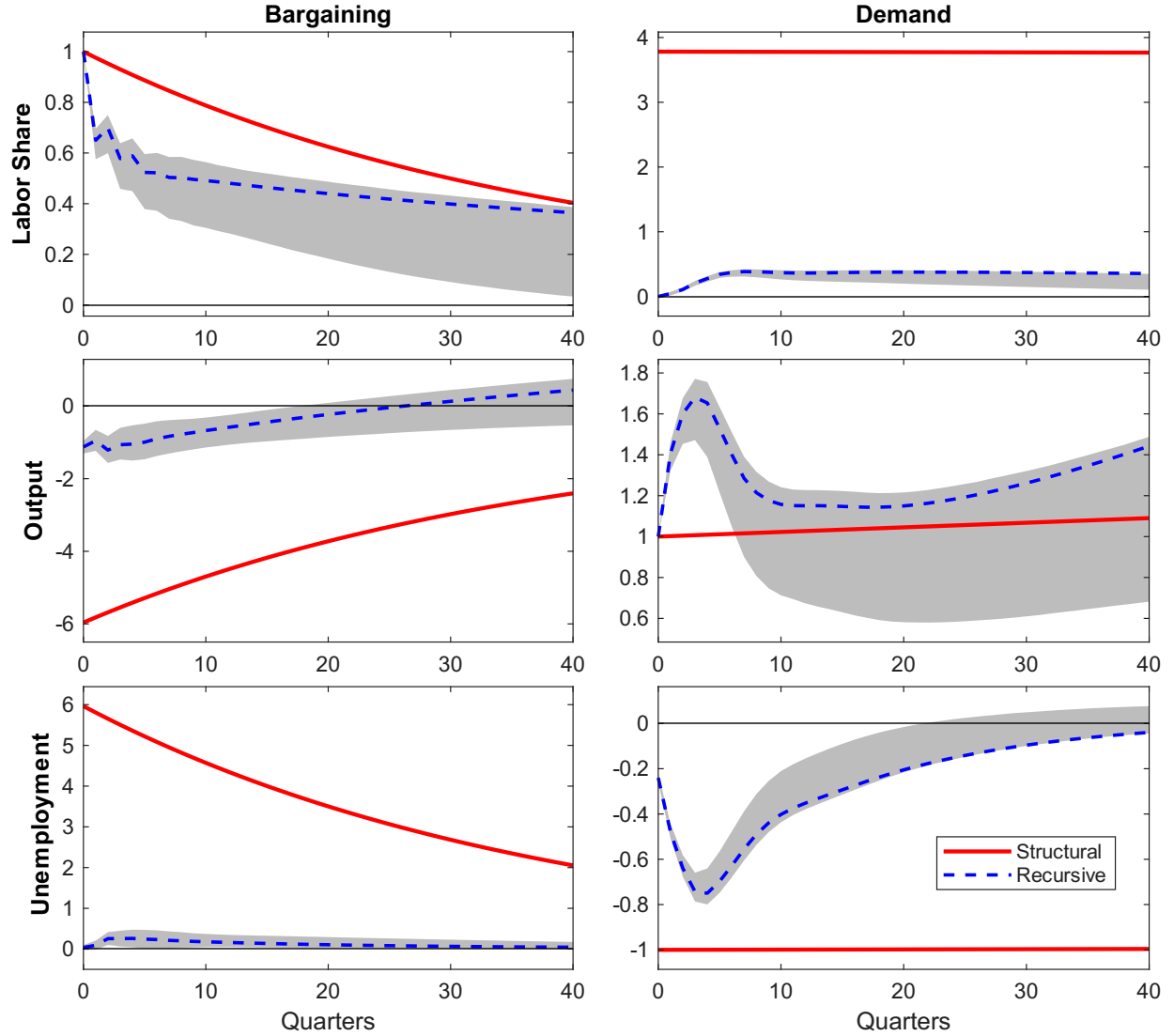
The most salient feature of Figure 2 is the large discrepancy between the recursive and structural responses to a bargaining shock. The recursive specification implies that output drops by a little over 1% upon impact, with no long-run effects. This is similar to the findings of Stockhammer and Onaran (2004) for the U.S. By contrast, the structural IRF implies that output falls by approximately 6% on impact and remains almost 2% below baseline after 40 quarters. The long-run response of output to a recursive specification is 0.4%, which means that an econometrician would wrongly conclude that the U.S. economy is slightly wage-led in the long-run, while the structural model implies that the economy is very strongly profit-led, even in the long-run. The recursive specification also implies that unemployment barely responds to a bargaining shock, while the structural model implies that unemployment rises sharply and is well above its steady-state value by horizon 40. This wide difference in the magnitudes of IRFs extends, to a lesser extent, to the importance that bargaining shocks have for output fluctuations. As shown in Appendix A.6, the structural estimates imply that bargaining shocks account for a quarter of output fluctuations at all horizons, while recursive estimates imply that they account for 18% in the long-run. When correcting for simultaneity bias, bargaining shocks are an important force behind business cycles and can have large effects on output.

