BANK OF ENGLAND

Appendix to Staff Working Paper No. 857

The missing link: monetary policy and the labor share

Cristiano Cantore, Filippo Ferroni and Miguel León-Ledesma

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Appendix A: Main Data Sources and Constructions

In this section we describe the data construction and source separately for each country.

A.1. US

The seven measures used for the US are constructed using data from the BLS and the BEA NIPA Tables for the time period 1955:Q1-2015:Q3 and are as follows:

1. *Labor share 1*: Labor share in the non-farm business sector. This is taken directly from BLS.[1] The series considers only the non-farm business sector. It calculates the labor share as compensation of employees of the non-farm business sector plus imputed self-employment income over gross value added of the non-farm business sector. Self-employment imputed income is calculated as follows: an implicit wage is calculated as compensation over hours worked and then the imputed labor income is the implicit wage times the number of hours worked by the self-employed.
2. *Labor share 2*: Labor share in the domestic corporate non-financial business sector. This follows Gomme and Rupert (2004) first alternative measure of the labor share. The use of data for the non-financial corporate sector only has the advantage of not having to apportion proprietors income and rental income, two ambiguous components of factor income. It also considers the wedge introduced between the labor share and one minus the capital share by indirect taxes (net of subsidies), and only makes use of unambiguous components of capital income. This approach also takes into account the definition of aggregate output in constructing the labor share. Usually we use GDP in constructing measures of the Labor share (as we do for some of the other proxies), however sectoral studies often use gross value added (GVA) (see Bentolila and Saint-Paul (2003), Young (2010) and Young (2013)). Valentinyi and Herrendorf (2008) and Muck et al. (2015) show that factor shares in value added differ systematically from factor income shares in GDP, albeit with annual data. By considering gross value added net interest and miscellaneous payments (NI_t^{gva}, NIPA Table 1.14), gross value added corporate profits (CP_t^{gva}, NIPA Table 1.14), net value added (NVA_t, NIPA Table 1.14) and gross value added taxes on production and imports less subsidies (Tax_t^{gva}, NIPA Table 1.14) the labor share is thus calculated as:

$$\textbf{Labor Share 2}: LS_t = 1 - \frac{CP_t^{gva} + NI_t^{gva} - Tax_t^{gva}}{NVA_t}.$$

1. FRED series PRS85006173 provided as an index number.

3. *Labor share 3*: This approach deals with imputing ambiguous income for the macroeconomy and corresponds to the second alternative measure of the labor share proposed in Gomme and Rupert (2004). The measure excludes the household and government sectors. They define unambiguous labor income (Y^{UL}) as compensation of employees, and unambiguous capital income (Y^{UK}) as corporate profits, rental income, net interest income, and depreciation (same series as above from NIPA Tables 1.12 and 1.7.5). The remaining (ambiguous) components are then proprietors' income plus indirect taxes net of subsidies (NIPA Table 1.12). These are apportioned to capital and labor in the same proportion as the unambiguous components. The resulting labor share measure is:

$$\textbf{Labor Share 3}: LS_t = \frac{CE_t}{CE_t + RI_t + CP_t + NI_t + \delta_t} = \frac{Y^{UL}}{Y^{UK} + Y^{UL}}.$$

4. *Labor share 4*: This is the same as the above *Labor Share 3* but not corrected for inventory valuation adjustment and an adjustment for capital consumption. Using rental income of persons (without CCAdj) (RI_t^a, NIPA Table 1.12) and corporate profits before tax (without IVA and CCAdj) (CP_t^a, NIPA Table 1.12):

$$\textbf{Labor Share 4}: LS_t = \frac{CE_t}{CE_t + RI_t^a + CP_t^a + NI_t + \delta_t} = \frac{Y^{UL}}{Y^{UK} + Y^{UL}}.$$

5. *Labor share 5*: Follows Cooley and Prescott (1995) in dealing with the issue of how to input mixed income. The labor share of income is defined as one minus capital income divided by output. To deal with mixed income, they assume that the proportion of ambiguous capital income to ambiguous income is the same as the proportion of unambiguous capital income to unambiguous income. It decomposes total income into two components: ambiguous income (AI_t) and unambiguous income (UI_t). AI_t is the sum of proprietors income (PI_t, NIPA table 1.12), taxes on production less subsidies ($Tax_t - Sub_t$, NIPA Table 1.12), business current transfer payments ($BCTP_t$, NIPA Table 1.12) and statistical discrepancy ($Sdis_t$, NIPA Table 1.12). UI_t instead can be easily separated into labor income (CE_t) and capital income (UCI_t) which consists of rental income (RI_t, NIPA Table 1.12), net interests (NI_t, NIPA Table 1.12), current surplus of government enterprises (GE_t, NIPA Table 1.12), and corporate profits (CP_t, NIPA Table 1.12). Using capital depreciation (δ_t, Consumption of fixed capital NIPA TABLE 1.7.5) we can construct the share of capital in unambiguous income (CS_t^U):

$$CS_t^U = \frac{UCI_t + \delta_t}{UI_t} = \frac{RI_t + NI_t + GE_t + CP_t + \delta_t}{RI_t + NI_t + GE_t + CP_t + \delta_t + CE_t}$$

Here the key assumption is that the share of capital/labor in ambiguous income is the same as in unambiguous income,

$$ACI_t = CS_t^U AI_t.$$

$$\textbf{Labor Share 5}: LS_t = 1 - CS_t = 1 - \frac{UCI_t + \delta_t + ACI_t}{GNP_t}$$

where we use Gross National Product instead of GDP (GNP_t, NIPA Table 1.7.5).

6. *Labor share 6*: Is taken from Fernald (2012) and it's utilization adjusted quarterly series. In computing the capital share he assumes that the non-corporate sector has the same factor shares as the corporate non-financial sector.
7. *Labor share 7*: Labor share in the non-finanical corporation sector. This is taken directly from BLS (FRED series id PRS88003173 provided as an index number). The series considers only the non-finanical corporations sector.

The remaining US variables are downloaded from the FRED database and their series ID is in parenthesis unless specified differently. For GDP we use Real Gross Domestic product (GDPC1). GDP deflator is the implicit price deflator of gross domestic product (GDPDEF). For CPI we used Consumer Price Index for All Urban Consumers and all Items for US (CPIAUCSL). For the price of commodity index we used the same CRB SPOT commodity index used by Olivei and Tenreyro (2007) and downloaded from datastream. Real wage is constructed as Wages and Salaries from NIPA 1.12 deflated by GDP Deflator and divided by hours worked in the total economy from the BLS. Labor productivity is the ratio between GDP and total hours from BLS. TFP is the measure of Utilization Adjusted TFP constructed in Fernald (2012) while credit spread is the corporate bond spread described in Gilchrist and Zakrajsek (2012). Money growth, used for sign restrictions, is the M2 for United states from the IMF database in log difference (MYAGM2USM052N). Federal Funds rates are downloaded from FRED database. Time span of the VAR analysis is the great moderation period in US, i.e. 1984Q1 to 2007Q4.

A.2. Australia

We use quarterly data for the 1959:Q3-2016:Q1 from the Australian Bureau of Statistics. We construct five alternative measures of labor share. The first two are total wages and salaries (including social security contributions) over GDP (AUS_LS1) or over total factor income (AUS_LS2). The third one is one minus gross operating surplus of private non-financial corporations as a percentage of total factor income (AUS_LS3). Fourth, one minus gross operating surplus of private non-financial corporations plus all financial corporations as a percentage of total factor income (AUS_LS4). The last measure is given by (total income minus surplus of all corporations minus gross operating surplus of government minus mixed income imputed to capital)/total income (AUS_LS5). For Real GDP and its deflator we use data from the OECD quarterly national accounts. For CPI we used OECD consumer prices of all goods and also the short term interest rates come from the OECD database. For the price of commodity index we used the same index used for the other countries. Money growth, used for sign restrictions, is constructed using money supply downloaded from datastream. Real wages are constructed by dividing nominal compensation of employees by the GDP deflator and the measure of total hours worked constructed by Ohanian and Raffo (2012). Time span for the VAR analysis is 1985:Q1-2009:Q4.

A.3. Canada

We consider quarterly data for the 1981:Q2-2016:Q1 period from Statistics Canada. We used two alternative measures. First, compensation of employees over total factor income (GDP corrected by taxes and subsidies) (CAN_LS1). Second, we imputed mixed income in the same proportion as unambiguous labor and capital income, and added it to the previous measure of labor income (CAN_LS2). For Real GDP and its deflator we use data from the OECD quarterly national accounts. For CPI we used OECD consumer prices of all goods and also the short term interest rates come from the OECD database. For the price of commodity index we used the same index used for the other countries. Money growth, used for sign restrictions, is constructed using money supply downloaded from datastream. For real wages we divide nominal compensation of employees by the GDP Deflator and the measure of total hours worked constructed by Ohanian and Raffo (2012). Time span for the VAR analysis is 1985:Q1-2011:Q1.

A.4. UK

Quarterly data for the 1971:Q1-2016:Q1 period from the Office for National Statistics (ONS). We used one measure of the labor share: compensation of employees (DTWM) over gross value added at factor costs (CGCB) (UK_LS). From the ONS we take Gross Domestic Product: chained volume measures: Seasonally adjusted (ABMI) and Implied deflator for Gross domestic product at market prices (YBGB). From the OECD we take the CPI of all items and the short term interest rates. The price of commodity index is the same used for the other countries. Money growth, used for sign restrictions, is constructed using money supply downloaded from datastream. Real wages are constructed by dividing nominal compensation of employees by the GDP Deflator and the measure of total hours worked constructed by Ohanian and Raffo (2012). Time span for the VAR analysis is 1986:Q1-2008:Q1.

A.5. EA

We take most of the data from the Area Wide Model database, where we use the following variables, real GDP and the GDP deflator, HICP excluding energy (seasonally adjusted) and the Short-term interest. The price of commodity index is the same used for the other countries. Money growth, used for sign restrictions, is taken from the IMF database on FRED (MYAGM2EZQ196N). We used one measure of the labor share: compensation of employees over GDP at factor costs. Real wages are given by nominal compensation of employees (from OECD Quarterly National Accounts) divided by the GDP Deflator and the measure of total employment from the New Area Wide Model Database. Time span of the VAR analysis is 1999Q1 to 2011Q3.

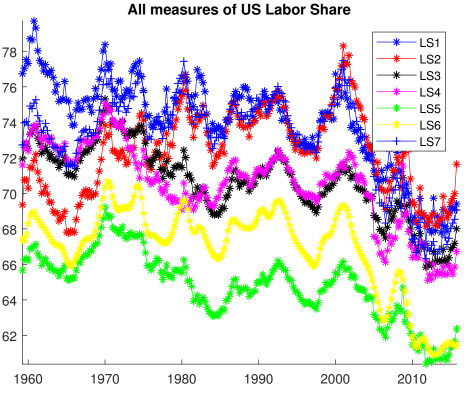
A.6. Monetary Policy instruments

In this section we describe in details the various proxy variables used for the monetary policy surprise. Some of these proxy variables are available at monthly frequency. In that case, we transformed into quarterly series by taking the cumulative sum, then computing the difference between the last months of adjacent quarters, e.g. December and September, March and December, June and March and September and June.

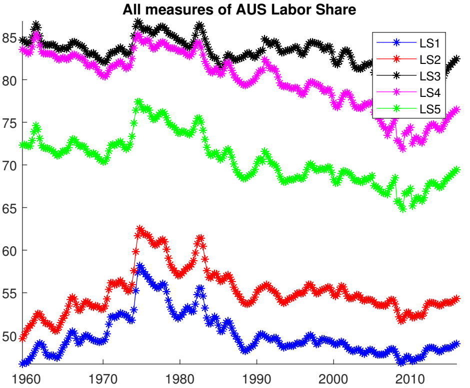
For the US, we considered three different proxies for the monetary policy surprise: the Romer and Romer (2004) narrative monetary policy shock (R&R), the Gertler and Karadi (2015) high frequency variations in current FFR around MP announcements (G&K) and the Miranda-Agrippino (2016) high frequency variation of the current FFR adjusted for the information set (or signaling effect) of FOMC (MIR).[2] The rationale behind the choice of these instruments is based on the consideration that they are constructed using slightly different information sets; e.g. the R&R narrative instrument based on FOMC minutes and other quantitative records; the G&K high frequency variations in federal funds rate in a narrow window around the FOMC monetary policy communications; the MIR is the component of the high frequency variation of the federal funds rate which is orthogonal to Greenbook and data records available before the FOMC decision. For Canada, we considered as external instrument the monetary policy surprise constructed by Champagne and Sekkel (2018) based on Bank of Canada's staff projections. For the EA, we considered the MP surprise in Andrade and Ferroni (2016) which is constructed as follows. Minute-by-minute midquote observations of EONIA Overnight Indexed Swap contracts (OIS) of maturities between 1 month and 2 years are considered around the time when monetary policy decisions are

2. We also considered the Smets and Wouters (2007) DSGE estimated monetary policy shock and the target factor in the Gürkaynak et al. (2005) HF identification; when adding them results do not change.

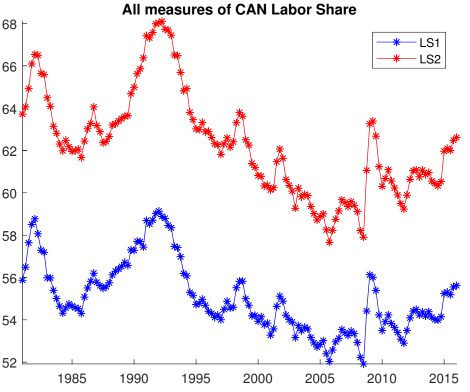
publicly released. The ECB communicates its decision in the following way: a monetary policy decision statement is first released at 1:45pm CET. It is then followed by a press conference with the ECB's President which begins around 2:30pm CET and lasts for about one hour. We compute the difference of OIS forward rates using five-minute averages ten minutes before the ECB interest rate communication and 20 minutes after the end of the press conference. The sample covers only the scheduled Governing Councils in between January 2002 to January 2015. The changes in the term structure of OIS futures is summarized following Gürkaynak et al. (2005)'s methodology by taking first principal components. After standardizing the variations, the first principal component is our measure of monetary policy surprise. For the UK, we considered as external instrument the monetary policy surprise constructed by Cloyne and Hürtgen (2016) where they employ a Romer-Romer identification approach to the UK experience.



(A) US



(B) Australia



(C) Canada

FIGURE A1. Labor share proxies for US, Australia and Canada.

Appendix B: VAR Robustness

VAR reduced form parameters and impulse response functions are estimated using the MATLAB toolbox discussed in Ferroni and Canova (2020). The response of the labor share after a monetary policy tightening under different information set, time span, labor share proxies and identification scheme are summarized in Table B1.

TABLE B1. Summary of the robustness exercises with the VAR model.

Country	**Info set**	**Sample**	**Identification**	**Reference**	**Positive LS IRF**
US	Baseline	84-07	Recursive	Figure B3	Yes
	Various LS proxy		Recursive	Figure B4	Yes
	Extended		Recursive	Figure B5	Yes
	Baseline*		Signs	Figure B2	Yes
	Baseline		Instruments	Figure B1	Yes
	Baseline	65-07; 65-95	Recursive	Figures B6-B7	Yes
EA	Baseline	99-11	Recursive	Figure B3	Yes
	Baseline		Signs	Figure B2	Yes
	Baseline		Instrument	Figure B8	Yes
UK	Baseline	86-08	Recursive	Figure B3	Yes
	Baseline		Signs	Figure B2	Yes
	Baseline	72-08	Instrument	Figure B9	Yes
CAN	Baseline	85-11	Recursive	Figure B3	Yes
	Various LS proxy		Recursive	Figure B11	Yes
	Baseline		Signs	Figure B2	Yes
	Baseline		Instrument	Figure B10	Yes
AUS	Baseline	85-09	Recursive	Figure B3	Yes
	Various LS proxy		Recursive	Figure B12	Yes but one
	Baseline		Signs	Figure B2	Yes

Baseline includes log of real GDP, the log of the GDP deflator, the log of an index of commodity prices, log of the CPI, log of real wages, the log of the labor share and short term interest rates.
*Baseline** includes the baseline variables and M2 which is used for identification using sign restrictions.
Extended includes the baseline variables plus the Fernald (2012) measure of Utilization Adjusted TFP, Labor Productivity and the Gilchrist and Zakrajsek (2012)) corporate bond spread.
US Instruments: Romer and Romer (2004), Gertler and Karadi (2015) and the Miranda-Agrippino (2016).
UK Instruments: Cloyne and Hürtgen (2016).
CAN Instruments: Champagne and Sekkel (2018).
EA Instruments: Andrade and Ferroni (2016).

