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NEUTRAL TECHNOLOGY SHOCKS AND THE DYNAMICS OF LABOR INPUT: RESULTS FROM AN AGNOSTIC IDENTIFICATION*

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This article studies the dynamic response of labor input to neutral technology shocks. It uses benchmark dynamic, stochastic, general equilibrium models enriched with labor market search and matching frictions and investment-specific technological progress that enables a new, agnostic, identification scheme based on sign restrictions on a structural vector autoregression (SVAR). The estimation supports an increase of labor input in response to neutral technology shocks. This finding is robust across different perturbations of the SVAR model.

1. INTRODUCTION

This article studies the dynamic response of labor input to neutral technology shocks. Neutral technology shocks are identified using the cyclical properties of benchmark dynamic, stochastic, general equilibrium (DSGE) models of the business cycle enriched with labor market search and matching frictions. Once the theoretical restrictions on the sign of the variables' reaction to shocks are imposed on the first period response of a structural vector autoregression (SVAR) model, except on the reaction of labor input, the data robustly support that neutral technology shocks increase labor input.

The theoretical frameworks used to inform the empirical investigation are standard DSGE models characterized by flexible and staggered price setting, enriched with search and matching frictions on the labor market and investment-specific technological progress. The addition of these two features is motivated by their empirical relevance and theoretical appeal. Moreover, importantly for the analysis of this article, as detailed below, they enable a new scheme to identify neutral technology shocks. Empirically, Rogerson and Shimer (2010) show that labor markets are characterized by frictions that prevent the competitive market mechanism from determining labor market equilibrium allocations, thereby suggesting that their presence is important for a realistic description of the functioning of the labor market. Additionally, the analysis by Greenwood et al. (1997), Fisher (2006), and Justiniano et al. (2010) points out that the inclusion of investment-specific technological progress is key to study the dynamics of the technological progress.

Theoretically, labor market frictions introduce the extensive margin of labor (i.e., (un)employment) into the model, whereas this dimension is absent in standard models of the labor market. In this way, the theoretical framework is able to detail the dynamics of hiring and labor market tightness—defined as the ratio between hiring and unemployment—whose reactions to shocks enable a new, agnostic, identification scheme that holds across models and is robust to plausible parameterizations. In particular, the reaction of unemployment and hiring provides two new short-run identification restrictions. First, neutral technology shocks increase

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the number of hirings and, second, raise labor market tightness. Investment-specific technology shocks instead have a reverse effect on these variables. These restrictions together with the opposite reaction of consumption to the two shocks enable us to uniquely identify neutral technology shocks. By imposing these sign restrictions on the impact responses of an SVAR model, while leaving labor input to freely react to shocks, the data show that neutral technology shocks increase labor 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 labor market variables, extending the length of sign restrictions on the SVAR, and including additional variables in the estimation procedure.

The approach proposed in this article has a number of 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), Francis et al. (2007), and Canova et al. (2010) point out, any procedure that includes low or medium frequencies generates an artificial positive comovement between labor input and neutral technology shocks that disappears once long cycles are controlled for. Second, Faust and Leeper (1997) argue that long-run restrictions may generate unreliable structural estimates, as such an identification scheme entails the use of finite sample information to approximate the infinite future with the results heavily dependent on the specification of the reduced-form model. Chari et al. (2008) and Ravenna (2007) demonstrate the relevance of this problem for identifying technology shocks and show that structural VARs with long-run restrictions are fairly unsuccessful at accurately recovering true underlying impulse response functions when estimated using data generated from a structural model. In contrast, we show that our identification scheme performs well in a Monte Carlo setting and is able to recover the impulse response functions associated with the data-generating process. Third, by using high-frequency restrictions we identify the reaction of labor input to technology shocks without incurring the estimation uncertainty and bias that long-run identification schemes produce, as documented by Erceg et al. (2005). 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 labor input is left unconstrained and the theoretical restrictions are imposed on the first-period reactions of the SVAR, thereby leaving the data to determine subsequent dynamics.[2]

The remainder of the article is organized as follows. Section 2 provides an overview of the literature. Section 3 lays out the theoretical model and describes the model's solution and calibration. Section 4 details the sign restrictions from the theoretical model. Section 5 describes the SVAR model and the implementation of the identification scheme. Section 6 presents the results and robustness analysis. Section 7 concludes.

2. AN OVERVIEW OF THE LITERATURE

A growing number of studies identify technology shocks by imposing 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 et al. (2003), Francis and Ramey (2005), Francis et al. (2005), Liu and Phaneuf (2007), Fisher (2006), and Canova et al. (2010) find that technology shocks have a contractionary effect on employment. On the other hand, despite using a similar methodology, Christiano et al. (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) point out that long-run restrictions are subject to considerable estimation uncertainty about the quantitative impact of technology shocks on macroeconomic

[2] For a detailed assessment on the shortcomings of long-run restrictions, see Dedola and Neri (2007) and references therein.

