DEPARTMENT OF ECONOMICS WORKING PAPER SERIES

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Ivan Mendieta-Muñoz
Codrina Rada
Márcio Santetti
Rüdiger von Arnim

Working Paper No: 2020-02

January 2020

University of Utah
Department of Economics
260 S. Central Campus Dr., GC. 4100
Tel: (801) 581-7481
Fax: (801) 585-5649
http://www.econ.utah.edu

The US labour share of income: What shocks matter?

Ivan Mendieta-Muñoz
Department of Economics, University of Utah
ivan.mendietamunoz@utah.edu

Codrina Rada
Department of Economics, University of Utah
rada@economics.utah.edu

Márcio Santetti
Department of Economics, University of Utah
santetti@gmail.com

Rüdiger von Arnim
Department of Economics, University of Utah
rudiger.vonarnim@economics.utah.edu

Abstract

We propose a novel methodological approach to disentangle the main structural shocks affecting the US labour share of income during the immediate post-war era (1948Q1-1984Q4) and the Great Moderation (1985Q1-2018Q3). We motivate a SVAR model in aggregate demand, unemployment rate, real wage and labour productivity, which captures key components of the labour share. The paper then (i) demonstrates statistical support for separating the sample into two periods; (ii) employs the model to identify four structural innovations: aggregate demand, labour supply, wage bargaining, and productivity; (iii) quantifies the dynamic responses of the labour share to each structural shock; (iv) compares these results across the two periods; and (v) indicates their robustness to estimation of the impulse responses with stationary variables or in levels, and via local projections. The results show that the two periods differ substantially. First, in order of magnitude, the labour share responded mainly to productivity, aggregate demand, and wage bargaining shocks during the immediate post-war era; whereas wage bargaining, productivity, and aggregate demand shocks mattered most during the Great Moderation. Second, these impulse responses are statistically significantly different across the two periods for wage bargaining and productivity shocks. Increased (decreased) sensitivity to wage bargaining (productivity) shocks during the Great Moderation suggests that the decline in the labour share is driven by the factors that govern wage setting.

Keywords: US labour share of income; wage bargaining shocks; productivity shocks; aggregate demand shocks; labour supply shocks.

JEL Classification: E25; E24; E32.

1 Introduction

The study of the evolution of the labour share of income has been a focal point in different strands of literature aimed at explaining income inequality over time. This paper proposes a novel methodological approach to disentangle the main structural shocks affecting the US labour share of income. We seek to deepen our understanding of the changing dynamics of the labour share through an analysis that emphasises the importance of macroeconomic shocks across different periods.

We propose an empirical approach based on Structural Vector Autoregression (SVAR) models that allows us to identify the structural innovations that can be regarded as the main drivers of the labour share, and to estimate the response of the labour share to such structural shocks. The focus of this paper is on the short–run dynamic interactions; and we explicitly consider two different periods: the *immediate post–war era* (1948Q1–1984Q4) and the *Great Moderation* (1985Q1–2018Q3), as there is ample evidence —also provided here in the context of the specific model put forth— that the characteristics of business cycles differed in each period.[1] The implication in the context of the SVAR models is that the immediate post–war era and Great Moderation periods featured their own policies and institutions, which find expression in the identified structural shocks. This in turn enables comparison of the two sub–sample regimes.

Specifically, our empirical investigation involves the following steps. First, we estimate a SVAR model in four variables: aggregate demand, unemployment rate, real wage and labour productivity. These variables circumscribe the components of the labour share, which is of course definitionally related to the level of output, employment, real wages and labour productivity. The structural innovations derived from this SVAR identify four shocks: aggregate demand shocks, labour supply shocks, wage bargaining shocks and productivity shocks. Second, we split the sample into two periods, 1948Q1–1984Q4 and 1985Q1–2018Q3. We corroborate the existence of two substantially different periods in the dynamics of the US labour share by finding a statistically significant structural break in the SVAR model; and we report the impulse response functions (IRFs) derived from our identification strategy in both periods. Third, we quantify the response of the labour share itself in each period to the structural innovations identified in the previous step, and report the respective IRFs using bootstrapped standard errors in order to avoid problems associated with imputed regressors. Finally, we show the difference between IRFs across the two periods.

The main findings can be summarised as follows. We find that the relative importance of the four structural shocks to explain fluctuations of the labour share of income is different in each period. During the immediate post–war era, the dynamics of the labour share were mainly associated with —in order of relative importance—

[1] To label the period post–Volcker shock the "Great Moderation" is standard; discussion and references are supplied further below. The period from 1948 to 1973 is often labeled a "golden age", but since we include the years of crises throughout the Seventies and early Eighties, we label it simply as the *immediate post–war era*.

productivity shocks, aggregate demand shocks and wage bargaining shocks. In contrast, during the Great Moderation, the labour share responded mainly to wage bargaining shocks, productivity shocks, and aggregate demand shocks, in that order. We see our main contribution in the comparison of these effects across the two periods. Crucially, (a) only wage bargaining shocks and productivity shocks have statistically significantly different effects on the labour share; and (b) the effect of wage bargaining shocks on the labour share has increased in the Great Moderation compared to the immediate post–war era, whereas that of productivity shocks has decreased. These results are robust to different SVAR model specifications (*i.e.*, considering all variables as stationary processes and in levels), and to the computation of local projections impulse response functions.

We derive one centrally important conclusion from these results: wage bargaining shocks stand out as the main driver of the labour share in the US economy since 1985. The implication is that labour's successes and setbacks in influencing the institutions and policies that govern wage setting take center stage in the structural change between post–war era and Great Moderation. The sustained decline in the labour share in the more recent period, hence, seems to be mainly associated with the erosion of the relative bargaining power of workers. This result potentially contrasts sharply with other research on changes in the functional distribution of income. For example, the declining importance of productivity shocks in our framework during the Great Moderation raises questions regarding the explanatory power of technological change as the only dominant force.

The remainder of the paper is organised as follows. Section 2 presents a review of selected literature. Our intent here is to provide relevant background regarding empirical and theoretical efforts that address the dynamics of the labour share, rather than being comprehensive. Section 3 describes our empirical approach and identification strategy. Section 4 presents and discusses our empirical results. Robustness tests are provided in Section 5. In the concluding section, we summarize the issues raised here.

2 Related literature

The decline in the labour share of income experienced by the US economy and other OECD countries in the last three to four decades has attracted considerable attention, and a multitude of explanations derived from distinct theoretical and empirical approaches have been suggested. The underlying causes are seen as related to, among others, technological change, financialization, globalization and structural changes in labour markets. Empirical approaches focus on the measurement of the labour share, including sectoral or firm–level decompositions. A common target is to identify correlations *vis–à–vis* a number of variables in the aforementioned dimensions, such as international or domestic outsourcing, the role of differential monetary and fiscal regimes, as well as deunionization and other institutional factors. Here, we do not aim to comprehensively review this rapidly growing literature, but rather provide a frame of reference for the approach laid out below.

Let us begin with a note on studies with sectoral or firm–level detail. Elsby et al. (2013) focus on the recent decline of the US labour share, investigating the magnitude, impacts, and main outcomes for the nonfarm business sector. According to their results, changes in the "payroll share," *i.e.* compensation of employees as a fraction of gross value added, dominate the decline in the overall labour share. They do not find evidence in favor of high capital–labour substitutability as a driving force, but report inconclusive findings regarding deunionization rates depressing workers' bargaining power. On the other hand, vertical specialisation (including through offshoring) appears to matter: increasing import exposure decreases payroll shares.

Giannoni and Mertens (2019) offer a broad array of results regarding sectoral labour shares, and several decomposition approaches are pursued. The authors pay careful attention to domestic outsourcing, specifically the purchase of service as inputs rather than provision thereof within the boundaries of the firm. The study concludes that there is no single dominant explanatory factor for the decline in the US labour share. Disaggregation is seen as critically important, since outsourcing of labour–intensive (service) activities implies a decline of labour shares in the outsourcing industry (or firm) that might not necessarily be reflected in the aggregate, as respective activities with higher labour shares expand.

Mendieta–Muñoz et al. (2019) provide detail on the sectoral components of the decline in the US labour share. The aggregate change in the labour share is decomposed into changes in real compensation, labour productivity, employment structure and relative prices in fourteen sectors. A central insight is that the relationship between average productivity and average real wages varies across sectors. In contrast, relatively low productivity sectors contribute heavily to the aggregate labour share, whereas in relatively high productivity sectors, pay has increasingly become de–linked from productivity. Indeed, a shift of employment and output towards tertiary activities buffers the overall decline, since these sectors have relatively high labour shares.

Focusing on firm–level data, Autor et al. (2017) demonstrate that market concentration, or the rise of "superstar firms" matters. Low in number but with a large share of their specific markets, these companies have high mark–ups, and pay relatively lower wages to employees. Based on US Census panel data for six sectors —manufacturing, retail trade, wholesale trade, services, utilities and transportation, and finance— the authors conclude that industries with a greater increase in market share see larger declines in the labour share, too. Additionally, industries with greater concentration are also those with faster technological progress, as measured by patent–intensity or total factor productivity. The presumption is that technological dynamism enables firms to achieve such status, although it is cautioned that status maintenance could be linked to barriers of entry or uncompetitive behavior rather than ongoing efforts to innovate. However, to the extent that the decline in the labour share is driven merely by super–profits earned by leading firms in innovation, it represents a possibly benign view on these developments.

Therefore, this literature emphasizes that the decline of the labour share appears to be driven by changes within sectors, rather than through reallocation of activity across sectors —especially since reallocation occurs to sectors with higher labour shares. Within those sectors, however, changes are dominated by reallocation of activity towards leading firms. Across units of observations, the unifying feature is that real wage gains do not keep pace with productivity gains.[2] Autor et al. (2017) note in conclusion that their analysis does not directly support a benign view of technological optimism, as it leaves questions regarding workplace fissuring and outsourcing unanswered. Sectoral and firm–level detail thus matter greatly, but these descriptive studies do not provide conclusive evidence for or against technological change or labour market institutions as dominant factors.

A separate set of papers leverages variation across OECD countries to investigate factors that affect labour shares at the country level. These factors often seek to proxy the major candidate variables, such as technological and/or structural change, financialization, globalization and labour market institutions. For example, Pariboni and Tridico (2019) control for financialization, unemployment, dividends–GDP ratio, globalization, GDP growth, manufacturing share in total employment, and social protection variables in several regression models with the labour share as the dependent variable. Their findings for a panel of 28 OECD countries during the period 1976-2016 imply that structural change towards services, dividend distribution, and policies aimed at labour market flexibility are detrimental to the labour share. The authors posit that financialization aggravated structural change from manufacturing to services, which critically weakened organised labour.

Hein (2013) draws similar conclusions by analysing fifteen developed economies. He emphasises three main channels that explain the fall in labour shares for the entire sample since the 1980s, namely adverse changes in labour's bargaining power through deunionisation, a shift toward financial activities with lower labour inputs, and an increase in managerial salaries. The latter decreases internal funds available to finance investment. Similarly, Rada and Kiefer (2016) find that declining unionization rates adversely affect OECD labour shares in a dynamic panel data estimation with an endogenous activity variable. Dünhaupt (2017) utilises yearly panel data for thirteen OECD countries between 1987 and 2007. Despite the short time period analysed, a decline in the labour share is predominantly caused by increases in shareholder value orientation, along with rising mark–ups resulting from larger interest and dividend obligations.

Ciminelli et al. (2018) further investigates the impact of labour market deregulation on the labour share of income. The authors apply local projection regression models for a sample of 26 developed economies in the period 1970–2015, obtaining IRFs that measure the reaction of the labour share to employees' protection legislation variables at

[2] This pattern is robust across various studies even when top wages and salaries are included in the calculation of respective averages. Since executive compensation packages through the inclusion of boni and stock options incorporate what should more properly be accounted for as profits, the decline in the "true" labour share would be more pronounced, and the measured gap between real wage and productivity growth wider.

the country and country–sector level. Building on the assumptions that deregulation should lower the elasticity of substitution between capital and labour, and increase the propensity to accommodate the labour force, a robust and statistically significant negative effect of deregulation on the labour share of income is found.

The last paper stands out among these panel studies in that it utilises an econometric method in order to compute IRFs. Our research here builds on these efforts, but differs in important dimensions. We focus on one country, rather than an OECD panel, but do identify structural shocks. Although we do not link these shocks to specific institutional measures, our results suggest —like several of these studies— that norms and institutions underpinning wage bargaining indeed matter for the decline in the labour share.