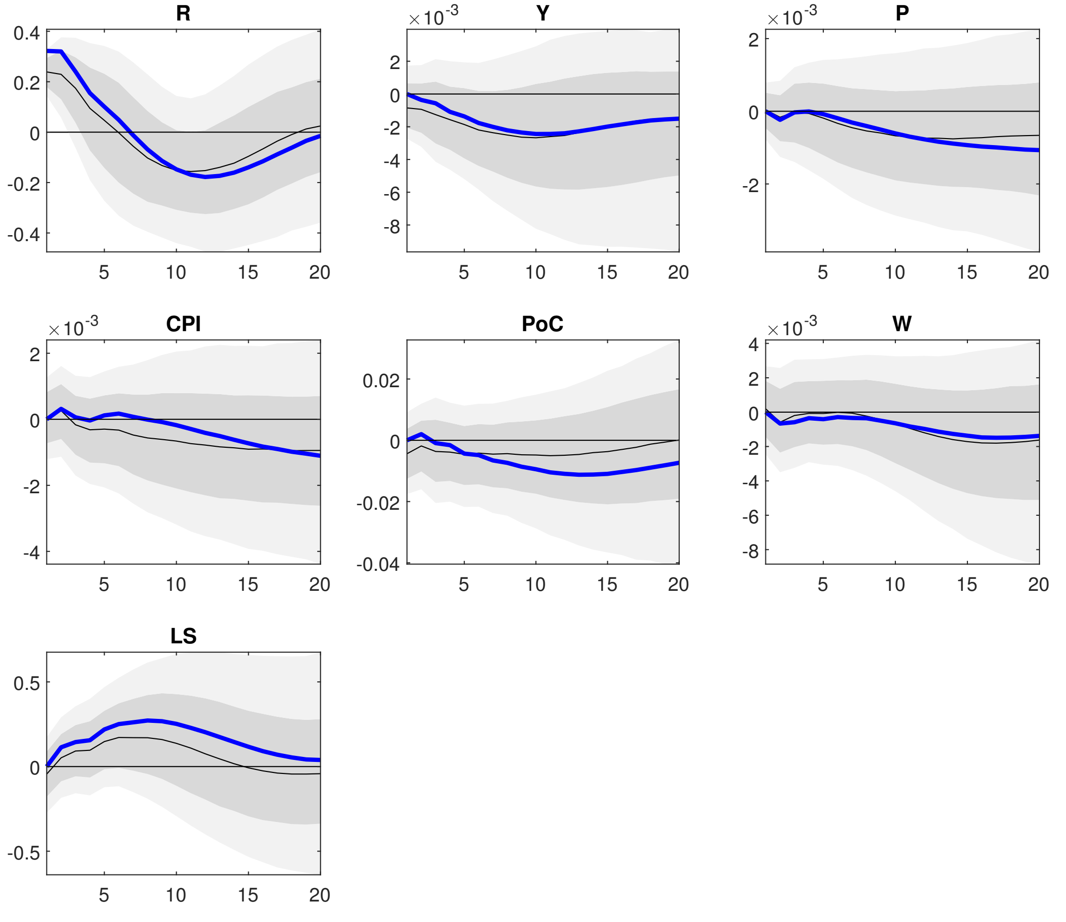


FIGURE B1. Impulse Response Function to a one standard deviation increase in the short term interest rate using an identification scheme based on **proxy variables or instruments** for the shock of interest. We considered three different proxies for the monetary policy surprise jointly: the Romer and Romer (2004) narrative, the Gertler and Karadi (2015) high frequency variations in interest rates around MP announcements and the Miranda-Agrippino (2016) high frequency variation adjusted for the information set (or signaling effect) of FOMC. Light (dark) gray 90% (68%) bands. The blue line reports the median IRF using a recursive identification scheme. US data

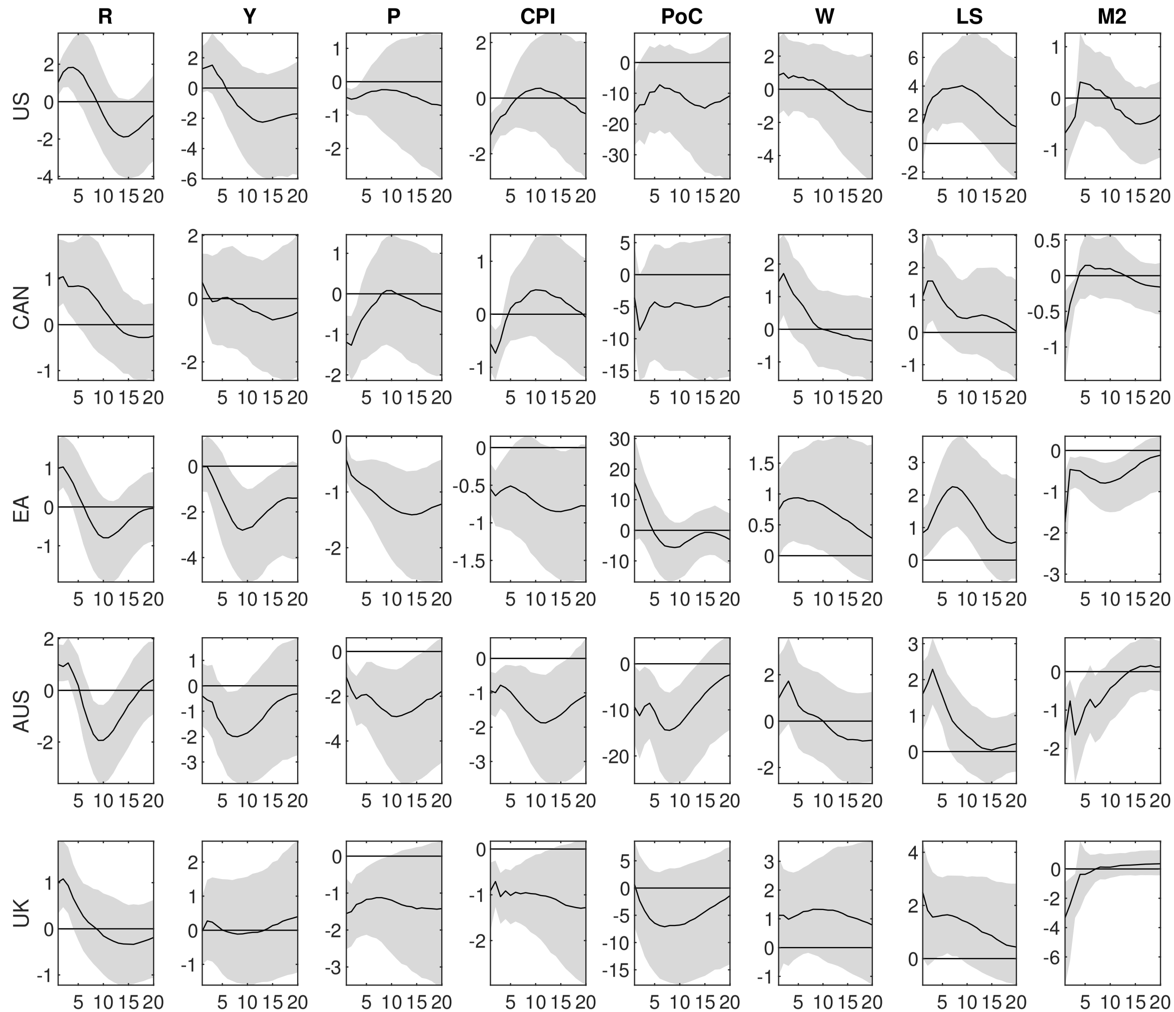


Figure B2. Impulse Response Function normalized to a 1% increase in the short term interest rate an identification scheme based on sign restrictions. From left to right, interest rate, (log of) real GDP, price deflator, CPI, Price of Commodities, real wages, labor share and M2. From top to bottom US, Euro Area, Australia, Canada and United Kingdom. Dark gray areas indicate 68% bands.

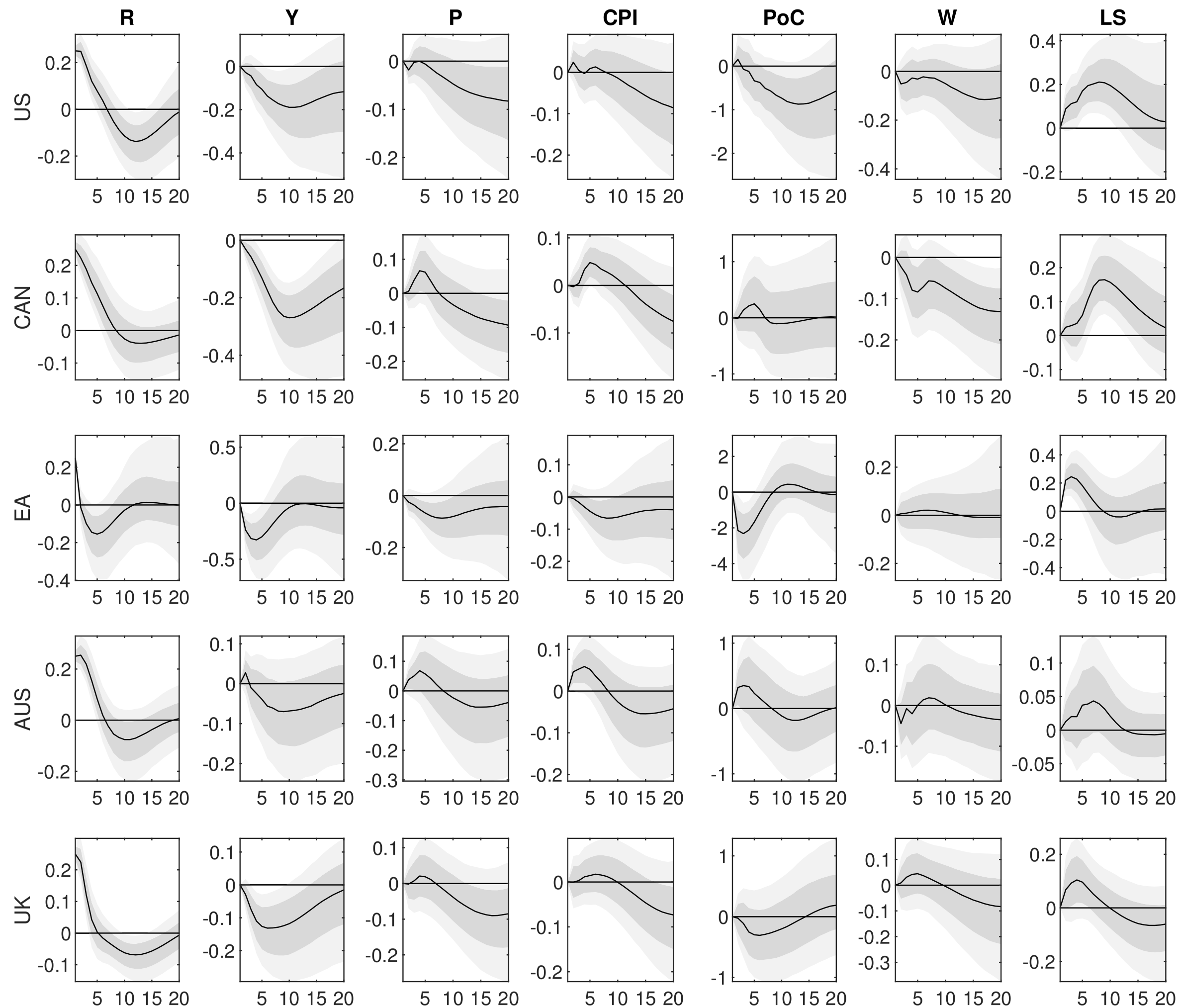


FIGURE B3. Impulse Response Functions normalized to a 1% percent increase in the short term nominal interest rate using an identification **recursive Cholesky** and the baseline variables specification. From left to right, interest rate, (log of) real GDP, price deflator, CPI, Price of Commodities, real wages and labor share. From top to bottom US, Euro Area, Australia, Canada and United Kingdom. Light (dark) gray areas indicate 90% (68%) bands.

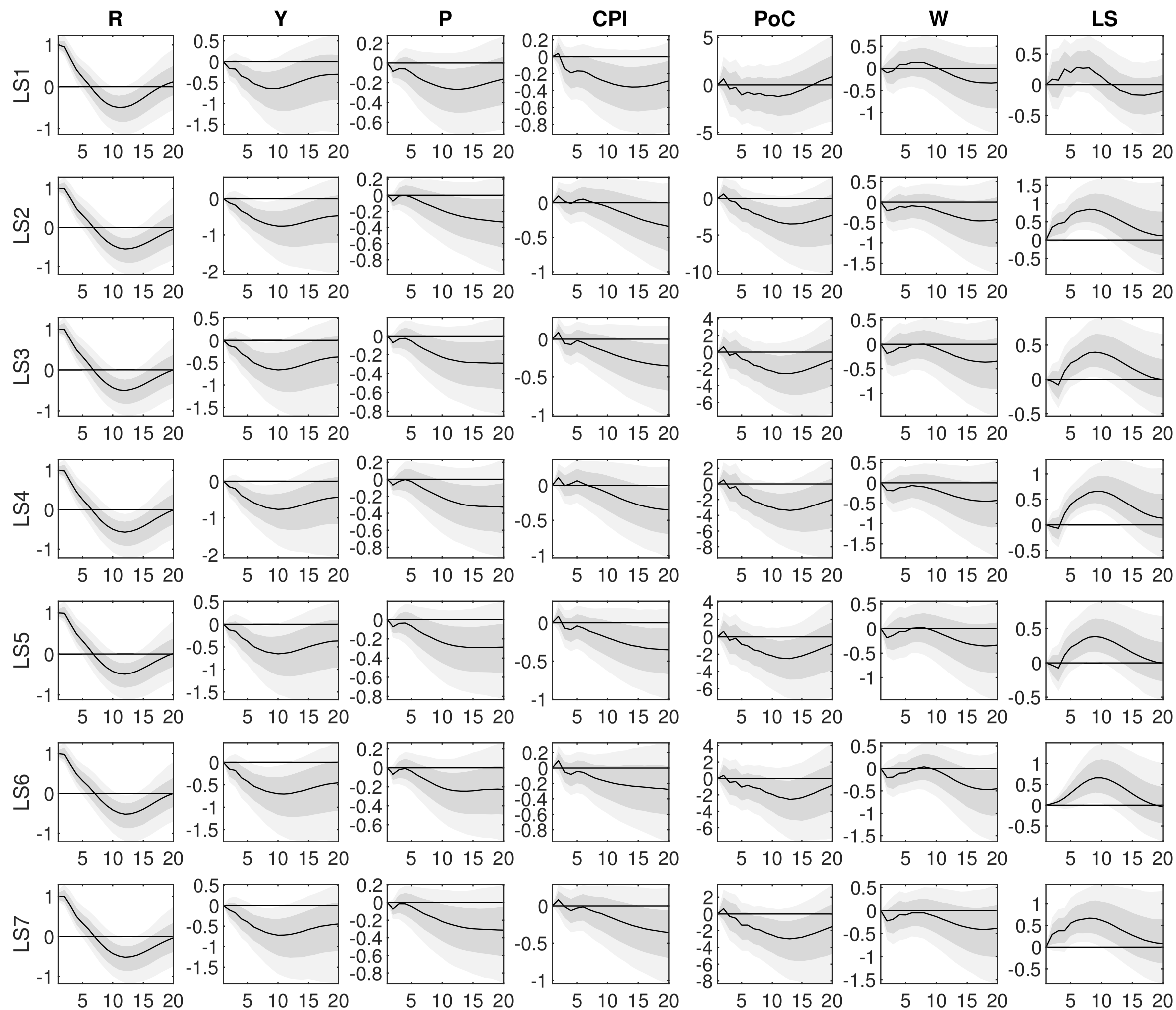


Figure B4. Impulse Response Function normalized to a 1% increase in the short term interest rate using recursive Cholesky. From top to bottom different proxy variables for the Labor Share in the US. Light (dark) gray 90% (68%) bands.