A skeptical reader might object that Figure 2 establishes only that the recursive and structural responses differ; it does not establish that the structural model recovers the true response of output to bargaining shocks. Several findings from alternative identification

¹²The size of the bargaining shock is very large, but it is chosen to make our results comparable to the previous literature. Since the estimated model is linear, this does not involve any loss of generality.

¹³Appendix A.6 shows similar results when using a VAR(1) for comparison.

Figure 2: IRFs: Structural vs Recursive



Note: Impulse response functions to a bargaining shock that raises the labor share by one percentage point, and to a demand shock that raises output by one percent. The red solid line plots the IRF implied by the structural model, while the blue dashed line plots the IRF of a recursive specification. The gray area shows 68% bootstrap confidence intervals.

strategies support the results from the structural model. Using very different identification approaches, Foroni et al. (2018), Drautzburg et al. (2021), Bergholt et al. (2022), and González (2025) all find that bargaining shocks produce a long-run, economically significant output drop in the U.S. economy. The structural model therefore appears consistent, at least qualitatively, with evidence obtained using several alternative identification strategies.

Why do recursive procedures perform so poorly in recovering the output effects of bargaining

shocks? As shown in Proposition 4, recursive procedures capture a linear combination of demand, bargaining and technology shocks. Because demand and technology shocks expand output, especially in the long run, recursive estimates attenuate the true effects of bargaining shocks. Estimates that correct this bias imply much larger effects of bargaining shocks on output.

A comparison of the demand-shock responses also yields a key insight: demand shocks have powerful stimulative effects on the labor share. The structural model implies that a demand shock that raises output by 1% raises the labor share by roughly 4 percentage points at all horizons. The recursive model imposes a zero impact response by construction and estimates subsequent effects below half a percentage point. In the model, this reflects the steep estimated wage curve: a 1 percent increase in output lowers unemployment by approximately one percentage point, which raises wage demands and substantially increases the labor share. The result that demand stimulus compresses the profit share is reminiscent of the profit-squeeze mechanism discussed by Weisskopf et al. (1985), and it emphasizes that models where income distribution is independent of demand fluctuations are at odds with the data.

Finally, the structural model also produces permanent output effects of demand shocks. This long-run feature of the model holds by construction, given that autonomous demand evolves like a random walk. The model nevertheless implies an increasing profile of demand multipliers, whereas the recursive specification produces much larger short-run multipliers. The path of our multipliers is consistent with the evidence from Antolin-Diaz and Surico (2025) for fiscal shocks, but it is also consistent with recent evidence on hysteresis from Li and Mendieta-Muñoz (2024), Furlanetto et al. (2025), Carnevale and Di Francesco (2025), Jorda et al. (2026), Gonzalez-Astudillo et al. (2026) and Moraitis (2026), among many others.

Given how sparsely parameterized the model is, a likelihood-ratio test against an unrestricted VAR would certainly blow it out of the water. But that is not the standard by which the model should be judged. Its purpose is not to provide a complete theory of U.S. business cycles, but to isolate a small set of mechanisms linking demand, income distribution, and the labor market. The fact that this sparse structure nonetheless reproduces qualitative evidence on the contractionary effects of bargaining shocks and hysteresis effects suggests that these mechanisms are worth taking seriously. In that sense, the model can serve as the skeleton of a richer research program to understand the connections between demand, distribution, fluctuations and growth.

5 Conclusion

A large empirical literature has attempted to identify the effects that exogenous changes in income distribution have on aggregate demand. Both single-equation methods in the tradition of the Cowles Commission and SVARs identified through short-run restrictions seem to imply that these effects are small. In this paper, I show that a simple model economy where demand shocks influence wage bargaining implies that both approaches produce biased estimates of the demand regime and the causal effects of bargaining shocks. The effect of the bias in both cases is to produce a demand regime that is more wage-led than what is implied by the model, and to bias the effects of bargaining shocks towards positive values. Numerical examples show that, using reasonable parameter values, the biases can be so severe that an econometrician could wrongly conclude that the economy is wage-led when the model is profit-led.

