Appendix for: Neutral technology shocks and the dynamics of labor input: results from an agnostic identification*

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Contents

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1 Appendix A: Robustness analysis

In order to establish whether the results are robust to perturbations to the benchmark specification of the model, we undertake a number of robustness checks. In particular, we deal with long run cycles by introducing a time varying trend in the specification of the SVAR, by filtering the data, and by considering a SVAR specification in differences. We also establish that the results hold if we split the sample period, we choose different time lags, we use alternative variables in the SVAR, we extend the length of sign restrictions, and we use the restrictions from the model to staggered prices to identify shocks. We also enrich the theoretical framework with additional shocks and establish that the identification of a neutral technology shock is unique. Finally, we relax the assumption that labor market tightness increases after a neutral technology shock.

The sign reversals on the effect of neutral technology shocks on labor input generated by using the SVAR specification in differences rather than in levels, as detected by Christiano et al. (2004) and Liu and Phaneuf (2007), may be reconciled when accounting for long cycles in the data, as documented by Canova et al. (2006) and Fernald (2007). For this reason, to ensure the results are extensively robust along this dimension, we control for long cycles in the data by introducing a time varying trend in the SVAR specification, by filtering the data with a low pass filter which removes cycles with periodicity higher than 52 quarters, and by considering a SVAR specification in differences. Figures 1-3 show impulses responses for specifications of the SVAR in differences, with de-trended and filtered variables respectively. It is evident that the results of the benchmark specification are preserved, since the variables' responses in these alternative specifications mirror closely those in the standard model. Additionally, the exercise suggests that controlling for long cycle reduces the degree of uncertainty surrounding the variables' responses, as the error bands around the median projections are reduced in the alternative specifications. The reduction in uncertainty supports Fernald (2007)'s advice on the importance of controlling for low frequency movements in the data to reduce estimation uncertainty.

Another important robustness check is to establish whether the results are similar across different time periods by splitting the sample. This is particularly important given the well-documented finding that a shift in the time series properties of output and other macroeconomic variables has occurred in the US data since the 1980s.[1] Such evidence is documented

[1] In particular, the data are split pre- and post 1970:Q4.

in papers by Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Stock and Watson (2003), Justiniano and Primiceri (2008), and Sims and Zha (2006). Though there is no consensus on the precise point in time of the shift, these studies identify the early 1980s as the relevant time period.[2] Figures 4-5, therefore, show the variables responses when the model is re-estimated over two distinct samples: the first for the pre-1980 data and the second for the post-1980 data. The impact responses are similar across the two sub-samples, which is evidence that the results based on our identification scheme are robust across different time periods, in line with the findings by Fisher (2006) and Canova et al. (2009). Interestingly, different from Canova et al. (2009), our identification scheme obtains this result without removing long cycles in the data. It is nonetheless noticeable that the uncertainty around the median reactions is higher for the two sub-samples compared with the estimation results from the whole period, reflecting the fact that the limited size data set makes the estimation less powerful.

Figure 6 shows that results hold if we estimate the SVAR with four lags rather than two lags. To ensure that the results are independent from the variable used to approximate labor input, we also represent labor input by using measures of unemployment level and unemployment rate in place of employment.[3] Figures 7-8 show impulses responses based on the SVAR with measures of unemployment in level and rate respectively. It is noticeable that in both instances the measure of unemployment decreases (rises) in reaction to a neutral (investment) specific technology shock, which is in line with the benchmark result. In addition, the dynamics of the other variables remains substantially unchanged with respect to the standard specification. Interestingly, the use of these alternative measures leaves the uncertainty around the variables' median response substantially unchanged.

In order to ensure that the results hold under perturbations to our short-lived identification procedure, we extend the length of sign restrictions. In particular, we impose the sign restrictions identified by the theoretical model up to 4 quarters, as in Uhlig (2004) and Dedola and Neri (2007). Again, we find that results of the baseline model remain qualitatively unaffected. The forecast error variance decompositions of the different specifications are similar to the benchmark case.

To ensure that the sign restriction that labor market tightness increases after a neutral

[2]As an additional robustness check, we have also estimated the model using 1984:Q4 as the breakpoint date and this does not affect the main conclusions.

[3]Note that movements in unemployment do not necessarily imply changes in employment since workers could move out of the labor force.

technology shock does not rule out a decline in employment we have estimated the model relaxing this assumption and established that the results hold, as shown in Figure 9. Similarly, to ensure that the sign restriction that hiring increases after a neutral technology shock does not rule out a decline in employment we have estimated the model relaxing this assumption and established that the results hold, as shown in Figure 10.