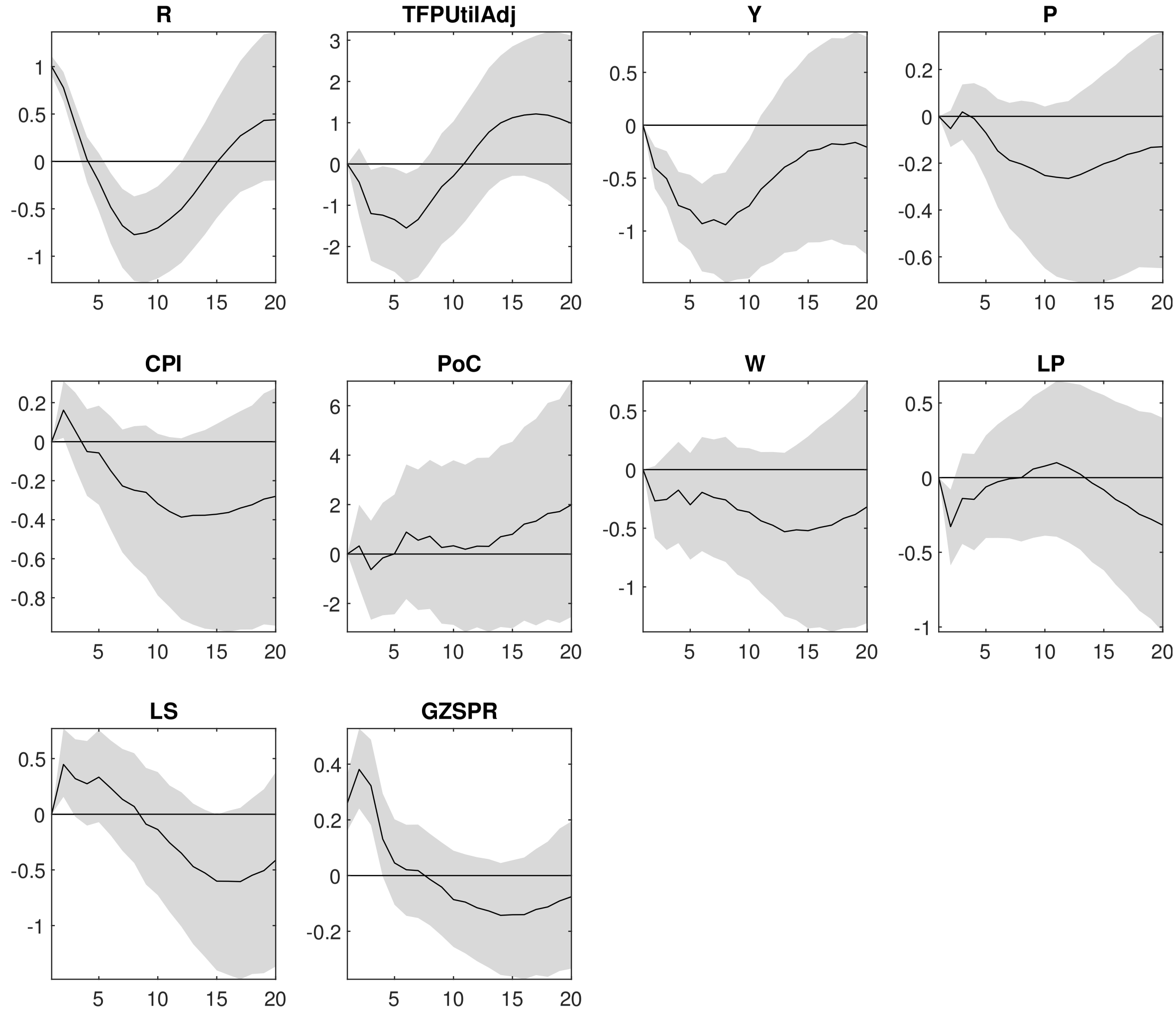


Figure B5. Impulse Response Function normalized to a 1% increase in the short term interest rate using recursive Cholesky and and extended variables specification for the US. From top left to bottom right, interest rate, Fernald (2012) measure of Utilization Adjusted TFP, real GDP, price deflator, CPI, Price of Commodities, real wages, Labor Productivity, labor share and the Gilchrist and Zakrajsek (2012) corporate bond spread. Dark gray areas indicate 68% bands.

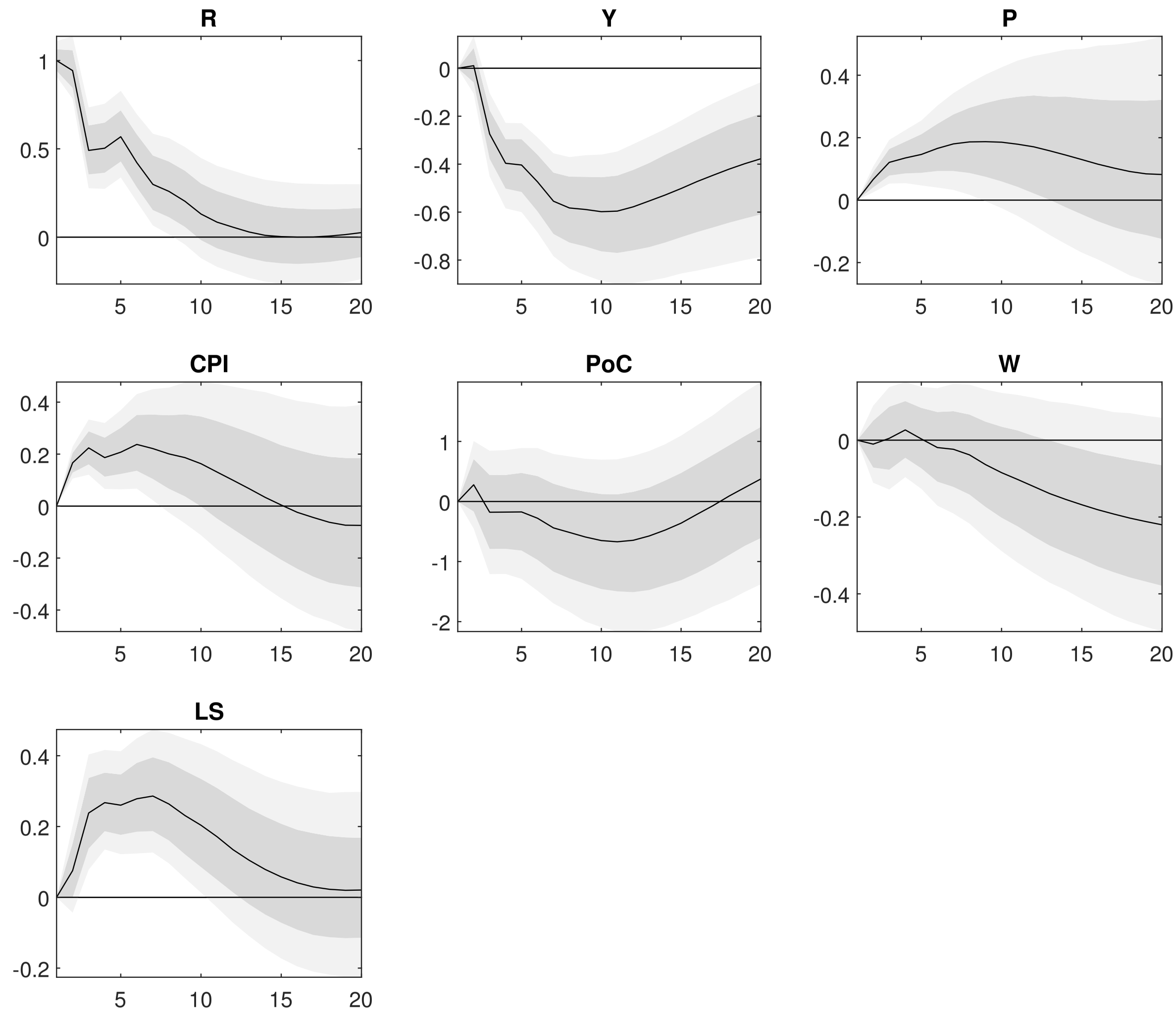


Figure B6. Impulse Response Functions normalized to a 1% percent increase in the short term nominal interest rate using an identification recursive Cholesky and the baseline variables specification. From left to right, interest rate, (log of) real GDP, price deflator, CPI, Price of Commodities, real wages and labor share. Sample span 1965q1-2007q4. Light (dark) gray areas indicate 90% (68%) bands.

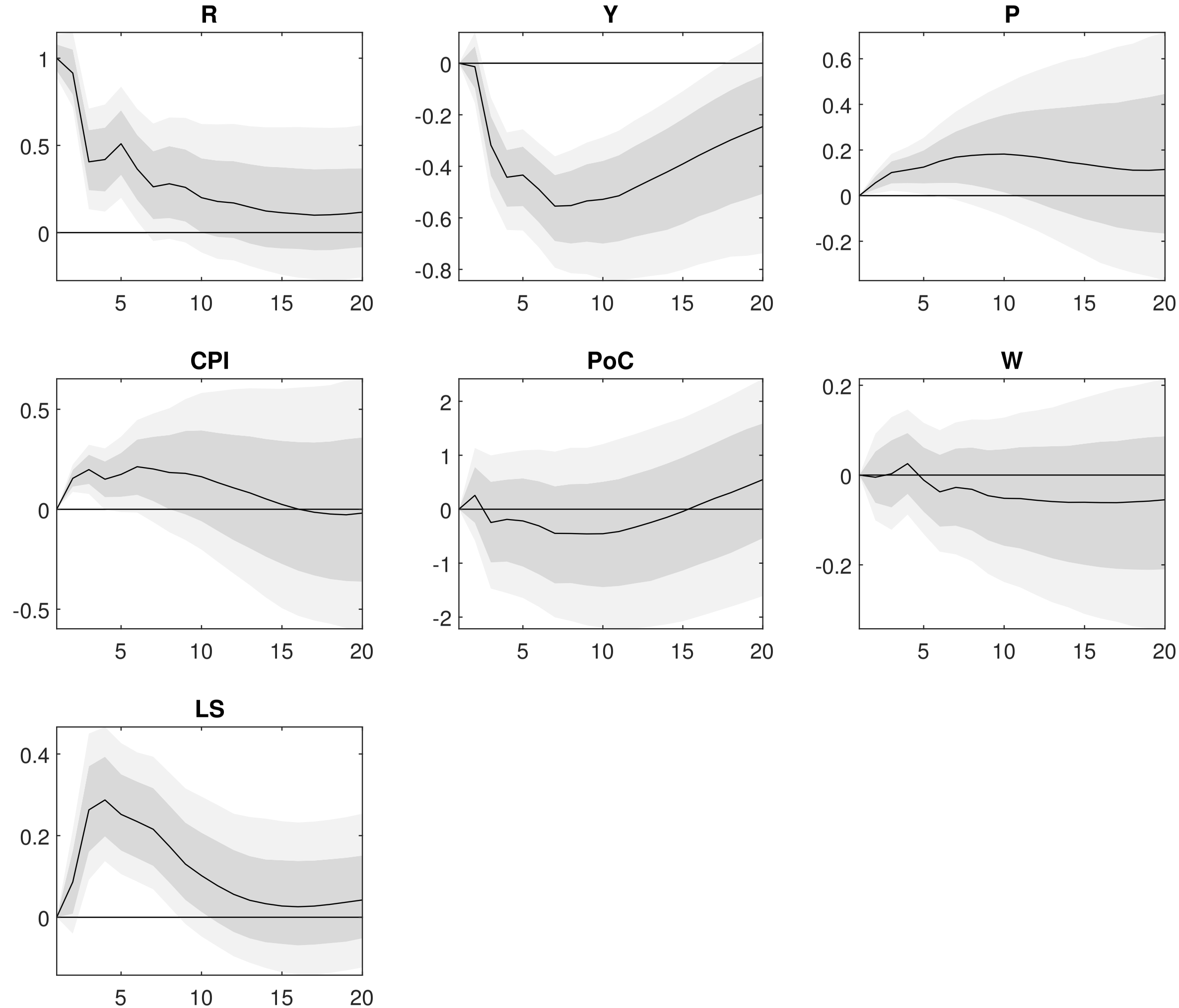


Figure B7. Impulse Response Functions normalized to a 1% percent increase in the short term nominal interest rate using an identification recursive Cholesky and the baseline variables specification. From left to right, interest rate, (log of) real GDP, price deflator, CPI, Price of Commodities, real wages and labor share. Sample span 1965q1-1995q4. Light (dark) gray areas indicate 90% (68%) bands.

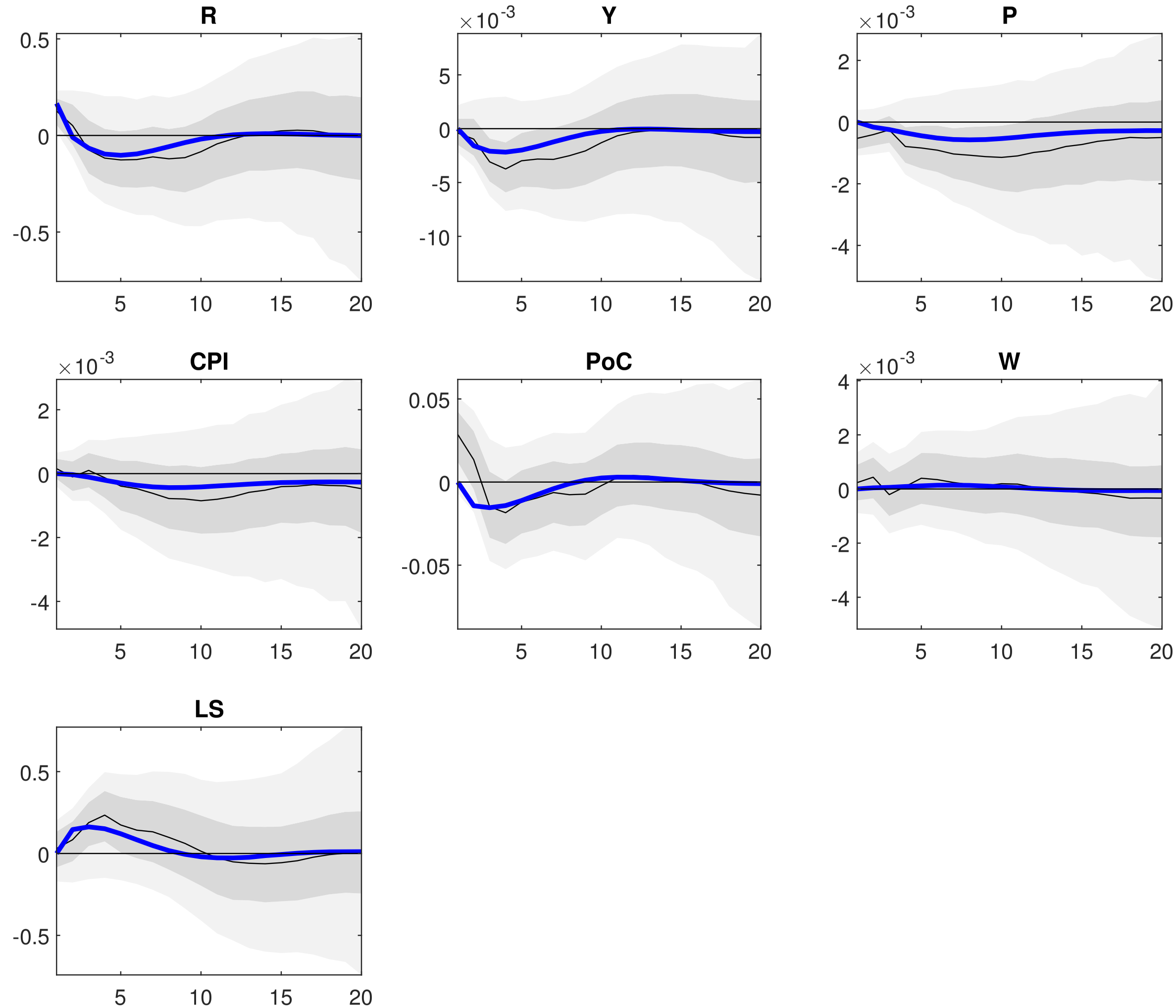


FIGURE B8. Impulse Response Function to a one standard deviation increase in the short term interest rate using an identification scheme based on **proxy variables or instruments** for the shock of interest. Monetary policy instrument constructed by Andrade and Andrade and Ferroni (2016). Light (dark) gray areas indicate 90% (68%) bands. The blue line reports the median IRF using a recursive identification scheme. EA data