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. (2010), we inform the empirical investigation with a search and matching model of the labor market, which, as mentioned, allows a new identification scheme and improves both the description of the functioning of the labor market and the understanding of the reaction of labor input to technology shocks.

Uhlig (2004), Dedola and Neri (2007), and Peersman and Straub (2009) 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 labor input to technology shocks. Our article has two differences. First, it uses an agnostic identification scheme, as labor input is left unconstrained while imposing sign restrictions on the impact responses of other key variables, thereby leaving the data to freely inform the variables' responses in the aftermath. Second, as described, it uses a novel identification scheme based on labor market variables such as hiring and labor market tightness. In this way, differently from related studies, the reaction of labor input is identified using the information provided by labor market variables.

3. THE THEORETICAL MODEL

This section lays out the theoretical model and describes its solution and calibration. We set up the model with nominal price rigidities, which, given certain restrictions, defined below, nests the standard model with flexible prices. A standard New Keynesian model is enriched to allow for labor market frictions, as in Blanchard and Gali (2010), and for investment-specific technological progress, as in Greenwood et al. (1997). The model economy consists of a representative household, a representative goods-producing firm, a continuum of intermediate-goods-producing firms indexed by $i \in [0, 1]$, and a central bank.

The labor market is based on the assumption that the processes of job search and recruitment are costly for both the firm and worker. Job creation takes place when a firm and a searching worker meet and agree to form a match at a negotiated wage, which depends on the parties' bargaining power. The match continues until the parties exogenously terminate the relationship. When this occurs, job destruction takes place and the worker moves from employment to unemployment, and the firm can either withdraw from the market or hire a new worker.

The goods market is comprised of a representative finished-goods-producing firm, and a continuum of intermediate-goods-producing firms indexed by $i \in [0, 1]$. During each period $t = 0, 1, 2, \ldots$, each intermediate-goods-producing firm hires workers and produces a distinct, perishable good. It sells its output to the finished-goods-producing firm in a monopolistically competitive market by setting the price as a markup over marginal cost, and it faces a cost to adjusting its nominal price, as in Rotemberg (1982). During each period $t = 0, 1, 2, \ldots$, the finished-goods-producing firm uses intermediate goods from the intermediate-goods-producing firms to produce a finished product and sells it to the household.

The central bank is modeled with a modified Taylor rule as in Clarida et al. (1998): It gradually adjusts the nominal interest rate in response to deviations of output and inflation from their steady-state levels.

The rest of this section describes the agents' tastes, technologies, the policy rule, and the structure of the labor and goods market in detail.

3.1. *The Representative Household.* During each period $t = 0, 1, 2, \ldots$, the representative household maximizes the expected utility function

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln C_t - \chi N_t^{1+\phi} / (1+\phi) \right], \tag{1}$$

where the variable C_t is consumption, N_t is units of labor, and β is the discount factor $0 < \beta < 1$. The representative household enters period t with bonds B_{t-1}. At the beginning of the period, the household receives nominal profits F_t from the intermediate-goods-producing firms. The household supplies N_t units of labor and K_t units of capital at the wage rate W_t and the capital remuneration rate Q_t, respectively, to each intermediate-goods-producing firm $i \in [0, 1]$ during period t. Then, the household's bonds mature, providing B_{t-1} additional units of currency. The household uses part of this additional currency to purchase B_t new bonds at nominal cost B_t/R_t, where R_t represents the gross nominal interest rate between t and $t+1$. The household uses its income for consumption, C_t, and investment, I_t, and carries B_t bonds into period $t+1$, subject to the budget constraint

$$P_tC_t + P_tI_t + B_t/R_t = B_{t-1} + W_tN_t + Q_tK_t + F_t, \tag{2}$$

for all $t = 0, 1, 2, \ldots$. By investing I_t units of output during period t, the household increases the capital stock K_{t+1} available during period $t+1$ according to

$$K_{t+1} = (1 - \delta_k)K_t + \upsilon_t I_t, \tag{3}$$

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

$$\ln(\upsilon_t) = (1 - \rho_\upsilon)\ln(\upsilon) + \rho_\upsilon \ln(\upsilon_{t-1}) + \varepsilon_{\upsilon t}, \tag{4}$$