Last but not least, we briefly consider further papers, which often have a theoretical focus. Blanchard and Giavazzi (2003) presents one influential effort to study the effects of labour market deregulation. Using a general equilibrium model, the authors assume monopolistic competition in the goods market, and an imperfect labour market with workers' bargaining power. The first determines the size of rents, while its distribution between workers and firms is determined in the second. The main conclusion is that workers face a trade–off: deregulation leads to lower equilibrium unemployment, at the cost of a likely compression in real wages.

Adopting a DSGE model with accumulation of physical and human capital, Ergül and Göksel (2019) analyse the effect of structural change on the labour share of income for developed and developing countries over the post-1980 period. In their simulations, more prominence is given to investment–specific technologies relative to educational activities, and the gap between these shocks is increased in each new experiment. The general result is that there is a decline in the labour share of income as more investments in automation are implemented. One of the main outcomes of the assumed process is an aggregate reduction of demand, as wages are reduced, which deteriorates consumers' confidence and disposable income.

Barkai (2017) and Karabarbounis and Neiman (2013) develop alternative frameworks to target specific determinants of the labour share's decline over the past three decades. The first attributes this fact to increased profit (markup) margins, the second to lower relative prices of computing and information technologies. As a consequence, a shift from labour to capital–intensive techniques of production was not capable of offsetting the decline in the US labour share of income, which Barkai (2017, p. 3) labels as an "inefficient outcome." Both of these influential studies require the elasticity of substitution between labour and capital to be larger than unity, which has very limited support in the literature (Raval, 2017; Chirinko and Mallick, 2017).

In summary, the decline in the labour share is driven by changes within sectors, where average real compensation growth does not keep pace with average productivity growth. Within sectors, lead firms with large and growing market shares have lower labour shares. Reallocation across sectors thus does not contribute to the decline, whereas that across firms does. Aggregate empirical studies suggest an important role for changes in institutions and policies during the Great Moderation, including those governing wage setting. However, the majority of these studies do not identify causal effects. Lastly, theoretical frameworks that detail a mechanism often require an unreasonably large elasticity of factor substitution. While we do not focus on this last aspect, and neither offer a specific mechanism, we seek to contribute to the broader literature by identifying the response of the labour share to its relevant structural shocks during the immediate post–war era and the Great Moderation. The following section describes the methodology applied.

3 Empirical methodology

In this section, we propose: (i) a SVAR model in demand, unemployment, real wage and labour productivity in order to identify structural shocks to aggregate demand, labour supply, wage bargaining and productivity; and (ii) a procedure to analyze the dynamic response of the labour share itself to the structural innovations identified in the previous step. Further, the section outlines the methodology of the test for a structural break in the model, motivates the bootstrapping of standard errors for step (ii), and describes the data used.

In contrast to much of the aforementioned literature, our approach emphasises the importance of time–series methods that help us to identify structural shocks, which allows for a richer comparison of the fundamental disturbances affecting simultaneously aggregate demand and income distribution, and a direct comparison of these effects across different periods. In brief, our empirical procedure consists of two main steps. The first step consists in retrieving the key unobserved structural shocks from a SVAR model that incorporates critical macro–labour linkages. The second step consists in directly estimating the response of the labour share of income to these structural shocks using IRFs.[3]

Let us first motivate a simple model. We assume that the labour share of income (Ψ_t) is well described by the interaction of four variables: real GDP Y_t, the unemployment rate u_t, real wages W_t and labour productivity X_t. These are of course definitionally related to the labour share itself. The following system of equations illustrates a stylised model in which the possible contemporaneous interactions among these variables are considered:

$$Y_t = Y(Y_t, W_t, X_t), \tag{1}$$
$$u_t = u(Y_t, u_t, W_t, X_t), \tag{2}$$
$$W_t = W(u_t, W_t, X_t), \tag{3}$$
$$X_t = X(Y_t, W_t, X_t). \tag{4}$$

[3] Our methodology is similar to the one proposed by Kilian (2009), who also followed a two–step econometric procedure based on a SVAR model and the use of IRFs to identify the underlying demand and supply shocks in the global crude oil market and to estimate their respective macroeconomic effects. Of course, our research question is entirely different.

Equation (1) represents an aggregate demand equation, showing that real GDP can be affected by W_t and X_t, and, of course, Y_t itself. The own–feedback of current levels (or growth rates) of demand into itself is central in the extensive literature on multiplier–accelerator models. This aggregate demand equation extends the set of variables to real wage and productivity. The real wage trades off with the profit rate, and since the latter has an effect on economic activity through the investment channel, it can be expected to play a role here.[4] In equilibrium, demand is of course equal to production, which will be affected positively by productivity.

Equation (2) depicts an equation for the unemployment rate in which u_t can depend on Y_t, W_t, X_t and itself. In the short run, the level of employment is determined primarily by the state of the business cycle, which is here captured by Y_t. In other words, the rate of unemployment will vary inversely with demand —which implies in turn that the structural shock emanating from this equation describes the labour force, *i.e.* labour supply. Further, real wages and productivity are linked to the determination of employment.

Equation (3) is a wage–setting relationship, where the real wage W_t can be affected by the rate of unemployment u_t, X_t and W_t. With stationary series, this implies a Phillips curve between real wage inflation and the rate of unemployment. Labour productivity can also be expected to matter in the determination of real wages.

Finally, labour productivity is considered as a partially endogenous variable in equation (4). Here, X_t depends on the level of aggregate demand Y_t and the real wage W_t (and itself). The dynamic interaction between output and employment —Okun's Law— implies, of course, endogeneity of labour productivity. In this specification, we allow for the direct interaction of aggregate demand and labour productivity with (un)employment (in equation 2), and also with labour productivity (in equation 4). The real wage can be expected to matter along the lines of the theory of induced technical change.

We consider that the dynamic interactions between the four variables of interest can be studied using a Vector Autoregression (VAR) model for the row vector $\mathbf{z_t} = (Y_t, u_t, W_t, X_t)'$, whose SVAR representation is:

$$\mathbf{A_0 z_t} = \alpha + \sum_{i=1}^{l} \mathbf{A_i z_{t-i}} + \varepsilon_\mathbf{t}, \tag{5}$$

where $\varepsilon_\mathbf{t}$ represents the vector of serially and mutually uncorrelated structural innovations.[5]

[4] As discussed above, the model abstracts from monetary factors. However, to the extent that the profit rate is inversely related to the real wage, and correlates with financial indicators, a contemporaneous link from the real wage to investment and hence aggregate demand could be justified based on standard q–theory.

[5] It is worth pointing out that our choice of variables is similar to that of Foroni et al. (2018), who showed that the incorporation of the unemployment rate and real wages in a VAR model aids in the identification of labour supply shocks and wage bargaining shocks. However, our research question and empirical identification strategy differ substantially from theirs, since our main interest is to determine

The structural shocks of interest contained in $\varepsilon_{\mathbf{t}}$ are not directly observable and need to be derived from the estimation of the reduced–form VAR model. Hence, we assume that the correlations of the reduced–form residuals $\mathbf{e_t}$ are derived from the contemporaneous interactions between these four variables. Since we have $n = 4$ variables in the VAR model, at least $n(n-1)/2 = 6$ restrictions are required in the $\mathbf{A_0^{-1}}$ matrix to provide exact identification of the system. Crucially, the estimation of the model represented by equations (1)–(4) cannot be performed because it yields an underidentified VAR. To include all required restrictions, we postulate that $\mathbf{e_t}$ can be decomposed as follows:

$$\mathbf{e_t} = \mathbf{A_0^{-1}} \varepsilon_{\mathbf{t}} = \begin{pmatrix} e_t^Y \\ e_t^u \\ e_t^W \\ e_t^X \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & a_{13} & a_{14} \\ a_{21} & a_{22} & 0 & a_{24} \\ 0 & a_{32} & a_{33} & 0 \\ a_{41} & 0 & 0 & a_{44} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{\text{demand shock}} \\ \varepsilon_t^{\text{labour supply shock}} \\ \varepsilon_t^{\text{wage bargaining shock}} \\ \varepsilon_t^{\text{productivity shock}} \end{pmatrix}. \quad (6)$$

The identification strategy presented in (6) implies the following contemporaneous restrictions: (i) aggregate demand Y_t reacts to W_t and X_t, but not to u_t; (ii) the unemployment rate u_t reacts to Y_t and X_t in the same period, but not to W_t; (iii) real wages W_t do not react to Y_t or X_t in the same period, but do to u_t; and (iv) productivity X_t can react to Y_t, but not to u_t or W_t. These restrictions are justifiable in light of the preceding discussion of standard macroeconomic short–run theory.

Further, this identification strategy renders the four structural innovations of interest as follows: the structural shock derived from the aggregate demand equation corresponds to an aggregate demand shock; the one derived from the unemployment rate equation corresponds to a labour supply shock; the one derived from the wage-setting equation corresponds to a wage-bargaining shock; and the structural shock derived from the productivity equation corresponds to a productivity shock. In other words, our identification strategy allows for the computation of the four structural shocks that we deem to be the main drivers of Ψ_t.

The next step is to estimate the response of Ψ_t to each of these structural shocks. Under the assumption that there is no feedback from Ψ_t to the structural innovations $\widehat{\varepsilon}_{j,t}$, $j = 1, 2, 3, 4$ in period t, these shocks can be treated as predetermined, and it is possible to examine the effects of these innovations on Ψ_t based on the following regression models:

$$\Psi_t = \beta_j + \sum_{i=0}^{12} \delta_{j,i} \widehat{\varepsilon}_{j,t-i} + v_{j,t}, \qquad j = 1, 2, 3, 4, \quad (7)$$

the structural drivers of the labour share of income, rather than to separate labour supply and wage bargaining shocks. Furthermore, they incorporate prices (or inflation) in a VAR model to identify demand shocks, while we consider an actual measure of real GDP preferable. Similarly, Basu and Gautham (2019) put forth a VAR to investigate the dynamics between the labour share and other key macroeconomic aggregates. As with Foroni et al. (2018), their research question critically differs, since their focus lies on the effect of a shock of the labour share itself on economic activity variables. Still, careful consideration of the IRFs presented in Basu and Gautham (2019) suggests that their results are —broadly speaking— consistent with our first–step SVAR results.

where $v_{j,t}$ represent the error terms. Our main interest lies with the coefficients $\delta_{j,i}$ at horizons h, which represent the responses of Ψ_t to each of the four structural shocks of interest $\widehat{\varepsilon}_{j,t-i}$, $j = 1, 2, 3, 4$.[6]

We conclude this section with details on the test for a structural break in the VAR model, a note on bootstrapping of standard errors, and a brief description of the data used.

As outlined above, we seek to compare two periods. The first we label the *immediate post–war era*, stretching from 1948Q1 to 1984Q4; the second is the *Great Moderation*, from 1985Q1 to 2018Q3. There are good reasons to assume a break in the mid–Eighties. For important examples of the literature on the changing nature of the business cycle during the Great Moderation, consider Stock and Watson (2002) and Fogli and Perri (2006). As detailed further below, there is strong support for a structural break at this point in time, with variables as stationary series (section 4), or in levels (section 5).

In order to corroborate the presence of a structural break in 1984Q4, we used the Chow–type quasi–Likelihood Ratio (LR) test for VAR models outlined by Bacchiocchi and Fanelli (2015). Consider that we collect the VAR reduced–form parameters in the p–dimensional vector $\theta := (\varphi', \sigma'_+)$, where $\varphi = \text{vec}(\Phi)$; $\Phi = (C, D)$; C and D are the matrix of time–invariant coefficients and the matrix of coefficients associated with the deterministic components of the VAR, respectively; $\sigma_+ = \text{vech}(\Sigma)$; and Σ is the positive definite time–invariant covariance matrix of the vector of residuals of the VAR. Therefore, a Chow-type quasi–LR test can be used to test for the joint null hypothesis that $H_0 : \theta_1 = \theta_2 = \theta$ against the alternative $H_a : \theta_1 \neq \theta_2$, where θ_1 and θ_2 correspond to the VAR reduced–form parameters in the first and second periods considered, respectively.

Our two–step empirical methodology is not exempt from problems associated with second–stage regressions with generated regressors. As Pagan (1984) and Murphy and Topel (1995) explain, two–step procedures fail to account for the fact that imputed regressors are measured with sampling error, so hypothesis tests based on the estimated covariance matrix of the second–step estimator are biased, even in large samples. Thus, we employed bootstrapped standard errors with five thousand replications in all cases to estimate the regression model in (7), both with variables as stationary series (section 4) and in levels (section 5). This allows us to derive conclusions regarding the statistical significance of the responses of the labour share to the four structural shocks of interest.