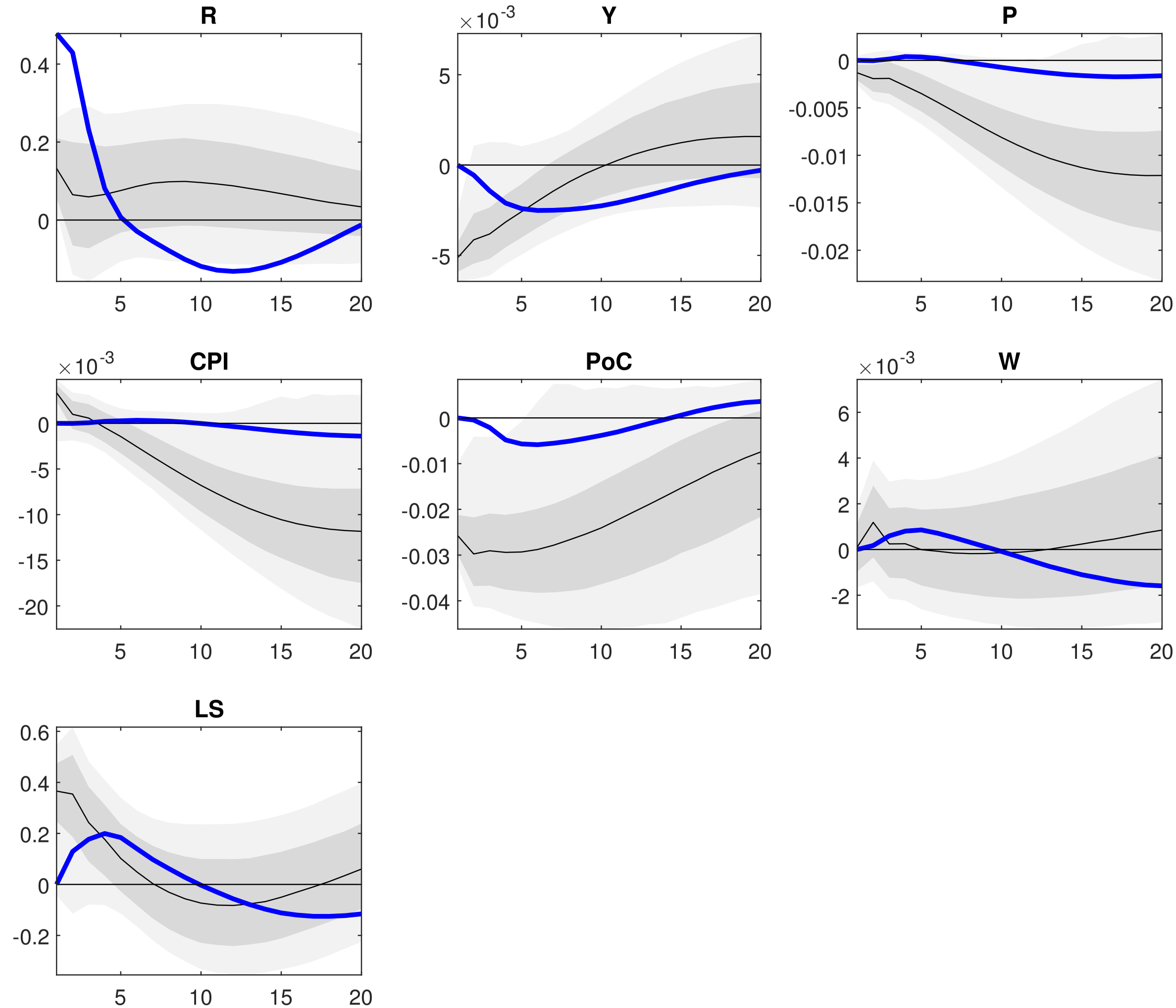


FIGURE B9. Impulse Response Function to a one standard deviation increase in the short term interest rate using an identification scheme based on **proxy variables or instruments** for the shock of interest. Monetary policy instrument constructed by Cloyne and Hürtgen (2016). Light (dark) gray areas indicate 90% (68%) bands. The blue line reports the median IRF using a recursive identification scheme. UK data

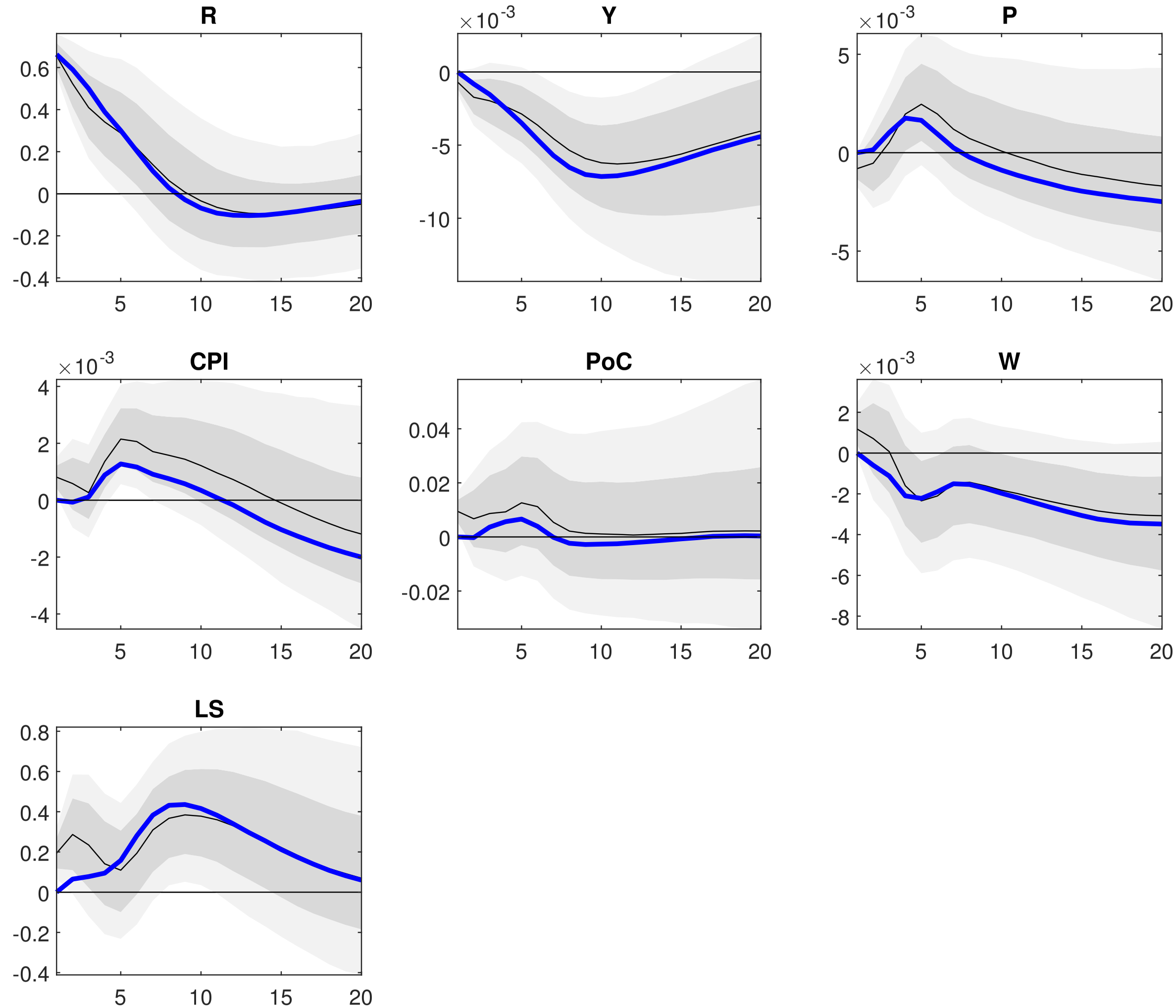


FIGURE B10. Impulse Response Function to a one standard deviation increase in the short term interest rate using an identification scheme based on **proxy variables or instruments** for the shock of interest. Monetary policy instrument constructed by Champagne and Sekkel (2018). Light (dark) gray areas indicate 90% (68%) bands. The blue line reports the median IRF using a recursive identification scheme. Canadian data

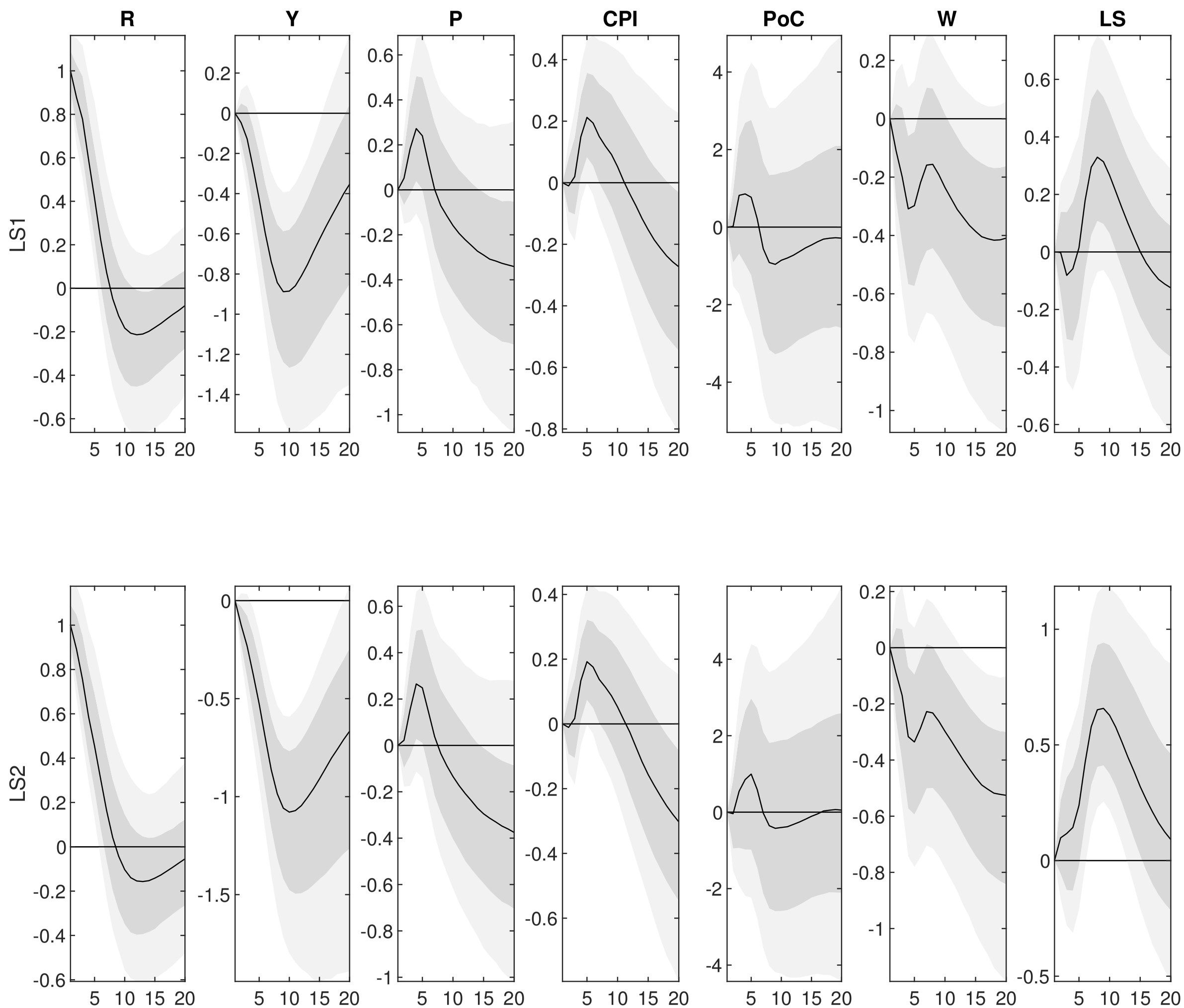


Figure B11. Impulse Response Function normalized to a 1% increase in the short term interest rate using recursive Cholesky. From top to bottom different proxy variables for the Labor Share in Canada. Light (dark) gray 90% (68%) bands.

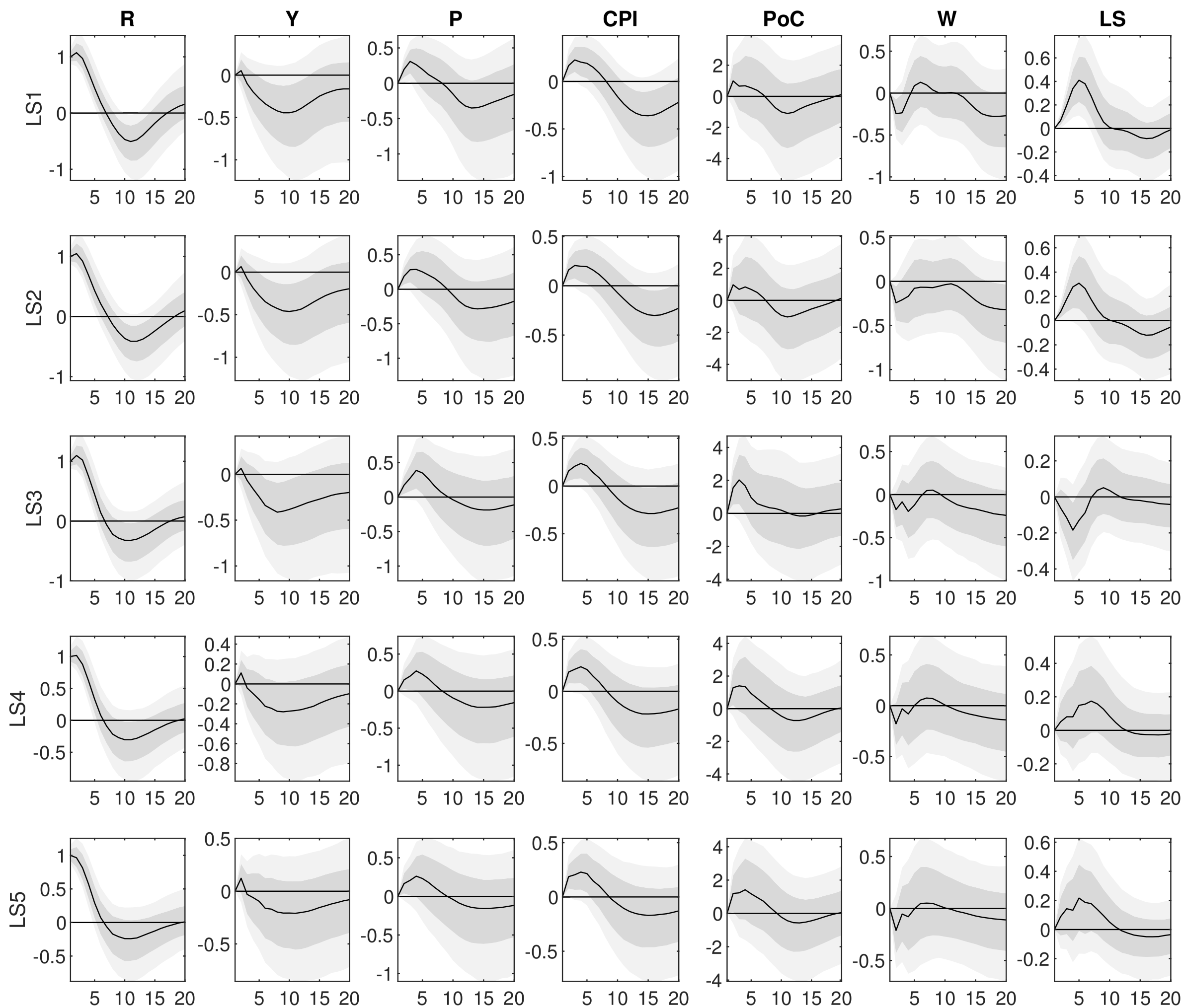


Figure B12. Impulse Response Function normalized to a 1% increase in the short term interest rate using recursive Cholesky. From top to bottom different proxy variables for the Labor Share in Australia. Light (dark) gray 90% (68%) bands.

Appendix C: Sectoral evidence

The results using different measures of the labor share, different countries, and identification methods, show a robust increase in the labor share after an MP contraction. We now look at whether this effect is also robust across sectors. I.e., it may be the case that the increase in the labor share is due to changes in the composition of output from sectors with low to sectors with high labor shares rather than a change of the labor share within sectors.

