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## Abstract

This paper studies the dynamic response of labour input to neutral technology shocks. It uses a standard real business cycle model enriched with labour market search and matching frictions and investment-specific technological progress that enables a new, agnostic, identification scheme based on sign restrictions on an SVAR. The estimation supports an increase of labour input in response to neutral technology shocks. This finding is robust across different perturbations of the SVAR model. The model is extended to allow for time-varying volatility of shocks and the identification scheme is used to investigate the importance of neutral and investment-specific technology shocks to explain the reduced volatility of US macroeconomic variables over the past two decades. Neutral technology shocks are found to be more important than investment-specific technology shocks.

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**Summary**

Estimating the impact of changes in technology on the economy is one of the key aims of recent empirical research. And policymakers are equally interested, because in order to determine the appropriate stance of monetary policy it is essential to know what shocks are hitting the economy, and what their impact will be. The consensus from this literature is that the estimated impact can depend quite heavily on the way changes or shocks to technology are measured.

This paper contributes to this strand of the literature by proposing an improved procedure for measuring shocks to technology. In particular, we use information from a theoretical model of the business cycle which embeds labour market frictions to disentangle changes in technology from other shocks hitting the economy.

The estimation method comprises the following steps. First, we use the theoretical model characterised by search and matching frictions in the labour market to gauge the impact of the technology shock on vacancies, labour market tightness and other key macroeconomic aggregates. Second, we impose the predicted movements in these variables on US data, which has been the subject of many studies in the past. This is done via an empirical model referred to as a vector autoregression (VAR) where each included variable depends on the past values of all variables in the model. By using restrictions implied by economic theory, we can identify different types of shock, thus making the model a 'structural' VAR (an SVAR). The restrictions that we use are on the signs of impacts over particular time horizons. The SVAR is then used to estimate the response of key macroeconomic variables to technology shocks. The resulting responses of key macroeconomic variables provide us an approximation of the variables' responses to a change in technology in the United States.

Our main results are as follows. A positive shock to technology which affects labour productivity acts to increase GDP, investment, consumption and employment. This shock explains around 30% to 60% of the variation in each of these variables. This result is robust to a number of different configurations of the benchmark model and transformations of the data, such as controlling for long cycles in the data, choosing different time lags in the VAR, splitting the sample period, using alternative measures of labour market variables, and extending the length of

sign restrictions on the SVAR.

One innovation is that we extend the benchmark model to allow the variance of the technology shock to change over time. We find that this shock played an important role in driving the volatility of US output during the 1970s and the 1980s. In particular, the volatility of technology declined since the early 1990s, which could explain the declined macroeconomic volatility over the same period, as highlighted in related studies.

## 1 Introduction

This paper studies the dynamic response of labour input to neutral technology shocks. Neutral technology shocks are identified using the cyclical properties of a theoretical model of the business cycle characterised by labour market search and matching frictions. Once the model's properties on the sign of the variables' reaction to shocks are imposed on the first-period responses of a structural vector autoregression (SVAR) model, the data robustly support that neutral technology shocks increase labour input.

The theoretical framework used to inform the empirical investigation is a standard real business cycle model enriched with search and matching frictions on the labour market and investment-specific technological progress. The addition of these two features is motivated by empirical evidence and, more importantly, it enables a new identification scheme to neutral technology shocks. Empirically, surveys by Bean (1994) and Nickell (1997) show that labour markets are characterised by frictions that prevent the competitive market mechanism from determining labour market equilibrium allocations, thereby suggesting that their presence is important for an accurate description of the functioning of the labour market and coincidentally to study the reaction of labour input to technology shocks. Additionally, the analysis by Greenwood, Hercowitz and Krusell (1997), Greenwood, Hercowitz and Krusell (2000), Pakko (2002), Fisher (2006) and Faccini and Ortigueira (2008) point out that the inclusion of investment-specific technological progress is key to study the dynamics of the technological progress.

Importantly for the analysis of this paper, the inclusion of search and matching frictions and of investment-specific technological progresses enables a new, agnostic, identification scheme. The presence of labour market search and matching frictions enriches the standard real business cycle model with additional variables, such as unemployment and hiring, whose reaction to neutral technology shocks is uniquely identified and provides two new short-run identification restrictions. First, neutral technology shocks increase the number of hiring and, second, raise labour market tightness—defined as the ratio between hiring and unemployment. Investment-specific technology shocks instead have a reverse effect on these variables. By imposing these sign restrictions on the impact responses of an SVAR model, while leaving labour input to freely react to shocks, the data show that neutral technology shocks increase labour input. This finding is robust across different perturbations of the model, such as controlling for long cycles in the data, choosing different time lags in the SVAR, splitting the sample period, using alternative measures of labour market variables, and extending the length of sign restrictions on the SVAR.

The identification scheme is used to investigate to what extent neutral and investment-specific technology shocks explain the reduced macroeconomic volatility in the United States over the past two decades. To this end, we extend the benchmark setting to allow for time-varying error covariance matrix which enables the model to evaluate the significance of shocks in explaining changes in the variables' volatility over time. The results show that neutral technology shocks significantly explain the reduced volatility of output since the early 1980s, while investment-specific technology shocks play a limited role. This result is in line with the findings in Arias, Hansen and Ohanian (2007), Justiniano, Primiceri and Tambalotti (2009) and Liu, Waggoner and Zha (2009), who, using structural models of the business cycle, find that neutral technology shocks play a more important role than investment-specific technology shocks in explaining the reduced macroeconomic volatility over the period. However, the result is in contrast with the similar study by Gali and Gambetti (2009), who use an SVAR in which technology shocks are identified by assuming that they are the only components that affect the level of productivity in the long run, rather than using sign restrictions informed by a structural model of the business cycle. Since the analysis in Gali and Gambetti (2009) differs in the identification scheme used, this paper calls for further investigation on the role of the identification scheme in order to establish the relevance of neutral and investment-specific technology shocks over the past decades.

The approach proposed in this paper has three advantages. First, we conduct the analysis without relying on low or medium-frequency identification schemes, thereby imposing a minimal set of constraints on the model. As Fernald (2007), Canova, López-Salido and Michelacci (2006) and Canova, López-Salido and Michelacci (2009) point out, any procedure that includes low or medium frequencies generates an artificial positive comovement between labour input and neutral technology shocks that disappears once controlling for long cycles, as also detected by Blanchard and Quah (1989), Francis and Ramey (2005) and Gali and Rabanal (2005). Second, by using high-frequency restrictions we identify the reaction of labour input to technology shocks without incurring the estimation uncertainty and bias that long-run identification schemes produce, as documented by Erceg, Guerrieri and Gust (2005) and Lindé (2009). Finally, in this setting the information from the theoretical framework is processed consistently with the empirical investigation, since the business cycle properties of the theoretical model provide short-run sign restrictions on the impulses of the SVAR. This allows us to effectively implement an agnostic identification scheme since, in the benchmark specification, the theoretical restrictions are imposed on the first-period reactions of the SVAR, thereby leaving the data to determine subsequent dynamics.

The remainder of the paper is organised as follows. Section 2 provides an overview of the literature, Section 3 describes the SVAR model and the identification scheme based on sign restrictions, Section 4 lays out the theoretical model and describes the model's solution and calibration, Section 5 presents the results, Section 6 performs robustness analysis, and Section 7 concludes.

## 2 An overview of the literature

A growing number of studies identify neutral technology shocks by imposing the restriction that they are the only component that can affect the level of productivity in the long run, as originally proposed by Blanchard and Quah (1989). Using this identification scheme Gali (1999), Gali, López-Salido and Valles (2003), Francis and Ramey (2005), Liu and Phaneuf (2007), Wang and Wen (2007), Whelan (2009), Canova *et al* (2006), and Canova *et al* (2009) find that technology shocks have a contractionary effect on employment. On the other hand, despite using a similar methodology, Fisher (2006), Christiano, Eichenbaum and Vigfusson (2003) and Christiano, Eichenbaum and Vigfusson (2004), obtain the opposite result. Irrespective of the findings, Fernald (2007) shows that such an analysis is sensitive to the treatment of low-frequency trends, thereby calling into question the validity of this approach. Moreover, Erceg *et al* (2005) and Lindé (2009) point out that long-run restrictions are subject to considerable estimation uncertainty about the quantitative impact of technology shocks on macroeconomic variables. We overcome these methodological pitfalls by using short-run restrictions, and we show that the results are robust to controlling for long cycles in the data. In addition, unlike the aforementioned studies, with the exception of Canova *et al* (2006) and Canova *et al* (2009), we inform the empirical investigation with a search and matching model of the labour market, which, as mentioned, allows a new identification scheme and improves both the description of the functioning of the labour market and the understanding of the reaction of labour input to technology shocks.