In order to establish that results hold in a model based on staggered prices, we extend the data set to include series for the marginal cost, inflation and the nominal interest rate and we impose on these variables the additional restrictions identified by the theoretical model with nominal price rigidities. In particular, as summarized in panel B of Table 2 in the paper, we impose as additional restrictions that inflation and the nominal interest rate both fall on the first-period reaction to a neutral technology shock, while they increase in response to an investment specific technology shock. Figure 11 shows that the response of employment to a neutral technology shocks is positive, and the response of the variables is similar to the estimated responses based on the model with flexible prices.[4]

As a final robustness check, in order to ensure that the identification is robust across alternative shocks, we enrich the theoretical framework with monetary policy, cost-push and labor supply shocks. Labor supply and cost-push shocks are embedded by allowing for time variation in the parameters χ and μ respectively, and by assuming that they follow an AR(1) process. Monetary policy shocks are embedded by adding a white noise error to the Taylor rule equation (23). To simulate the model the autoregressive coefficients and the variances for all the shocks is set equal to 0.75 and 1 respectively. Appendix D details the specification of the additional shocks. Table 1 summarizes the sign restrictions derived from the theoretical model enriched with these additional shocks. We are able to uniquely identify neutral technology shocks since they generate positive comovements in hiring, labor market tightness and consumption. Figure 12 shows that the response of employment to a neutral technology shocks is positive, and the response of the variables is similar to the benchmark specification of the model.

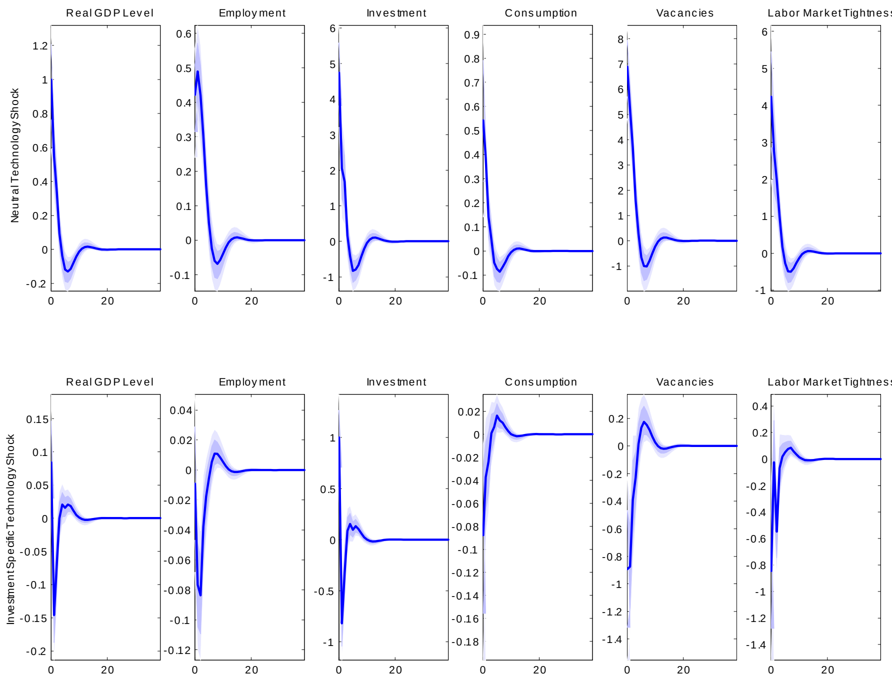
[4] Using the model with nominal price rigidities, we undertook the same robustness checks described for the model with flexible prices and we established that all the qualitative results hold.

Table 1. Sign restrictions on the first-period SVAR variables, model with staggered prices and multiple shocks

	Output	Investment	Consumption	Hiring	Labor market tightness	Inflation	Nominal interest rate	Marginal cost
Neutral technology shock	+	+	+	+	+	–	–	Free
Investment specific shock	+	+	–	–	–	+	+	+
Cost-push shock	–	–	+	Free	Free	+	–	–
Monetary policy shock	–	–	Free	Free	Free	–	+	–
Labour supply shock	Free	Free	–	+	+	Free	Free	–

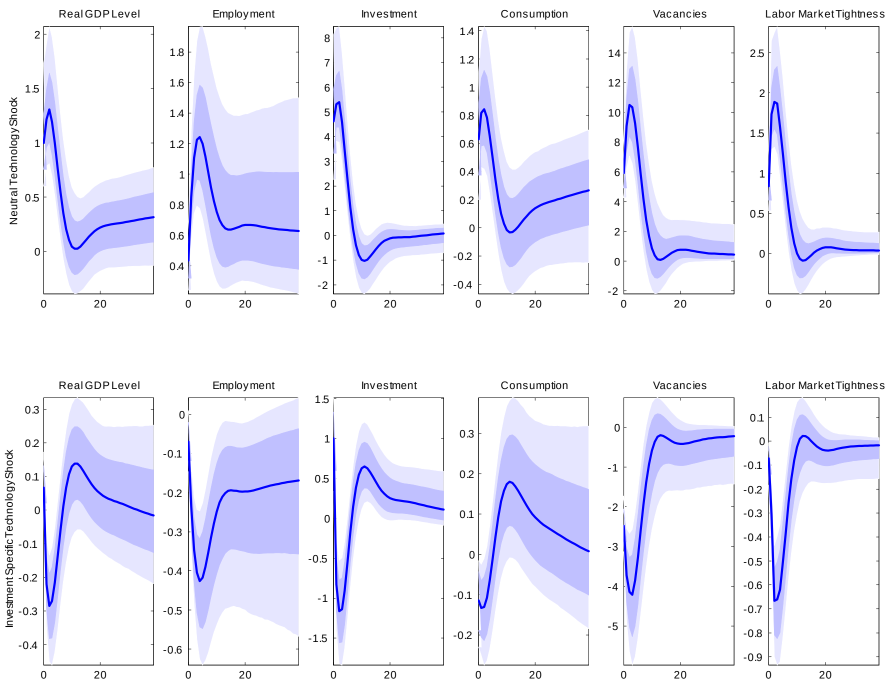
Notes: Entries show sign restrictions on the first-period SVAR variables to neutral and investment specific technological progresses, cost-push shocks, monetary policy shocks, and labor supply shocks. We are able to uniquely identify neutral technology shocks since they generate positive comovements in hiring, labor market tightness and consumption.