To do this, we exploit the cross-section and time-series variation of labor shares at the disaggregated sector level. Define the (log) labor share for sector i at time t as $LSH_{i,t}$, and the (cross-section invariant) aggregate monetary policy shock as MP_t. We can estimate the impact of the shock on sectoral labor shares by running the following panel model:

$$LSH_{i,t} = \alpha_i + \alpha_t + \rho LSH_{i,t-1} + \theta MP_t + \varepsilon_{i,t}, \tag{C.1}$$

where α_i and α_t are sector and time-specific fixed effects, and $\varepsilon_{i,t}$ is an error term. The fixed effects capture unobserved sector characteristics that are time-invariant, whereas the time-effect captures aggregate time variation in the labor share that is independent of the sector. Coefficient θ then captures the contemporaneous effect of the MP shock on the labor share controlling for past values of the labor share as well as sector and time fixed effects.[3] To capture the effect of the MP shock on the labor share after the shock, we estimate:

$$LSH_{i,t+h} = \alpha_i + \alpha_{t+h} + \rho LSH_{i,t+h-1} + \theta_h MP_t + \varepsilon_{i,t+h}. \tag{C.2}$$

with $h = 1, 2, 3, 4$. Coefficient θ_h then captures the effect of the MP shock at time t on the labor share $t + h$ periods ahead. The time profile of the θ_h coefficients thus gives us an impulse response for the labor share at the sectoral level.

C.1. Data

We use two databases for the US economy. The first one is the NBER-CES productivity database. This annual database covers a highly disaggregated split of the US manufacturing sector. The second is the Klems database that has a less disaggregated split by sectors but covers not only manufacturing but all sectors in the economy including services.

The labor share at the sector level is defined as compensation of employees over value added, which is the only available proxy. After eliminating sectors for which the labor share exceeded one in any period, we are left with 464 sectors for the CES-NBER database, and 30 sectors for Klems.

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3. With yearly data, a single lag appears to be sufficient to capture the persistence of the labor share. Adding more lags does not change the results in a significant way.

The measure of MP_t is obtained by aggregating quarterly shocks from the Cholesky VAR using aggregate data. The sample period is 1985-2007 for the NBER database and 1987-2007 for the Klems database as compensation of employees is only available from that point onwards.

Pre-tests showed that, using the NBER data, the model displayed heteroskedasticity and autocorrelation. Hence the standard errors reported are robust clustered standard errors. For the Klems data, as well as heteroscedasticity and autocorrelation, there were signs of contemporaneous cross-sectional correlation. Thus, the standard errors are estimated following Driscoll and Kraay (1998). The error structure is assumed to be heteroskedastic, autocorrelated up to one lag, and correlated between the sectors. Time effects appeared to be significant in all specifications. This is consistent with the general fall in the labor share experienced by all sectors as is evidenced by figure C1. Between 1985 and 2007, the labor share falls in the manufacturing sector by 10 percentage points.

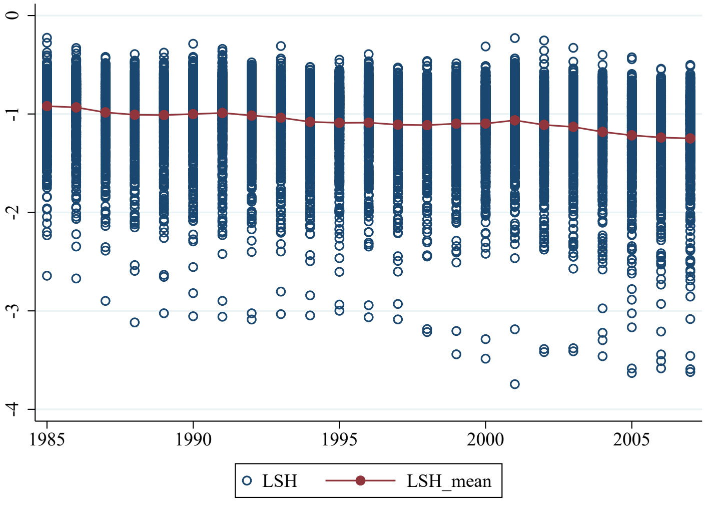


FIGURE C1. Average and dispersion of (log) labor shares in the NBER productivity database, 1985-2007.

C.2. Results

The results from the estimated θ_h for horizons $h = 1, ..., 5$ for the NBER database are reported in figure C2, where t_1 represents the contemporaneous effect. The MP shock leads to a significant increase in the labor share on impact and a further increase in the second year. The effect then falls as the horizon increases. Quantitatively, the impact is similar to that obtained from the aggregate VAR, although slightly less pronounced. The shape is also consistent with the aggregate results, where the labor share peaks between quarters 5 and 10 after the shock. Finally, figure C3 presents the results using the Cholesky VAR proxy for MP shocks and using the Klems database. The standard errors are larger given the much smaller sample size. On impact, the effect is not significant, but the labor share increases one year later and then falls, though not monotonically. The quantitative impact is smaller than using aggregate data, however, it is still positive and significant one and three years after the shock. These results, thus, confirm that the increase in the labor share

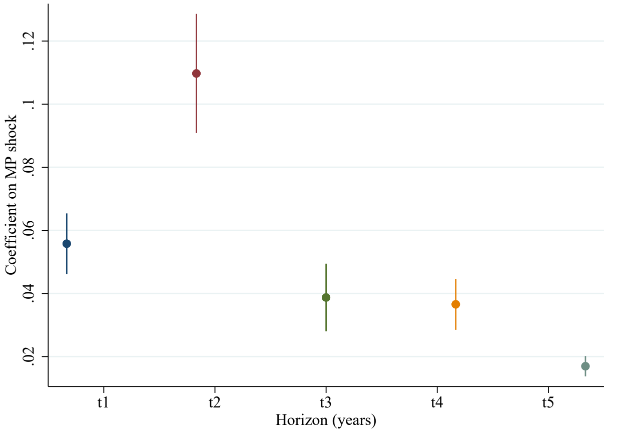


FIGURE C2. Coefficient on monetary policy shock variable (Cholesky VAR) using the NBER manufacturing database (464 manufacturing sectors). Period is 1985-2007. The plot shows the coefficient on the year of impact (t_1) and four years after.

after a MP contraction is also a feature that occurs within sectors and not the result of cross-sectional aggregation of sectors with different labor shares.

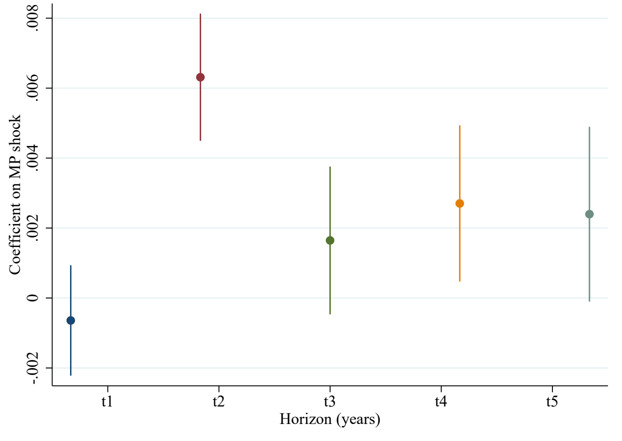


FIGURE C3. Coefficient on monetary policy shock variable (Cholesky VAR) using the Klems database (30 sectors). Period is 1987-2007. The plot shows the coefficient on the year of impact (t_1) and four years after.

Appendix D: Composition Bias and the response of wages and productivity

One of the advantages of using the labor share is that the *composition bias* in the response of real wages and productivity is alleviated when one takes their ratio as argued convincingly by Basu and House (2016). However, this bias can still affect the results for real wages (and labor productivity if entered separately). It is then important to analyze whether, given our results, the composition bias may invalidate our results.[4]

In order to understand this, we simplify the argument in Basu and House (2016). We abstract from entry and exit of new workers and matching quality, since these effects would only reinforce our argument here. Define x_t as our measure of *aggregate* labor productivity or real hourly wages (LP_t,W_t^r). Now assume we can classify workers in a discreet grid of N levels of "human capital" or skills from lowest to highest, $j = 1, \ldots, N$. We implicitly assume that wages/productivity increase with the level of human capital. Then, aggregate productivity or wages are simply the weighted sum by level of human capital: $x_t = \sum_j x_{j,t}\alpha_{j,t}$ where $\alpha_{j,t}$ is the weight of hours worked by workers of human capital level j in total hours worked ($\alpha_{j,t} = \frac{H_{j,t}}{\sum_j H_{j,t}}$). It is easy to show that we can decompose that measure in two terms:

$$x_t = \sum_j x_{j,t}\alpha_{j,t} = \overline{x}_t + \sum_j \left(x_{j,t} - \overline{x}_t\right)\left(\alpha_{j,t} - \overline{\alpha}_t\right) = \mu_t + \varrho_t,$$

where $\overline{x}_t$ and $\overline{\alpha}_t$ are the averages of wages/productivity and the shares of workers of different levels of human capital respectively. This expression tells us that observed aggregate wages or productivity can be decomposed into two components: the un-weighted average wage/productivity of workers (μ_t), and the covariance between wages/productivity and the share of workers by level of human capital (ϱ_t). The first term is the wage/productivity of the "representative" worker. The second term tells us about the structure of the labor force: whether shares are increasing or decreasing in productivity (the skill-composition). Changes in this term would precisely be related to the composition bias: they tell us whether during booms or recessions the composition of the labor force changes. For instance, if during booms the share of high productivity workers decreases, then the covariance would fall.

Our interest is in the cyclical evolution of μ_t conditional on a MP tightening, since this is the direct correspondence between data and models in a large class of representative agent DSGEs. To settle notation, call $f(.,t)_{MP}$ the

4. Another important dimension of heterogeneity has been emphasised by Gouin-Bonenfant (2018) where the way productivity gains pass through onto wages depends on the productivity dispersion across firms. When firm productivity dispersion is high, pass through of productivity changes onto wages is low.

impulse response function (IRF) over $t = 1, \ldots, T$ of any variable to a MP tightening. Since the IRF of two additive variables is also additive, we have that: $f(x_t, t)_{MP} = f(\mu_t, t)_{MP} + f(\varrho_t, t)_{MP}$ $\forall t$. Now suppose, for simplicity, that the effect of a MP shock on aggregate wages/productivity is zero at all horizons of the IRF. This implies that: $f(\mu_t, t)_{MP} = -f(\varrho_t, t)_{MP}$. Now, suppose we know that, in an expansion, the share of low skilled workers increases and it falls in a recession as discussed in Basu and House (2016). Thus, the change in this covariance is negative during an expansion. Basu and House (2016) also show that, conditional on a MP shock, the composition bias changes: the covariance increases (falls) with a MP tightening (loosening). It immediately follows then that, if the aggregate response is zero, then the "representative worker" response must be negative with a MP tightening.

Our findings show that aggregate real wages respond *at least* non-positively (and negatively in many cases) and the response of aggregate labor productivity is negative. From the above argument, the response of the representative agent wage/productivity would then be negative. That is, it will be more negative than the one obtained using aggregate data. If there is a composition bias and that bias is counter-cyclical, at least we know that the *sign* of the response of real wages and productivity is negative.[5]

As a second cross-check of this argument, we use data on composition bias corrected measures of wages for the US. Here we present results using the baseline Cholesky specification used in the paper substituting the real wages with data on composition bias corrected measures of wages as constructed by Haefke et al. (2013). The sample is 1984-2006 as their dataset stops in 2006.[6] For details about data construction we refer the reader to the original paper of Haefke et al. (2013). As expected the negative response of adjusted wages is more pronounced than that of unadjusted wages.[7]

5. Note that this is not to say that, from our VAR results, we know the *magnitude* of this effect, but at least we do know its *sign*. Had we found a positive response of wages and productivity, then the true sign would be indeterminate unless we know the exact magnitude of the composition bias. Also, if the composition bias in wages and productivity cancels out when constructing the labor share, both the sign and value of this response would be identified.

6. In their original dataset there are 4 missing observations in the sample. We interpolate the data but our results are robust to this interpolation. For the last two specification with wages of newly hired workers the BIC criterion suggested 2 lags instead of 3 as in the baseline specification.

7. Note, however, that Gertler et al. (2019) claim that: *"[...] the interpretation of new hire wage cyclicality as direct evidence of wage flexibility ignores confounding cyclical variation in wages that is due to workers moving to better job matches during expansions. [...] We find that, after controlling for composition effects, the wages of new hires are no more flexible than those of existing workers. A key implication, which we make precise, is that the low variability of existing workers' wages provides a better guide to the cyclicality of the marginal cost of labor".*

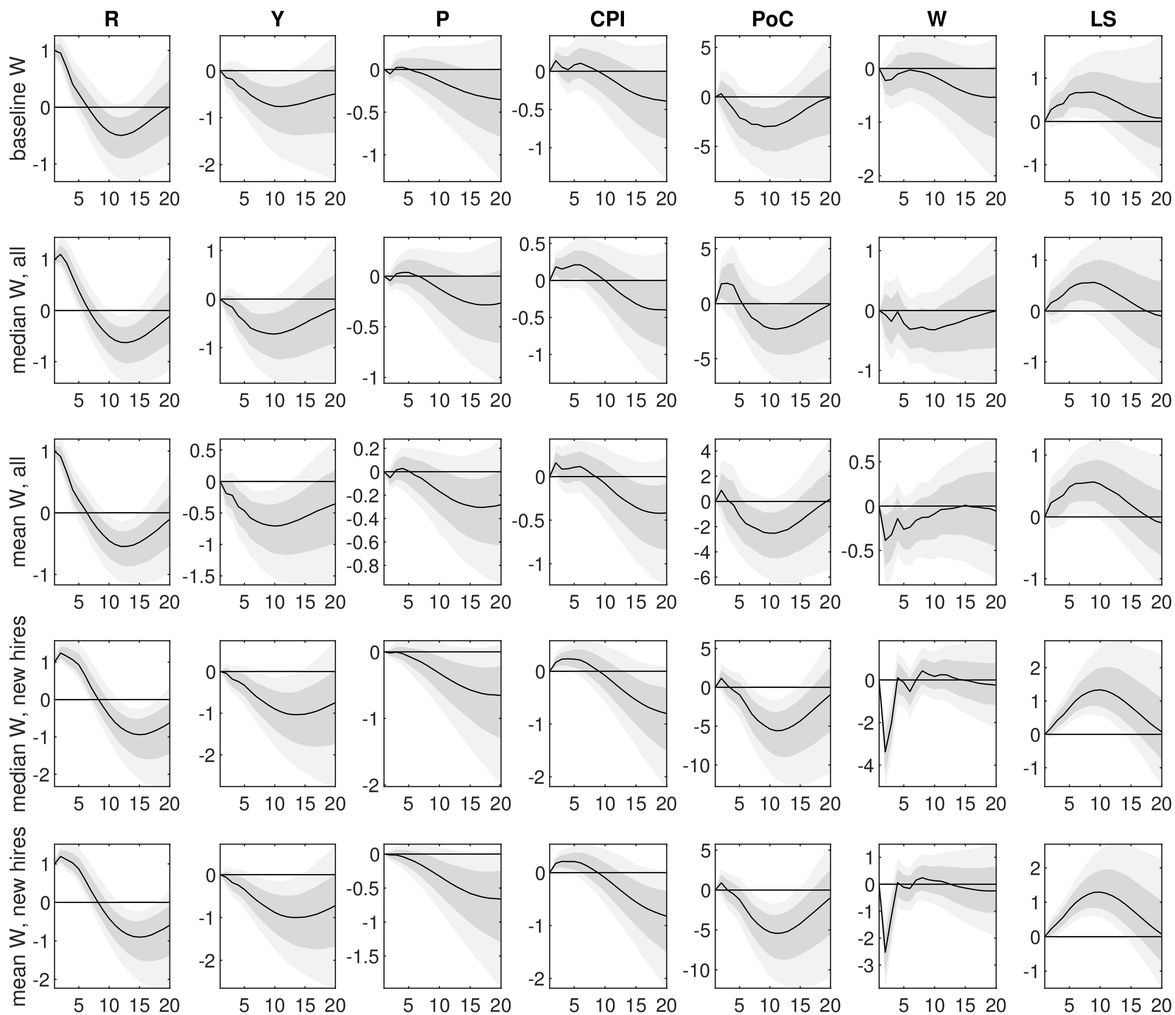


FIGURE D1. Impulse Response Functions comparing the response of Aggregate Wages in the US and composition bias corrected measures for all and newly hired workers.