with $0 < \rho_\upsilon < 1$, and where the zero-mean, serially uncorrelated innovation $\varepsilon_{\upsilon t}$ is normally distributed with standard deviation σ_υ. Thus the household chooses $\{C_t, K_{t+1}, B_t\}_{t=0}^{\infty}$ to maximize its utility (1) subject to the budget constraint (2) and the law of capital accumulation (3) for all $t = 0, 1, 2, \ldots$. Letting $\pi_t = P_t/P_{t-1}$ denote the gross inflation rate and Λ_t the nonnegative Lagrange multiplier on the budget constraint (2), the first-order conditions for this problem are

$$\Lambda_t = 1/C_t, \tag{5}$$

$$\Lambda_t/\upsilon_t = \beta E_t \Lambda_{t+1}[Q_{t+1}/P_{t+1} + (1 - \delta_k)/\upsilon_{t+1}], \tag{6}$$

and

$$\Lambda_t = \beta R_t E_t(\Lambda_{t+1}/\pi_{t+1}). \tag{7}$$

According to Equation (5), the Lagrange multiplier equals the household's marginal utility of consumption. Equation (6) is the standard Euler equation for capital, which links the intertemporal marginal utility of consumption with the real remuneration of capital. Equation (7), once Equation (5) is substituted in, is the representative household's Euler equation that describes the optimal consumption decision.

3.2. *The Labor Market.* During each period $t = 0, 1, 2, \ldots,$ in each intermediate-goods-producing firm i, the flow into employment results from the number of workers who survive the exogenous separation and the number of new hires, $H_t(i)$. Hence, total employment evolves according to

$$N_t(i) = (1 - \delta_n)N_{t-1}(i) + H_t(i), \tag{8}$$

where $N_t(i)$ and $H_t(i)$ represent the number of workers employed and hired by firm i in period t, and δ_n is the exogenous separation rate and $0 < \delta_n < 1$. For all $t = 0, 1, 2, \ldots,$ the fraction of aggregate employment and hires supplied by the representative household must satisfy $N_t = \int_0^1 N_t(i)\,di$ and $H_t = \int_0^1 H_t(i)\,di$, respectively. Accounting for job destruction, the pool of household's members unemployed and available to work before hiring takes place is

$$U_t = 1 - (1 - \delta_n)N_{t-1}. \tag{9}$$

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

$$x_t = H_t/U_t, \tag{10}$$

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 labor market tightness, since it indicates the proportion of hires over the number of workers in search for a job. The cost of hiring a worker is equal to G_t and, as in Blanchard and Gali (2010), is a function of labor market tightness x_t:

$$G_t = Bx_t^{\alpha}, \tag{11}$$

where α is the elasticity of labor 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 Rotemberg (2006), this formulation expresses the idea that the tighter the labor 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

$$u_t = 1 - N_t. \tag{12}$$

Let $\mathcal{W}_t^N$ and $\mathcal{W}_t^U$ denote the marginal value of the expected income of an employed and unemployed worker, respectively. The employed worker earns a wage, suffers disutility from work, and might lose her job with probability δ_n. Hence, the marginal value of a new match is

$$\mathcal{W}_t^N = \frac{W_t}{P_t} - \frac{\chi N_t^{\phi}}{\Lambda_t} + \beta E_t \frac{\Lambda_{t+1}}{\Lambda_t}\left\{\left[1 - \delta_n\left(1 - x_{t+1}\right)\right]\mathcal{W}_{t+1}^N + \delta_n\left(1 - x_{t+1}\right)\mathcal{W}_{t+1}^U\right\}. \tag{13}$$

This equation states that the marginal value of a job for a worker is given by the wage less the marginal disutility that the job produces to the worker and the expected-discounted net gain from being either employed or unemployed.

The unemployed worker expects to move into employment with probability x_t. Hence, the marginal value of unemployment is

$$\mathcal{W}_t^U = \beta E_t \frac{\Lambda_{t+1}}{\Lambda_t}\left[x_{t+1}\mathcal{W}_{t+1}^N + \left(1 - x_{t+1}\right)\mathcal{W}_{t+1}^U\right]. \tag{14}$$

This equation states that the marginal value of unemployment is made up of the expected-discounted capital gain from being either employed or unemployed.