I then exploit the cross-equation restrictions implied by the linearized version of the model to provide a constructive identification result. Generically, the econometrician can globally identify all the structural parameters of the model, including the demand-regime, the slope of the wage curve, and concomitantly, the causal effects of bargaining shocks on the labor share, output and unemployment. Estimating the model on U.S. data reveals that the economy is strongly profit-led, over six times more than what is implied by traditional regression methods. Given that aggregate demand is so sensitive to the labor share, bargaining shocks have long-run effects on output that are over five times larger than what is implied by SVARs identified through short-run restrictions. Bargaining shocks are a powerful candidate to understand output fluctuations at all horizons, provided that we correct the biases that plague traditional methods.

An important caveat with these results is that the model presented in this paper is semi-structural, in the sense that the aggregate demand equation is derived from reduced-form consumption and investment functions. Naturally, this makes the estimates subject to the Lucas critique and not yet suitable for policy analysis. A natural direction for future research is to use microfounded approaches to demand-led growth, such as the ones described by Petach and Tavani (2026) or González (2022), and amend them to incorporate a Nash Bargaining protocol to determine wage setting. Structural estimation and policy analysis can then be conducted in a single framework that is immune to the Lucas critique.

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A Appendix

A.1 Capital Accumulation and the Investment function

In this appendix, I discuss our choice of the investment function and the consistency between the long-run behavior of investment and capital accumulation. An equation left out in the main text is the capital accumulation equation:

$$K_{t+1} = I_t + (1 - \delta)K_t. \quad (26)$$

With a few manipulations, this yields the following equation for the investment share:

$$\frac{I_t}{Y_t} = \frac{K_{t+1}}{Y_t} - (1 - \delta)\frac{K_t}{Y_t}. \quad (27)$$

Using the optimality condition from the Leontief production function $K_t = vY_t$, to re-write in terms of output, and remembering that along the balanced growth path, capital and output

grow at the same rate:

$$\frac{I_t}{Y_t} = v(1 + g_z) - v(1 - \delta) = v(g_z + \delta). \quad (28)$$

This relation that arises from the supermultiplier - where g_z is the exogenous variable and the investment share is endogenous - has been empirically tested by Girardi and Pariboni (2020), Haluska, Braga and Summa (2021), and Fazzari and González (2025), among others, using a variety of identification strategies. This steady-state relation must be consistent with the equation used in the main text:

$$I_t = \lambda Y_t + \gamma Y_t[(1 - \omega_t) - (1 - \bar{\omega})]. \quad (29)$$

It can be readily seen that as long as we set $\lambda = v(g_z + \delta)$, along the balanced growth path, $\bar{\omega} = \omega_t$, this equation is consistent with the long-run investment share implied by capital accumulation. This explains why the profit share cannot exert an independent, long-run influence on the investment share, since this would imply the model is over-determined.

A.2 Comparative Statics

We can summarize the behavior of our model using two simple diagrams. Figure 3 below shows the balanced growth path. On the top panel, the aggregate demand and aggregate supply curves determine growth and unemployment. Given the level of unemployment, the bottom panel shows how the wage curve determines the distribution of income.

We can perform a number of interesting comparative statics regarding the labor share, which can be used to think about the decline of the labor share that has taken place in the last few decades. It should be obvious that institutional changes that increase the bargaining power of workers, parametrized by $\bar{\eta}$, will increase the labor share without affecting the long-run growth rate or unemployment. It can thus accommodate explanations of the decline in the labor share based on the decline of the bargaining power of labor, which has been emphasized by Stansbury and Summers (2020).

However, the share of the surplus that workers can extract will depend on the unemployment rate, so any parameters that affect the steady-state unemployment rate will affect the labor share. In our environment, changes in technology, like an increase in ϕ_0 , the exogenous rate of technical progress, increase unemployment with no effect on output, which will then lower the labor share. Hence, the model can accommodate automation-based stories for the