Lastly, on data. We used quarterly data from 1948Q1 to 2018Q3 for the US business sector. Seasonally adjusted time–series for real GDP, the unemployment rate, and the wage share were obtained from the Federal Reserve Bank of St. Louis Economic Database (FRED). The first corresponds to real output of the US business sector (billions of chained 2012 dollars); the second to the civilian unemployment rate (in percentages); and the third is the US business sector's labour share (index

[6] We introduced twelve lags in the estimation of (7) in order to incorporate approximately three years of data, as in Kilian (2009). The great majority of the regression models estimated according to (7) —with variables as stationary series (section 4), or in levels (section 5)— do not show serial correlation problems at the 5% level of significance when twelve lags were included; and none of these models presented autocorrelation problems at the 10% level of significance.

2012=100). Data on real wages and productivity come from the US Bureau of labour Statistics (BLS): the former corresponds to real hourly compensation (index 2012=100), while the latter is defined as real output per hour (index 2012=100). All variables except the unemployment rate are log–transformed to facilitate interpretation of results. Specifically, $r_t = 100 * \ln(R_t)$, where ln denotes the natural logarithm of the R_t variable of interest and r_t is the log–transformed series.

4 Results

Our preferred specification considers the model with all variables differenced sufficiently to achieve stationarity since the focus of our paper lies on short–run dynamic interactions.[7] Hence, in this section we report IRFs derived from the SVAR model identified according to equation (6), followed by the ones based on equation (7) considering only stationary variables.

In order to determine the order of integration of the series, different unit root tests were implemented: Augmented Dickey–Fuller (ADF) (Said and Dickey, 1984), Dickey–Fuller Generalized Least Squares (ADF-GLS) (Elliot et al., 1996), Ng–Perron's Modified Phillips (M–P) (Ng and Perron, 1995), and the Kwiatowski–Phillips–Schmidt–Shin (KPSS) (Kwiatowski et al., 1992) test. All tests showed that the log–transformed series of the labour share ψ_t, real output y_t, real wages w_t, and labour productivity x_t are integrated series of order one (*i.e.*, $I(1)$ series), and that the unemployment rate u_t is an $I(0)$ series. Therefore, the variables incorporated in the first–step SVAR estimation were $\mathbf{z_t} = (\Delta y_t, u_t, \Delta w_t, \Delta x_t)'$, and we considered $\Delta\psi_t$ as the dependent variable in the second–step estimation in order to quantify the response of the labour share to the four structural shocks.

The lag length selected for the VAR models was 3 in both subperiods. These models did not present serial correlation problems, according to serial correlation Lagrange Multiplier–type tests, or heteroskedasticity problems, according to White–type heteroskedasticity tests, thus indicating well–specified models at the 95% confidence level.

We then corroborated the presence of a structural break in the VAR models in 1984Q4 using the Chow–type LR test described in the previous section. The dimension of θ is $p := \dim(\theta) = 62$. Therefore, the quasi–LR test corresponds to $\text{LR} = -2\,[\lambda_R - \lambda_U]$, where $\lambda_R = -839.20$ is the log–Likelihood obtained from the restricted VAR for the period 1948Q1–2018Q3, and $\lambda_U = -463.90 - 256.54 = -720.44$ is the log–Likelihood obtained from the unrestricted VAR —*i.e.*, the sum of the log–Likelihoods estimated from the VAR models for the two sub–samples, 1948Q1–1984Q4 and 1985Q1–2018Q3, respectively. Therefore, $\text{LR} = -2\,[-839.20 + 720.44] = 237.52$, which has a p–value of less than

[7] This allows us to focus on the short-run dynamics of the labour share without making assumptions concerning any long–run equilibrium, which would require the estimation of an error correction model and the use of cointegration analyses. Section 5 presents results with all variables in levels, showing that the main results are robust to this change in specification.

0.00001 (taken from the $\chi^2(62)$ distribution), which means that the H_0 of no structural break in the VAR model is strongly rejected and that it is appropriate to separate the postwar sample into the post–war era and the Great Moderation.

Figures 1 and 2 below present the IRFs derived from the SVAR models using the identification strategy proposed in model 6 for the two subperiods.

[INSERT FIGURE 1 ABOUT HERE]
[INSERT FIGURE 2 ABOUT HERE]

The empirical results indicate important differences regarding the responses of the variables to the structural shocks, thus highlighting that the US macroeconomy underwent significant changes.

During the post–war era, the response of output to the four structural shocks is statistically significant. Productivity shocks generate the largest positive response of output, followed by labour supply shocks and aggregate demand shocks. We find a negative response of output to wage bargaining shocks. Unemployment reacts negatively to demand shocks and productivity shocks, and positively to wage bargaining shocks. The third row of panels suggests that real wages react positively only to demand shocks and productivity shocks. Finally, only productivity shocks and —marginally— wage bargaining shocks affect productivity positively.

In contrast, during the Great Moderation, output reacts only to productivity shocks and, quite marginally, to aggregate demand shocks. The response to both shocks is smaller than that in Figure 1. The unemployment rate reacts negatively to both demand and productivity shocks, and its response to both shocks is more persistent than in the earlier period, likely reflecting consecutive "jobless recoveries." Likewise, a labour supply shock now has a significant positive effect on the unemployment rate that lasts for approximately seven quarters. Further, real wages react positively only to wage bargaining shocks and (marginally) to productivity shocks; while productivity reacts again only to productivity and wage bargaining shocks, but less strongly than during the preceding period.

Next, we present results for equation 7, showing the responses of the labour share to the four structural shocks in Figure 3 below.[8] Since ψ_t is an $I(1)$ series, we compute the cumulative IRFs (CIRFs) of each structural shock on $\Delta\psi_t$ over a sixteen quarter horizon in the two sub–samples. The CIRFs are shown together with bootstrapped 95% confidence intervals in order to address problems associated with second–stage regressions with generated regressors.[9]

[8]The four structural shocks employed as regressors, $\widehat{\varepsilon}_{j,t}$, $j = 1, 2, 3, 4$, are shown in Figure A.1 in Appendix A. Based on the Jarque–Bera normality test, these shocks are normally distributed, except for productivity shocks during the Great Moderation.

[9]We also tested whether the structural shocks can be treated as predetermined with respect to $\Delta\psi_t$, following Kilian (2009): first, an AR model for $\Delta\psi_t$ with three lags —as in the SVAR— is estimated; second, the contemporaneous correlation between the residuals obtained therefrom and the structural shocks is calculated. The great majority of the correlations are low (i.e., below 50%), with the exception of productivity shocks during the post–war era (59%), and wage bargaining shocks during the Great Moderation (64%).

[INSERT FIGURE 3 ABOUT HERE]

Figure 3 indicates that the labour share reacted significantly to all shocks during the first period: positively to both aggregate demand shocks and wage bargaining shocks; and negatively to labour supply shocks and productivity shocks. The largest response of the labour share is to productivity shocks (the one–quarter ahead response of the labour share to a 1% productivity shock was approximately -0.61%, and the response was statistically significant for approximately 5 quarters), followed by aggregate demand shocks (a 1% aggregate demand shock generated a 0.51% response of the labour share after one quarter, and the effect was significant for approximately three quarters), wage bargaining shocks (a 1% wage bargaining shock generated a significant response of 0.24% of the labour share two–quarters ahead) and, finally, labour supply shocks (a 1 percentage point labour supply shock generated a -0.24% response of the labour share, and the response was significant for approximately 1 quarter).

In contrast, during the Great Moderation only three shocks generated statistically significant effects on the US labour share of income: aggregate demand shocks, wage bargaining shocks, and productivity shocks. As before, the response of the labour share to the first two shocks is positive, while its response to the last shock is negative. The largest and most significant response of the labour share is now associated with the wage bargaining shock (the response of the labour share to a 1% wage bargaining shock is approximately 0.64%, and the response is statistically significant for approximately six quarters), followed by the productivity shock (a 1% productivity shock generated a -0.46% response of the labour share after one-quarter, and the effect was significant only for that quarter), and, finally, the aggregate demand shock (a 1% aggregate demand shock generated a 0.36% response of the labour share after one quarter, and the effect was significant for approximately one quarter).

To summarise, during the period 1948Q1–1984Q4 the labour share reacted to all four structural shocks —productivity, aggregate demand, wage bargaining and labour supply, in that order of magnitude— while during the period 1985Q1–2018Q3 the labour share reacted to wage bargaining, productivity and aggregate demand. Specifically, the effects related to productivity shocks, aggregate demand shocks, and labour supply shocks have decreased during the period 1985Q1–2018Q3 compared to 1948Q1–1984Q4; while the role of wage bargaining shocks has become more prominent since 1985.

To highlight this latter point, we evaluate to what extent the dynamic responses of the labour share to the structural shocks between both periods are statistically different. We do so by subtracting CIRFs of the immediate post–war era from those of the Great Moderation. These differences are plotted in Figure 4.

[INSERT FIGURE 4 ABOUT HERE]

From these panels it is clear that there are no statistically significant differences in the cumulative responses of the labour share to aggregate demand shocks and labour supply shocks between the two periods. However, the difference of the cumulative response of the labour share to wage bargaining shocks and productivity shocks is statistically significant. Specifically, the response of the labour share to (i) a productivity shock is statistically different between both periods in the two–, three– and five–quarters ahead CIRFs; (ii) a wage bargaining shock is statistically different between both periods in the one–quarter ahead CIRFs, and also from quarters five through eleven. This means that the negative response of the labour share to productivity shocks has diminished; and, importantly, the positive response of the labour share to wage bargaining shocks has increased.

5 Robustness of results

This section presents robustness analyses. First, we report results obtained from equations 6 and 7 with all variables in levels. Second, we use local projections to study the effects of the structural shocks on the US labour share of income with an additional method.

To begin, we estimated the reduced–form VARs with a lag length of three for the two periods, with all variables in levels. These models do not present autocorrelation problems, according to Lagrange Multiplier–type tests, at the 5% level of significance, but they do show heteroskedasticity problems, according to White–type VAR residual heteroskedasticity tests.

Second, we corroborated the presence of a structural break in the VAR models in 1984Q4 using the Chow–type quasi–LR test described in the Section 3. The dimension of θ in this case is again $p = 62$; and the quasi–LR test is $\mathrm{LR} = -2\left[-832.25 - (-700.04)\right] = 264.42$, where -832.25 is the log–Likelihood obtained from the VAR model considering only one period (1948Q1-2018Q3), and -700.04 corresponds to the sum of the log-Likelihoods obtained from the VAR models considering two periods (1948Q1–1984Q4 and 1985Q1–2018Q3). This $\mathrm{LR} = 264.42$ has a p–value of less than 0.00001 (taken from the $\chi^2(62)$ distribution), so we strongly reject the null hypothesis of no structural break in the VAR model. As before, it is appropriate to separate the sample into the two subperiods.

The IRFs derived from the SVAR model represented in (6) for the two subperiods are presented in Figures 5 and 6.

[INSERT FIGURE 5 ABOUT HERE]
[INSERT FIGURE 6 ABOUT HERE]

The IRFs derived from these SVAR models also show important differences between both periods. During the post–war era, the response of output is mainly associated with productivity shocks. We also see a significant negative response of output to demand shocks for some quarters. The unemployment rate responded negatively to demand shocks and productivity shocks, and positively to labour supply shocks. Real wages reacted mainly positively to wage bargaining shocks and productivity shocks, and (marginally) negatively to labour supply shocks; and productivity reacted mainly positively to productivity shocks and wage bargaining shocks —there is also a negative response of productivity to demand shocks for some quarters.

In the period 1985Q1–2018Q3, output reacts only to productivity shocks, and its response is smaller than in the first period. The unemployment rate reacts positively to labour supply shocks and negatively to both demand shocks and productivity shocks. Its response to the last two shocks is more persistent compared to the first subperiod. Real wages react mainly positively to wage bargaining shocks and to productivity shocks for some quarters; and its response to wage bargaining shocks is relatively less persistent than during the first period. Finally, productivity and wage bargaining shocks are the ones that generate the most important responses of productivity, although its response is also smaller relative to the period 1948Q1–1984Q4. We also find a negative response of productivity to demand shocks for some quarters, as in the previous period.

The responses of Ψ_t to the structural shocks obtained from the SVAR models estimated in levels over a sixteen quarter horizon are presented in Figure 7 below, again with bootstrapped 95% confidence intervals.

[INSERT FIGURE 7 ABOUT HERE]

The results indicate that the post–war era labour share responded positively to aggregate demand shocks and wage bargaining shocks, and negatively to productivity shocks. Productivity shocks and aggregate demand shocks generated the largest response of the labour share during this first period (the one–quarter ahead response of the labour share to a 1% productivity shock was approximately -0.58% and the response was statistically significant for approximately three quarters; while the response of the labour share to a 1% aggregate demand shock was approximately 0.46% and the response was statistically significant for approximately seven quarters); followed by wage bargaining shocks (a 1% wage bargaining shock generated a one–quarter ahead significant response of 0.29% of the labour share).