Uhlig (2004) and Dedola and Neri (2007) report related work using a medium-run identification scheme, where the sign of the variables' responses to technology shocks are imposed for a number of periods on an SVAR to investigate the reaction of labour input to technology shocks. Our paper has two differences. First, it uses an agnostic identification scheme as the variables' responses are imposed on the impact response and the data can freely inform the variables' responses in the aftermath, and, second, as described, it uses a novel identification scheme based on labour market variables such as hirings and labour market tightness.

## 3 The Bayesian SVAR model

In this section, we describe the empirical SVAR model, how the prior is used to compute the posterior, and the identification scheme based on sign restrictions.

Our analysis is based on the following standard SVAR model

$$Z_t = \sum_{j=1}^{P} \beta_j Z_{t-j} + \varepsilon_t, \tag{1}$$

where the variance of $\varepsilon_t$ is equal to $\Sigma$ and the $T \times N$ data matrix $Z_t$ contains the data. We assume a Bayesian approach to the estimation of equation **(1)** and adopt a Normal Inverted Wishart prior for the SVAR coefficients and the covariance matrix, as in Kadiyala and Karlsson (1997) and Sims and Zha (1998), with the distribution:

$$p(\Sigma) \backsim IW\left(\Sigma^0, T^0\right) \text{ and } p(B/\Sigma) \backsim N\left(\beta^0, \Sigma \otimes \Psi^0\right). \tag{2}$$

Essentially, the prior in equation **(2)** is a generalisation of the Minnesota prior discussed in Litterman (1986) and assumes that the variables included in the SVAR follow a random walk.[1] This is based on the idea that recent lags provide more reliable information on the dynamics of the system and therefore the estimation should assign them a higher weighting. Unlike the original formulation in Litterman (1986) however, the prior in equation **(2)** does not assume a diagonal, fixed and known covariance matrix making it more suitable for VARs designed for

[1] An AR(1) prior is used for the VAR coefficients when the equation is re-cast in first differences or de-trended form.

structural analysis. As described in Banbura, Giannone and Reichlin (2007) and commonly used in the literature, we impose the prior by using dummy observations. In this way, the Normal Inverted Wishart prior in equation **(2)** is implemented by adding $T_d$ dummy observations $Y^0$ and $X^0$ to the system in equation **(1)**. It can be shown that $\beta^0 = \left(X^{0\prime}X^0\right)^{-1}\left(X^{0\prime}Y^0\right)$ and $\Sigma^0 = \left(Y^0 - X^0\beta^0\right)'\left(Y^0 - X^0\beta^0\right)$. The dummy observations are defined as

$$Y^0 = \begin{pmatrix} \frac{diag\left(\gamma_1\sigma_1...\gamma_N\sigma_N\right)}{\varpi} \\ 0_{N\times(P-1)\times N} \\ ............. \\ diag\left(\sigma_1...\sigma_N\right) \\ ............. \\ 0_{1\times N} \end{pmatrix}, \text{ and } X^0 = \begin{pmatrix} \frac{J_P\otimes diag(\sigma_1...\sigma_N)}{\varpi} & 0_{NP\times 1} \\ 0_{N\times NP} & 0_{N\times 1} \\ ............. & \\ 0_{1\times NP} & \mu \end{pmatrix}$$

where $\gamma_1, \gamma_2, ..., \gamma_N$ are the prior mean for each coefficient. Note that the parameter $\varpi$ controls for the tightness of the prior on the SVAR coefficients, such that a large number for $\varpi$ corresponds to a loose prior. The parameter $\mu$ controls the prior on the intercept, such that a small number makes the prior uniformative. Finally, following common practice, the parameters $\sigma_1, \sigma_2, ..., \sigma_N$ are scaling parameters and are approximated using the variance of univariate autoregressions for each variable in the SVAR. After imposing the prior, the posterior for the SVAR has the following form

$$g\left(\Sigma\right) \backsim IW\left(\hat{\Sigma}, T_d + 2 + T - K\right) \text{ and } g\left(\beta/\Sigma\right) \backsim N\left(\hat{B}, \Sigma\otimes\left(X^{*\prime}X^*\right)^{-1}\right), \qquad \textbf{(3)}$$

where $\hat{B} = \left(X^{*\prime}X^*\right)^{-1}\left(X^{*\prime}Y^*\right)$ and $\hat{\Sigma} = \left(Y^* - X^*\hat{B}\right)'\left(Y^* - X^*\hat{B}\right)$, and the terms $Y^*$ and $X^*$ denote the left and the right-hand side of equation **(1)** with the data $Z_t$ augmented by dummy observations. We use Gibbs sampling to draw 15,000 samples from this posterior and use the final 1,000 for inference.

### *3.1 Identification*

As mentioned, the structural analysis using the SVAR model is based on the identification of two shocks: neutral and investment-specific technology shocks. Following Uhlig (2005) and Dedola and Neri (2007), we employ sign restrictions to identify these shocks. The identification scheme is implemented as follows. We compute the structural impact matrix, $A_0$ via the procedure introduced by Rubio-Ramírez, Waggoner and Zha (2008). Specifically, let $\Sigma = PDP'$ be the eigenvalue-eigenvector decomposition of the SVAR's covariance matrix $\Sigma$, and let $\tilde{A}_0 \equiv PD^{\frac{1}{2}}$.

We draw an $N \times N$ matrix $K$ from the $N(0, 1)$ distribution and then take the QR decomposition of $K$. That is, we compute $Q$ and $R$ such that $K = QR$. We then compute a structural impact matrix as $A_0 = \tilde{A}_0 \times Q'$. If $A_0$ satisfies the sign restrictions we keep it. We repeat this algorithm until we recover 100 $A_0$ matrices that satisfy the sign restrictions for each Gibbs iteration. Our structural analysis is based on the $A_0$ matrix closest to the median of the estimated distribution of $A^0$ for each draw from the SVAR posterior. The sign restrictions that we use to identify the neutral and investment-specific technology shocks are derived using the structural model set out in the next section.

## 4 The theoretical model

This section lays out the theoretical model and describes its solution and calibration.

A standard real business cycle (RBC) model is enriched to allow for labour market frictions of the Diamond-Mortensen-Pissarides model of search and matching, as in Blanchard and Gali (2010), and for investment-specific technological progress, as in Greenwood *et al* (1997). This framework relies on the assumption that the processes of job search and hiring are costly for both the firm and the worker and a constant fraction of jobs is dismissed during each period, $t = 0, 1, 2, ....$ Moreover, the technological process occurs either by increasing production or by stimulating investment.

The economy is populated by a continuum of infinitely lived identical households who produce goods by employing labour. During each period, $t = 0, 1, 2, ...$, each household maximizes the utility function:

$$E \sum_{t=0}^{\infty} \beta^t \left[ \ln C_t - \chi N_t^{1+\phi} / (1 + \phi) \right], \qquad \textbf{(4)}$$

where $C_t$ is consumption, $N_t$ is the fraction of household members who are employed,[2] $\beta$ is the discount factor such that $0 < \beta < 1$, and $\phi$ is the inverse of the Frisch intertemporal elasticity of substitution in labour supply such that $\phi \geq 0$. In this model we assume full participation, such that the members of a household can be either employed or unemployed, which implies $0 < N_t < 1$. By investing $I_t$ units of output during period $t$, the household increases the capital

[2]In order to keep the analysis simple, we focus on the extensive margin.

stock $K_{t+1}$ available during period $t+1$ according to

$$K_{t+1} = (1-\delta_k)K_t + q_t I_t, \tag{5}$$

where the depreciation rate satisfies $1 < \delta_k < 0$, and the disturbance $q_t$ is the Greenwood *et al* (1997) investment-specific technology shock, which follows the autoregressive process

$$\ln(q_t) = (1-\rho_q)\ln(q) + \rho_q \ln(q_{t-1}) + \varepsilon_{qt}, \tag{6}$$

with $1 < \rho_q < 0$, and where the zero-mean, serially uncorrelated innovation $\varepsilon_{qt}$ is normally distributed with standard deviation $\sigma_q$.

During each period, $t = 0, 1, 2, ...$, each representative firm manufactures $Y_t$ units of goods using $N_t$ units of labour input and $K_t$ units of capital from the representative household according to the production technology

$$Y_t = A_t K_t^{\theta} N_t^{1-\theta}, \tag{7}$$

where $1 < \theta < 0$ represents the capital share of production. The disturbance $A_t$ is the neutral technology shock, which follows the autoregressive process

$$\ln(A_t) = (1-\rho_a)\ln(A) + \rho_a \ln(A_{t-1}) + \varepsilon_{at}, \tag{8}$$

with $1 < \rho_a < 0$, and where the zero-mean, serially uncorrelated innovation $\varepsilon_{at}$ is normally distributed with standard deviation $\sigma_a$.