Appendix E: Theoretical response of prices conditional on the observed labor share

We show how the theoretical impulse response of prices to a MP shock can be derived from the Phillips Curve given an impulse response for the labor share in the data as in Figure 3 in the main text. We take a New Keynesian Phillips Curve (NKPC) using standard parameter values and feed it the response of the labor share assuming, as is the case in the basic NK model, that the labor share is the marginal cost. We then compare the implied response of inflation to the MP shock from the PC and that from the VAR.

Take a basic NKPC of the form:

$$\pi_t = \beta E_t[\pi_{t+1}] + \kappa_p mc_t, \tag{E.1}$$

where π_t is inflation, mc_t are marginal costs, parameter $\kappa_p = \frac{(1-\theta_p)(1-\theta_p\beta)}{\theta_p}$, and $(1-\theta_p)$ is the proportion of firms that are allowed to reset prices. β the discount factor.

The NKPC can be solved forward like an asset price, such that inflation today is simply the present discounted value of all future expected marginal costs:

$$\pi_t = \kappa_p \sum_{k=0}^{\infty} \beta^k E_t[mc_{t+k}], \tag{E.2}$$

Now, using this expression, we can compute π_t, π_{t+1}, π_{t+2}, etc., conditional on an MP shock. We set $mc_t = ls_t$ for $\forall$ t. The expectation today of ls_{t+k} conditional on an MP shock, $E_t[lsh_{t+k}|\varepsilon_{MP,t} = 1]$ is the impulse response series of the labor share to a MP shock. Because this IRF converges to zero as $t+k$ grows large, the expected value at $t+k+1, 2, 3...$ is zero. We then obtain the IRF, and compute the discounted present value of π_t, given parameter values for θ_p and β, from $t = 1$ to $t = S$, where S is the period when the response becomes insignificant. We then compute the price level from inflation and compare it to the response of prices in the VAR.

Appendix F: Labor share response to other shocks

We briefly look at the transmission of other non-policy shocks to the labor share for the US. It is interesting to see how TFP or cost-push shocks propagate in our empirical environment and the extent to which they are consistent with the NK model predictions. In theoretical NK models, a positive technology shock increases the marginal product of labor; since producing the same quantity of goods becomes cheaper, the marginal cost falls, profit share rises and, by construction, the labor share falls. In the aggregate, output increases and prices drop. Cost-push shocks dynamics are slightly different. An exogenous fall in prices induce an immediate increase in the real wage; this generates a rise in marginal cost which in turn pushes the share of labor to total income up. At the same time, an increase in real wages pushes hours up and hence aggregate output expands. To summarize, after a positive technology shock we expect GDP to be positive, price negative, and labor share negative. After a negative cost-push shock we expect GDP to be positive, prices negative, and labor share positive. While these two supply-side shocks imply negative comovements between prices and quantities, they have different implications on the labor share. So care is needed when confronting these theoretical predictions with empirical outcome.

With this caveat in mind, we can nevertheless try to identify technology and cost-push shocks in our empirical VARs. Identifying the former is relatively straightforward. We considered the Fernald measure of utilization adjusted TFP, ordered this variable first and looked at the transmission of orthogonalized innovation to it. Identifying the latter is more difficult. Our strategy relied on sign restrictions and we assumed that a cost-push shock generates a negative comovement between output and prices. However, many other supply-side shocks can generate this pattern, e.g. the very same technology shocks or a combination of all of them.

Results for the are mixed. Figures F1 and F2 present the results. The TFP shock is identified only for the US as we do not have good proxies for quarterly TFP for the other countries. For the technology shock, the empirical IRFs clash with the theory see figures F1; in fact, we obtain that the labor share typically increases after a positive technology shocks. This is, nevertheless, a well known result in the literature following Ríos-Rull and Santaeulália-Llopis (2010) and León-Ledesma and Satchi (2019). However, a generic supply side shock identified with sign restrictions would generate labor share dynamics that are consistent (except for the EA) with the labor share propagation after a cost-push shock in the NK model.

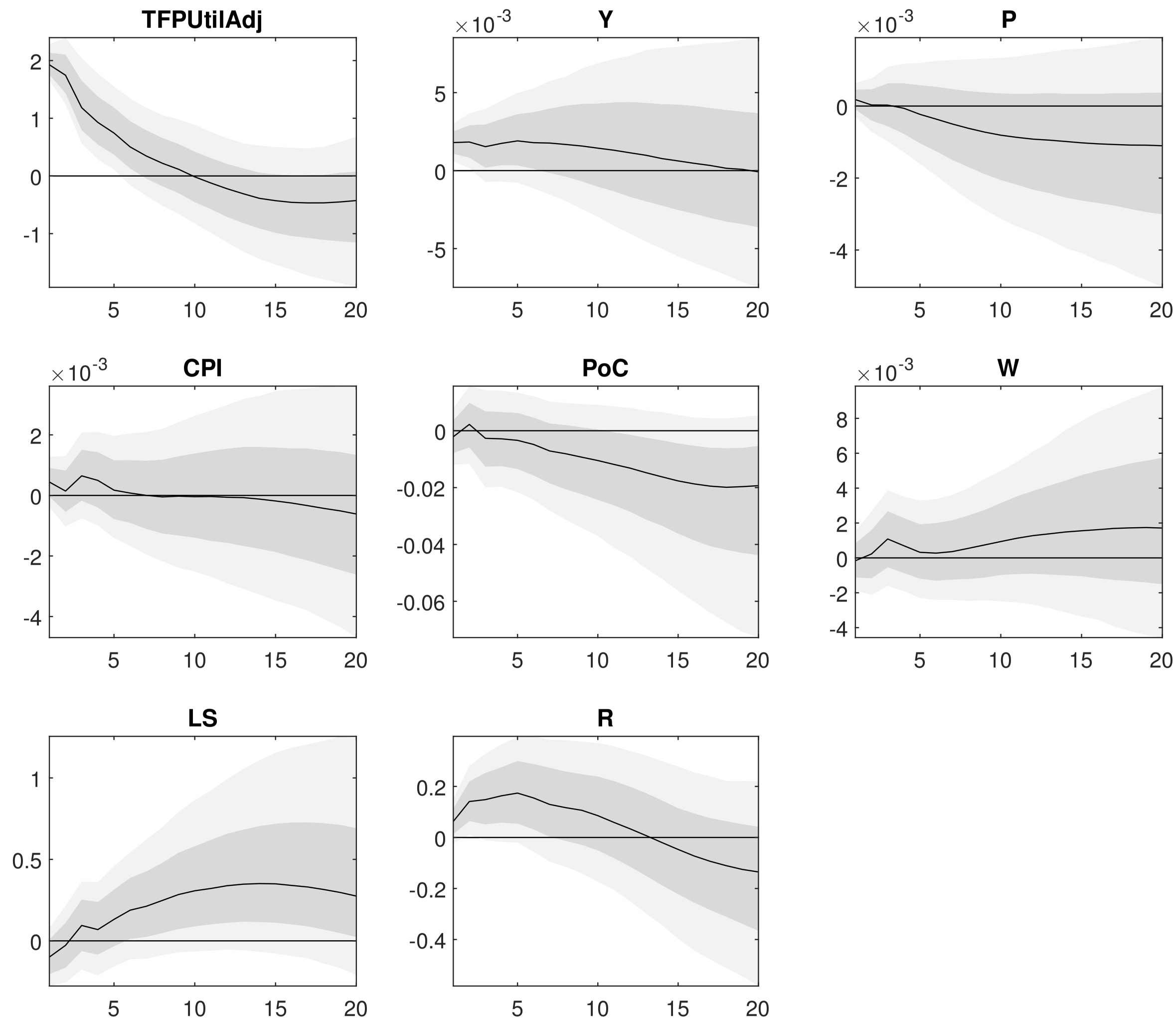


Figure F1. Impulse Response Function to TFP shock (recursive ordering).

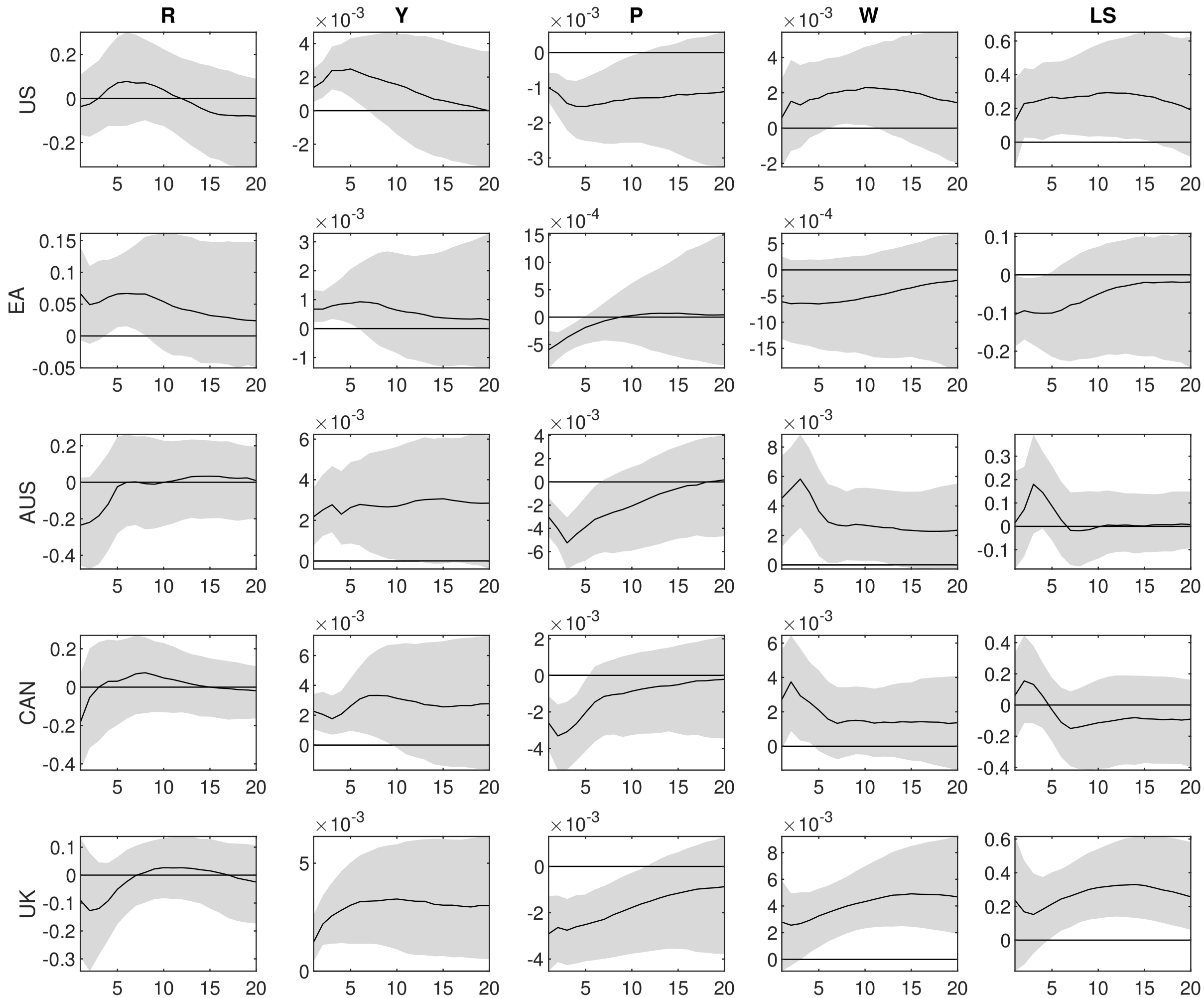


Figure F2. Impulse Response Function to a supply side shock (sign restrictions).

Appendix G: Wage-price stickiness and the response of the labor share: derivation

Here, we show the full derivation of the analytical results of the NK model with price and wage rigidity in Section 2. To make the derivation easier to follow, we reproduce the model equations below. Note that, since we only care about MP shocks, we assume a constant TFP level (fixed to one, zero in logs). The set of equations describing the model are:

$$y_t = E_t[y_{t+1}] + (i_t - E_t[\pi_{t+1}]) \qquad \text{(IS Curve)}$$

$$y_t = (1-\alpha)n_t \qquad \text{(Production function)}$$

$$\pi_t = \beta E_t[\pi_{t+1}] + \lambda_p y_t + \kappa_p w_t \qquad \text{(Price Phillips Curve)}$$

$$\pi_t^w = \beta E_t[\pi_{t+1}^w] + \lambda_w y_t - \kappa_w w_t \qquad \text{(Wage Phillips Curve)}$$

$$ls_t \equiv w_t + n_t - y_t \qquad \text{(Labor share definition)}$$

Here, y_t is the output gap (deviations from the flexible economy), w_t is the real wage gap, π_t and π_t^w are price and nominal wage inflation respectively, n_t is the employment gap, and i_t is the *interest rate in deviation from the natural real rate of interest (r^n).* β is the discount factor, α is the degree of DRS in production, and λ_p, λ_w, κ_p, and κ_w are slope coefficients of the Phillips Curves that are a function of deep parameters of the model as follows:

$$\kappa_p = \frac{(1-\theta_p)(1-\beta\theta_p)}{\theta_p} \tag{G.1}$$

$$\kappa_w = \frac{(1-\theta_w)(1-\beta\theta_w)}{(1+\eta\varepsilon_w)\theta_w} \tag{G.2}$$

where $(1-\theta_p)$ is the fraction of firms that readjust prices, $(1-\theta_w)$ the fraction of workers that readjust wages, ε_w is the elasticity of substitution of differentiated labor inputs, and η is the inverse Frisch elasticity. Finally:

$$\lambda_p = \frac{\alpha}{1-\alpha}\kappa_p \tag{G.3}$$

$$\lambda_w = \left(\frac{1}{1-\alpha}\right)\kappa_w \tag{G.4}$$

As mentioned in the main text, we are interested in the impact response of real wages and the labor share to a MP shock. To obtain that, we assume that the monetary authority is able to set the interest rate to track the natural real rate of interest (and hence make the gaps zero) in every period except for the initial period in which it deviates by an amount ε_t^{MP}, the MP shock. Written in terms of deviations from r^n, this then implies:

$$
\begin{aligned}
i_t &= E_t[\pi_{t+1}] + \varepsilon_t^{MP} \\
i_{t+j} &= E_{t+j}[\pi_{t+1+j}] \text{ for } j > 0
\end{aligned} \tag{MP rule}
$$

Finally, we have the definition of the change in the real wage gap as:

$$
w_t \equiv w_{t-1} + \pi_t^w - \pi_t + \Delta w_t^n \tag{Real wage gap change}
$$

where w_t^n is the flexible price/flexible wage economy real wage. Note that w_t^n only responds to supply shocks and hence $\Delta w_t^n = 0$ in our model. Since we assume that the economy starts in period $t-1$ from an equilibrium with zero gaps, $w_{t-1} = 0$ too, and we have that:

$$
w_t \equiv \pi_t^w - \pi_t. \tag{G.5}
$$

Iterating the IS curve forward, we obtain an expression for the output gap as the sum of expected deviations of the real interest rate from its natural level. And given the MP rule above, this implies that the output gap at time t is just the negative of the MP shock:

$$
y_t = \sum_{j=0}^{\infty}(i_{t+j} - E_t[\pi_{t+j+1}]) = -\varepsilon_t^{MP} \tag{G.6}
$$

Using (G.5), (G.6), the price and wage Phillips Curves and, since MP sets all gaps to zero beyond time t then $E_t[\pi_{t+1}] = E_t[\pi_{t+1}^w] = 0$, we can obtain an expression for the real wage gap as a function of the shock:

$$
w_t = \frac{\lambda_p - \lambda_w}{1 + \kappa_w + \kappa_p}\varepsilon_t^{MP} \tag{G.7}
$$

To obtain the response of the labor share, we use the definition of the labor share and the production function to obtain:

$$
ls_t = \left(\frac{\lambda_p - \lambda_w}{1 + \kappa_w + \kappa_p} - \frac{\alpha}{1-\alpha}\right)\varepsilon_t^{MP} \tag{G.8}
$$

which, given that $\alpha > 0$, is always going to be more negative than the response of real wages.

We now have an expression for the impact responses to a MP shock of real wages and the labor share. Quantitatively, the response will depend on the degree of price and wage rigidity through parameters κ_p and κ_w (and, by implication, λ_p and λ_w). A numerical example can visually illustrate this point. We pick certain common values in the literature for the deep parameters fixing θ_p and varying θ_w and show the response of the labor share for different degrees of wage rigidity. We set $\beta = 0.99$, $\alpha = 0.1$, $\sigma = 1$, $\eta = 0.4$, $\varepsilon_w = 8$, $\theta_p = 0.6$, and allow θ_w to vary between 0.1 and 0.99. Figure G1 shows the response of the real wage gap and the labor share. As it is clear, both responses are increasing in

θ_w. The real wage response turns positive, for this parameterization, for a value slightly above 0.7. The labor share response is always negative. As discussed in the main body of the paper, the higher the degree of wage rigidity relative to price rigidity, the higher the response of real wages and the labor share.