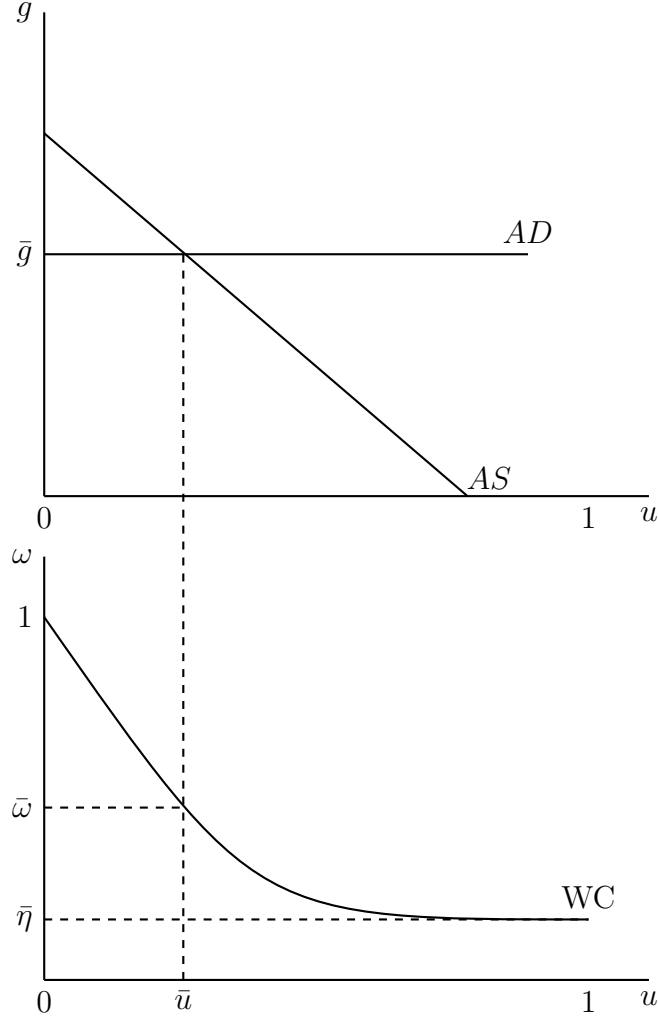


Figure 3: The Balanced Growth Path

decline of the labor share, like the one put forward by Acemoglu and Restrepo (2020). In a sense, all labor augmenting technical change in our environment acts as automation.

A.3 Linearization

I first linearize the wage curve around its balanced growth path. A first order approximation of ω around $(\bar{u}, \bar{\eta})$:

$$\omega_t \approx h(\bar{u}, \bar{\eta}) + h_u(\bar{u}, \bar{\eta})(u_t - \bar{u}) + h_\eta(\bar{u}, \bar{\eta})(\eta_t - \bar{\eta})$$

$$\omega_t \approx \frac{\bar{\eta}}{\bar{\eta} + (1 - \bar{\eta})\bar{u}} - \frac{\bar{\eta}(1 - \bar{\eta})}{[\bar{\eta} + (1 - \bar{\eta})\bar{u}]^2}(u_t - \bar{u}) + \frac{\bar{u}}{[\bar{\eta} + (1 - \bar{\eta})\bar{u}]^2}(\eta_t - \bar{\eta})$$

$$\omega_t \approx \bar{\omega} + \Psi_u(u_t - \bar{u}) + \Psi_\eta(\eta_t - \bar{\eta}), \quad (30)$$

where $\Psi_u = -\frac{\bar{\eta}(1-\bar{\eta})}{[\bar{\eta}+(1-\bar{\eta})\bar{u}]^2}$ and $\Psi_\eta = \frac{\bar{u}}{[\bar{\eta}+(1-\bar{\eta})\bar{u}]^2}$. From lemma 1 we know $\Psi_u \leq 0$, and it is easy to verify that $\Psi_\eta \geq 0$. The law of motion for bargaining power follows:

$$(\eta_t - \bar{\eta}) = \rho(\eta_{t-1} - \bar{\eta}) + \varepsilon_t^\eta.$$

Premultiplying the linearized wage curve by $(1 - \rho L)$, we get the following expression:

$$\omega_t = (1 - \rho)\bar{\omega} + \rho\omega_{t-1} + \Psi_u(u_t - \bar{u}) - \rho\Psi_u(u_{t-1} - \bar{u}) + \Psi_\eta\varepsilon_t^\eta, \quad (31)$$

which is the first row of the matrix equation (8) used in the main text. Next, I linearize the aggregate demand equation around the balanced growth path:

$$\Delta y_t \approx g_z + \Delta(f(\bar{\omega}) + f_\omega(\bar{\omega})(\omega_t - \bar{\omega})) + \varepsilon_t^z. \quad (32)$$

We compute the approximation for the non-linear part:

$$f(\bar{\omega}) = -\ln[s_\pi - \lambda - (s_\pi - s_w)\bar{\omega}],$$

$$f_\omega(\bar{\omega}) = \frac{(s_\pi - s_w - \gamma)}{s_\pi - \lambda - (s_\pi - s_w)\bar{\omega}}.$$

Plugging these expressions back, and using the first difference operator, we have the equation:

$$\Delta y_t = g_z + \alpha \Delta \omega_t + \varepsilon_t^z, \quad (33)$$

with $\alpha = \frac{(s_\pi - s_w - \gamma)}{s_\pi - \lambda - (s_\pi - s_w)\bar{\omega}}$. This is equation (LL-AD) in the main text. Since the denominator is positive, the sign of α will depend on the sign of $s_\pi - s_w - \gamma$.