During each period, $t = 0, 1, 2, ...$, total employment is given by the sum of the number of workers who survive the exogenous separation, and the number of new hires, $H_t$. Hence, total employment evolves according to

$$N_t = (1-\delta_n)N_{t-1} + H_t, \tag{9}$$

where $\delta_n$ is the job destruction rate, and $0 < \delta_n < 1$. Accounting for job destruction, the pool of household's members unemployed and available to work before hiring takes place is:

$$U_t = 1 - (1-\delta_n)N_{t-1}. \tag{10}$$

It is convenient to represent the job creation rate, $x_t$, by the ratio of new hires over the number of unemployed workers such that:

$$x_t = H_t / U_t, \tag{11}$$

with $0 < x_t < 1$, given that all new hires represent a fraction of the pool of unemployed workers. The job creation rate, $x_t$, is also an index of labour market tightness, since it indicates the proportion of hires over the number of workers in search for a job. This rate also has an alternative interpretation: from the viewpoint of the unemployed, it is the probability of being hired in period $t$, or in other words, the job-finding rate. The cost of hiring a worker is equal to $G_t$ and, as in Blanchard and Gali (2010), is a function of labour market tightness $x_t$:

$$G_t = Bx_t^{\alpha}, \qquad \textbf{(12)}$$

where $\alpha$ is the elasticity of labour market tightness with respect to hiring costs such that $\alpha \geq 0$; and $B$ is a scale parameter such that $B \geq 0$. As pointed out in Yashiv (2000) and Rotemberg (2006), this formulation expresses the idea that the tighter the labour market the more costly hiring may be. Note that, given the assumption of full participation, the unemployment rate, defined as the fraction of household members left without a job after hiring takes place, is

$$u_t = 1 - N_t. \qquad \textbf{(13)}$$

The aggregate resource constraint

$$Y_t = C_t + I_t + G_t H_t \qquad \textbf{(14)}$$

completes the description of the model.

Since the two welfare theorems apply, resource allocations can be characterised by solving the social planner's problem.[3] The social planner chooses $\{Y_t, C_t, H_t, K_t, I_t, G_t, x_t, U_t, N_{t-1}\}_{t=0}^{\infty}$ to maximise the household's utility **(4)** subject to the aggregate resource constraints, represented by equations **(5)-(14)**. To solve this problem it is convenient to use equation **(14)**, together with the other constraints, to obtain the aggregate resource constraint of the economy expressed in terms of capital, consumption and employment. The aggregate resource constraint of the economy can therefore be written as:[4]

$$A_t K_t^{\theta} N_t^{1-\theta} = C_t + \frac{K_{t+1}}{q_t} - (1-\delta)\frac{K_t}{q_t} + B\frac{H_t^{1+\alpha}}{U_t^{\alpha}}. \qquad \textbf{(15)}$$

In this way, the social planner chooses $\{C_t, N_t, K_{t+1}\}_{t=0}^{\infty}$ to maximise the household's utility **(4)** subject to the aggregate resource constraint **(15)**. Letting $\Lambda_t$ be the non-negative Lagrangian

[3] As detailed in Section 4.1, the Hosios' condition for efficiency holds.

[4] To do so, use equation **(7)** to substitute for $Y_t$ into equation **(14)**; use equation **(9)** to substitute for $H_t$ into equation **(14)**; use equations **(9)** and **(10)** into **(11)** and substitute the outcome into **(12)** so to obtain an expression of $G_t$ that can be used into equation **(14)**.

multiplier on the resource constraint **(15)**, the first-order conditions for $C_t$, $N_t$, and $K_{t+1}$ are:

$$\Lambda_t = 1/C_t, \quad \textbf{(16)}$$

$$\chi N_t^{\phi}/\Lambda_t = (1-\theta)Y_t/N_t - B(1+\alpha)x_t^{\alpha} + B\beta(1-\delta_n)\left(\Lambda_{t+1}/\Lambda_t\right)\left[(1+\alpha)x_{t+1}^{\alpha} - \alpha x_{t+1}^{1+\alpha}\right], \quad \textbf{(17)}$$

and

$$\Lambda_t/q_t = \beta\Lambda_{t+1}\left[\theta Y_{t+1}/K_{t+1} + (1-\delta_k)/q_{t+1}\right]. \quad \textbf{(18)}$$

Equation **(16)** is the standard Euler equation for consumption, which equates the Lagrange multiplier to the marginal utility of consumption. Equation **(17)** equates the marginal rate of substitution between consumption and labour input to the marginal rate of transformation. The marginal rate of transformation depends on labour productivity, $Y_t/N_t$, as in the standard RBC model, but also, due to the presence of labour market frictions, on present and future foregone costs of hiring. More specifically, the three terms composing the marginal rate of transformation are the following. The first term, $(1-\theta)Y_t/N_t$, corresponds to the additional output generated by the marginal employed worker. The second term represents the cost of hiring an additional worker, and the third term captures the savings in hiring costs resulting from the reduced hiring needs in period $t+1$. In the standard RBC model only the first term appears. Finally, equation **(18)** is the standard Euler equation for capital, which links the intertemporal marginal utility of consumption with the real remuneration of capital.

### *4.1 Model solution and calibration*

Equations **(5)-(15)** and **(16)-(18)** describe the behaviour of the endogenous variables $\{Y_t, C_t, H_t, K_t, I_t, G_t, x_t, U_t, N_{t-1}, \Lambda_t\}$, and persistent autoregressive processes of the exogenous shocks $\{\varepsilon_{at}, \varepsilon_{qt}\}$. The equilibrium conditions do not have an analytical solution. Consequently, the system is approximated by loglinearising its equations around the stationary steady state. In this way, a linear dynamic system describes the path of the endogenous variables' relative deviations from their steady-state value, accounting for the exogenous shocks. The solution to this system is derived using Klein (2000).

The model is calibrated on quarterly frequencies using US data. Since the model is used to identify the sign of the variables' response to shocks, we need to ensure that the reactions are robust across a broad range of parameters' calibration. For this reason, as in Canova (2002) and

Dedola and Neri (2007), we assume that the parameters values are uniformly and independently distributed over a wide range of plausible values. The range value for each parameter is described below and reported in Table A. As in Blanchard and Gali (2010), to satisfy the Hosios condition for efficiency, we impose that the relative bargaining power of the worker, $\varsigma$, is equal to the elasticity of labour market tightness with respect to hiring costs, $\alpha$, such that $\varsigma = \alpha$. The elasticity of labour market tightness with respect to hiring costs, $\alpha$, is allowed to vary between 0 and 10, which covers a broad range of plausible values. We allow the real interest rate to vary between 2% and 6.5% annually, whose values are commonly used in the literature, and they pin down the quarterly discount factor $\beta$ between 0.985 and 0.995. We calibrate the inverse of the Frisch intertemporal elasticity of substitution in labour supply, $\phi$, to vary between 0 and 10, such that the elasticity of labour supply is between 0 and 5, whose values are in line with micro and macro-evidence as detailed in Card (1994) and King and Rebelo (1999). Consistent with US data, as in den Haan, Ramey and Watson (2000) and Fujita and Ramey (2009), the steady-state value of the job destruction rate, $\delta_n$, is allowed to vary between 0% and 10%, and the the steady-state value of the capital destruction rate, $\delta_k$, is set between 0% and 5%, as in King and Rebelo (1999). The parameter of the production capital share, $\theta$, is set between 0.2 and 0.4 in line with studies such as Ireland (2004) and King and Rebelo (1999). We need to set a value for $B$, which determines the steady-state share of hiring costs over total output, $GH/Y$. Since a precise empirical evidence on this parameter is unavailable, in line with Blanchard and Gali (2010), we choose $B$ such that hiring costs represent between 1% and 5% of total output, which cover reasonable lower and upper bounds for this parameter. The steady-state values of the neutral and investment-specific technological progresses, $a$ and $q$, since they do not affect the dynamics of the system, are conveniently set equal to 1. The autoregressive coefficients of the neutral and investment-specific technological progresses, $\rho_a$ and $\rho_q$, are free to vary between 0.75 and 0.999 in line with King and Rebelo (1999) and Ireland (2003). The standard deviation of the neutral and investment-specific technological progresses, $\sigma_a$ and $\sigma_q$, are normalised to be equal to 1%. Finally, in line with Blanchard and Gali (2010), we calibrate the parameter of the disutility of labour, $\chi$, equal to 1.5.