In contrast, the response of the labour share to these shocks is different during the Great Moderation. Wage bargaining shocks generate the largest response of the labour share (the one–quarter ahead response of the labour share to a 1% wage bargaining shock is approximately 0.58%); followed by productivity shocks (a 1% productivity shock generated a -0.41% response of the labour share after one quarter) and the aggregate demand shock (the 1% demand shock generated a 0.37% response of the labour share after one quarter).

These results corroborate the findings discussed in the previous section. The results line up, with the single exception that the stationary models in section 4 suggest a significant response of the labour share to the labour supply shock for one quarter during the post–war era. Clearly, the role of these structural shocks on the labour share has changed: during the first period, the labour share reacted mainly to productivity shocks, aggregate demand shocks, and wage bargaining shocks; while the second sees the labour share reacting mainly to wage bargaining shocks, productivity shocks and aggregate demand shocks.

Figure 4 shows the differences in the responses of the labour share to the four structural shocks between the periods 1985Q1–2018Q3 and 1948Q1–1984Q4 in order to evaluate if these are statistically significant.

[INSERT FIGURE 8 ABOUT HERE]

These panels also corroborate the findings discussed in the previous section. Again, we find: (i) no statistically significant differences in the responses of the labour share to both aggregate demand shocks and labour supply shocks between both periods; (ii) that the response of the labour share to both wage bargaining and productivity shocks is statistically significantly different between both periods in the one–quarter ahead and two–quarters ahead IRFs, respectively; and (iii) that the positive (negative) sensitivity of the labour share associated with wage bargaining shocks (productivity shocks) has increased (decreased).

The remainder of this section discusses the implementation of LPs, and results.

Specifically, we additionally study the dynamic response of the labour share of income to the four structural shocks as shown in equation (7) using LPs. Since Jordà (2005), LPs have become an increasingly widespread alternative to study the propagation of structural shocks. In brief, instead of using one set of VAR coefficients as in the Vector IRFs technique, LPs estimate a new set of estimates for each horizon, thus being more closely associated with multi–step forecasting. The LP technique collects new estimates for each forecast horizon by regressing the dependent variable (vector) at horizon $t + h$ on the information set at t; thus, the projections of forward values of the dependent variable (vector) on the information set are local to each horizon.

It has been commonly believed that LPs and VAR IRFs represent conceptually different procedures. Moreover, it has been argued that the former are more robust to misspecification of the data–generating process, because the generation of a new set of estimates for each horizon avoids escalation of the misspecification error. However, Brugnolini (2018) has shown that, when the data generating process is a well–specified VAR, standard IRFs estimators are the best option; and that LPs are a competitive alternative only when the sample size is small and the model lag–length is misspecified. Similarly, Plagborg-Møller and Wolf (2019) offer a thorough comparison between both approaches, finding that LPs and VARs in fact estimate the same population and sample IRFs and should not be regarded as conceptually distinct methods. These authors conclude that no single method dominates for all empirically relevant data–generating process. As will be seen momentarily, results from LPs here broadly confirm those based on SVAR, both with variables as stationary series and in levels.[10]

[10] An alternative comparison between moving average representations and local projections to recover impulse responses in the presence of persistence in the shock is provided by Alloza et al. (2019), who find that both methods treat persistence differently (namely, standard local projections identify responses that include an effect due to the persistence of the shock, while moving average representations implicitly account for it). They propose the inclusion of leads of the shock in local projections in order to control for its persistence, which renders the resulting responses equivalent to those associated to counterfactual non-serially correlated shocks.

First, we present the LPs CIRFs of each structural shock on $\Delta\psi_t$ over a sixteen quarter horizon for the periods 1948Q1–1984Q4 and 1985Q1–2018Q3 in Figure 9. We then evaluate to what extent the differences in the responses of the labour share to these shocks between the two periods are statistically significant in Figure 10.[11]

[INSERT FIGURE 9 ABOUT HERE]
[INSERT FIGURE 10 ABOUT HERE]

The results shown above can be summarised as follows: (i) during the first period, the response of the labour share to the four structural shocks is statistically significant for at least 1 quarter, and the labour share responded mainly to productivity shocks (the elasticity is around -0.60%), followed by demand shocks (0.50%), wage bargaining shocks (0.20%) and labour supply shocks (-0.20%); (ii) during the second period, the response of the labour share is statistically significant only with respect to wage bargaining shocks (the elasticity is around 0.70%), productivity shocks (-0.50%) and aggregate demand shocks (0.40%); and (iii) the only shock that presents statistically significant different effects on the labour share between the two different periods considered is the wage bargaining shock. As in the preceding analyses, (iii) confirms the growing importance of wage bargaining shocks in order to explain changes of the US labour share.

Second, Figures 11 and 12 show the LPs IRFs of each structural shock on ψ_t for the two subperiods[12] and the differences in the responses of ψ_t, respectively.

[INSERT FIGURE 11 ABOUT HERE]
[INSERT FIGURE 12 ABOUT HERE]

These figures show that the results obtained from the LPs IRFs considering all variables in levels are similar to the previous estimations. During the period 1948Q1–1984Q4, the labour share responded mainly to productivity shocks, aggregate demand shocks and wage bargaining shocks (the one–quarter ahead elasticities are -0.57%, 0.47% and 0.31%, respectively; and the response is statistically significant for approximately three, eleven and one quarter, respectively). With respect to the period 1985Q1–2018Q3, the labour share responded to wage bargaining shocks, productivity shocks, aggregate demand shocks and labour supply shocks (the one–quarter ahead elasticities are 0.59%, -0.43%, 0.41%, and -0.15%, respectively).[13] Finally, and as before, the response of the labour share to the wage bargaining shock presents the largest statistical difference between the two periods. There is a marginal difference with respect to the responses to productivity shocks and aggregate demand shocks, too. Thus, according to these results, the sensitivity of the labour share to

[11] Figure B.1 in Appendix B plots a direct comparison of the responses of $\Delta\psi_t$ obtained from both LPs and VAR IRFs.

[12] Figure B.2 in Appendix B also plots the IRFs of ψ_t to the shocks obtained using LPs and VAR.

[13] During the Great Moderation, the response of the labour share is statistically significant for only one quarter, except for aggregate demand shocks, which have statistically significant effects also in quarters six through twelve.

wage bargaining shocks increased significantly, and it decreased with respect to both productivity and demand shocks.

6 Conclusions

In this paper, we propose a novel methodological approach to identify the main structural shocks affecting the US labour share of income. We utilize a Structural Vector Autoregression (SVAR) model in real GDP, unemployment, real wage and labour productivity in the *immediate post–war era* and *Great Moderation* to obtain structural shocks —namely, aggregate demand shocks, labour supply shocks, wage bargaining shocks, and productivity shocks— for both periods, conditional on plausible short–run macroeconomic restrictions. These structural shocks are then employed as regressors on the US labour share in the two periods to evaluate their relative importance via impulse response functions (IRFs). We discuss the resulting impulse response functions on their own merits, and, crucially, compare responses across the two periods.

Impulse responses from the various estimations —Vector Autoregression and local projections, with variables as stationary processes and in levels— all indicate statistically significant support for an *increased* importance of wage bargaining shocks for the US labour share of income during the Great Moderation. Labour productivity shocks play a statistically significant role, too —but their importance has *decreased* with the advent of the Great Moderation. The role of demand shocks and labour supply shocks appears to not have changed significantly across the two periods.

Lastly, our paper hints at further research questions. First, the empirical strategy applied here does not seek to identify underlying components of the four structural shocks. However, the relative importance of structural shocks to wage bargaining suggests that future research should investigate this regime shift in labour markets, and how the relevant institutions and policies interacted with other candidate variables, such as technology, globalization and monetary factors. Second, our approach remains at the aggregate level, thus overlooking important sectoral and firm-level developments (such as domestic outsourcing, or concentration of market shares), and employee-level differences (such as the well-known changes to wage and salary distributions). In summary, our findings suggest that research on the regime shift in labour markets, its underlying components, and connections to microeconomic data sets, promise further insights on the decline in the labour share.

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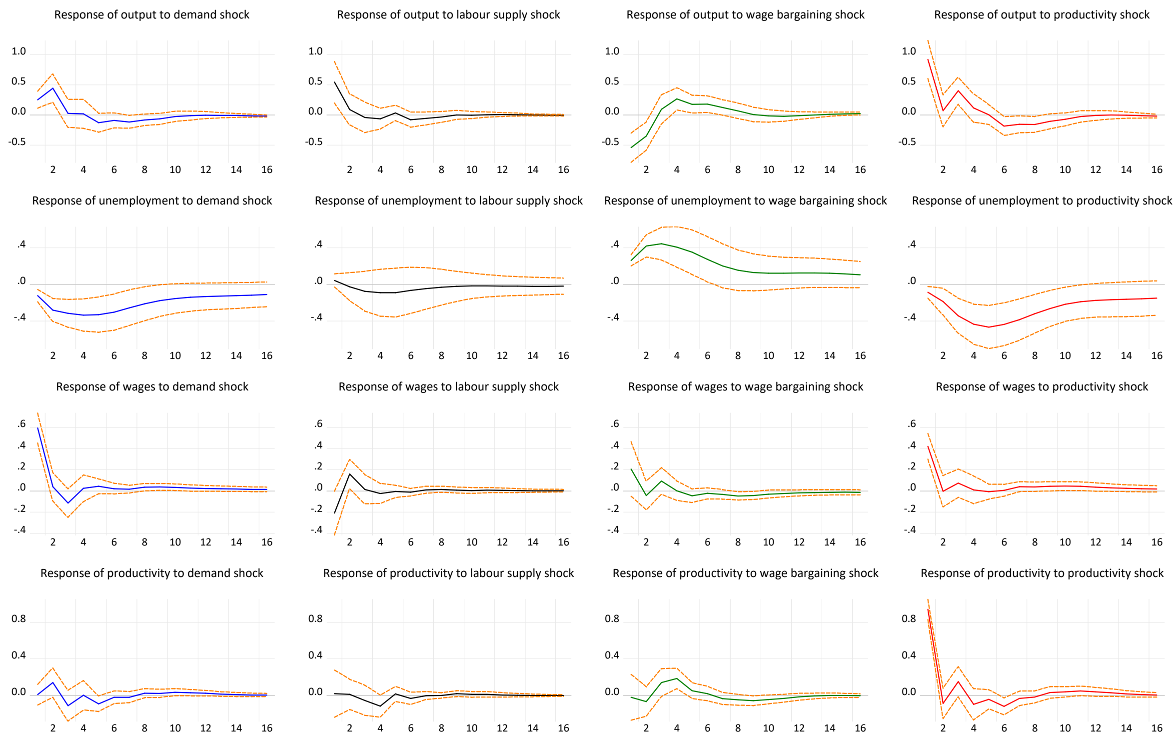


Figure 1: Impulse-responses derived from the SVAR model for the period 1948Q1–1984Q4 (considering all variables as stationary processes). These figures show the impulse-responses obtained from the identification strategy based on model (6). The dynamic responses of the variables to a 1% aggregate demand shock, 1 percentage point labour supply shock, 1% wage bargaining shock and 1% productivity shock are shown in blue, black, green and red, respectively. Orange dotted lines correspond to the respective 95% asymptotic confidence intervals. The horizontal axis shows quarters ahead in all figures.