A.4 Proof of Proposition 2

Proof. Start by reducing the three dimensional system into a single equation for the unemployment rate, which can be done after a few substitutions and some tedious algebra:

$$u_t = \frac{(1 - \rho)(\phi_0 - g_z)}{1 + \alpha\Psi_u} + \left[\rho + \frac{1 + \alpha\Psi_u - \phi_1}{1 + \alpha\Psi_u} \right] u_{t-1} - \rho \left(\frac{1 + \alpha\Psi_u - \phi_1}{1 + \alpha\Psi_u} \right) u_{t-2}.$$

Note that the shocks are absent from this equation, since, as it is well known, the stability of the system (the deterministic one or the structural VAR analyzed in the main text) does not depend on the variance of the innovations. Hence we can shut down the shocks with no

loss of generality.

The unemployment rate follows a second-order difference equation, with characteristic polynomial:

$$\lambda^2 - \left(\frac{m - \phi_1}{m} + \rho \right) \lambda + \rho \left(\frac{m - \phi_1}{m} \right) = \left(\lambda - \frac{m - \phi_1}{m} \right) (\lambda - \rho),$$

where $m \equiv (1 + \alpha\Psi_u)$. In order for the system to be stable, the autoregressive roots must satisfy:

$$\lambda_1 = \rho \in (-1, 1), \quad (34)$$

which is satisfied by assumption, as $\rho \in [0, 1)$. The second root must satisfy:

$$\lambda_2 = \frac{1 + \alpha\Psi_u - \phi_1}{1 + \alpha\Psi_u} \in (-1, 1). \quad (35)$$

To ensure that $\lambda_2 < 1$, the following inequality must hold:

$$-\phi_1 < 0. \quad (36)$$

Given that $\phi_1 \in (0, 1)$, this condition is always satisfied. Next, we need to check that the coefficient is larger than -1, which is equivalent to:

$$1 + \alpha\Psi_u - \phi_1 > -(1 + \alpha\Psi_u), \quad (37)$$

with a bit of algebra, we can re-arrange this as:

$$m \equiv (1 + \alpha\Psi_u) > \frac{\phi_1}{2}. \quad (38)$$

Recall that $\Psi_u < 0$ and $\phi_1 < 1$. Hence, in the profit-led and neutral cases ($\alpha \leq 0$), we have that $m \geq 1$ as $\alpha\Psi_u \geq 0$, and the stability condition is always satisfied. However, in the wage-led case ($\alpha > 0$) we have that $m < 1$, and hence, the stability condition could be violated. It follows that in the wage-led case, the effects of income distribution on aggregate demand cannot be too strong; otherwise, instability ensues. $\square$

A.5 Proof of Proposition 4

Proof. The econometrician uses the following identification scheme:

$$v_t = P\varepsilon_t^{chol},$$

where P is the lower-triangular Cholesky matrix of Σ_v . In matrix form:

$$\begin{bmatrix} v_t^\omega \\ v_t^y \\ v_t^u \end{bmatrix} = \begin{bmatrix} P_{11} & 0 & 0 \\ P_{21} & P_{22} & 0 \\ P_{31} & P_{32} & P_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\eta, chol} \\ \varepsilon_t^{z, chol} \\ \varepsilon_t^{a, chol} \end{bmatrix}.$$

Hence, we know that the ‘bargaining shock’ must equal:

$$\varepsilon_t^{\omega, chol} = \frac{v_t^\omega}{P_{11}}.$$

The contemporaneous impact of a bargaining shock on the labor share and output is given by:

$$\begin{aligned} \frac{\partial \omega_t}{\partial \varepsilon_t^{\omega, chol}} &= P_{11} \\ \frac{\partial \Delta y_t}{\partial \varepsilon_t^{\omega, chol}} &= P_{21}. \end{aligned}$$

Therefore, our task is reduced to finding expressions for P_{ij} to compute the objects of interest. We can obtain these by solving the system of equations $PP' = \Sigma_v$, where Σ_v is the variance-covariance matrix of the reduced-form shocks.¹⁴ The first two entries of the first column of this system are:

$$\begin{aligned} \text{Var}(v_t^w) &= P_{11}^2 \\ \text{Cov}(v_t^y, v_t^w) &= P_{11}P_{21}, \end{aligned}$$

which can be solved in terms of the second moments of the reduced-form errors

$$\begin{aligned} P_{11} &= \sqrt{\text{Var}(v_t^w)}, \\ P_{21} &= \frac{\text{Cov}(v_t^y, v_t^w)}{\sqrt{\text{Var}(v_t^w)}}. \end{aligned}$$

We can then use the DGP to plug in the true values of v_t^ω and the corresponding variances and covariances. Computing $B^{-1}D\varepsilon_t = v_t$ gives the reduced-form error for the labor share:

¹⁴Here we have made the auxiliary assumption $\text{Var}(\varepsilon_t^{chol}) = I$. This involves no loss of generality as it simply scales ε_t^{chol} to have unit variance, and hence the IRFs are cast in terms of one standard deviation. Since we will scale IRFs of both the structural and recursive models to raise the labor share by the same amount, this assumption is innocuous.

$$v_t^\omega = \frac{\Psi_\eta \varepsilon_t^\eta - \Psi_u \varepsilon_t^z + \Psi_u \varepsilon_t^a}{m}.$$

Likewise,

$$v_t^y = \frac{\alpha \Psi_\eta \varepsilon_t^\eta + \varepsilon_t^z + \alpha \Psi_u \varepsilon_t^a}{m}.$$

Orthogonality of the structural shocks implies

$$\text{Var}(v_t^\omega) = \frac{\Psi_\eta^2 \sigma_\eta^2 + \Psi_u^2 (\sigma_z^2 + \sigma_a^2)}{m^2}.$$

The covariance between the reduced-form shocks is equal to

$$\begin{aligned} \text{Cov}(v_t^y, v_t^\omega) &= \text{Cov}\left(\frac{\alpha \Psi_\eta \varepsilon_t^\eta + \varepsilon_t^z + \alpha \Psi_u \varepsilon_t^a}{m}, \frac{\Psi_\eta \varepsilon_t^\eta - \Psi_u \varepsilon_t^z + \Psi_u \varepsilon_t^a}{m}\right) \\ &= \frac{\alpha \Psi_\eta^2}{m^2} \text{Var}(\varepsilon_t^\eta) - \frac{\Psi_u}{m^2} \text{Var}(\varepsilon_t^z) + \frac{\alpha \Psi_u^2}{m^2} \text{Var}(\varepsilon_t^a) \\ &= \frac{\alpha \Psi_\eta^2 \sigma_\eta^2 - \Psi_u \sigma_z^2 + \alpha \Psi_u^2 \sigma_a^2}{m^2}. \end{aligned}$$

This calculation exploits orthogonality of the structural shocks again. Substituting these moments into the expressions for the Cholesky coefficients yields

$$\begin{aligned} P_{11} &= \frac{\sqrt{\Psi_\eta^2 \sigma_\eta^2 + \Psi_u^2 (\sigma_z^2 + \sigma_a^2)}}{m}, \\ P_{21} &= \frac{\alpha \Psi_\eta^2 \sigma_\eta^2 - \Psi_u \sigma_z^2 + \alpha \Psi_u^2 \sigma_a^2}{m \sqrt{\Psi_\eta^2 \sigma_\eta^2 + \Psi_u^2 (\sigma_z^2 + \sigma_a^2)}}. \end{aligned}$$

Consequently, the recovered bargaining shock is

$$\varepsilon_t^{\eta, chol} = \frac{v_t^\omega}{P_{11}} = \frac{\Psi_\eta \varepsilon_t^\eta - \Psi_u \varepsilon_t^z + \Psi_u \varepsilon_t^a}{\sqrt{\Psi_\eta^2 \sigma_\eta^2 + \Psi_u^2 (\sigma_z^2 + \sigma_a^2)}}.$$

This is the expression in the main text. To compare the impact responses, normalize both shocks to raise the labor share by one unit. In the true model:

$$\frac{\partial \omega_t}{\partial \varepsilon_t^\eta} = \frac{\Psi_\eta}{m}, \quad \frac{\partial \Delta y_t}{\partial \varepsilon_t^\eta} = \frac{\alpha \Psi_\eta}{m}.$$

A bargaining shock that increases the labor share by one unit raises log-output by α . For the recursive model

$$\frac{\partial \omega_t}{\partial \varepsilon_t^{\omega, chol}} = P_{11} = \frac{\sqrt{\Psi_\eta^2 \sigma_\eta^2 + \Psi_u^2 (\sigma_z^2 + \sigma_a^2)}}{m},$$

$$\frac{\partial \Delta y_t}{\partial \varepsilon_t^{\omega, chol}} = P_{21} = \frac{\alpha \Psi_\eta^2 \sigma_\eta^2 - \Psi_u \sigma_z^2 + \alpha \Psi_u^2 \sigma_a^2}{m^2} \cdot \frac{1}{P_{11}}.$$