## 5 Findings

This section documents the findings. First we produce robust responses of the variables in the theoretical model to both neutral and investment-specific technology shocks. We then use the signs of the theoretical responses to constrain the first-period reaction of an SVAR model and determine the dynamics of labour input.

To apply the identification scheme we use the theoretical model to determine how each variable reacts to shocks. To derive robust implications for the model's responses to a 1 percentage point positive neutral and investment-specific technology shocks we simulate the theoretical model by drawing 10,000 times from the parameters' ranges. As in Dedola and Neri (2007) and Pappa (2009), to eliminate extreme responses, we discard the regions of two distributions below and above the 2.5 and 97.5 percentiles respectively. To illustrate how the variables of the theoretical model reacts to each shock, Figures 1-2 plot impulse responses of variables to 1 positive percentage deviation of neutral and investment-specific technology shock. Independently from the shock considered, capital and investment show similar dynamics, as they both rise. In addition, the long-run response of output is positive for both shocks, although the impact response is more pronounced in the case of a neutral technology shock, which corroborates the findings in Greenwood *et al* (1997), Greenwood *et al* (2000) and Fisher (2006). The reactions of consumption, hiring, labour market tightness and the cost of hiring to a neutral technology shock are positive, while they are negative in response to an investment-specific shock. The intuition of these results is straightforward. In response to a positive technology shock hiring increases as firms expand production by increasing labour input. Consequently, unemployment falls which, combined with the increase in hiring, generates a rise in labour market tightness and the cost of hiring. On the other hand, in the face of an investment-specific technology shock labour input falls since capital is more productive and, as described, firms respond to this by expanding production. As a consequence, hiring and the number of workers decrease, thereby softening labour market tightness and reducing the cost of hiring. Importantly for the analysis of this paper, the opposite theoretical responses of the variables to the two shocks enable the identification of neutral technology shocks.

To implement the estimation, before using these theoretical restrictions, we need to specify the variables that enter in the SVAR model. To maintain the closest mapping between the theoretical and the empirical models, we set up an SVAR that includes all the variables that enter the theoretical model, with the exception of hiring costs, which is unavailable, thereby using the level of real GDP, investment, consumption, hiring, labour market tightness, and employment.

The data for real GDP, investment, consumption and employment are from the FRED database.[5] The data for hiring and labour market tightness are from Shimer (2007). The data are quarterly, seasonally adjusted, and cover the period 1951 Q1 to 2006 Q3. Based on maximum likelihood methods, we specify an SVAR in levels with two lags but, as detailed below, results are robust to higher lags order.

Since consumption, hiring, and labour market tightness have opposite reactions to neutral or investment-specific technology shocks we are able to disentangle the effect of these two shocks in the data. To implement an agnostic identification scheme we impose the described sign restrictions, as summarised in Table B, on the first-period reaction of the SVAR model and subsequently the data can freely inform the dynamics of the response. Of course, as described, the responses of labour input is left unrestricted at all times.

Figure 3 plots the estimated impulse responses to a positive neutral and 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 top row shows that a positive neutral technology shock produces a rise in real GDP, investment, consumption, vacancies and labour market tightness, which is statistically significant as the 16th percentile is above zero for approximately the initial $2\frac{1}{2}$ years. As expected from theory, as in Fisher (2006), the response of investment is stronger than those of the other variables, and also the response of consumption is lower than that of real GDP. Employment, which is left unconstrained by the identification procedure, displays a positive and statistically significant response, as its 16th percentile reaches zero after more than six years. Similarly to Dedola and Neri (2007), Christiano *et al* (2003) and Christiano *et al* (2004), the median response of labour input is hump shaped, and reaches its peak after approximately four quarters. The bottom row shows that a positive investment-specific technology shock generates an impact fall on all the variables. In the case of consumption, vacancies, labour market tightness and labour input the impact reaction is significantly different from zero for about five years, while in the case of real GDP and investment the 16th percentile reaches zero after approximately twelve quarters.

To understand the extent to which the movements of each variable are explained by the shocks,

[5]The FRED codes for the 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.

Figure 4 reports the forecast error variance decompositions for the SVAR model. Each graph reports the median and the 5th, 16th, 84th and 95th percentiles error bands. The top row shows that neutral technology shocks explain 60% of real GDP at high frequencies, while their importance almost halves at low frequencies. Similarly, neutral technology shocks are the main contributors to short-run fluctuations in investment, consumption, vacancies, labour market tightness and employment although their contribution significantly declines at low frequencies. As depicted in the bottom row, the contribution of the investment-specific technology shocks is approximately 30% for investment in the short run and then it quickly stabilises at around 10%. In general, investment-specific technology shocks contribute significantly and steadily to explain the variance of the variables, although their explanation power is lower than neutral technology shocks, which corroborates the findings in Ireland (2001b) and Zanetti (2008) obtained by estimating a standard RBC model of the business cycle. Both neutral and investment-specific technology shocks contribute to explain around 55% of employment fluctuations at low frequencies, in line with Fisher (2006) and Christiano *et al* (2004). Moreover, both neutral and investment specific shocks are unable to explain the whole variance of the variables, therefore indicating that other shocks, not included in the model, are important to describe the dynamics in the data. For both shocks, the forecast error variance decompositions are always statistically significant albeit a sizable degree of uncertainty surrounds the estimates.

## 6 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 an SVAR specification in differences. We also establish that the results hold if we split the sample period, if we use alternative variables in the SVAR, and if we extend the length of sign restrictions.

The sign reversals on the effect of neutral technology shocks on labour 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 an SVAR specification in differences. Figures 5-7 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. Such evidence is documented 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. Figures 8-9, 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 subsamples, 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 subsamples compared with the estimation results from the whole period, reflecting the fact that the limited size data set makes the estimation less powerful.

To ensure that the results are independent of the choice of variable used to approximate labour input, we also represent labour input with measures of the unemployment level and unemployment rate in place of employment. Figures 10-11 show impulses responses based on the SVAR with measures of unemployment in the 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.

As a final robustness check, 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 four 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.[6]

## 7 Time-varying volatility and technology shocks

In this section we first modify the benchmark model to allow for time-varying error covariance matrix and we then use the identification scheme to investigate to what extent neutral and investment-specific technology shocks explain the reduced macroeconomic volatility in the United States over the sample period.

As mentioned, a large literature has documented the remarkable decline in the volatility of macroeconomic data in the United States, often referred to as the Great Moderation. Cogley and Sargent (2005), Primiceri (2005) and Benati and Mumtaz (2007), using formal statistical hypothesis tests, show that the volatility of output growth, unemployment rate and inflation has declined post-1979. Gali and Gambetti (2009) show that these findings also extend to hours and labour productivity.

To focus on the role of neutral and investment-specific technology shocks identified within our framework to explain the Great Moderation we extend the benchmark model to allow for a time-varying error covariance matrix $\Sigma$. In this way, the model can be used to investigate the role played by the structural shocks in generating the changes in the volatility of the endogenous variables over the same period. To introduce a time-varying error covariance matrix the

[6]These statistics are not reported in the paper, but are available upon request to the authors.

benchmark model in equation **(1)** is re-written as

$$\Delta Z_t = \sum_{j=1}^{P} \beta_j \Delta Z_{t-j} + \varepsilon_t, \tag{19}$$

where the variance of $\varepsilon_t$ is equal to $\Sigma_t$, and following Primiceri (2005), we factor the covariance matrix as

$$\Sigma_t = A_t^{-1} H_t (A_t^{-1})', \tag{20}$$

where the time-varying matrices $H_t$ and $A_t$ are defined as

$$H_t \equiv \begin{bmatrix} h_{1,t} & 0 & 0 & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 & 0 & 0 \\ 0 & 0 & 0 & h_{4,t} & 0 & 0 \\ 0 & 0 & 0 & 0 & h_{5,t} & 0 \\ 0 & 0 & 0 & 0 & 0 & h_{6,t} \end{bmatrix} \qquad A_t \equiv \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 & 0 \\ \alpha_{61,t} & \alpha_{62,t} & \alpha_{63,t} & \alpha_{64,t} & \alpha_{64,t} & 1 \end{bmatrix}, \tag{21}$$

and each term $h_{i,t}$ evolves as a geometric random walk with law of motion $\ln h_{i,t} = \ln h_{i,t-1} + \nu_t$, and, similarly to Primiceri (2005), each term $\alpha_{ij,t}$ evolves as a driftless random walk $\alpha_{ij,t} = \alpha_{ij,t-1} + \tau_t$. Note that although the model allows for a time-varying covariance matrix, it does not allow for time-variation in the coefficients $\beta_j$. There are two reasons for this choice. First, the results in Section 5 suggest that there is little evidence in favour of a significant change in the impulse response functions across the sample period, since technology shocks of a given magnitude produce virtually identical results pre and post-1984 suggesting that the transmission mechanism (as captured by the SVAR coefficients) is fairly stable, once the magnitude of the initial shock is accounted for. This corroborates the findings in Ireland (2001a) and Liu *et al* (2009), who find that the estimated parameter of a structural model that allows for regime switching in shock variances remain substantially unchanged. Second, imposing fixed coefficients in equation **(19)** substantially reduces the computational burden involved in the model estimation.[7]

[7] A system stability condition is imposed on the time-varying SVAR coefficients using rejection sampling. Since the number of endogenous variables in the SVAR is high, it is difficult to impose the stability condition at each point in time and it leads to substantially increase the computation burden. For this reason, we estimate the model using the MCMC algorithm described in Cogley and Sargent (2005) which combines the Metropolis-Hastings algorithm described in Jacquier, Polson and Rossi (2004) to draw $H_t$ with a Gibbs sampling algorithm to draw $A_t$, $\beta$ and the hyper-parameters of the model.