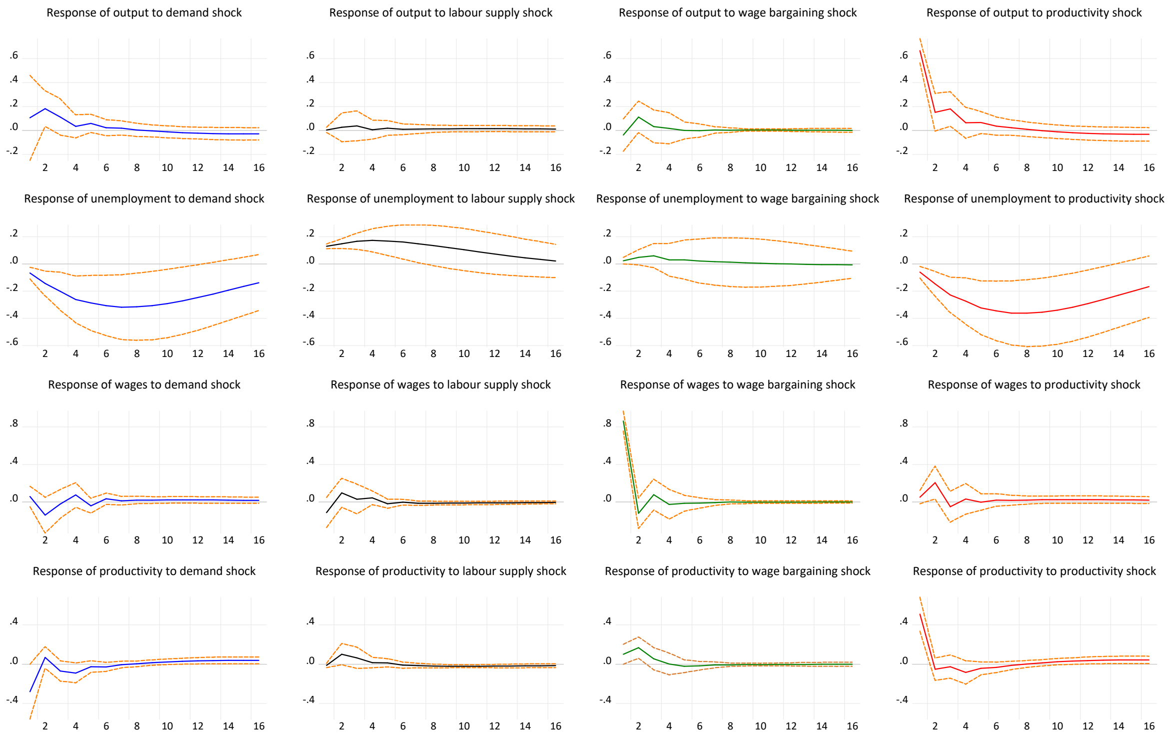
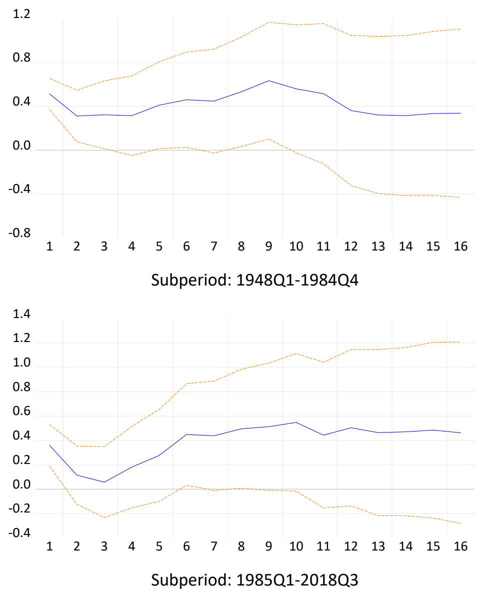
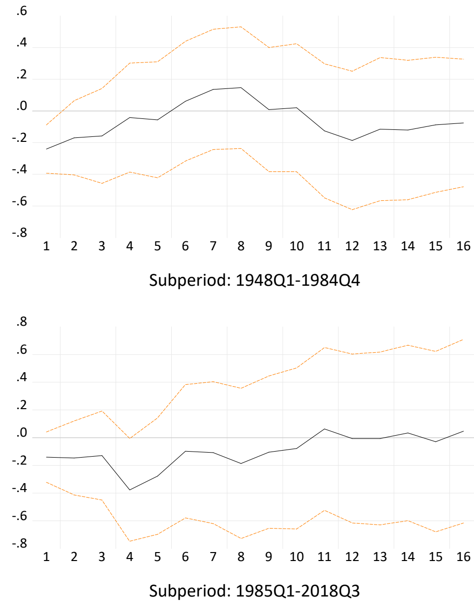


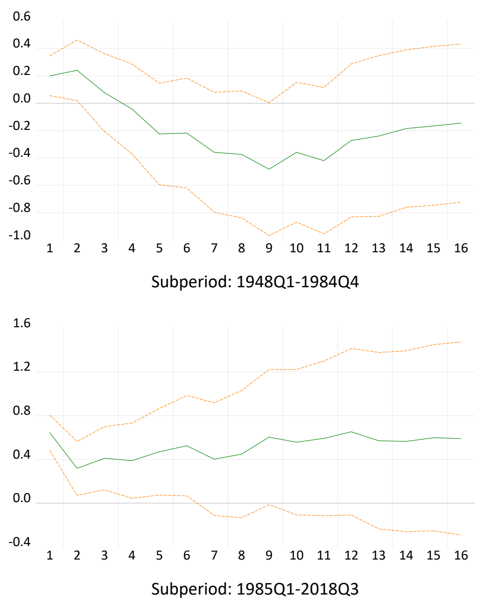
Figure 2: Impulse-responses derived from the SVAR model for the period 1985Q1–2018Q3 (considering all variables as stationary processes). These figures show the impulse-responses obtained from the identification strategy based on model (6). The dynamic responses of the variables to a 1% aggregate demand shock, 1 percentage point labour supply shock, 1% wage bargaining shock and 1% productivity shock are shown in blue, black, green and red, respectively. Orange dotted lines correspond to the respective 95% asymptotic confidence intervals. The horizontal axis shows quarters ahead in all figures.



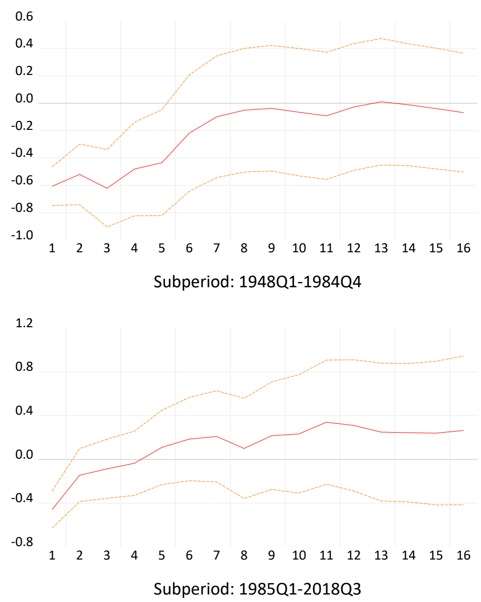
(a) Accumulated response of the labour share to a 1% aggregate demand shock



(b) Accumulated response of the labour share to a 1 percentage point labour supply shock



(c) Accumulated response of the labour share to a 1% wage bargaining shock



(d) Accumulated response of the labour share to a 1% productivity shock

Figure 3: Accumulated responses of the labour share to structural shocks for the periods 1948Q1–1984Q4 and 1985Q1–2018Q3. These figures correspond to the Cumulative Impulse-Response Functions (CIRFs) of the first-differences of the labour share ($\Delta\psi_t$) with respect to the different structural innovations. Orange dotted lines correspond to the respective bootstrapped 95% confidence intervals (5,000 replications in all cases). The horizontal axis shows quarters ahead in all figures.

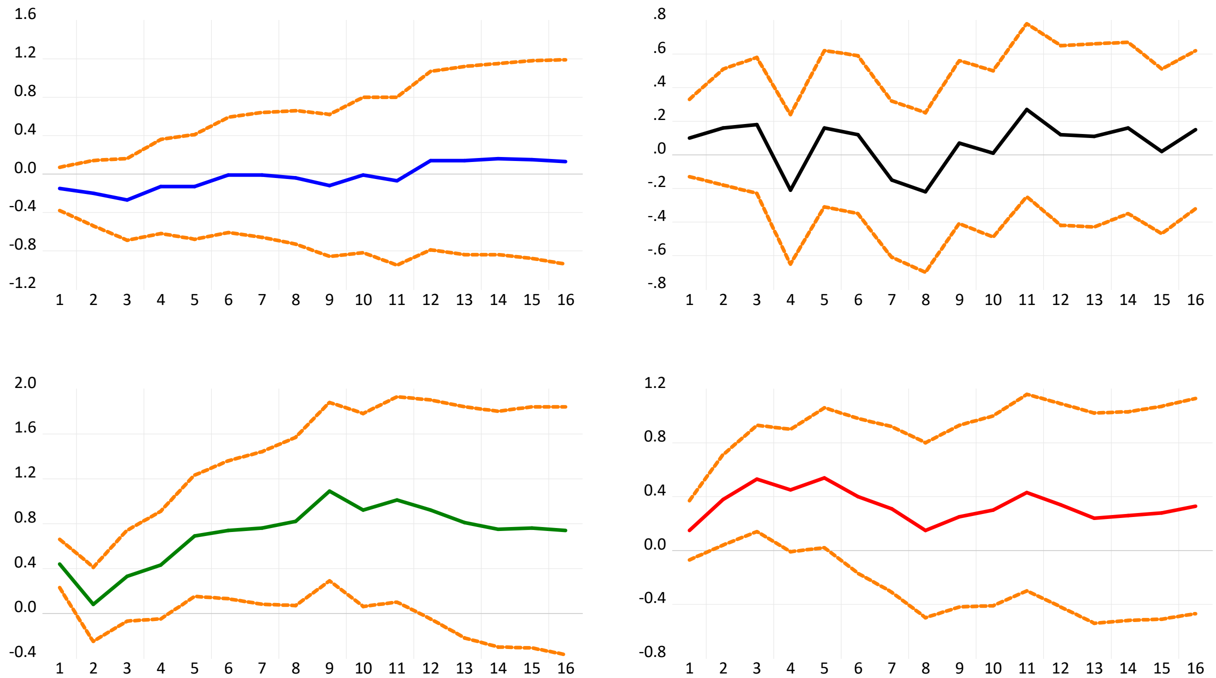


Figure 4: Differences in the accumulated responses of the labour share to structural shocks between the periods 1948Q1–1984Q4 and 1985Q1–2018Q3. These figures correspond to the cumulative responses of the first-differences of the labour share ($\Delta\psi_t$) to the structural shocks for the period 1985Q1–2018Q3 minus the ones for the period 1948Q1–1984Q4 (both shown in Figure 3). The differences in the cumulative responses of $\Delta\psi_t$ to a 1% aggregate demand shock, 1 percentage point labour supply shock, 1% wage bargaining shock and 1% productivity shocks between both subperiods are shown in blue, black, green and red, respectively. Orange dotted lines correspond to the respective bootstrapped 95% confidence intervals (5,000 replications in all cases). The horizontal axis shows quarters ahead in all figures.

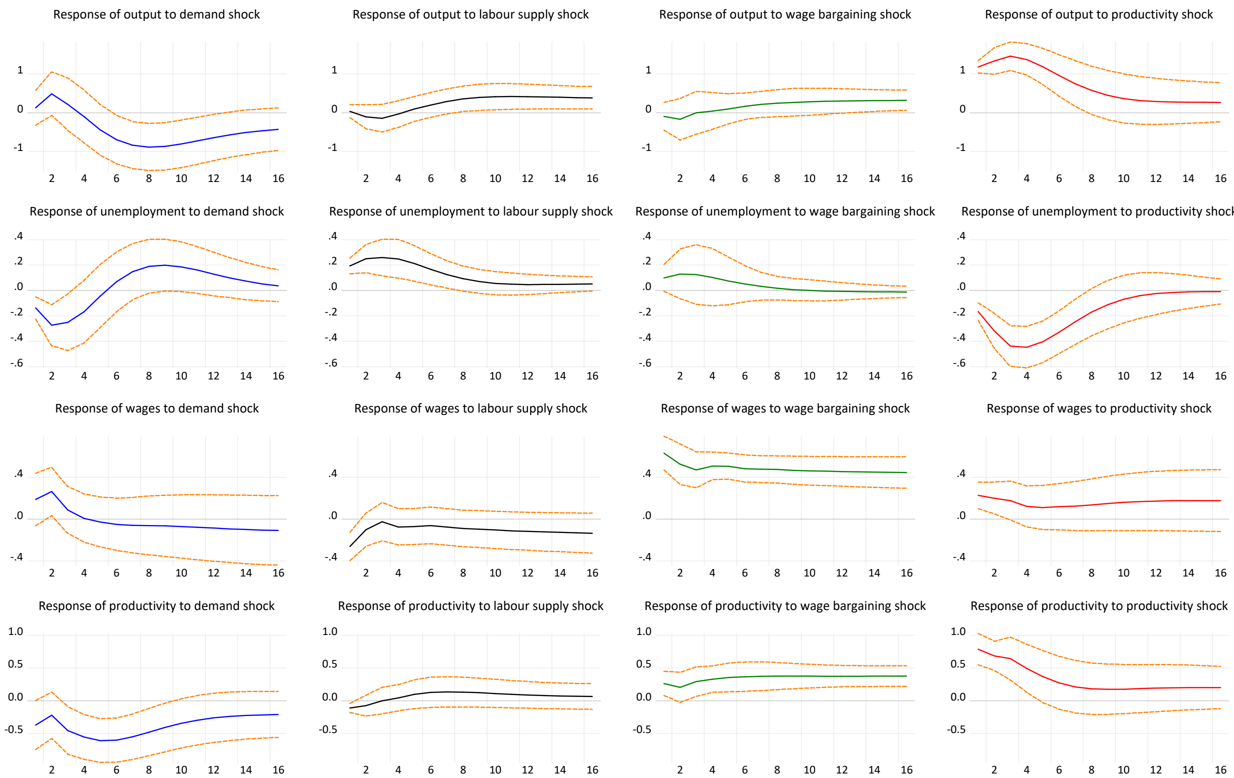


Figure 5: Impulse-responses derived from the SVAR model for the period 1948Q1–1984Q4 (considering all variables in levels). These figures show the impulse-responses obtained from the identification strategy based on model (6). The dynamic responses of the variables to a 1% aggregate demand shock, 1 percentage point labour supply shock, 1% wage bargaining shock and 1% productivity shock are shown in blue, black, green and red, respectively. Orange dotted lines correspond to the respective 95% asymptotic confidence intervals. The horizontal axis shows quarters ahead in all figures.