Figure 1. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock for the SVAR in Differences



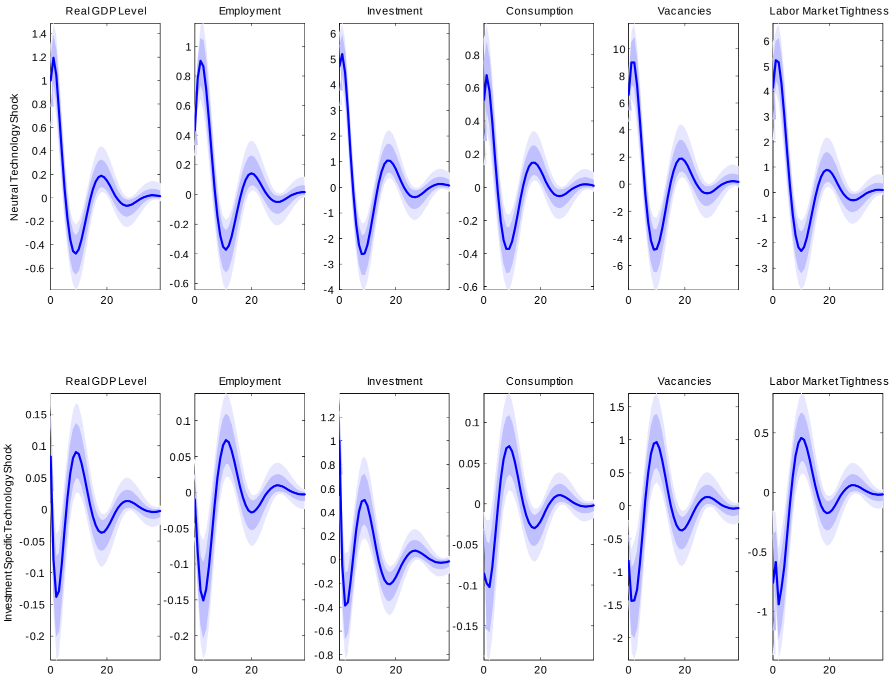
Notes: The variables in the SVAR model are specified in differences. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses.

Figure 2. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock for the De-trended SVAR



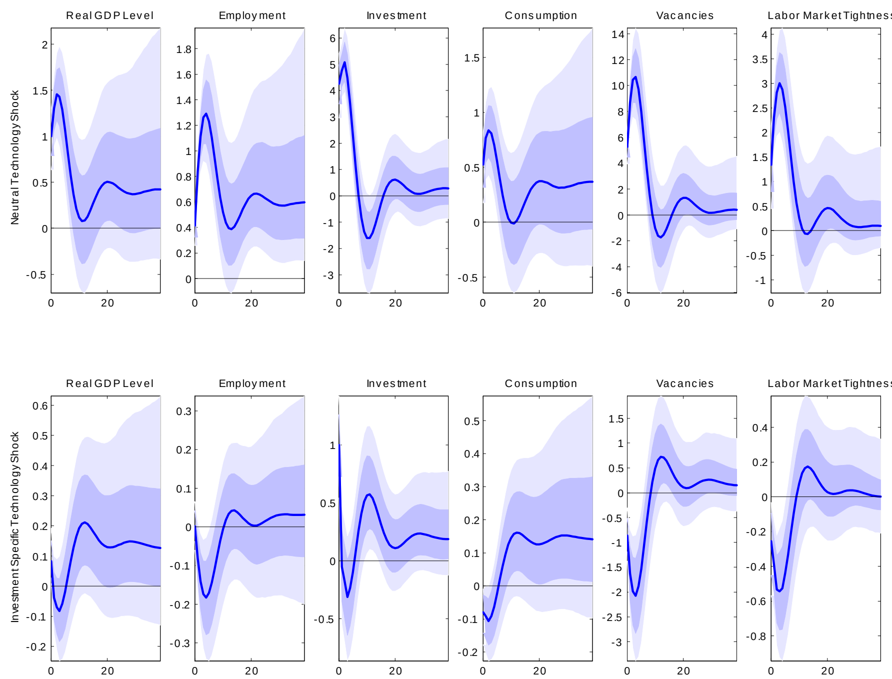
Notes: The variables in the SVAR model are de-trended by allowing the constant term in the VAR to vary over time. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses.