Figure 12 plots the time-varying variance of a neutral and investment-specific technology shock identified by applying the identification scheme described in Section 2 at each period. Each graph reports the median and the 16th and 84th percentiles error bands. The variance of the neutral technology shock shows a sharp decline in the early 1970s before increasing in 1975. The median estimate declines again during the mid-1980s to then sharply increase until 1990 and subsequently falls and fluctuates steadily until the early 2000. Following this date the variance of neutral technology shocks decreases until it becomes very close to zero in mid-2005. The variance of the investment-specific technology shock is generally larger in magnitude than the neutral technology shock, with more noticeable changes across time. The 1970s were associated with high volatility of this shock, while the mid-1980s experienced a sharp decline, with the rest of the sample period characterised by a low volatility. Overall, the analysis suggests that both the level and the volatility of neutral shocks have a greater importance than investment-specific technology shocks in describing the dynamics in the data.

To evaluate the relevance of neutral and investment-specific technology shocks for aggregate fluctuations, Figure 13 considers the implications of the change in the variance of shocks over time for the volatility in the variables. The dashed black line plots the unconditional volatility implied by the SVAR model for each variable. The thick blue line in each graph plots the estimated unconditional volatility assuming that the variance of the considered shock is zero over the entire sample, such that these estimates produce the counterfactual scenario where the considered shock is absent from the economy. This allows the model to establish whether the presence of either neutral or investment-specific technology shocks are significantly different from zero to test their importance in explaining the estimated volatility in the data. The top row shows that neutral technology shocks significantly explain the volatility of output over the whole sample period, since the black line is outside the error band where the shock is assumed equal to zero. In contrast, investment-specific shocks play a limited role in determining the variables' volatilities, as for all the variables, except investment, the estimates are not significantly different from zero. This result corroborates the findings in Arias *et al* (2007), Justiniano *et al* (2009) and Liu *et al* (2009), who, using a structural model of the business cycle, find that neutral technology shocks are more important than investment-specific technology shocks in explaining the variables' volatility over the sample period. Notwithstanding, this result is in contrast to Gali and Gambetti (2009) whose findings detect a limited role for neutral technology shocks to explain the reduction in output volatility and support a stronger role for the investment-specific technology shocks. The final column of the figure shows that a similar result applies to employment growth, where neutral technology shocks appear to be significantly more important than investment-specific shocks in explaining the variables' volatilities. Finally, as mentioned, it is noticeable that investment-specific technology shocks play an important role in determining the volatility of investment, as the variance of investment is significantly different from zero. Since Gali and Gambetti (2009) and our paper mainly differ in the identification scheme of the SVAR, as these authors identify technology shocks by assuming that they are the only component that affect the level of productivity in the long run, this result calls for further research on the sensitivity of the findings to the identification scheme before establishing the relevance of neutral and investment-specific technology shocks to explain the Great Moderation.

## 8 Conclusion

This paper has investigated the dynamic response of labour input to neutral technology shocks. Neutral technology shocks are identified using the cyclical properties of a theoretical model of the business cycle characterised by labour market search frictions and investment-specific technology shocks. By imposing the signs of the theoretical responses on the first-period reaction of an SVAR model, the estimation supports an increase in labour input in response to neutral technology shocks. The finding is robust across different perturbations of the SVAR model such as controlling for long cycles in the data, choosing different time lags, using alternative measures of labour market variables, splitting the sample period, and extending the length of sign restrictions. The benchmark framework is extended to allow for a time-varying error covariance matrix to investigate the importance of neutral and investment-specific technology shocks in explaining the reduced macroeconomic volatility in the United States over the past two decades. Similarly to structural models of the business cycle, we find neutral technology shocks to be significant to explain the reduced output volatility in the data, which is in contrast with studies which identify technology shocks by assuming that they are the only components that affect the level of productivity in the long run, thereby calling for further research on the role of the identification scheme.

While the results do robustly support a positive response of labour input to neutral technology shocks, it should also be noted that the theoretical framework used to derive the theoretical restrictions could be extended to assign a role to nominal shocks to influence the variables' dynamics, that would require modelling the firm's price-setting decisions, and might, in principle, provide additional identifying restrictions which could potentially affect the results. These investigations remain outstanding tasks for future research.

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**Table A. Parameters ranges**

| Parameter | | Range |
|---|---|---|
| $\alpha$ | Elasticity of labour market tightness | [0, 10] |
| $\beta$ | Discount factor | [0.985 , 0.995] |
| $\phi$ | Inverse of the Frisch intertemporal elasticity | [0, 0.1] |
| $\delta_n$ | Job destruction rate | [0, 0.1] |
| $\delta_k$ | Capital destruction rate | [0, 0.5] |
| $\theta$ | Capital share | [0.2, 0.4] |
| $GH/Y$ | Share of hiring costs over total output | [0.01, 0.05] |
| $\rho_a$ | Autoregressive coefficient, neutral technological progress | [0.75, 0.99] |
| $\rho_q$ | Autoregressive coefficient, investment-specific technological progress | [0.75, 0.99] |

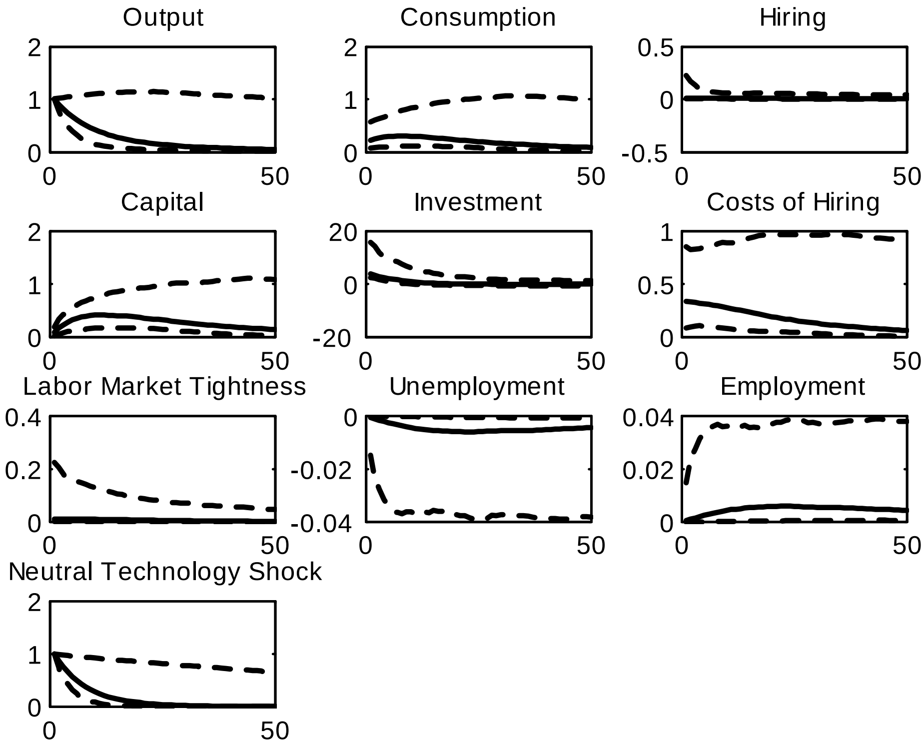
Notes: The table shows the parameters ranges used to simulate the theoretical model.