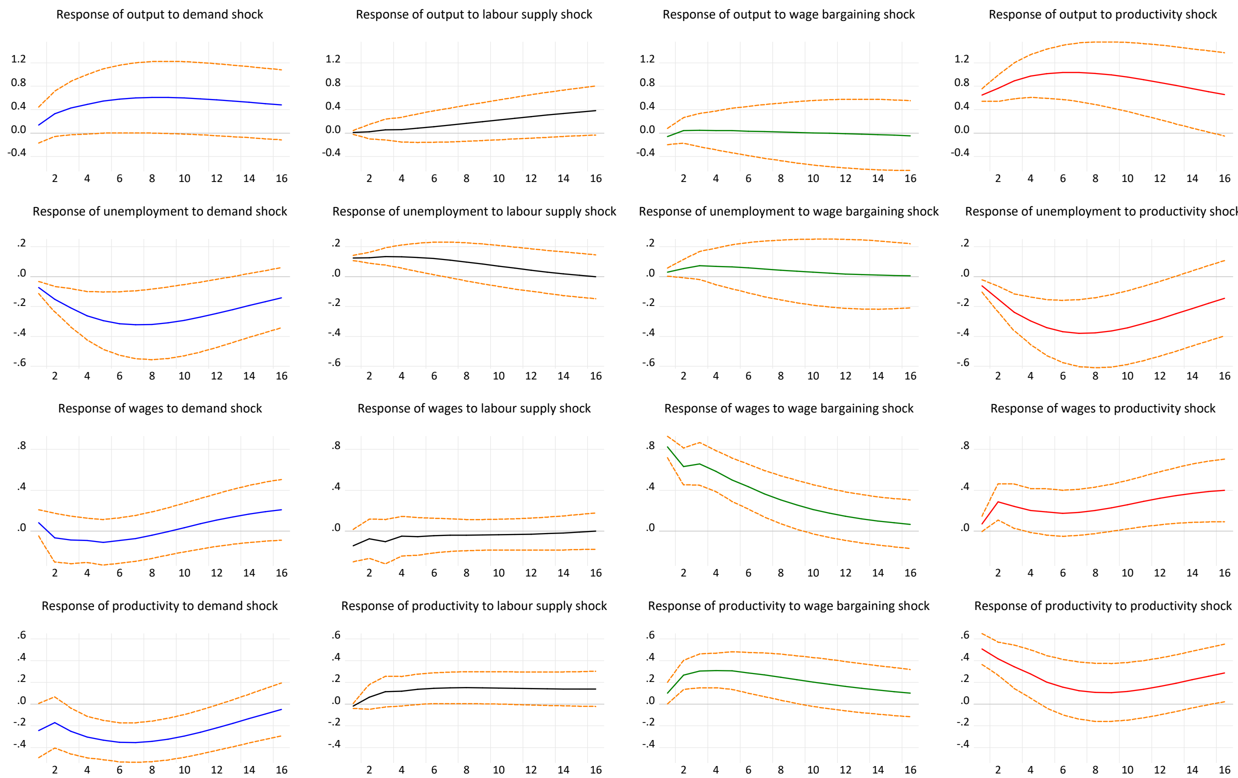
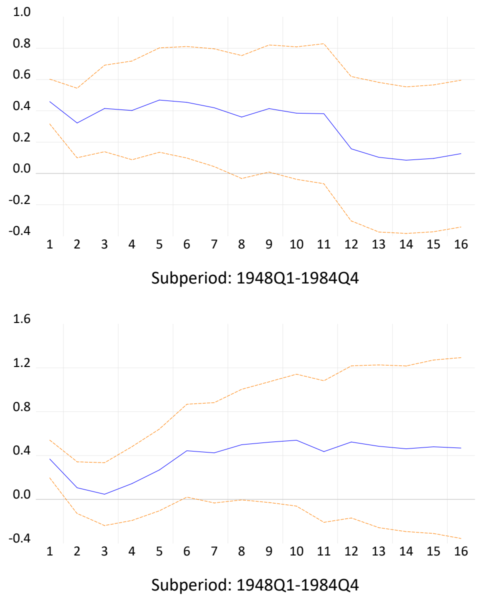
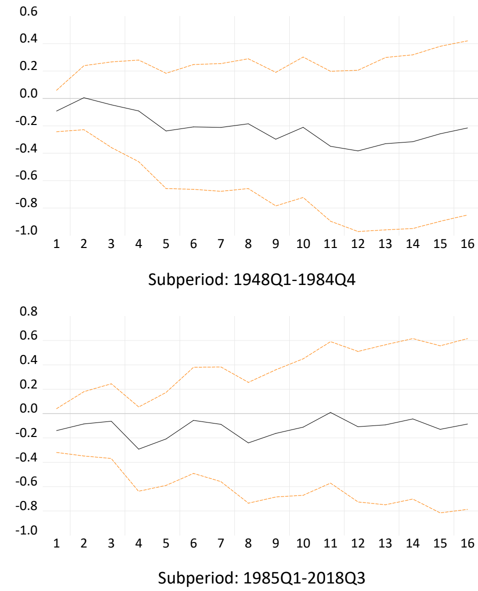


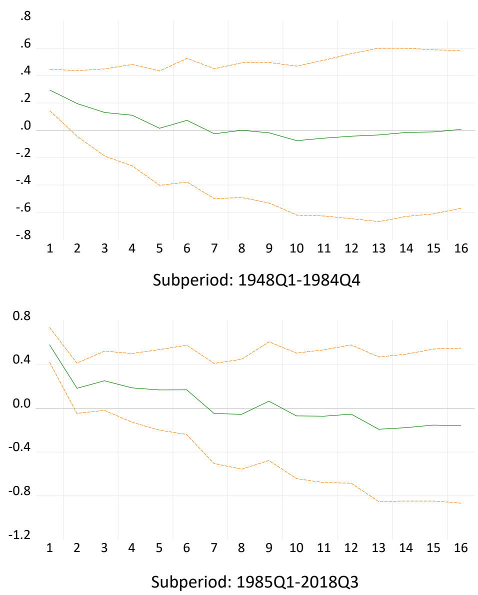
Figure 6: Impulse-responses derived from the SVAR model for the period 1985Q1–2018Q3 (considering all variables in levels). These figures show the impulse-responses obtained from the identification strategy based on model (6). The dynamic responses of the variables to a 1% aggregate demand shock, 1 percentage point labour supply shock, 1% wage bargaining shock and 1% productivity shock are shown in blue, black, green and red, respectively. Orange dotted lines correspond to the respective 95% asymptotic confidence intervals. The horizontal axis shows quarters ahead in all figures.



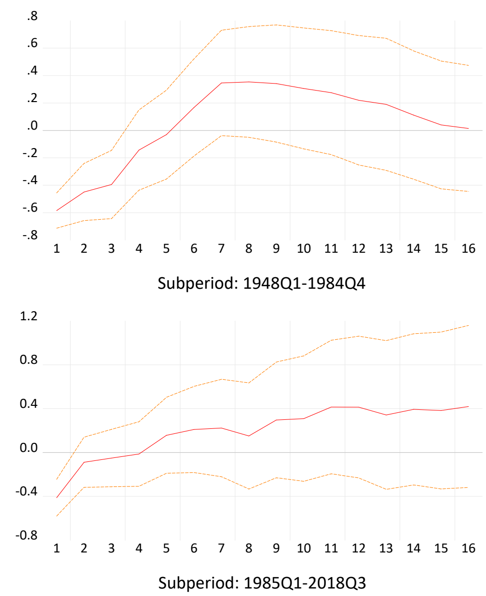
(a) Response of the labour share to a 1% aggregate demand shock



(b) Response of the labour share to a 1 percentage point labour supply shock



(c) Response of the labour share to a 1% wage bargaining shock



(d) Response of the labour share to a 1% productivity shock

Figure 7: Responses of the labour share to structural shocks for the subperiods 1948Q1–1984Q4 and 1985Q1–2018Q3. These figures correspond to the Impulse-Response Functions (IRFs) of the labour share (ψ_t) with respect to the different structural innovations. Orange dotted lines correspond to the respective bootstrapped 95% confidence intervals (5,000 replications in all cases). The horizontal axis shows quarters ahead in all figures.

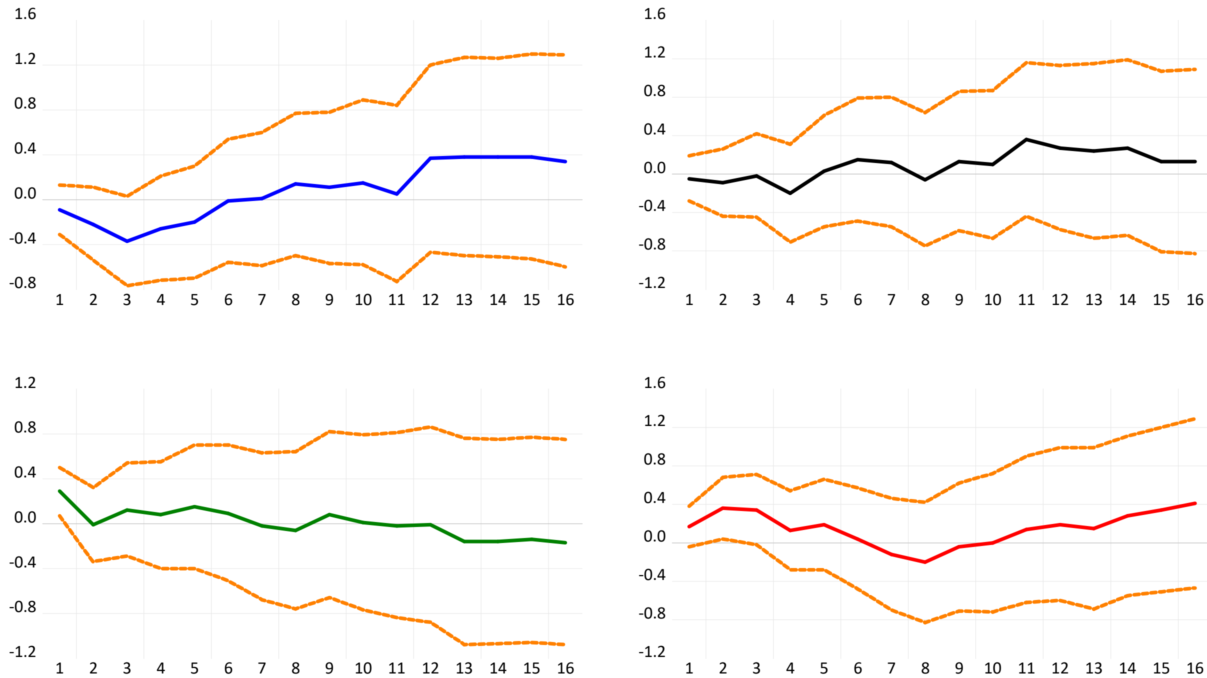
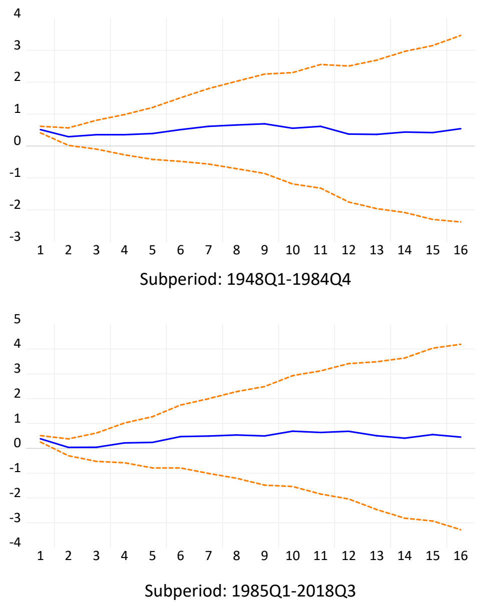
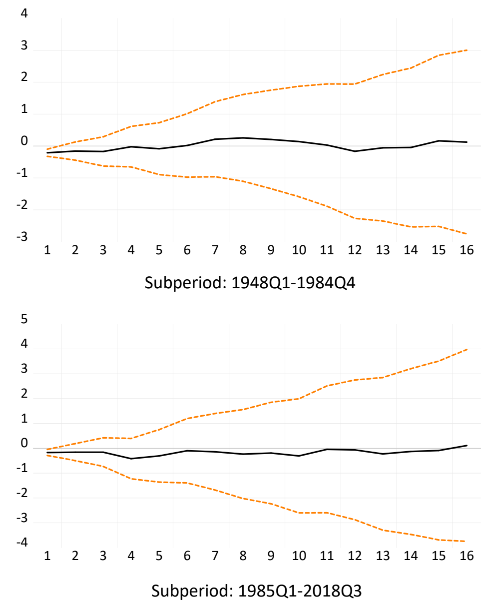