Figure 3. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock for the Filtered SVAR



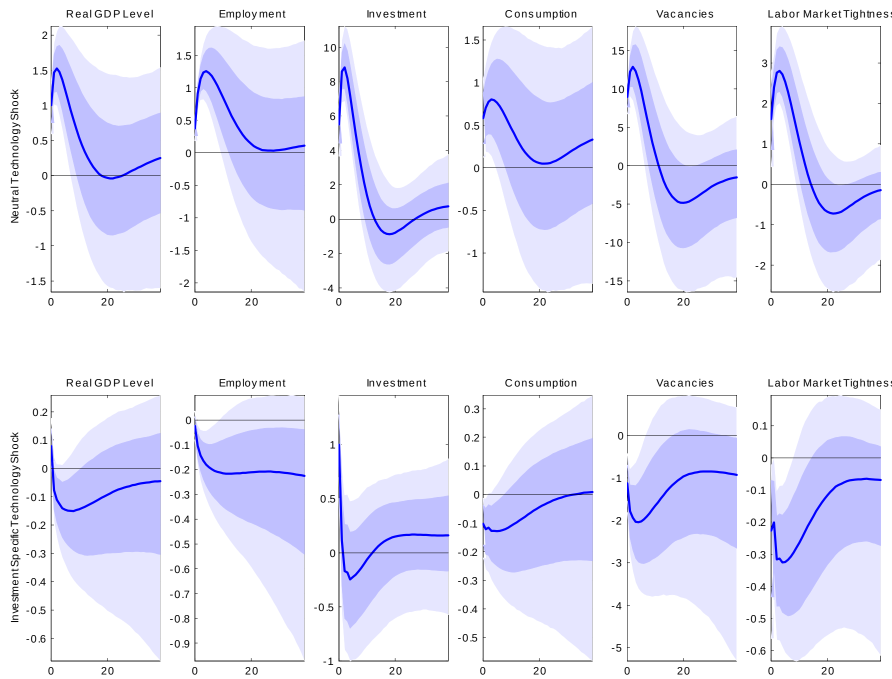
Notes: The variables in the SVAR model are filtered using the HP filter. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses.

Figure 4. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock for the period pre-1980



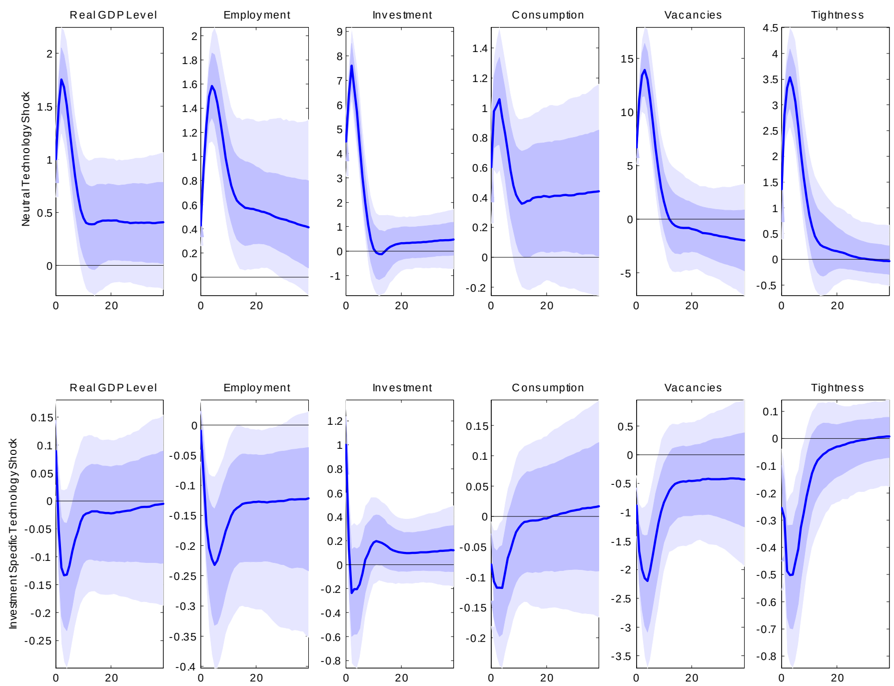
Notes: The SVAR model is estimated 1951:Q1 – 1979:Q4. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses.

Figure 5. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock for the period post-1980