Hence, a bargaining shock that raises the labor share by 1 unit must be of magnitude P_{11}^{-1} . Therefore, the equivalent output response is P_{21}/P_{11} , which is equal to:

$$\begin{aligned} \frac{P_{21}}{P_{11}} &= \frac{\text{Cov}(v_t^y, v_t^\omega)}{\text{Var}(v_t^\omega)} \\ &= \frac{\alpha \Psi_\eta^2 \sigma_\eta^2 - \Psi_u \sigma_z^2 + \alpha \Psi_u^2 \sigma_a^2}{\Psi_\eta^2 \sigma_\eta^2 + \Psi_u^2 (\sigma_z^2 + \sigma_a^2)} \\ &= \frac{\alpha \Psi_\eta^2 \sigma_\eta^2 - \Psi_u \sigma_z^2 + \alpha \Psi_u^2 \sigma_a^2 + \underbrace{\alpha \Psi_u^2 \sigma_z^2 - \alpha \Psi_u^2 \sigma_z^2}_0}{\Psi_\eta^2 \sigma_\eta^2 + \Psi_u^2 (\sigma_z^2 + \sigma_a^2)} \\ &= \alpha - \frac{m \Psi_u \sigma_z^2}{\Psi_\eta^2 \sigma_\eta^2 + \Psi_u^2 (\sigma_z^2 + \sigma_a^2)}. \end{aligned}$$

The first line plugs in directly the expressions for P_{ij} in terms of the second moments of the reduced form errors. The third line adds a convenient 0 to simplify the α terms; the fourth line uses the definition of m . Therefore, the difference between the recursive and the true log-output impact is:

$$\frac{P_{21}}{P_{11}} - \alpha = -\frac{m \Psi_u \sigma_z^2}{\Psi_\eta^2 \sigma_\eta^2 + \Psi_u^2 (\sigma_z^2 + \sigma_a^2)} \geq 0.$$