The structure of the model guarantees that a realized job match yields some pure economic surplus. The share of this surplus between the worker and the firm is determined by the wage level, in addition to compensating each side for its costs from forming the job. As in Pissarides (2000), the wage is set according to the Nash bargaining solution. The worker and the firm split the surplus of their matches with the absolute share $0 < \eta < 1$. The difference between Equations (13) and (14) determines the worker's economic surplus. The firm's surplus is simply given by the real cost per hire, G_t, as in Blanchard and Gali (2010). Hence, the total surplus from a match is the sum of the worker's and firm's surpluses. The wage bargaining rule for a match is

$\eta G_t = (1-\eta)(\mathcal{W}_t^N - \mathcal{W}_t^U)$. Substituting Equations (13) and (14) into the wage bargaining rule produces the agreed wage:

$$W_t/P_t = \chi N_t^{\phi}/\Lambda_t + \zeta\{G_t - \beta(1-\delta_n)E_t(\Lambda_{t+1}/\Lambda_t)[(1-x_{t+1})G_{t+1}]\}, \quad (15)$$

where $\zeta = \eta/(1-\eta)$ is the relative bargaining power of the worker. Equation (15) shows that the wage equals the marginal rate of substitution between consumption and leisure together with current hiring costs, and the expected savings in terms of the future hiring costs if the match continues in period $t+1$.

3.3. *The Goods Market.* As described above, the production sector is comprised of a representative finished-goods-producing firm and a continuum of intermediate-goods-producing firms indexed by $i \in [0, 1]$, characterized by staggered price setting as in Rotemberg (1982).

During each period $t = 0, 1, 2, \ldots,$ the representative finished-goods-producing firm uses $Y_t(i)$ units of each intermediate good $i \in [0, 1]$, purchased at nominal price $P_t(i)$, to produce Y_t units of the finished product at constant returns to scale technology $[\int_0^1 Y_t(i)^{\frac{\mu-1}{\mu}} di]^{\frac{\mu}{\mu-1}} \geq Y_t$, where $\mu > 1$ is the elasticity of substitution among different goods. By maximizing its profits the firm's demand for $Y_t(i)$ units of intermediate good i is

$$Y_t(i) = [P_t(i)/P_t]^{-\mu}\, Y_t \quad (16)$$

for all $i \in [0, 1]$, where $P_t = [\int_0^1 P_t(i)^{1-\mu} di]^{\frac{1}{1-\mu}}$ for all $t = 0, 1, 2, \ldots$.

During each period $t = 0, 1, 2, \ldots,$ the representative intermediate-goods-producing firm hires $N_t(i)$ units of labor from the representative household, in order to produce $Y_t(i)$ units of intermediate good i according to the constant returns to scale production technology

$$Y_t(i) = A_t K(i)_t^{\theta} N(i)_t^{1-\theta}, \quad (17)$$

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

$$\ln(A_t) = (1-\rho_a)\ln(A) + \rho_a \ln(A_{t-1}) + \varepsilon_{at}, \quad (18)$$

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

Since the intermediate goods are not perfect substitutes in the production of the final goods, the intermediate-goods-producing firm faces an imperfectly competitive market. During each period $t = 0, 1, 2, \ldots$ it sets the nominal price $P_t(i)$ for its output, subject to satisfying the representative finished-goods-producing firm's demand. The intermediate-goods-producing firm faces a quadratic cost to adjusting nominal prices, measured in terms of the finished goods and given by $(\phi_p/2)\,[P_t(i)/(\pi P_{t-1}(i)) - 1]^2\, Y_t$, where $\phi_p > 0$ is the degree of adjustment cost and π is the steady-state gross inflation rate.[3] This relationship, as stressed in Rotemberg (1982), looks to account for the negative effects of price changes on customer–firm relationships. These negative effects increase in magnitude with the size of the price change and with the overall scale of economic activity, Y_t.

The problem for the firm is to maximize its total market value given by $E_0 \sum_{t=0}^{\infty} (\beta^t \Lambda_t/P_t)\, F_t(i)$, where $\beta^t \Lambda_t/P_t$ measures the marginal utility value to the representative household of an additional dollar in profits received during period t and

$$F_t(i) = P_t(i)Y_t(i) - N_t(i)W_t - K_t(i)Q_t - H_t(i)G_t - \frac{\phi_p}{2}\left[\frac{P_t(i)}{\pi P_{t-1}(i)} - 1\right]^2 Y_t P_t(i) \quad (19)$$

[3] Note that when $\phi_p = 0$ the model nests the standard model with flexible prices.

for all $t = 0, 1, 2, \dots$. Thus the firm chooses $\{N_t(i), K_t(i), P_t(i)\}_{t=0}^{\infty}$ to maximize its profits (19) subject to the law of employment accumulation (8), the demand for goods (16), and the production technology (17) for all $t = 0, 1, 2, \dots$. Letting Ξ_t denote the nonnegative Lagrange multiplier on the production technology (17), the first-order conditions for this problem are

$$W_t/P_t(i) = \Xi_t(1-\theta)Y_t/(N_t\Lambda_t) - G_t + \beta(1-\delta_n)\,E_t\,(\Lambda_{t+1}/\Lambda_t)\,G_{t+1}, \tag{20}$$