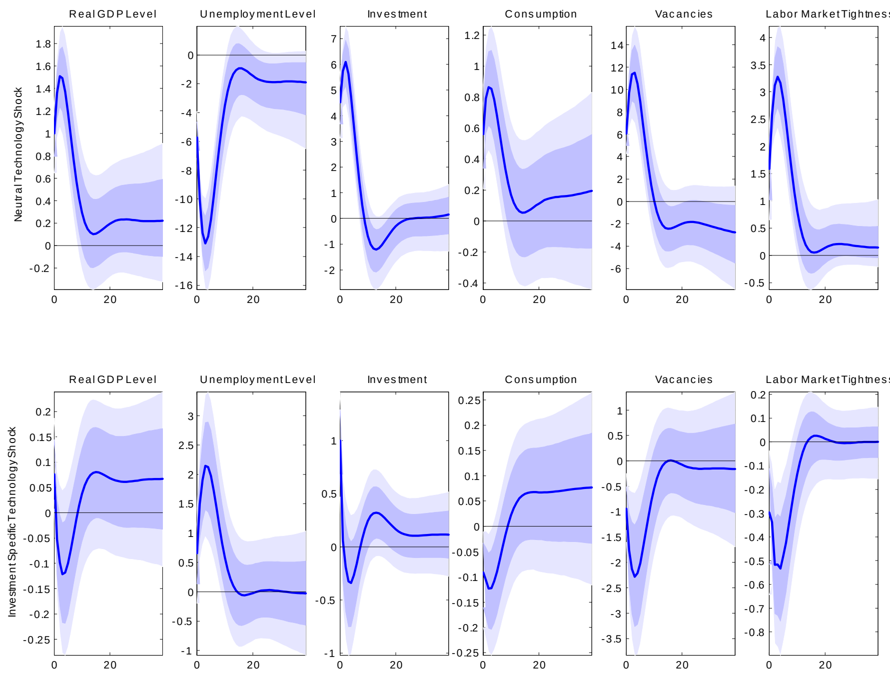
Notes: The SVAR model is estimated 1980:Q1 – 2006:Q3. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses.

Figure 6. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock, Model with Four Lags



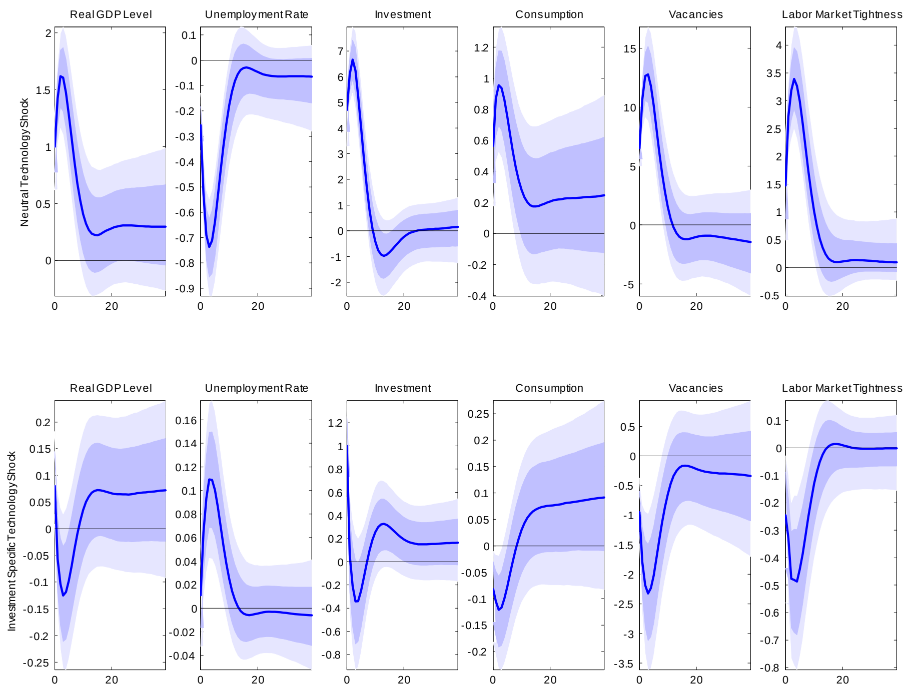
Notes: The SVAR model is estimated using four lags. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses.

Figure 7. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock using Unemployment Level



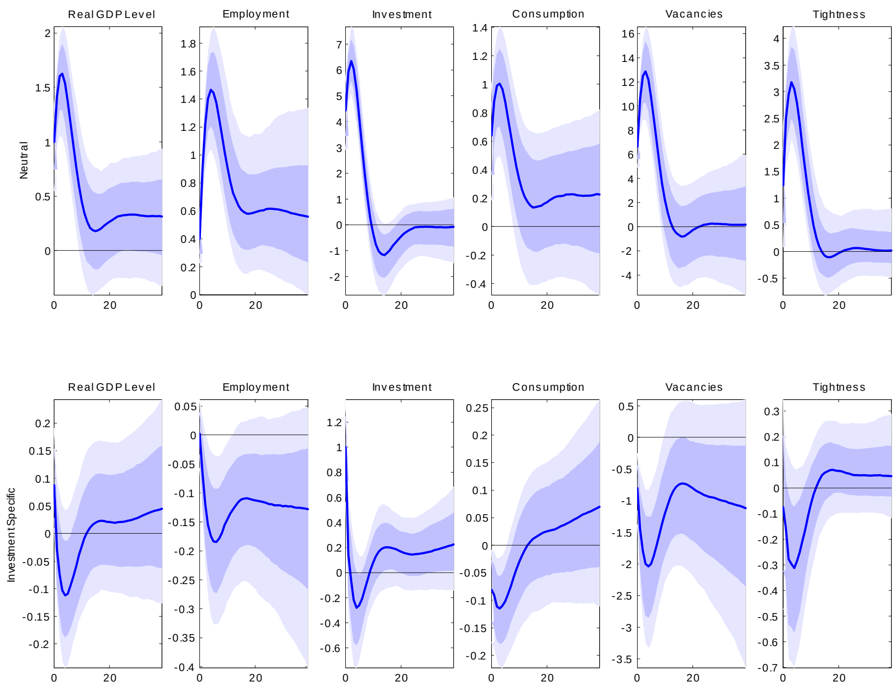
Notes: The SVAR model is defines labor input with unemployment level. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses.