**Table B. Sign restrictions on the first-period SVAR variables**

| | Neutral technological progress | Investment-specific technological progress |
|---|---|---|
| Variable | | |
| Real output | + | + |
| Investment | + | + |
| Consumption | + | − |
| Vacancies | + | − |
| Labour market tightness | + | − |

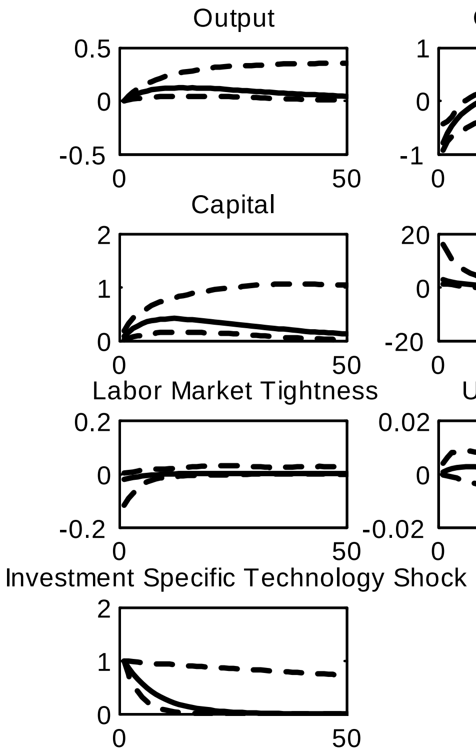
Notes: Entries show sign restrictions on the first-period SVAR variables to neutral and investment-specific technological progresses.

**Figure 1. Theoretical impulse-response functions to a neutral technology shock**



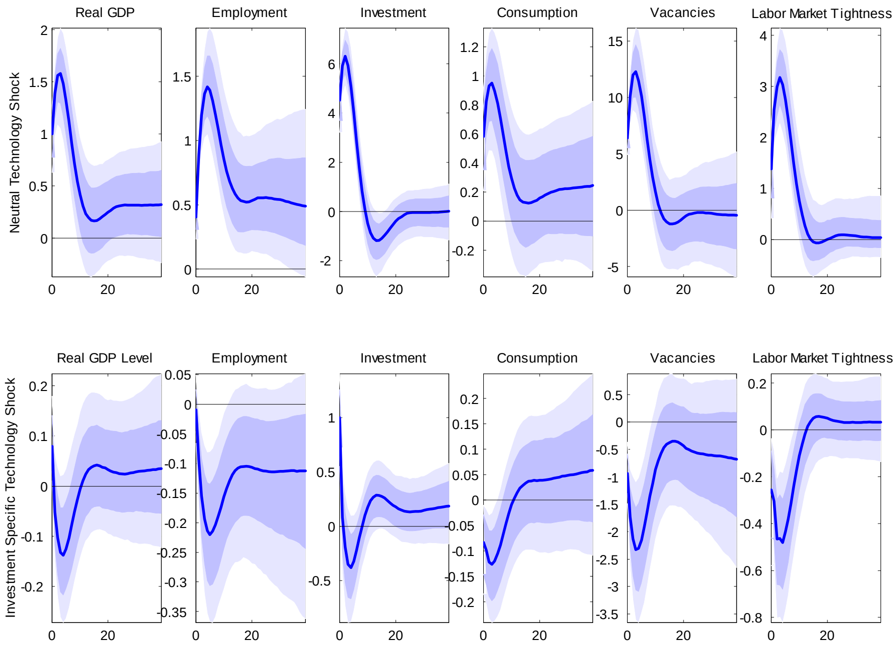

Notes: Each panel shows the percentage point response of one of the model's variables to a one percentage deviation neutral technology shock. The solid line reports the median responses and the dashed lines report the 2.5 and 97.5 percentiles of the responses.

**Figure 2. Theoretical impulse-response functions to an investment-specific technology shock**



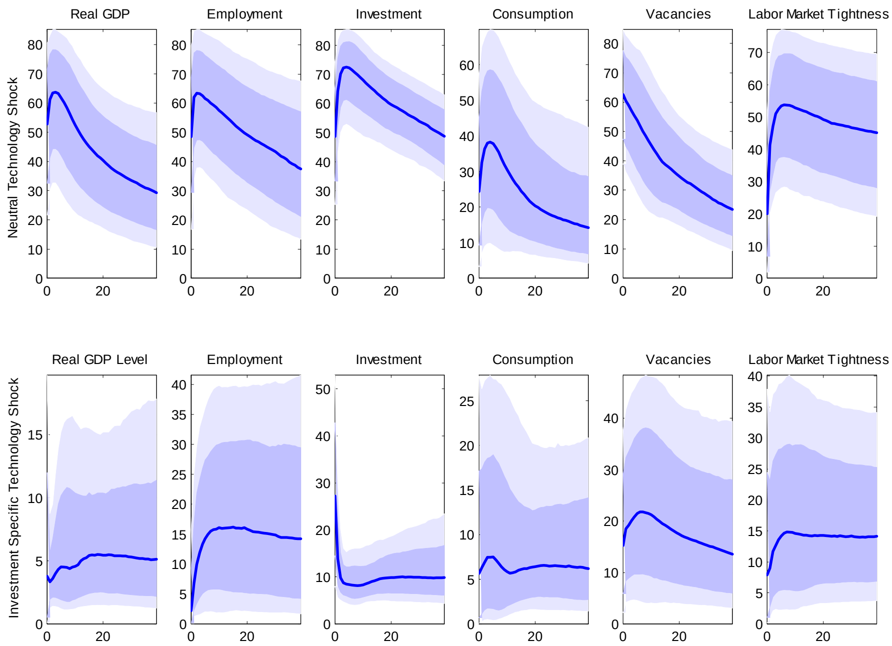

Notes: Each panel shows the percentage point response of one of the model's variables to a one percentage deviation investment-specific technology shock. The solid line reports the median responses and the dashed lines report the 2.5 and 97.5 percentiles of the responses.

**Figure 3. Empirical impulse-response functions to a neutral and investment-specific technology shock**



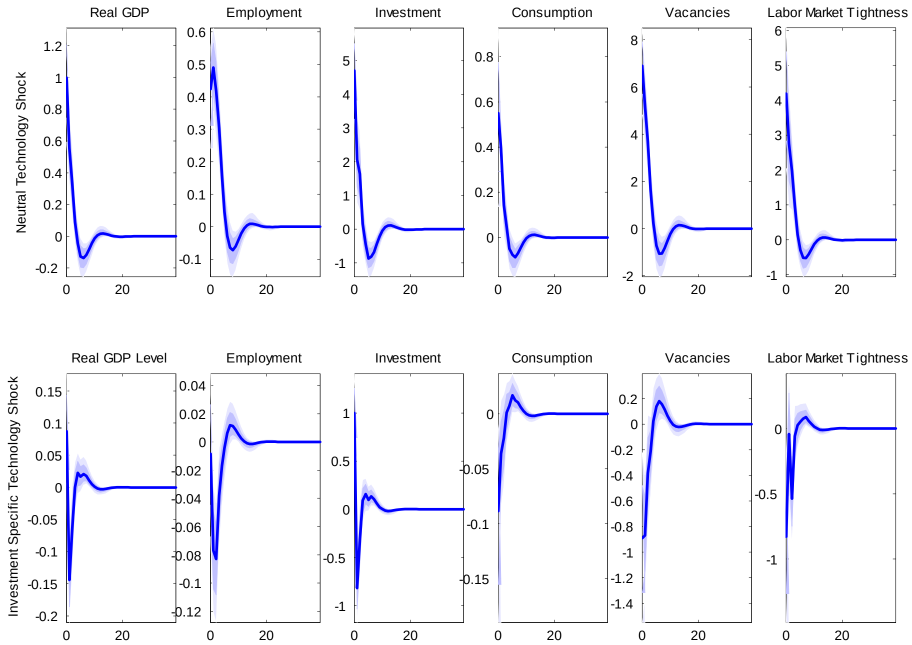

Notes: The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment-specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution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