This is the expression provided in the main text. □

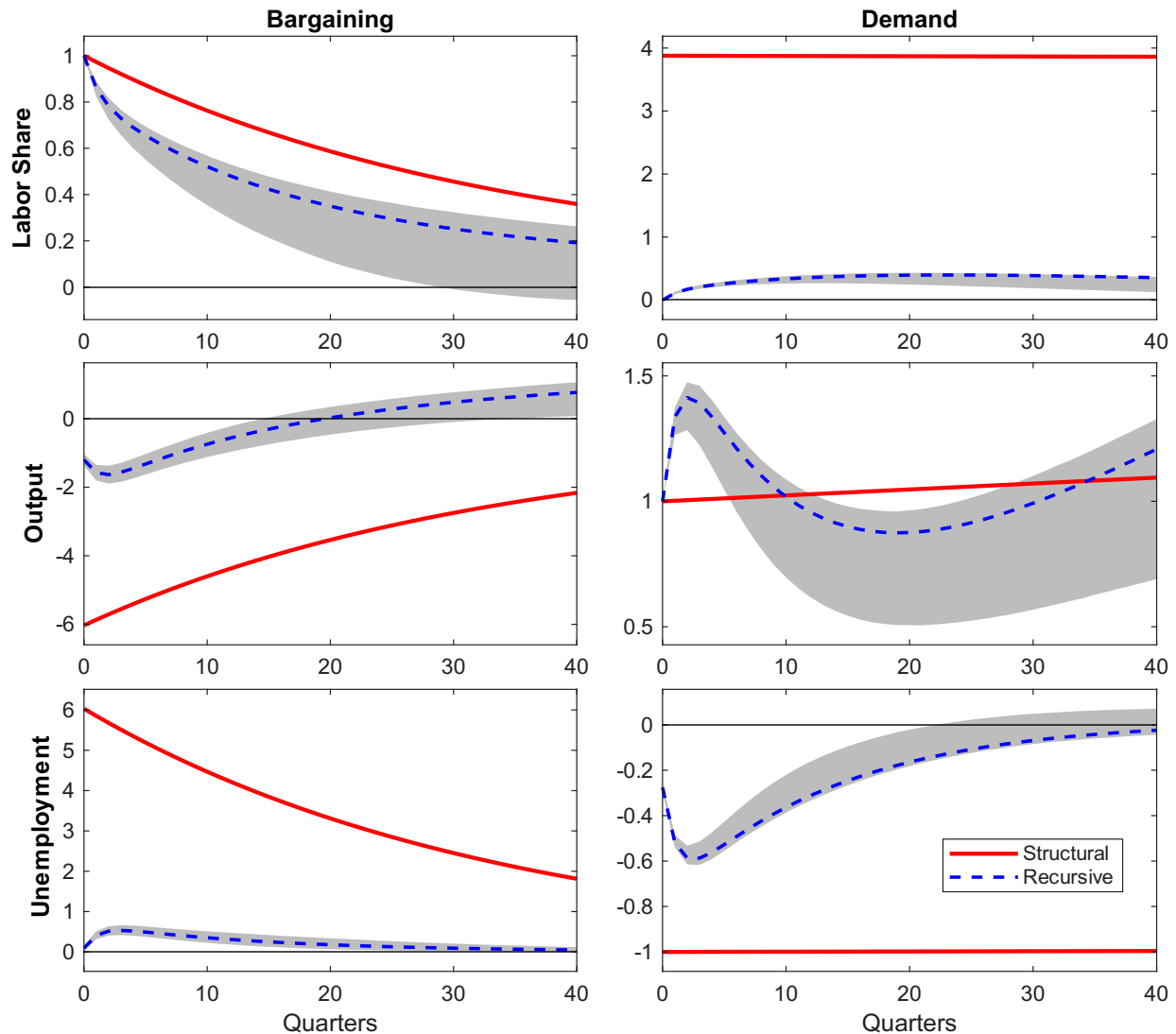
A.6 Additional Empirical Results

A.6.1 Dynamic Specifications

Figure 2 in the main text shows the IRFs of the labor share, output and unemployment to a bargaining shock that raises the labor share by 1 percentage point, and to a demand shock that raises output by 1 percent. The IRFs of the structural model, which has a restricted VAR(1) representation, are compared to a recursive specification that is a VAR(5), as would be common in empirical work. This stacks the deck against the structural model, since the VAR(5) has more flexibility to estimate the dynamics of the endogenous variables. However, the resulting IRFs reflect a mix of differences in dynamic specification as well as the iden-

tification of the contemporaneous impact matrix. Figure 4 below compares the structural model to a recursive VAR(1) specification, which allows us to isolate the effects of differences in identification on the estimations of IRFs.

Figure 4: IRFs: Structural vs Recursive



Note: Impulse response functions to a bargaining shock that raises the labor share by one percentage point, and to a demand shock that raises output by one percent. The red solid line plots the IRF implied by the structural model, while the blue dashed line plots the IRF of a recursive specification. The gray area shows 68% bootstrap confidence intervals.

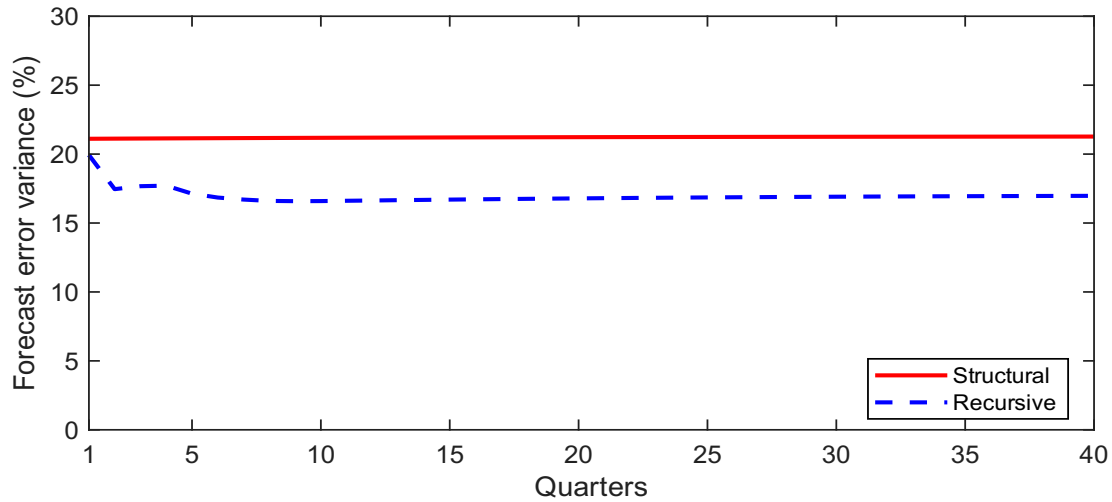
The results are strikingly similar to the ones obtained in the main text. They slightly amplify the differences between both sets of estimators: the long-run output response to a recursive scheme is now 0.7% instead of 0.4%, which increases the estimated bias between both sets

of estimators. The response of output to a demand shock is now more similar to what is implied by the structural model, with the long-run response of the model being inside the confidence intervals of the recursive specification. However, the response of the labor share to a demand shock remains negligible in the recursive specification, as it was the case with longer lag lengths. I conclude that most of the differences between both estimators are driven by differences in the identification of the impact matrix and not by differences in the length of the VAR.

A.6.2 Variance Decomposition

How important are bargaining shocks to explain the variance of output growth at different horizons? Figure 5 below shows that recursive estimates assign around 18% of the variance of output growth at horizons longer than 8 to bargaining shocks, while the structural estimates indicate a larger contribution of 22% at all horizons. These structural estimates are in the same ballpark as the estimates by Foroni et al. (2018), González (2025) and Budrys et al. (2026).

Figure 5: FEVD of Output Growth



Note: The contribution of bargaining shocks to Forecast Error Variance Decompositions of output growth. Dashed blue lines indicate a VAR(5) recursive specification, while red solid lines are the structural estimates.