$$\Lambda_t Q_t/P_t(i) = \Xi_t\theta Y_t/K_t, \tag{21}$$

and

$$\begin{aligned}\phi_p\left[\frac{\pi_t(i)}{\pi}-1\right]\frac{\pi_t(i)}{\pi} &= (1-\mu)\left[\frac{P_t(i)}{P_t}\right]^{-\mu} + \mu\left[\frac{P_t(i)}{P_t}\right]^{-(1+\mu)} \\ &\quad + \beta\phi_p\,E_t\left\{\frac{\Lambda_{t+1}}{\Lambda_t}\left[\frac{\pi_{t+1}(i)}{\pi}-1\right]\left[\frac{\pi_{t+1}(i)}{\pi}\frac{Y_{t+1}}{Y_t}\right]\right\}.\end{aligned} \tag{22}$$

Equation (20) equates the wage to the marginal rate of transformation. The marginal rate of transformation depends on labor productivity, Y_t/N_t, as in a model without labor market search, but also, due to the presence of labor market frictions, on present and future forgone costs of hiring. More specifically, the three terms composing the marginal rate of transformation are the following. The first term, $\Xi_t(1-\theta)Y_t/N_t$, 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 a model without labor market search, only the first term appears. Equation (21) equates the remuneration of capital to the additional output generated by a marginal unit of capital. Finally, Equation (22) is the New Keynesian Phillips curve in its nonlinearized form, as in Ireland (2003).

3.4. *The Central Bank.* During each period $t = 0, 1, 2, \dots$, the central bank conducts monetary policy using a modified Taylor rule,

$$\ln(R_t/R) = \rho_r \ln(R_{t-1}/R) + \rho_y \ln(Y_t/Y) + \rho_\pi \ln(\pi_t/\pi), \tag{23}$$

where R, Y, and π are the steady-state values of the nominal interest rate, output, and gross inflation rate, respectively. According to Equation (23), the central bank gradually adjusts the nominal interest rate in response to movements in output and inflation. As pointed out in Clarida et al. (1998), this modeling strategy for the central bank is broadly consistent with the actual monetary policy in the United States.

3.5. *Model Solution and Calibration.* In a symmetric, dynamic equilibrium, all intermediate-goods-producing firms make identical decisions, so that $Y_t(i) = Y_t$, $N_t(i) = N_t$, $H_t(i) = H_t$, $F_t(i) = F_t$, and $P_t(i) = P_t$, for all $i \in [0, 1]$ and $t = 0, 1, 2, \dots$. In addition, the market clearing condition $B_t = B_{t-1} = 0$ must hold for all $t = 0, 1, 2, \dots$. These conditions, together with the firm's profit conditions (19) and the household's budget constraint (2), produce the aggregate resource constraint

$$Y_t = C_t + I_t + (\phi_p/2)\,(\pi_t/\pi - 1)^2\, Y_t + G_t H_t. \tag{24}$$

Substituting the Lagrange multiplier, Λ_t, from Equation (5) into Equations (6), (7), (9), (15), (20), and (22), equating the wage from Equation (15) to Equation (20), and equating the remuneration of capital from Equation (6) to Equation (21), the model describes the behavior of the 13 endogenous variables $\{Y_t, C_t, H_t, K_t, I_t, G_t, x_t, U_t, u_t, N_{t-1}, \Xi_t, R_t, \pi_t\}$,

TABLE 1
PARAMETERS RANGES

Parameter		Range
α	Elasticity of labor market tightness	[0, 10]
β	Discount factor	[0.985, 0.995]
ϕ	Inverse of the Frisch intertemporal elasticity	[0.1, 4]
δ_n	Job destruction rate	[0, 0.1]
δ_k	Capital destruction rate	[0, 0.05]
θ	Capital share	[0.2, 0.4]
GH/Y	Share of hiring costs over total output	[0.01, 0.05]
ϕ_p	Degree of nominal price rigidities	[0, 50]
μ	Degree of substitution among goods	[5, 15]
ρ_r	Interest rate inertia	[0, 0.99]
ρ_y	Interest rate reaction to output	[0, 1]
ρ_π	Interest rate reaction to inflation	[1, 3]
ρ_a	Autoregressive coefficient, neutral technological progress	[0.75, 0.99]
ρ_υ	Autoregressive coefficient, investment specific technological progress	[0.75, 0.99]

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

and persistent autoregressive processes of the exogenous shocks $\{\varepsilon_{at}, \varepsilon_{\upsilon t}\}$. The equilibrium conditions do not have an analytical solution. Consequently, the system is approximated by loglinearizing 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).[4]