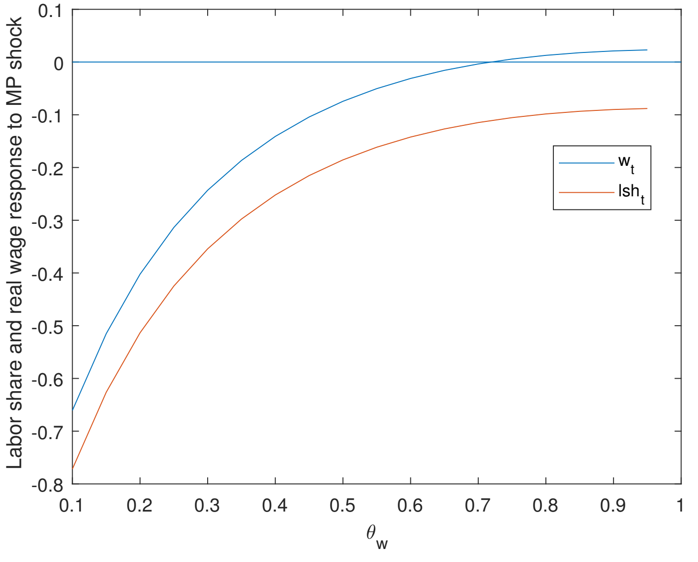


FIGURE G1. Response of real wages and the labor share for different values of wage rigidity. $\theta_p = 0.6$.

The responses of both variables will be negative when the production function has CRS. It is easy to see that, if we set $\alpha = 0$, then the expressions above collapse to:

$$w_t = -\frac{\lambda_w}{1 + \kappa_w + \kappa_p}\varepsilon_t^{MP} \tag{G.9}$$

$$ls_t = -\frac{\lambda_w}{1 + \kappa_w + \kappa_p}\varepsilon_t^{MP} \tag{G.10}$$

which will always be negative regardless of the values of θ_p and θ_w. This is intuitive as, in this case, the labor share is equal to the real wage which, in turn, is equal to the marginal cost. Hence, any policy that reduces current inflation relative to future inflation must decrease marginal costs and hence real wages and the labor share.

Furthermore, we can show that, as long as κ_w is positive (which must be the case) then the response of the labor share will always be negative. To see this, note that the labor share only increases if $\left(\frac{\lambda_p - \lambda_w}{1+\kappa_w+\kappa_p} - \frac{\alpha}{1-\alpha}\right) > 0$. Substituting the expressions for λ_p and λ_w, we obtain $\alpha\kappa_p - \kappa_w - \alpha - \alpha\kappa_w - \alpha\kappa_p > 0$. Rearranging, this implies that $\kappa_w < -\frac{\alpha}{1+\alpha} < 0$. This would imply a negative κ_w which is impossible given its definition above. Thus, whatever the degree of wage stickiness, the labor share and, by implication, marginal costs must decrease after a MP contraction.

Appendix H: Theory

As discussed in the main body of the paper, we discuss possible extensions of the standard NK framework that can break up the one-to-one relationship between the labor share and marginal costs (inverse of the markup) and therefore help the model match the empirical evidence.

In what follows, for ease of exposition, we will assume that the production function is linear in labor.[8] Given a linear production function with labor as the only variable input ($y_t = n_t$) now the real wage is also equal to the labor share and real marginal costs mc_t:

$$w_t = ls_t = mc_t. \tag{H.1}$$

H.1. The labor share and fixed costs in production

Nekarda and Ramey (2019), among others, discuss two production function generalizations that are able to break the r.h.s. equality of (H.1): overhead and overtime labor. Both specifications introduce a wedge between the average wage and the marginal product of labor, which is a necessary condition to be able to generate impulse responses in line with our empirical evidence.

However the procyclicality of marginal costs still dominates quantitatively the response of the labor share to a MP shock. Moreover, it can be shown that the inclusion of fixed costs in production to ensure no entry in steady state, as usually assumed in DSGE models, acts in the same way as the presence of overhead labor in production. Consider a NK economy with a simple linear production in labor with the presence of fixed costs F: $Y_t = N_t - F$. In log deviations from the steady state the labor share is now:

$$ls_t = mc_t - n_t \frac{F}{Y}. \tag{H.2}$$

Given that hours (output) responds procyclically to a MP shock then the higher $\frac{F}{Y}$ the higher the wedge between labor share and marginal costs.[9] Numerical results (not reported here) show that this might work only on impact and for implausibly high values of $\frac{F}{Y}$.

8. Assuming a decreasing returns to scale production function $y_t = \alpha n_t$ does not change the results.

9. This is also the reason why sometimes estimated DSGE models find a very large proportion of fixed costs in production (see Smets and Wouters (2007)).

H.2. The cost-push channel of Monetary Policy

The cost-push channel introduces a direct effect of the nominal interest rate (i_t) on the marginal cost and it has been used in the literature in order to explain the well-known *price puzzle* after a MP shock and to reproduce the pro-cyclical price markup documented by Nekarda and Ramey (2019).

Following the set up of Ravenna and Walsh (2006), we can augment the basic NK model with Calvo pricing by adding a credit channel and the cost of working capital by assuming a cash in advance constraint for the firms. The need to finance in advance their working capital (wage bill) induces a need for credit from financial intermediaries.

In this set up, the real wage is now given by

$$w_t = mc_t + y_t - n_t - i_t.^{10} \tag{H.3}$$

This implies that, in this model, the labor share is given by

$$w_t = ls_t = mc_t - i_t. \tag{H.4}$$

This channel is thus able to break the link between the labor share and the price markup. Because the marginal cost now depends on the cost of financing working capital, as shown in Phaneuf et al. (2018), the markup can become pro-cyclical consistent with the evidence in Nekarda and Ramey (2019). However, as the nominal interest rate moves counter-cyclically by definition, the direct effect of i_t in (H.4) reinforces the pro-cyclicality of the labour share. Hence, one needs to rely on numerical analysis to check which of the two competing effects dominates. The Monte Carlo Filtering results presented in Appendix J show how the working capital fraction is in principle a parameter that might be able to generate a switch in the sign of the labor share after a few quarters from a MP shock. However the quantitative analysis in section 3 of the paper shows that this is not enough to generate IRFs in line with the empirical evidence in the Christiano et al. (2016) model.

H.3. Search and Matching

We now turn our attention to labor market frictions in the form of search and matching. While in the paper we use the model of Christiano et al. (2016) that uses alternate offer bargaining, it is easier to present here the intuition of this channel using the more standard Nash bargaining model as in Galí (2010). In this set up, real wages are not set competitively but are the result of a bilateral Nash bargaining process between workers and firms, while an aggregate matching function explains the evolution of aggregate employment.

10. This follows the log-lnearization of equation (6) in Ravenna and Walsh (2006).

Hence now real wages are not set anymore equal to a markup over labor productivity (lp_t). If $w_t \neq mc_t + lp_t$, it follows then that $ls_t \neq mc_t$. The dynamics of the labor share will differ since now wages and marginal product of labor behave differently. Considering only the extensive margin here and again a linear production function $y_t = n_t$ we can see how the labor share is now given by:

$$ls_t = w_t \neq mc_t. \tag{H.5}$$

Hence to generate an increase in the labor share the only possibility is to have a counter-factual response of wages to a monetary policy shock. Without wage rigidities, it would be difficult for wages to display a positive response given that the bargaining power of workers is bounded by one. The combination of both nominal wage and labor market rigidities, instead, proves to be enough to generate a positive response of real wages. Of course the introduction of capital and further real rigidities might overturn this result in larger DSGE model. Once again this can only be checked using numerical techniques as we do in the main body of the paper.

H.4. Open economy

Consider the small open economy NK model of Galí and Monacelli (2005), also discussed in chapter 8 in Galí (2015).[11] In this set up the (log-linear) Phillips curve for domestic inflation, production function and real marginal costs are:

$$\pi_{H,t} = \beta E_t(\pi_{H,t+1}) + \lambda mc_t \tag{H.6}$$

$$y_t = a_t + (1-\alpha)n_t \tag{H.7}$$

$$mc_t = w_t - p_{h,t} - a_t + \alpha n_t \tag{H.8}$$

where $\pi_{H,t}$ is domestic inflation, mc_t real marginal costs, β the discount factor, α the degree of decreasing returns in production, λ the slope of the Phillips curve, w_t nominal wages, $p_{h,t}$ the domestic price level, y_t is real output, a_t exogenous tfp, and n_t is employment. It follows straight away from H.8 that the labor share in this economy is equal to the real marginal costs plus the difference between domestic and overall price level:

$$ls_t = mc_t + p_{h,t} - p_t.$$

Hence it follows that the open economy setting introduces a wedge between marginal costs and labor share that could be affected by the degree of complementarity/susbstitutability in consumption between domestic and foreign goods (η in Galí (2015) terminology).

11. Throughout we assume that the central bank reacts to CPI and not to domestic inflation. However results are not sensitive to this assumption and we checked all the alternative Taylor rule specification present in the Galí (2015).

Moreover we note that, given that the consumption is a CES aggregator of domestic and foreign goods, the linearised price level can also be written as:

$$p_t = \upsilon p_t^h + (1-\upsilon)p_t^f, \tag{H.9}$$

where υ is the degree of home bias in consumption (share of domestic consumption when relative prices are 1). This then leads to an expression for the labor share as:

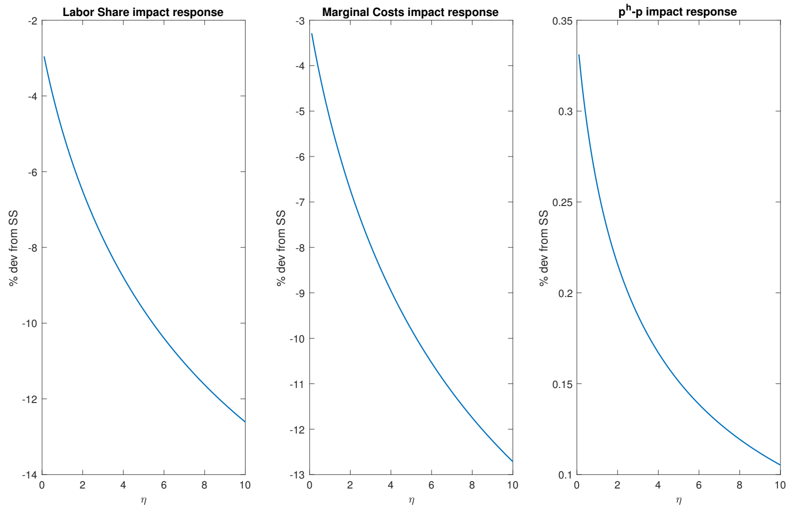
$$ls_t = mc_t + (1-\upsilon)(p_t^h - p_t^f), \tag{H.10}$$

where the last term in parenthesis is just the terms of trade. Therefore, the reaction of the labor share will depend on η and υ.

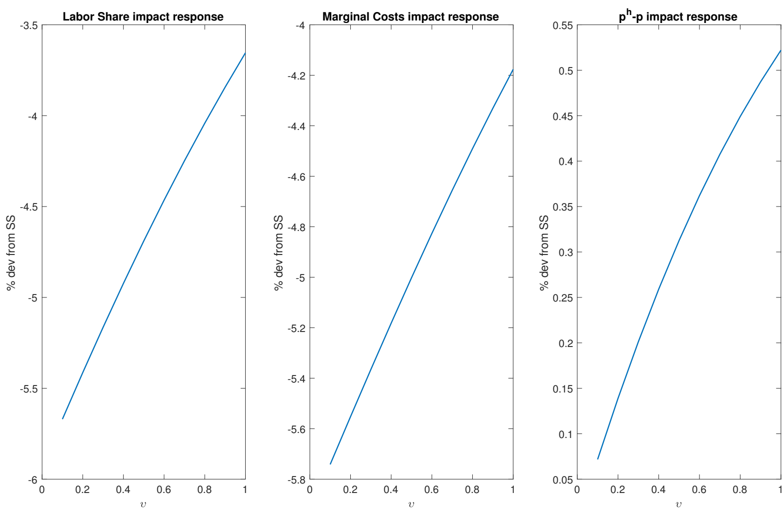
For this reason we checked how both parameters affect the IRFs of the labor share and it's components, which in this context are the marginal costs and the log difference between domestic price and overall price level. Using the same calibration as in Galí (2015) we show how the impact response of the labor share and its components change when varying in turn η and υ. The top three panels of Figure H1 show the case when varying η from 0.1 to 10. The lower the elasticity η the larger the effect of the terms of trades that goes in the right direction of pushing the labor share up. However we see how the procylical movement of marginal costs, driven by the phillips curve on domestic inflation, still dominates and even in the case of a almost Leontieff aggregate consumption aggregator the labor share response is still negative.

The bottom three panels of the figure repeat the same exercise by changing the degree of openness υ from 0 to 1 and show that the terms of trade have a positive effect on the labor share the higher the value of υ. Once again however this is not enough the turn the labor share response into positive territory due to the fact that the marginal costs response always dominates. We show this also in figure H2 where we compare IRFs using the standard calibration as in Galí (2015) with the ones produced by setting $\eta = 0.01$ and $\upsilon = 1$.

In summary a low elasticity of substitution and/or a low degree of home bias do increase the effect of the terms of trade on the labor share which goes in the 'right' direction but is not enough to switch the sign of the labor share response. We have also looked if the combination of these parameters with alternative calibrations of all the others in the model could deliver the right sign of the labor share by running a PSA on the whole parameter space of the model. Results show that there is no combination of parameters in the model that can produce a positive response of the labor share at any quarter from 2 to 8 after a monetary policy shock.



(A) η



(B) υ

Figure H1. Change in the impact IRFs of selected variables when varying η or υ.

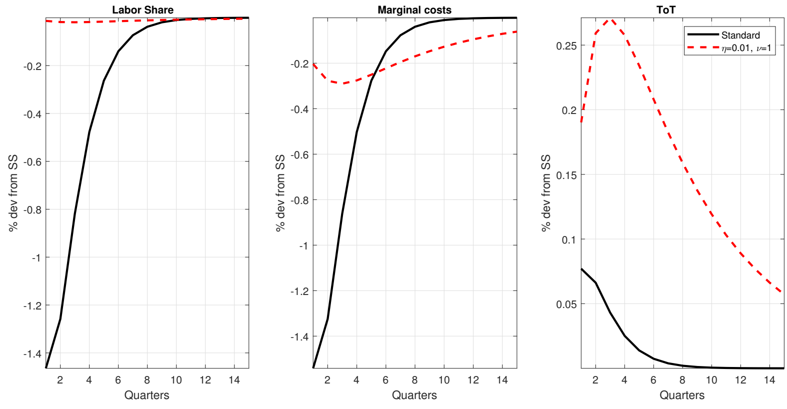


FIGURE H2. Change in the impact IRFs of selected variables when varying η or υ.

H.5. The labor share and CES production

Extending the NK model with investment and capital accumulation and assuming a CES production function[12] provides a simple way of introducing a wedge between the labor share and the marginal costs (mc_t) :

$$lsh_t^{CES} = mc_t + \frac{1-\sigma}{\sigma}(y_t - n_t), \tag{H.11}$$

where σ is the elasticity of substitution between capital and labor. As we show in previous versions of the paper, for any reasonable parameterization of the elasticity of substitution (σ), the reaction of mc_t to an MP shock always dominates, and the CES assumption does not change significantly the reaction of the labor share, which is always strongly correlated with marginal costs.

12. See Galí et al. (2007) and Nekarda and Ramey (2019) for details and Cantore et al. (2015) for a medium scale DSGE model with CES production

Appendix I: VAR with model simulated data

We quantitatively analyze the ability of the recursive VAR to reproduce impulse responses to a MP shock generated by the model. To do so, we follow Erceg et al. (2005), and generate samples of 150 observations of simulated data from the model for the interest rate, output, price, real wage, and the labor share using the estimated posterior modes of Christiano et al. (2016). We generate 150 different simulations from the model each of which is then used to estimate a recursive VAR. We then compare the IRFs arising from the VAR to those arising directly from the DSGE model. Specifically, we compare the median (true) IRF from the model to that in the VAR for the repeated samples.