Figure 8. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock using Unemployment Rate



Notes: The SVAR model is defines labor input with unemployment rate. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses.

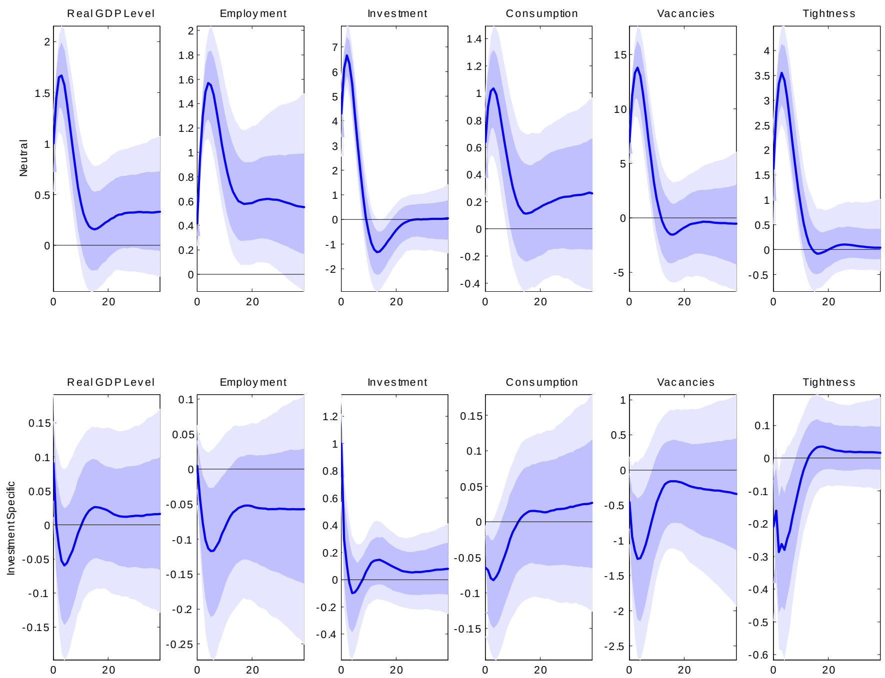
Figure 9. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock, with no Sign Restriction on Labor Market Tightness



Estimated impulse response to technology shocks with no sign restriction on labour market tightness.

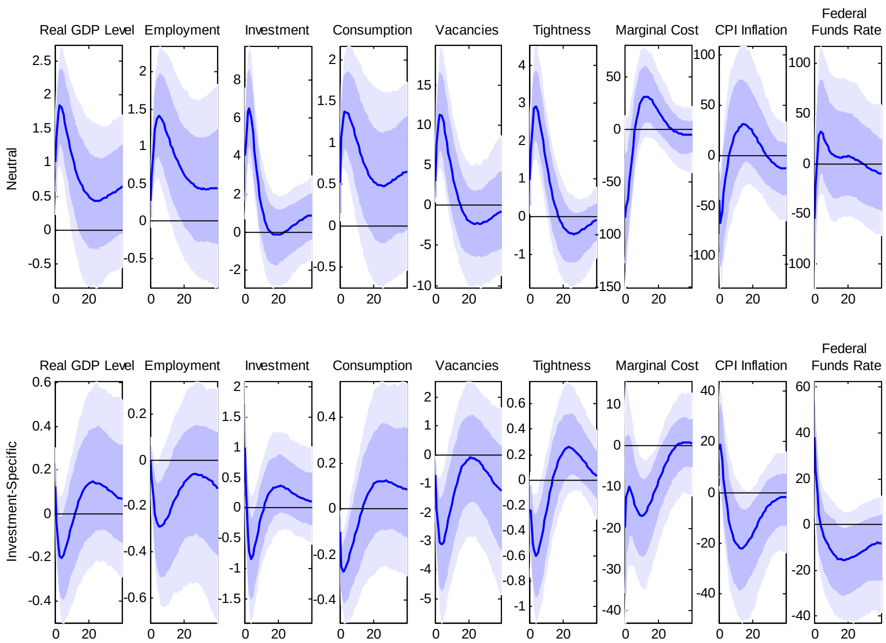
Notes: The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses. The identification imposes no sign restriction on labour market tightness.