The model is calibrated on quarterly frequencies using U.S. 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 Dedola and Neri (2007) and Pappa (2009), 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 1. As in Blanchard and Gali (2010), to satisfy the Hosios condition, which ensures that the equilibrium of the decentralized economy is Pareto efficient, we impose that the relative bargaining power of the worker, ς, is equal to the elasticity of labor market tightness with respect to hiring costs, α, such that $\varsigma = \alpha$.[5] The elasticity of labor market tightness with respect to hiring costs, α, 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 β to be between 0.985 and 0.995. We calibrate the inverse of the Frisch intertemporal elasticity of substitution in labor supply, ϕ, to vary between 0.1 and 4, such that the elasticity of labor supply is between 10 and 0.25, whose values are in line with micro- and macro-evidence as detailed in Card (1994) and King and Rebelo (1999). Consistent with U.S. data, as in Fujita and Ramey (2009), the steady-state value of the job destruction rate, δ_n, is allowed to vary between 0 and 10%, and the steady-state value of the capital destruction rate, δ_k, is set between 0 and 5%, as in King and Rebelo (1999). The parameter of the production capital share, θ, 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 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 covers reasonable lower and upper bounds for this parameter. The degree of nominal price rigidities, ϕ_p, is allowed to cover values between 1 and

[4] Note that the model with flexible prices is recovered by imposing that prices are flexible ($\phi_p = 0$), there is no imperfect competition on the goods market ($\mu = 0$), and there is no role for the central bank ($\rho_r = \rho_y = \rho_\pi = 0$).

[5] See Hosios (1990) for the formal derivation of this condition.

50, as suggested in Ireland (2000). We allow the degree of substitution among different goods, μ, to vary between 5 and 15, which covers the values suggested in Rotemberg and Woodford (1998). Similarly to Dedola and Neri (2007) and Peersman and Straub (2009), the monetary policy parameters are allowed to vary in the following ranges: $\rho_r \in [0, 0.99]$, $\rho_y \in [0, 1]$, and $\rho_\pi \in [1, 3]$.

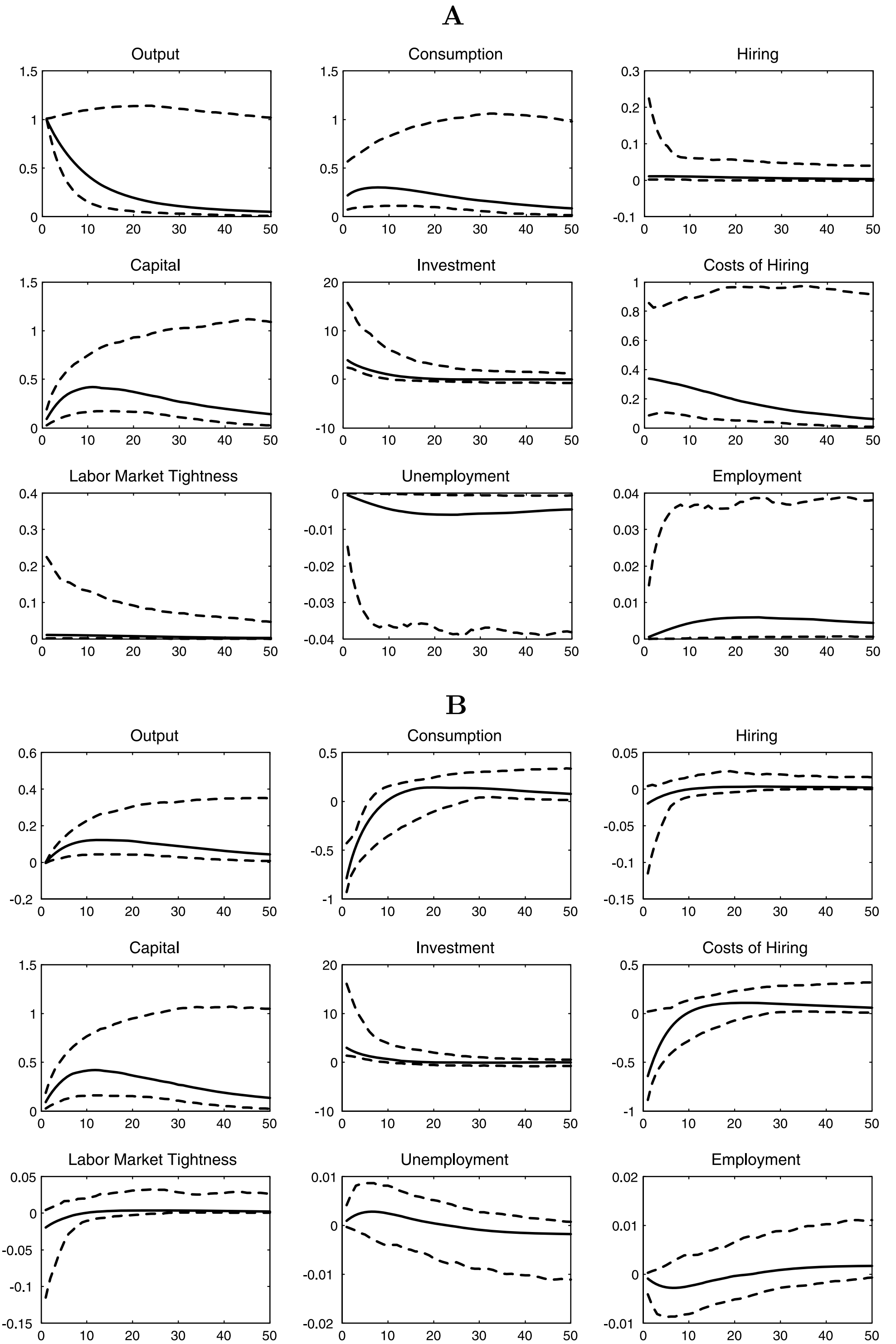
The steady-state values of the neutral and investment-specific technological progresses, a and υ, are conveniently set equal to 1, as they do not affect the dynamics of the system. The autoregressive coefficients of the neutral and investment-specific technological progresses, ρ_a and ρ_υ, are free to vary between 0.75 and 0.99 in line with King and Rebelo (1999) and Ireland (2003). The standard deviation of the neutral and investment-specific technological progresses, σ_a and σ_υ, are normalized to be equal to 1%. Finally, in line with Blanchard and Gali (2010), we calibrate the parameter of the disutility of labor, χ, to be equal to 1.5.