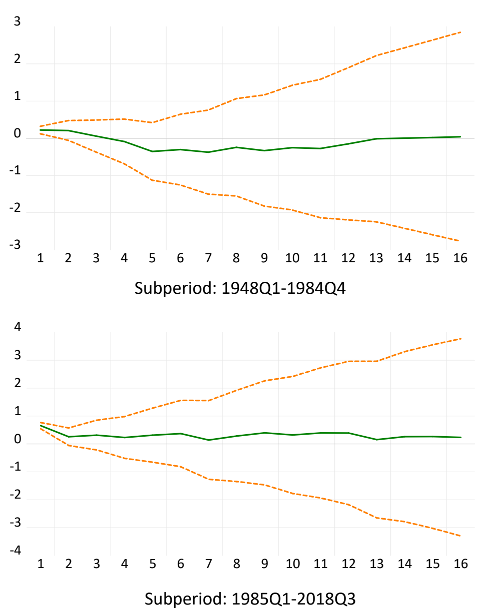
Figure 8: Differences in the responses of the labour share to structural shocks between the subperiods 1948Q1–1984Q4 and 1985Q1–2018Q3. These figures correspond to the responses of the labour share (ψ_t) to the structural shocks for the subperiod 1985Q1–2018Q3 minus the ones for the subperiod 1948Q1–1984Q4 (both shown in Figure 7). The differences in the responses of ψ_t to a 1% aggregate demand shock, 1 percentage point labour supply shock, 1% wage bargaining shocks and 1% productivity shocks between both subperiods are shown in blue, black, green and red, respectively. Orange dotted lines correspond to the respective bootstrapped 95% confidence intervals. The horizontal axis shows quarters ahead in all figures.



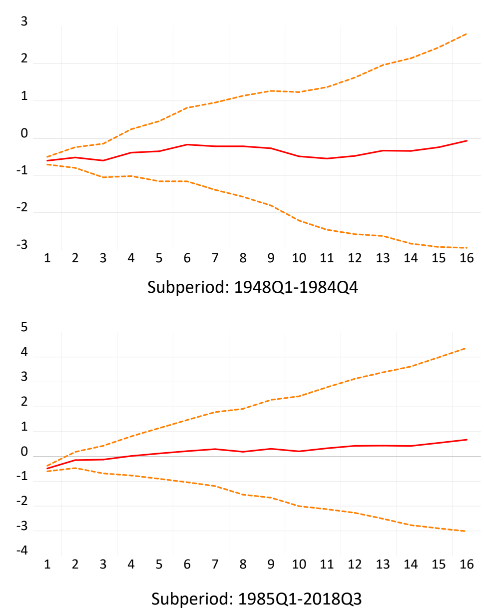
(a) Accumulated response of the labour share to a 1% aggregate demand shock



(b) Accumulated response of the labour share to a 1 percentage point labour supply shock



(c) Accumulated response of the labour share to a 1% wage bargaining shock



(d) Accumulated response of the labour share to a 1% productivity shock

Figure 9: Accumulated responses of the labour share to structural shocks for the periods 1948Q1–1984Q4 and 1985Q1–2018Q3 obtained via local projections. These figures correspond to the Cumulative Impulse-Response Functions (CIRFs) of the first-differences of the labour share ($\Delta\psi_t$) with respect to the different structural innovations obtained via local projections. Orange dotted lines correspond to the respective marginal 95% confidence intervals. The horizontal axis shows quarters ahead in all figures.

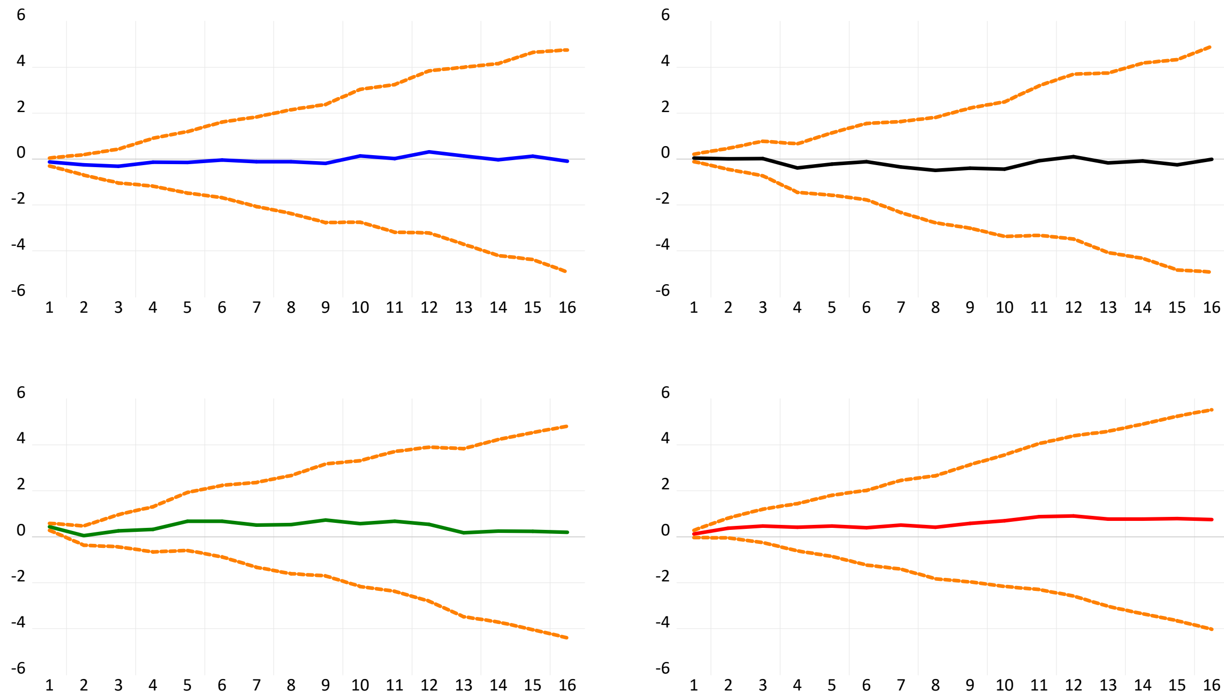
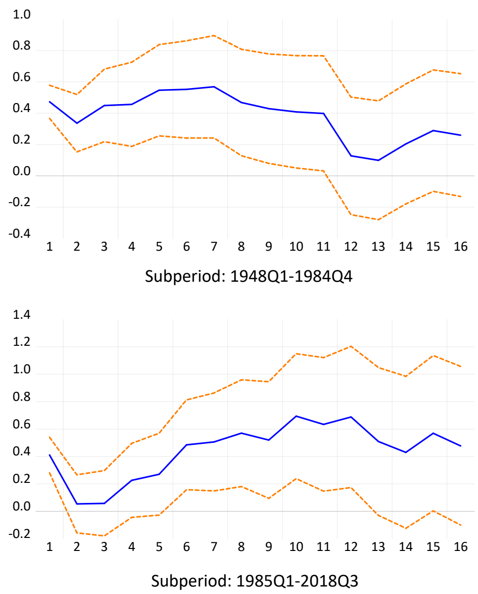
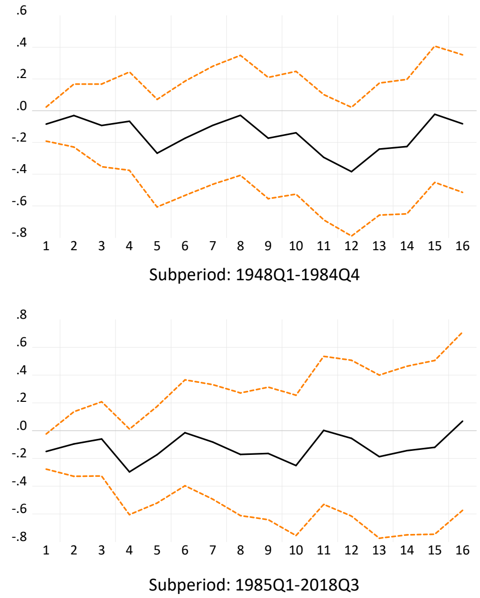


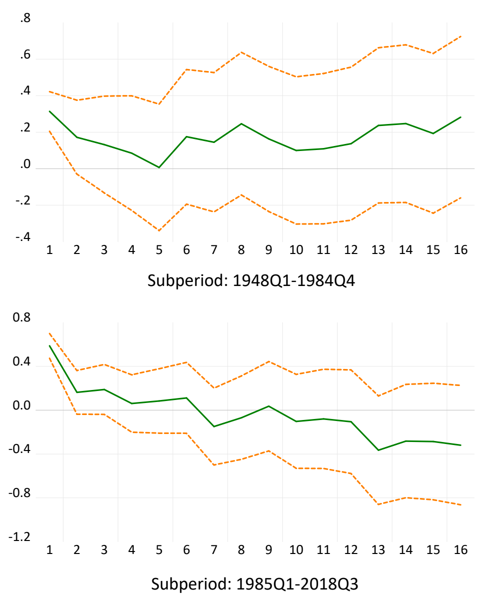
Figure 10: Differences in the accumulated responses of the labour share to structural shocks between the periods 1948Q1–1984Q4 and 1985Q1–2018Q3 obtained via local projections. These figures correspond to the cumulative responses of the first-differences of the labour share ($\Delta\psi_t$) to the structural shocks for the subperiod 1985Q1–2018Q3 minus the ones for the subperiod 1948Q1–1984Q4 obtained via local projections (both shown in Figure 9). The differences in the cumulative responses of $\Delta\psi_t$ to a 1% aggregate demand shock, 1 percentage point labour supply shock, 1% wage bargaining shock and 1% productivity shocks between both subperiods are shown in blue, black, green and red, respectively. Orange dotted lines correspond to the respective marginal 95% confidence intervals. The horizontal axis shows quarters ahead in all figures.



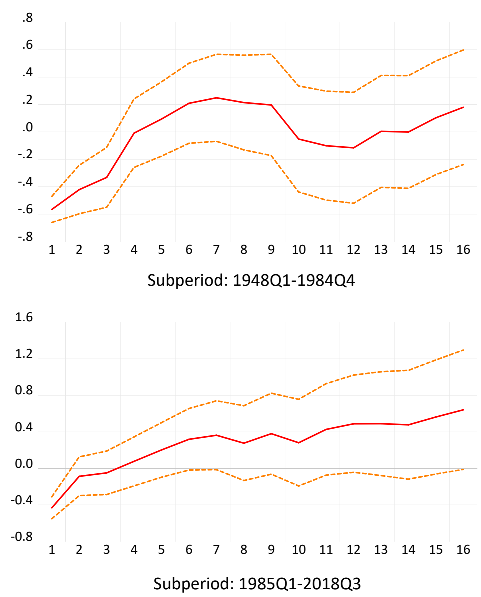
(a) Response of the labour share to a 1% aggregate demand shock



(b) Response of the labour share to a 1 percentage point labour supply shock



(c) Response of the labour share to a 1% wage bargaining shock



(d) Response of the labour share to a 1% productivity shock

Figure 11: Responses of the labour share to structural shocks for the subperiods 1948Q1–1984Q4 and 1985Q1–2018Q3 obtained via local projections. These figures correspond to the Impulse-Response Functions (IRFs) of the labour share (ψ_t) with respect to the different structural innovations obtained via local projections. Orange dotted lines correspond to the respective marginal 95% confidence intervals. The horizontal axis shows quarters ahead in all figures.