Figure 10. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock, with no Sign Restriction on Hiring



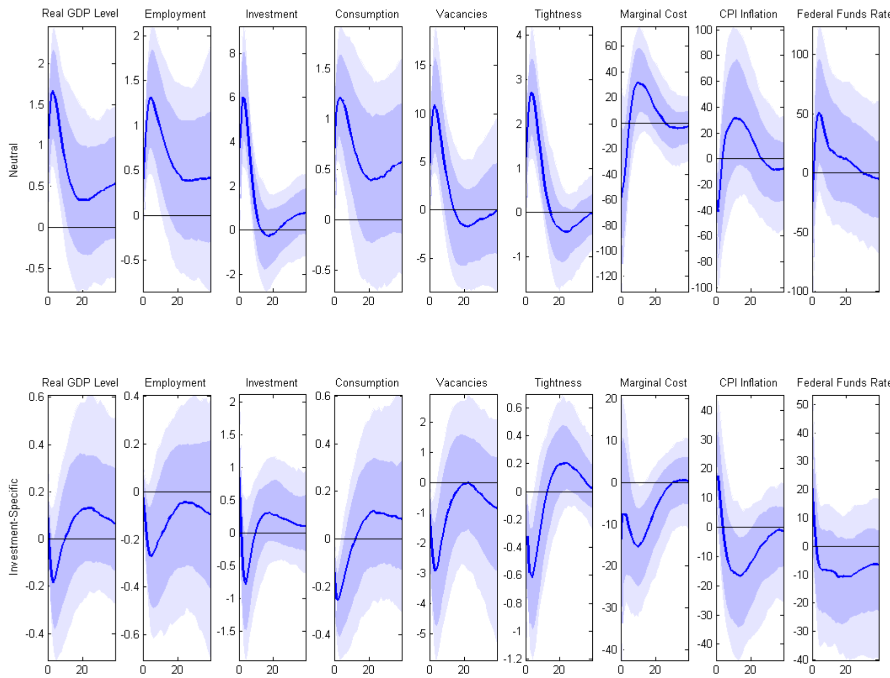
Notes: The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses. The identification imposes no sign restriction on hiring.

Figure 11. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock, Model with Staggered Prices



Notes: The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses. The identification is based on the model with staggered prices.

Figure 12. Empirical Impulse-Response Functions to a Neutral and Investment Specific Technology Shock, Model with Staggered Prices and Multiple Shocks



Notes: The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses. The identification is based on the model with staggered prices and multiple shocks as indicated in Table 1.

2 Appendix B: New Keynesian model: specification of additional shocks

In Section 6 of the paper, in order to establish that results hold in a model based on staggered prices, we extend the data set to include series for marginal cost, inflation and the nominal interest rate. As stated in footnote 8, to include these additional series we enrich the model with labor supply shocks, cost-push shocks and monetary policy shocks. Labor supply and cost-push shocks are embedded by allowing for time variation in the parameters χ and μ respectively, and by assuming that they follow an AR(1) process. Monetary policy shocks are embedded by adding a white noise error to the Taylor rule equation (23). In particular, labor supply and cost-push shocks follow the autoregressive processes

$$\ln(\chi_t) = (1 - \rho_\chi)\ln(\chi) + \rho_\chi \ln(\chi_{t-1}) + \varepsilon_{\chi t},$$

and

$$\ln(\mu_t) = (1 - \rho_\mu)\ln(\mu) + \rho_\mu \ln(\mu_{t-1}) + \varepsilon_{\mu t},$$

with $0 < [\rho_\chi, \rho_\mu] < 1$, and where the zero-mean, serially uncorrelated innovations $\varepsilon_{\chi t}$ and $\varepsilon_{\mu t}$ are normally distributed with standard deviation σ_χ and σ_μ.

As mentioned, monetary policy shocks are embedded into the Taylor rule, which becomes

$$\ln(R_t/R) = \rho_r \ln(R_{t-1}/R) + \rho_y \ln(Y_t/Y) + \rho_\pi \ln(\pi_t/\pi) + \varepsilon_{Rt},$$

where the zero-mean ε_{Rt} innovation is normally distribute with standard deviation σ_R.

As detailed in the paper, to simulate the model the autoregressive coefficients ρ_χ and ρ_μ are calibrated equal to 0.75, and the variances of the shocks σ_χ, σ_μ and σ_R are set equal to 1.

3 Appendix C: Data

The data are quarterly, seasonally adjusted, and cover the period 1951:Q1 2006:Q3. In the model without nominal price rigidities we use series for the level of real GDP, investment, consumption, hiring, labor market tightness, and employment. The data for real GDP, investment, consumption and employment are from the FRED database. The FRED codes for these variables are GDPC96, PNFI, PCECC96 and CE16OV respectively. We use US data as it is a standard benchmark that has been widely explored in the previous literature. The data for hiring and labor market tightness are from Shimer (2007).