4. THE THEORETICAL RESTRICTIONS

To derive the sign restrictions to impose on the empirical SVAR model, we use the theoretical model to determine how each variable reacts to shocks. To produce robust responses to one positive percentage point 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 the two distributions below and above 2.5 and 97.5 percentiles, respectively. To illustrate how the variables of the theoretical model react to each shock, Figures 1 and 2 plot impulse responses of variables to one positive percentage-point deviation of neutral and investment-specific technology shock for the model with flexible and staggered price setting, respectively. 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) and Fisher (2006). The reactions of consumption, hiring, labor market tightness, and the cost of hiring to a neutral technology shock are positive. The intuition for these results is straightforward. In response to a positive technology shock, hiring increases as firms expand production by increasing labor input. Consequently, unemployment falls, which combined with the increase in hiring generates a rise in labor market tightness and the cost of hiring. On the other hand, in the face of an investment-specific technology shock, labor 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 labor market tightness and reducing the cost of hiring. Importantly for the analysis of this article, the opposite theoretical responses of hiring, labor market tightness, and consumption to the two shocks enable the identification of neutral technology shocks. Note that the model with nominal price rigidities provides two additional restrictions on the response of inflation and the nominal interest rate. As shown in Figure 2, inflation and the nominal interest rate both fall in reaction to a neutral technology shock, whereas they increase in response to an investment-specific technology shock.

Since consumption, hiring, and labor 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 summarized in panel A of Table 2, on the first-period reaction of the SVAR model, and subsequently the data can freely inform the dynamics of the response.[6] Of course, as described, the response of labor input is left unrestricted at all times.

[6] To ensure that the sign restriction that labor market tightness increases after a neutral technology shock does not rule out a decline in labor input, we have estimated the model relaxing this assumption and established that the results remain unchanged.