**Figure 4. Forecast error variance decompositions**



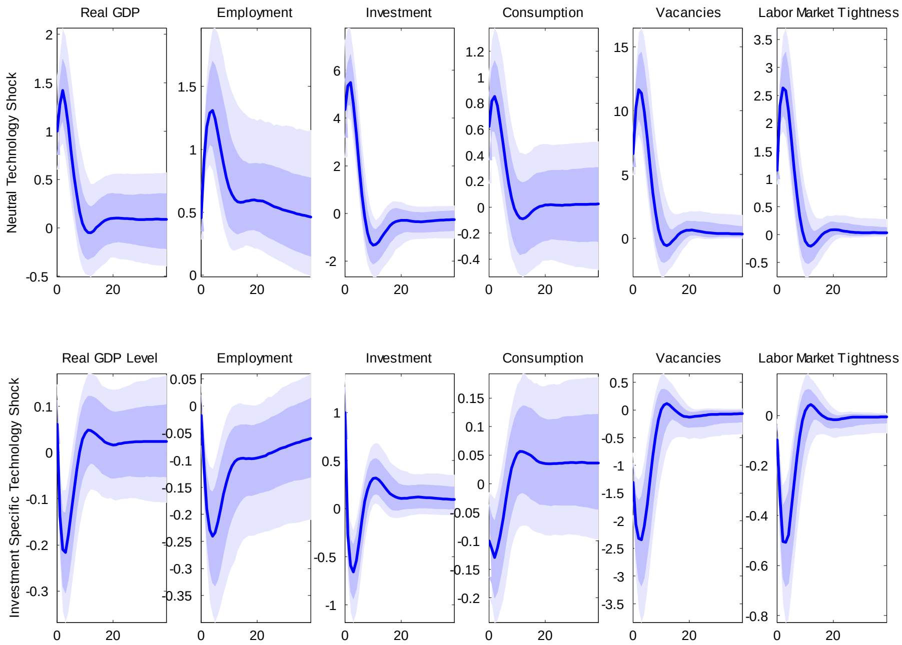

Notes: The top row shows the forecast error variance decompositions from the SVAR model to a positive neutral technology shock. The bottom row shows forecast error variance decompositions from the SVAR model to a positive investment-specific technology shock. Each plot shows the median, the 5th, 16th, 84th and 95th percentiles of the posterior distribution of the impulse responses.

**Figure 5. Empirical impulse-response functions to a neutral and investment-specific technology shock for the SVAR in differences**



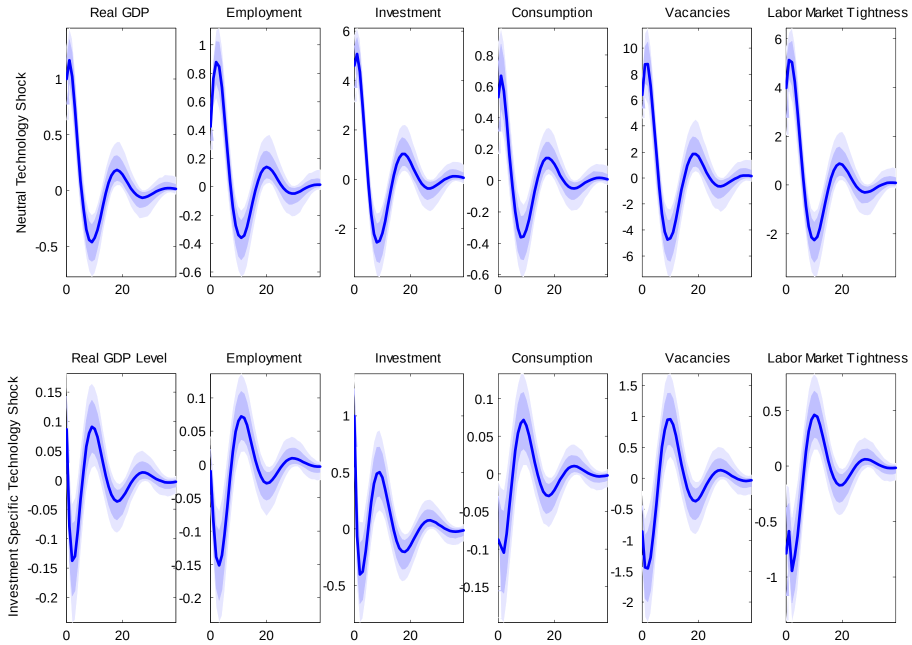

Notes: The variables in the SVAR model are specified in differences. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment-specific technology shock. Each plot shows the median,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

**Figure 6. Empirical impulse-response functions to a neutral and investment specific technology shock for the de-trended SVAR**



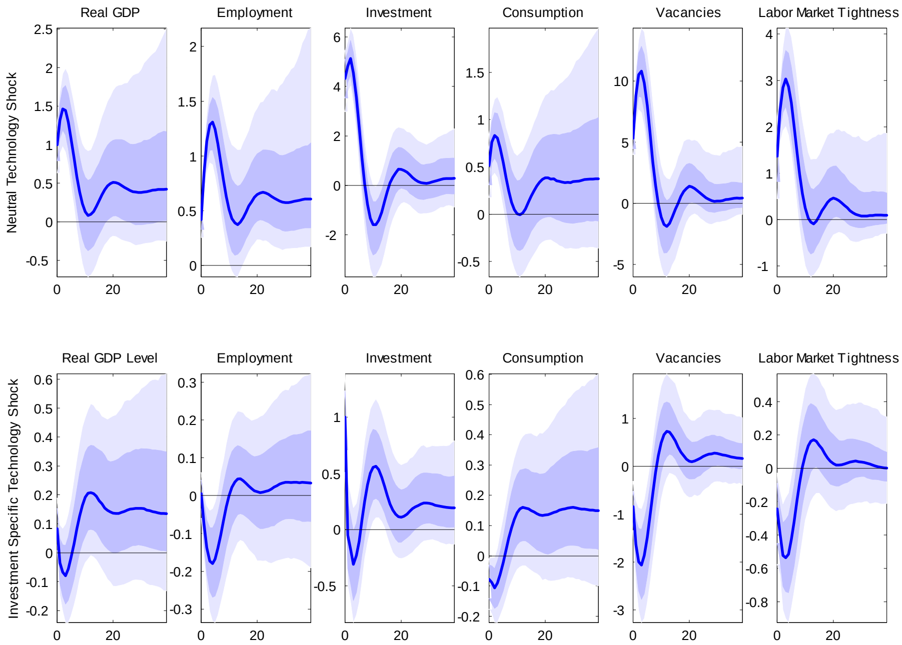

Notes: The variables in the SVAR model are de-trended. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment-specific technology shock. Each plot shows the median, the 5th, 16th, 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 for the filtered SVAR**



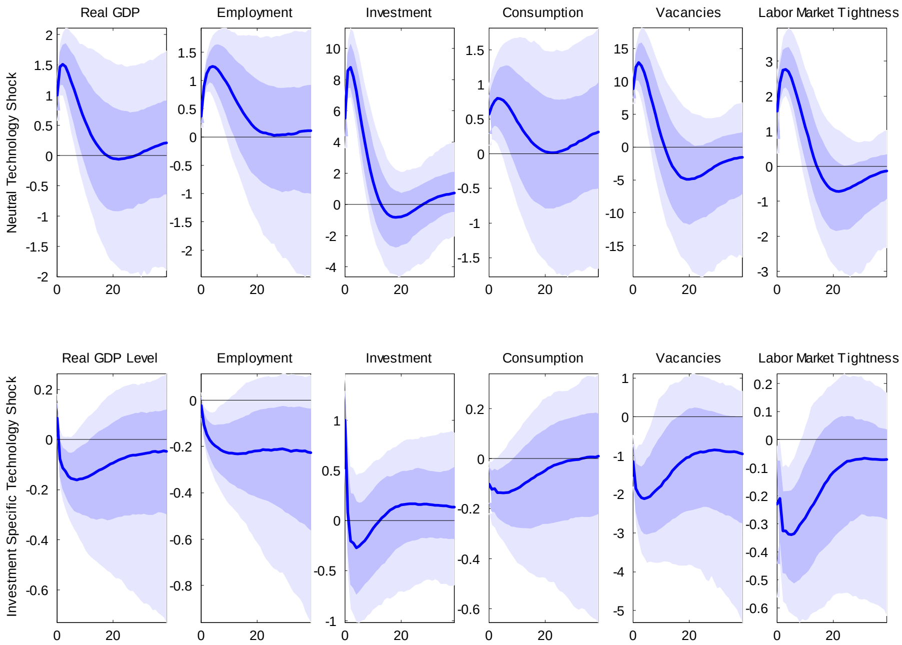

Notes: The variables in the SVAR model are filtered. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment-specific technology shock. Each plot shows the median, the 5th, 16th, 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 for the period pre-1980**