To allow for the invertibility of the VAR, we simulate the model with 5 shocks.[13] We set the standard deviation of the MP shock to 1% and for the rest of the shocks to 0.01%. Note that the aim of this exercise is to check whether the VAR is able to identify the key shock for our analysis and, thus, we are not inferring anything about the identification of other structural shocks.

The comparison between VAR and model IRFs is presented in figure I1, where the blue line is the model IRF and VAR IRF is presented with 68% confidence sets. Clearly, the MP shock is neatly identified in the VAR and especially so for the labor share and real wages.

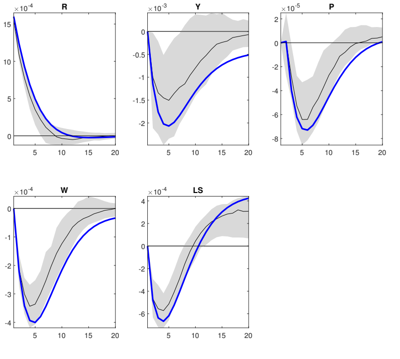


FIGURE I1. Blue line true (model) IRF, black line median VAR IRF, grey area 68% confidence sets.

13. As the original model has only three shocks we add two ad hoc iid shocks to the Euler equation and the resource constraint, but this does not affect the comparison for MP shocks.

Appendix J: Monte Carlo Filtering

As in the prior predictive analysis, a random sample of the prior[14] is drawn and the associated model-implied statistics of interest are computed. Then, based on a set of constraints (e.g. rank conditions or signs of impulse responses), a categorization is defined for each MC model realization as lying either within or outside the target region. The terms behavior (B) or non-behavior ($\bar{B}$) are used in the MCF literature. The $B - \bar{B}$ categorization is mapped back onto the input structural parameters, each of which is thus also partitioned into a B and $\bar{B}$ sub-sample. Given a full set of N Monte Carlo runs, one obtains two subsets: $(\Psi_i|B)$ of size n and $(\Psi_i|\bar{B})$ of size $\bar{n}$, where $n + \bar{n} = N$ and Ψ_i, for $i = 1, .., k$, are model parameters. In general, the two sub-samples will come from different unknown probability density functions: $f_n(\Psi_i|B)$ of size n and $f_{\bar{n}}(\Psi_i|\bar{B})$ of size $\bar{n}$.

In order to identify the parameters that mostly drive the DSGE model into the target behavior, the distributions f_n and $f_{\bar{n}}$ are compared for each parameter independently. The Montecarlo sampling allows us to avoid computing analytical integration over the remaining parameters. If for a given parameter Ψ_i the two distributions are significantly different, then Ψ_i is a key factor driving the model behavior and there will be clearly identifiable subsets of values in its predefined range that are more likely to fall under B than under $\bar{B}$. If the two distributions are not significantly different, then Ψ_i is unimportant and any value in its predefined range is likely to fall either in B than under $\bar{B}$. Ideally, we are comparing the supports of the conditional cumulative distribution functions (CDF) of a parameter and compute the distance under standard statistical metrics. The Smirnov two-sample test (two-sided version) provides us with a statistical concept of distance. The lower the α associated to the Smirnoff test, the more likely is to reject the null hypothesis that the $CDF(\Psi_i|B)$ is equal to the $CDF(\Psi_i|\bar{B})$. The B and $\bar{B}$ subsets can be further inspected through bi-dimensional projections, in order to detect patterns characterizing two-way interactions. The standard procedure consists of computing the correlation coefficients ρ_{ij} between all parameters under the B and $\bar{B}$ subsets, and plotting the bi-dimensional projections of the sample for the couples having $|\rho_{ij}|$ larger than a significance threshold.

Table J1 below summarizes the results of applying this analysis to the calvo-sticky-wage model of Christiano et al. (2016) as discussed in section 3.3.2 of the paper. Parameters analized and respective priors are shown in table 3 of the paper.

14. Priors used are described in table 3 in the main article text.

2:5 quarters								
ls (+)			w (-)			ls (+); w (-)		
Parameter	D-Stat	P-value	**Parameter**	D-Stat	P-value	**Parameter**	D-Stat	P-value
Wage stickiness	0.292	0.000	Price stickiness	0.541	0.000	Wage stickines	0.502	0.000
Price stickiness	0.287	0.000	Wage stickiness	0.222	0.000	Price markup	0.389	0.000
Price markup	0.251	0.000	AR(1) MP shock	0.165	0.000	Interest rate smoothing	0.216	0.000
AR(1) MP shock	0.238	0.000	Interest rate smoothing	0.142	0.000	Working capital fraction	0.213	0.000
Habits in consumption	0.167	0.000	Wage indexation	0.081	0.000	Wage indexation	0.210	0.000
Wage indexation	0.141	0.000	Habits in consumption	0.076	0.000	Investment adjustment costs	0.193	0.000
Working capital fraction	0.132	0.000	Price indexation	0.071	0.000	Habits in consumption	0.170	0.000
Investment adjustment costs	0.126	0.000	Taylor rule response to inflation	0.051	0.000	Taylor rule response to output	0.106	0.000
Price indexation	0.115	0.000	Price markup	0.050	0.000	AR(1) MP shock	0.100	0.000
Interest rate smoothing	0.094	0.000	Taylor rule response to output	0.049	0.000			
Taylor rule response to inflation	0.087	0.000						

5:8 quarters								
ls (+)			w (-)			ls (+); w (-)		
Parameter	D-Stat	P-value	**Parameter**	D-Stat	P-value	**Parameter**	D-Stat	P-value
Price stickiness	0.486	0.000	Price stickiness	0.485	0.000	Wage stickiness	0.434	0.000
AR(1) MP shock	0.120	0.000	Price indexation	0.235	0.000	Price markup	0.283	0.000
Investment adjustment costs	0.110	0.000	Wage stickiness	0.219	0.000	Investment adjustment costs	0.265	0.000
Wage stickiness	0.094	0.000	Interest rate smoothing	0.095	0.000	Working capital fraction	0.216	0.000
Working capital fraction	0.087	0.000	AR(1) MP shock	0.087	0.000	Interest rate smoothing	0.164	0.000
Price markup	0.083	0.000	Working capital fraction	0.081	0.000	Wage indexation	0.153	0.000
Price indexation	0.071	0.000	Wage indexation	0.055	0.000	Price indexation	0.152	0.001
Inverse of Frish Elasticity	0.053	0.000	Price markup	0.053	0.000	AR(1) MP shock	0.150	0.000
Taylor rule response to inflation	0.052	0.000	Taylor rule response to output	0.052	0.000	Price stickiness	0.131	0.000
Interest rate smoothing	0.042	0.000	Habits in consumption	0.046	0.000	Taylor rule response to output	0.083	0.000

TABLE J1. Smirnov statistics in driving prior restrictions.

Appendix K: Alternating offer bargaining model

This section shows robustness results by using the alternate offer bargaining model of Christiano et al. (2016) as opposed to the one with sticky wages a la Calvo used in the paper.

Description	
Investment adjustment costs	$U[1, 20]$
Habits in Consumption	$U[0, 1]$
Capacity utilization costs	$U[0, 1]$
price stickiness	$U[0, 1]$
Price markup	$U[1.1, 2]$
Interest rate smoothing	$U[0, 1]$
Taylor rule response to inflation	$U[1.01, 5]$
Taylor rule response to output	$U[0, 1]$
Working capital fraction	$U[0, 1]$
Technology diffusion	$U[0, 1]$
AR(1) MP shock	$U[0, 1]$
Replacement ratio	$U[0, 1]$
Prob. of barg. session determination	$U[0, 1]$
Hiring fixed cost relative to output %	$U[0, 2]$
Search cost relative to output %	$U[0, 2]$
Matching function share of unemployment	$U[0, 1]$
Job survival rate	$U[0, 1]$
Vacancy filling rate	$U[0, 1]$

Table K1. Uniform Distribution bounds for PSA and MCF, AOB model.

Restrictions					
2:5 quarters			5:8 quarters		
ls (+)	w (-)	ls (+); w (-)	ls (+)	w (-)	ls (+); w (-)
42.5%	9.1%	0.2%	29.1%	17.6%	0.9%

Table K2. Results from prior sensitivity analysis AOB model. Percentage of the prior support that matches all the restrictions.

2:5 quarters								
ls (+)			w (-)			ls (+); w (-)		
Parameter	D-Stat	P-value	**Parameter**	D-Stat	P-value	**Parameter**	D-Stat	P-value
Price stickiness	0.391	0.000	Price stickiness	0.387	0.000	Job survival rate	0.579	0.000
Price markup	0.226	0.000	AR(1) MP shock	0.296	0.000	Interest rate smoothing	0.379	0.000
Job survival rate	0.183	0.000	Interest rate smoothing	0.275	0.000	Price markup	0.323	0.000
Matching function share	0.128	0.000	Working capital fraction	0.232	0.000	Price stickiness	0.312	0.000
Investment adjustment costs	0.096	0.000	Matching function share	0.108	0.000			
Interest rate smoothing	0.093	0.000	Price markup	0.099	0.000			
AR(1) MP shock	0.069	0.000	Taylor rule response to inflation	0.096	0.000			
Habits in Consumption	0.068	0.000	Taylor rule response to output	0.085	0.000			
Replacement ratio	0.056	0.000						
Hiring fixed cost relative to output %	0.053	0.000						

5:8 quarters								
ls (+)			w (-)			ls (+); w (-)		
Parameter	D-Stat	P-value	**Parameter**	D-Stat	P-value	**Parameter**	D-Stat	P-value
Price stickiness	0.338	0.000	AR(1) MP shock	0.381	0.000	Job survival rate	0.405	0.000
Price markup	0.181	0.000	Price stickiness	0.329	0.000	AR(1) MP shock	0.309	0.000
Job survival rate	0.115	0.000	Job survival rate	0.170	0.000	Price stickiness	0.283	0.000
Investment adjustment costs	0.105	0.000	Matching function share	0.164	0.000	Habits in Consumption	0.202	0.000
Matching function share	0.103	0.000	Working capital fraction	0.140	0.000	Interest rate smoothing	0.189	0.000
AR(1) MP shock	0.079	0.000	Hiring fixed cost relative to output %	0.073	0.000	Price markup	0.182	0.000
Habits in Consumption	0.056	0.000	Interest rate smoothing	0.064	0.000	Replacement ratio	0.152	0.000
Interest rate smoothing	0.055	0.000	Habits in Consumption	0.061	0.001			
Working capital fraction	0.054	0.000						

TABLE K3. Smirnov statistics in driving prior restrictions, AOB model.

Description	Priors	Posteriors
Investment adjustment costs	$\Gamma(8,2)$	7.10 (3.75,10.77)
Habits in Consumption	$B(0.5,0.15)$	0.61 (0.36,0.84)
Capacity utilization costs	$\Gamma(0.5,0.3)$	0.53 (0.05,1.14)
Price stickiness	$B(0.66,0.1)$	0.64 (0.50,0.77)
Price markup	$\Gamma(1.2,0.05)$	1.24 (1.14,1.33)
Interest rate smoothing	$B(0.7,0.15)$	0.67 (0.48,0.83)
Taylor rule response to inflation	$\Gamma(1.7,0.15)$	1.73 (1.45,2.02)
Taylor rule response to output	$\Gamma(0.1,0.05)$	0.05 (0.01,0.11)
Working capital fraction	$B(0.8,0.1)$	0.77 (0.56,0.96)
MP shock stdev	$\Gamma(0.27,0.05)$	0.30 (0.25,0.34)
AR(1) MP shock	$\Gamma(0.5,0.15)$	0.43 (0.18,0.72)
Replacement ratio	$B(0.4,0.1)$	0.41 (0.22,0.61)
Prob. of barg. session determination	$\Gamma(0.5,0.4)$	0.33 (0.01,0.81)
Hiring fixed cost relative to output %	$\Gamma(1,0.3)$	0.98 (0.44, 1.56)
Search cost relative to output %	$\Gamma(0.1,0.07)$	0.10 (0.00, 0.23)
Matching function share of unemployment	$B(0.5,0.1)$	0.50 (0.30, 0.69)
Job survival rate	$B(0.8,0.1)$	0.74 (0.55,0.90)

Table K4. AOB model: Priors and posterior means the parameters (95% HDP interval in parenthesis) - Bayesian Impulse Response Matching as in Christiano et al. (2010). Distributions: Γ *Gamma*, B *Beta*.

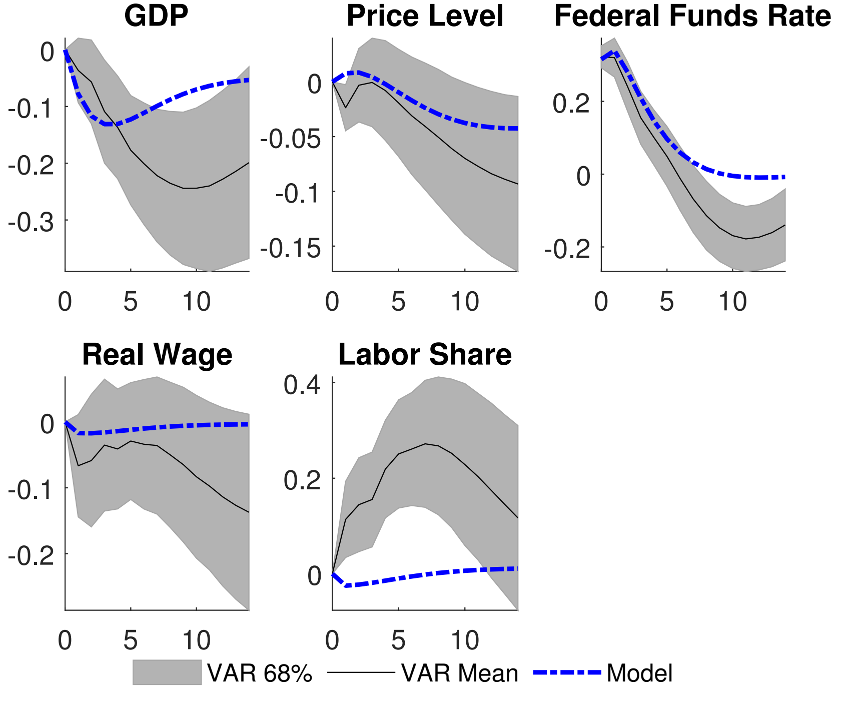


Figure K1. AOB Model: Bayesian Impulse Responses Matching - VAR vs DSGE model

Appendix L: Bayesian Impulse Responses

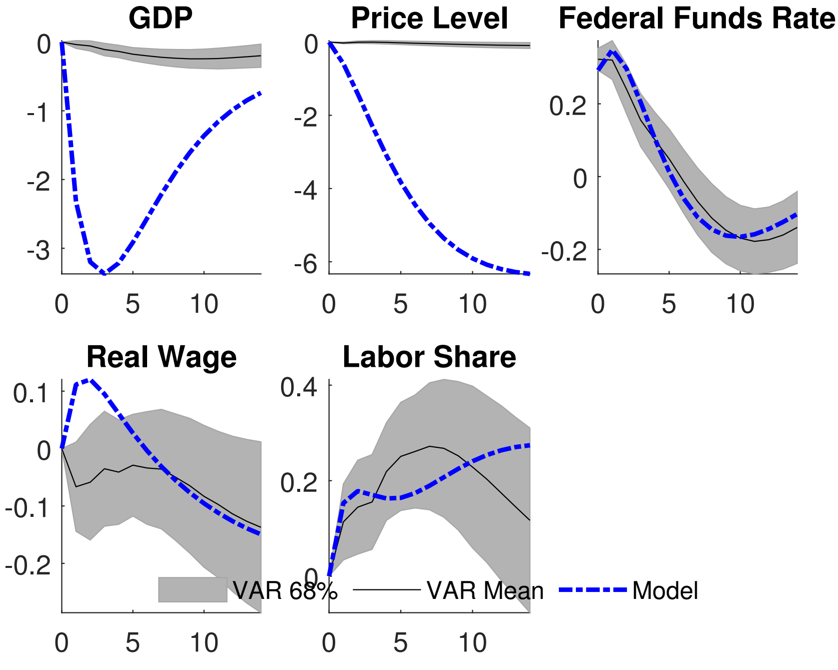


FIGURE L1. Bayesian Impulse Responses Matching - Matching only Federal Funds Rates and the Labor share.

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