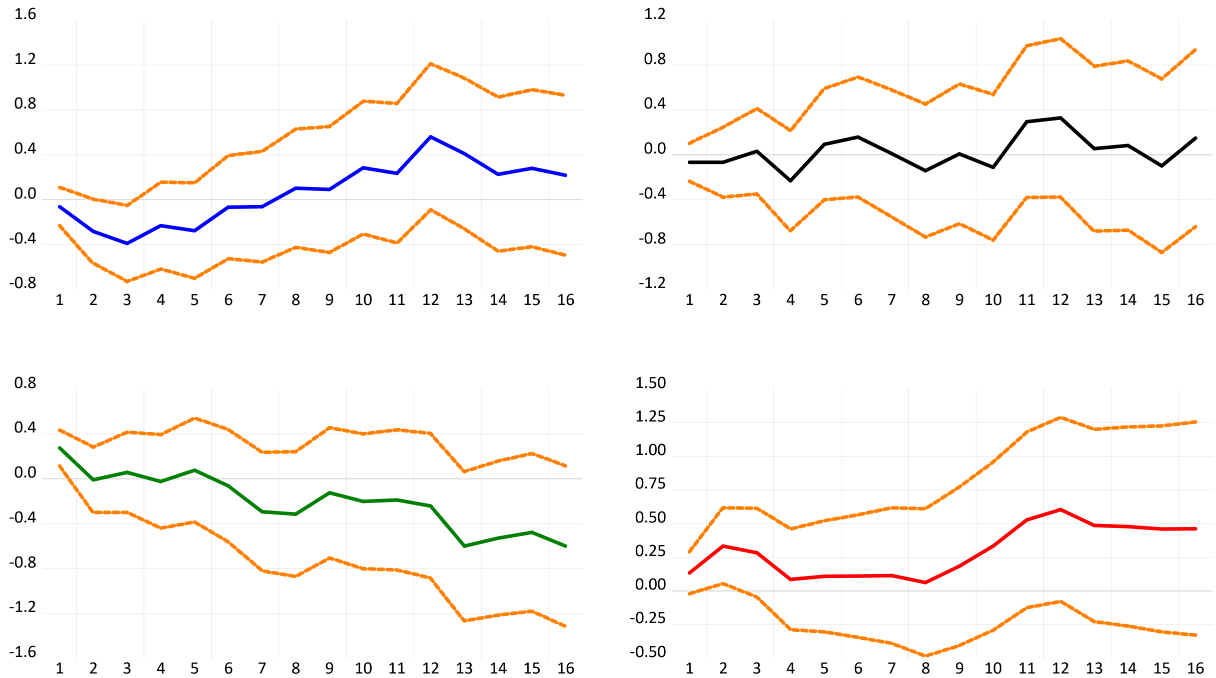
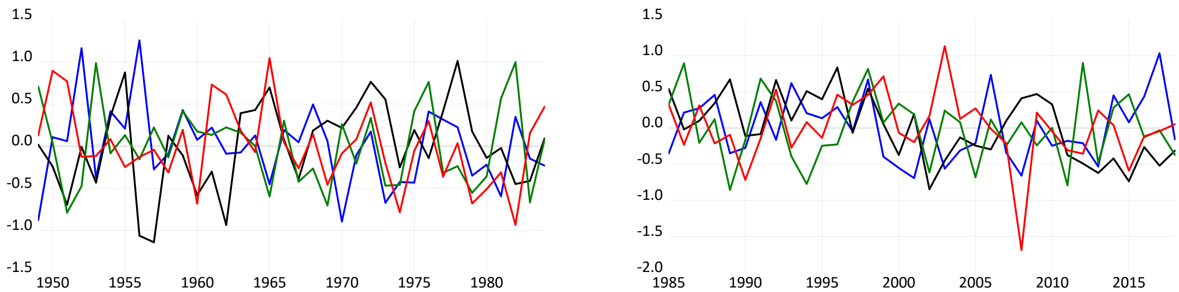


Figure 12: Differences in the responses of the labour share to structural shocks between the subperiods 1948Q1–1984Q4 and 1985Q1–2018Q3 obtained via local projections. These figures correspond to the responses of the labour share (ψ_t) to the structural shocks obtained using local projections for the subperiod 1985Q1–2018Q3 minus the ones for the subperiod 1948Q1–1984Q4 (both shown in Figure 11). The differences in the responses of ψ_t to a 1% aggregate demand shock, 1 percentage point labour supply shock, 1% wage bargaining shocks and 1% productivity shocks between both subperiods are shown in blue, black, green and red, respectively. Orange dotted lines correspond to the respective marginal 95% confidence intervals. The horizontal axis shows quarters ahead in all figures.

A Evolution of the structural shocks

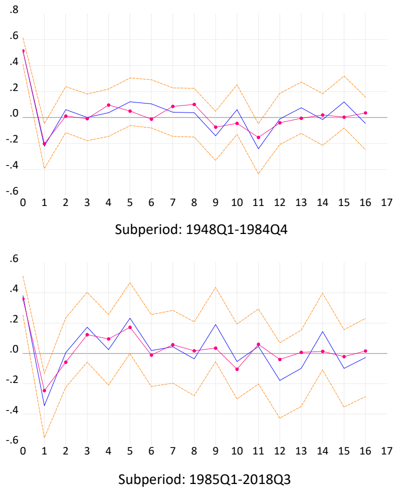


(a) Subperiod: 1948–1984

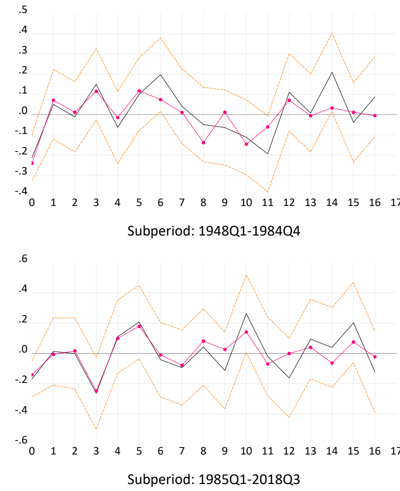
(b) Subperiod: 1985–2018

Figure A.1: USA. Historical evolution of the structural shocks in the two subperiods. These figures correspond to the structural residuals implied by the identification strategy presented in model (6), averaged to annual frequencies. In the left panel, the first year (1948) is hence not included. The structural innovations are presented as follows: aggregate demand shock is shown in blue, labour supply shock is shown in black, wage bargaining shock is shown in green, and productivity shock is shown in red.

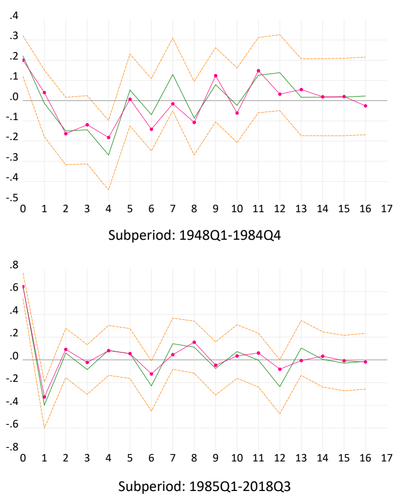
B Impulse-response functions obtained via Local Projections and Vector Autoregressions



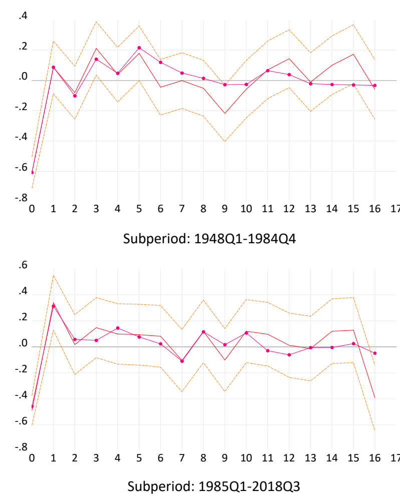
(a) Response of the labour share to a 1% aggregate demand shock



(b) Response of the labour share to a 1 percentage point labour supply shock

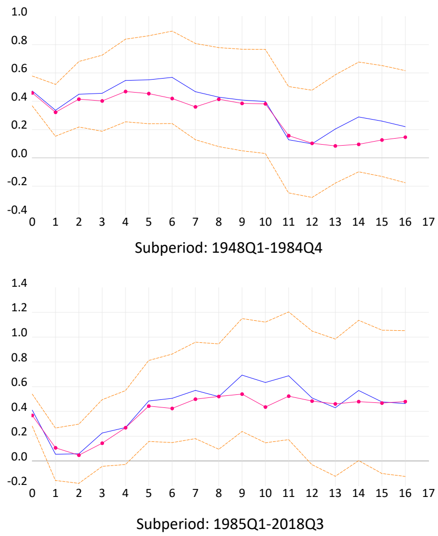


(c) Response of the labour share to a 1% wage bargaining shock

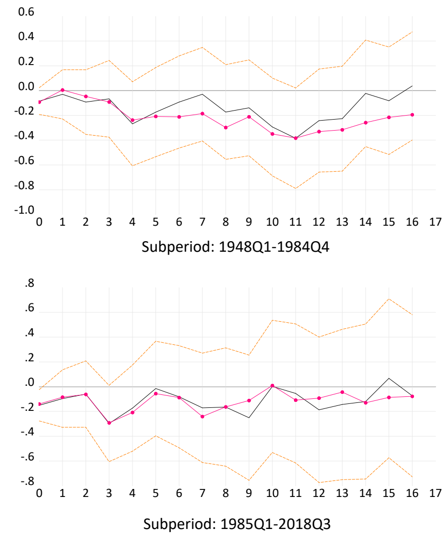


(d) Response of the labour share to a 1% productivity shock

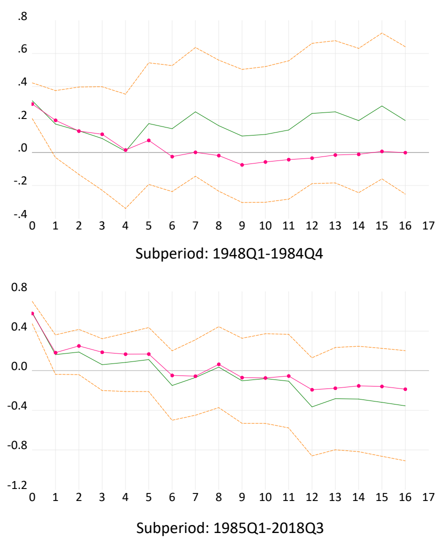
Figure B.1: Comparison of the impulse-responses of the first-differences of the labour share ($\Delta\psi_t$) to structural shocks for the subperiods 1948Q1–1984Q4 and 1985Q1–2018Q3 obtained via local projections and Vector Autoregressions. These figures correspond to the Impulse-Response Functions (IRFs) of $\Delta\psi_t$ with respect to the different structural innovations obtained via local projections and Vector Autoregressions. Orange dotted lines correspond to the respective marginal 95% confidence intervals around the local projections estimates. Pink straight lines with circles correspond to the VAR IRFs used to construct the Cumulative IRFs shown in Figure 3. The horizontal axis shows quarters ahead in all figures.



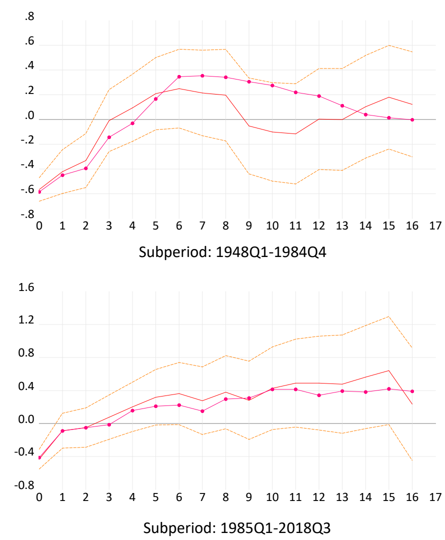
(a) Response of the labour share to a 1% aggregate demand shock



(b) Response of the labour share to a 1 percentage point labour supply shock



(c) Response of the labour share to a 1% wage bargaining shock



(d) Response of the labour share to a 1% productivity shock

Figure B.2: Comparison of the impulse-responses of the labour share (ψ_t) to structural shocks for the subperiods 1948Q1–1984Q4 and 1985Q1–2018Q3 obtained via local projections and Vector Autoregressions. These figures correspond to the Impulse-Response Functions (IRFs) of ψ_t with respect to the different structural innovations obtained via local projections and Vector Autoregressions. Orange dotted lines correspond to the respective marginal 95% confidence intervals around the Local Projections estimates. Pink straight lines with circles correspond to the VAR IRFs shown in Figure 7. The horizontal axis shows quarters ahead in all figures.