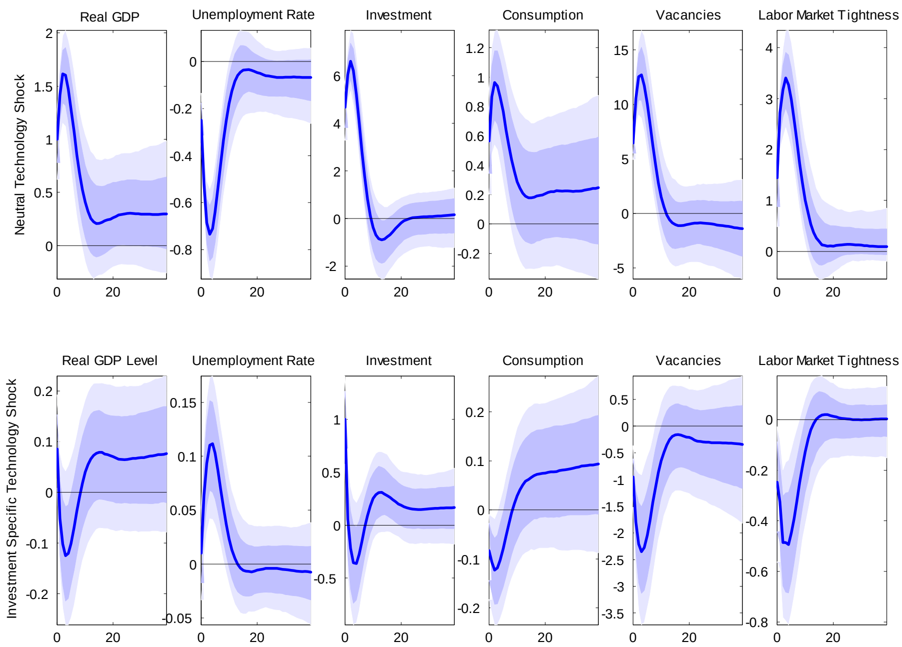

Notes: The SVAR model is estimated 1951:Q1 – 1979:Q4. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR to a positive investment-specific technology shock. Each plot shows the median, the 5th, 16th, 84th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

# Figure 9. Empirical impulse-response functions to a neutral and investment-specific technology shock for the period post-1980



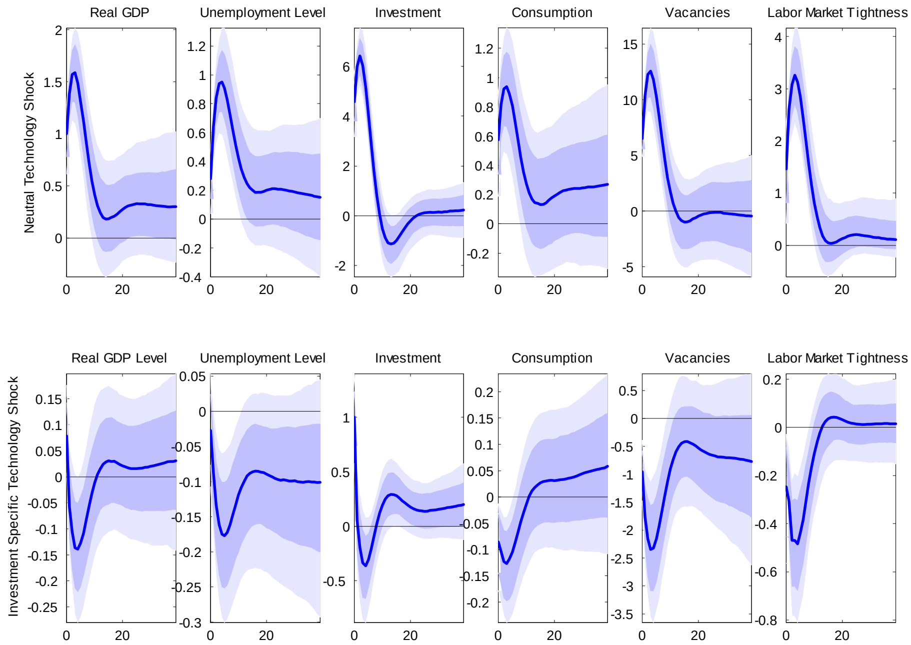

Notes: The SVAR model is estimated 1980:Q1 – 2006:Q3. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment-specific technology shock. Each plot shows the median, the 5th, 16th,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

**Figure 10. Empirical impulse-response functions to a neutral and investment-specific technology shock using unemployment level**



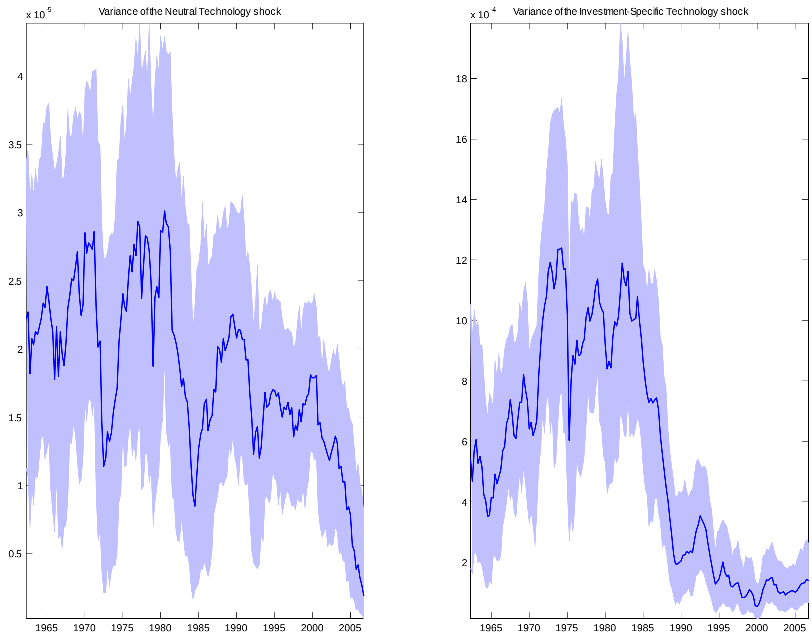

Notes: The SVAR model is defines labour input with unemployment level. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment-specific technology shock. Each plot shows the median,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

## Figure 11. Empirical impulse-response functions to a neutral and investment-specific technology shock using unemployment rate



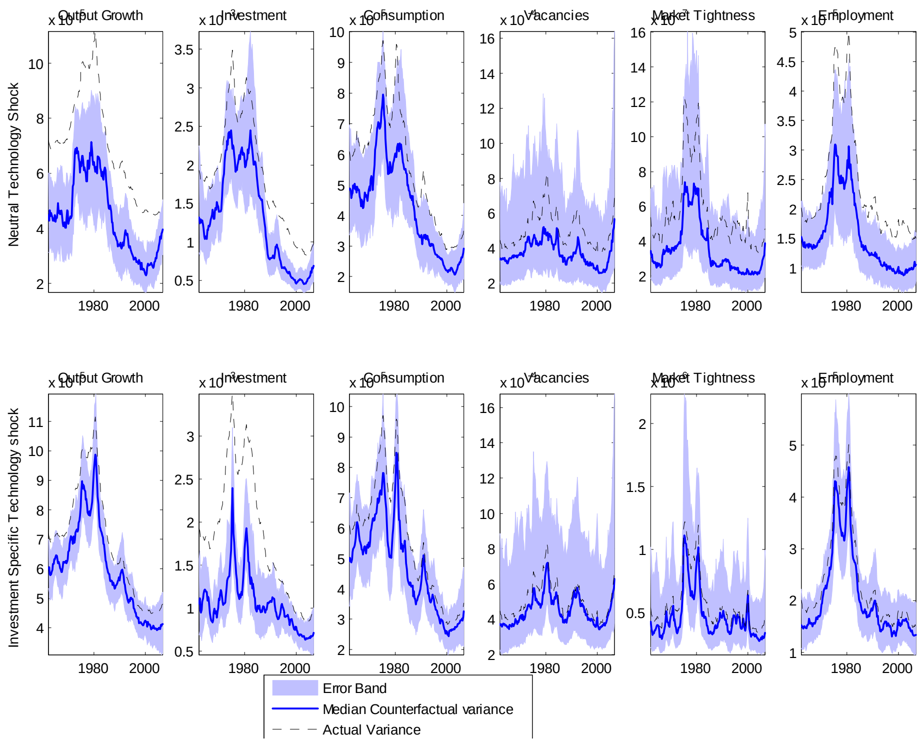

Notes: The SVAR model is defines labour input with unemployment rate. The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment-specific technology shock. Each plot shows the median,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

**Figure 12.Time-varying variance of neutral and investment-specific technology shocks**




Notes: Each panel shows time-varying variance of a neutral and investment-specific technology shock identified by applying the identification scheme described in Section 2 at each period. Each graph reports the median and the 16th and 84th percentiles error bands.

**Figure 13. Actual and counterfactual estimates of volatility**




Notes: The dashed black line plots the unconditional volatility implied by the SVAR model for each variable. The thick blue line in each graph plots the estimated unconditional volatility assuming that the variance of the considered shock is zero over the entire sample, such that these estimates produce the counterfactual scenario where the considered shock is absent from the economy.