In the model with nominal price rigidities we extend the data set to include series for the marginal cost, inflation and the nominal interest rate. Inflation is defined as the quarterly growth rate of the CPI index, while the nominal interest rate is proxied by the federal funds rate. Data on CPI and the federal funds rate are from the FRED database, whose codes are CPIAUCSL and FEDFUNDS respectively. We proxy the marginal cost with the labour share. We construct the labour share directly using the neoclassical growth framework, suggesting constant long-run shares of capital and labour inputs in production

$$Y_t = A_t K_t^{\theta} N_t^{1-\theta}, \tag{1}$$

which is the standard Cobb-Douglas production function used in the paper. We use the income categories in the US Bureau of Economic Analysis' National Income and Product Accounts (NIPA) to establish the share of *unambiguous* labour income of income generated by the private sector. In constructing total private sector labour income one needs to take a stand on how much of the more ambiguous income categories, such as proprietors' income as well as supplements to wages and salaries, should be allocated to private sector labour income. We allocate these ambiguous income categories to private labour income according to the share of labour income in measured GDP. Following the line of reasoning in Cooley and Prescott (1995), we can define now the labour share (or unit labour costs) as (for notational convenience we suppress the time indexes):

$$\frac{WN}{PY} = \frac{\text{Unambiguous Labour Income} + \text{Private Share Supplements}}{\text{GDP} - \text{Ambiguous Labour Income} - \text{Government Labour Income}} \tag{2}$$

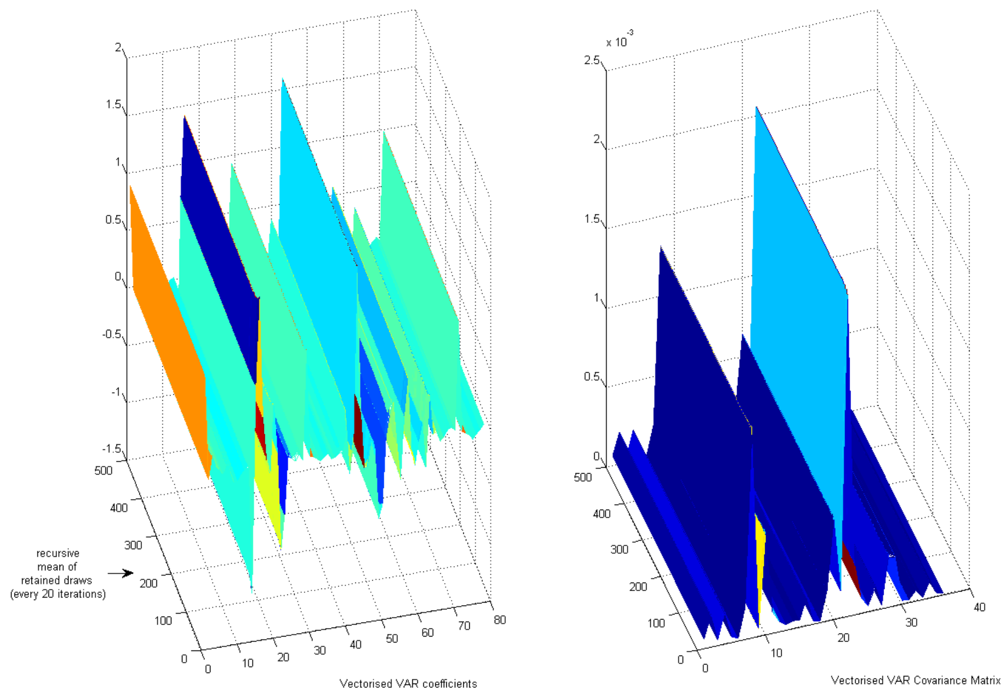
where

- *Unambiguous Labour Income* equals ‘wages and salary accruals, other’, ie row B203RC1, Table 1.12 in NIPA.
- *Private Share Supplements* equals ‘supplements to wages and salaries’ (row A038RC1, Table 1.12 in NIPA) times the ratio of ‘wages and salary accruals, other’ (row B203RC1, Table 1.12 in NIPA) to ‘wages and salary accruals’ (row A034RC1, Table 1.12 in NIPA).
- *GDP* is nominal GDP from row A191RC1, Table 1.1.5 in NIPA.
- *Ambiguous Labour Income* equals the sum of
  - ‘Proprietors’ income with IVA and CCAdj’ (row A041RC1, Table 1.12 in NIPA).
  - The difference between nominal GDP (row A191RC1, Table 1.1.5 in NIPA) and national income (row A032RC1, Table 1.12 in NIPA).
- *Government Labour Income* equals the sum of
  - ‘Wages and salary accruals, government’ (row A553RC1, Table 1.12 in NIPA).
  - ‘Supplements to wages and salaries’ (row A038RC1, Table 1.12 in NIPA) times the ratio of ‘wages and salary accruals, government’ (row A553RC1, Table 1.12 in NIPA) to ‘wages and salary accruals’ (row A034RC1, Table 1.12 in NIPA).

Groen and Mumtaz (2008) provide additional details on the construction of these series as well as an application on their use to investigate the structural stability of the Phillips curve.

4 Appendix D: Convergence of the MCMC algorithm

To estimate the VAR model we use 500,000 Gibbs iterations discarding the first 400,000 as burn-in. Out of the remaining 100,000 draws we retain every 10th draw to reduce autocorrelation in the chain. The figure below plots the recursive mean (computed at every 20 draws) of the retained Gibbs iterations for our benchmark model. The fact that there is very little fluctuation in the recursive mean provides evidence for convergence of the MCMC algorithm.



Recursive means of the retained draws of the VAR parameters

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