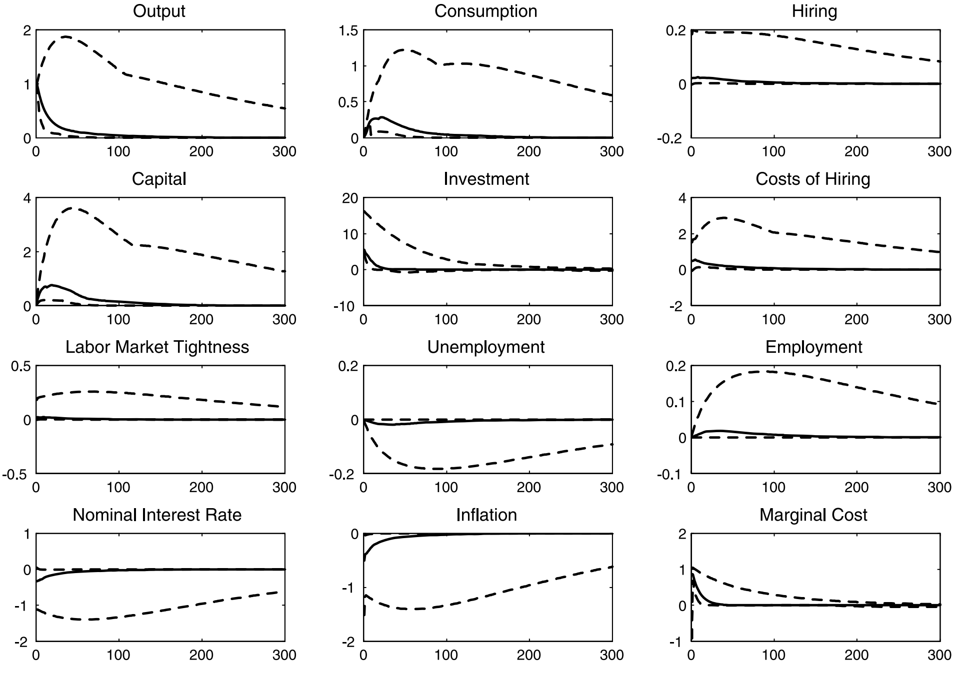


NOTES: Panel A (Panel B) shows the percentage-point response of one of the model's variables to a one-percentage-deviation neutral (investment-specific) technology shock. The solid line reports the median responses and the dashed lines report the 2.5 and 97.5 percentiles of the responses.

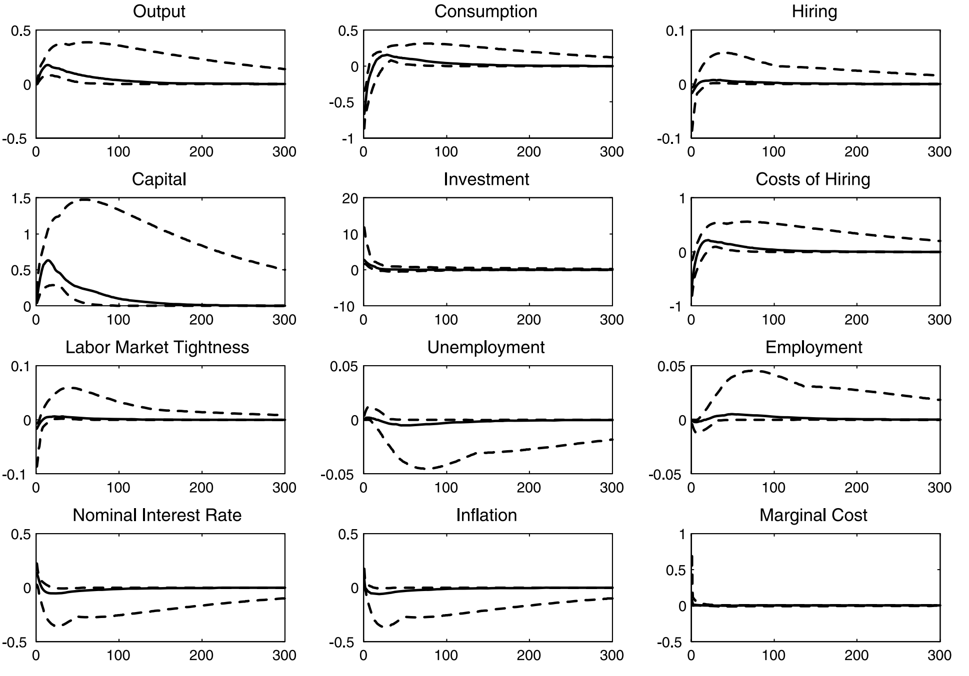
FIGURE 1

MODEL WITH FLEXIBLE PRICES: THEORETICAL IMPULSE-RESPONSE FUNCTIONS. (A) NEUTRAL TECHNOLOGY SHOCK; (B) INVESTMENT-SPECIFIC TECHNOLOGY SHOCK

A



B



NOTES: Panel A (Panel B) shows the percentage-point response of one of the model's variables to a one-percentage-deviation neutral (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 2

MODEL WITH STAGGERED PRICES: THEORETICAL IMPULSE-RESPONSE FUNCTIONS. (A) NEUTRAL TECHNOLOGY SHOCK; (B) INVESTMENT-SPECIFIC TECHNOLOGY SHOCK

TABLE 2
SIGN RESTRICTIONS ON THE FIRST-PERIOD SVAR VARIABLES

Variable	Neutral Technological Progress	Investment-Specific Technological Progress
	A: Model with Flexible Prices	
Real output	+	+
Investment	+	+
Consumption	+	−
Hiring	+	−
Labor market tightness	+	−
	B: Model with Staggered Prices	
Real output	+	+
Investment	+	+
Consumption	+	−
Hiring	+	−
Labor market tightness	+	−
Inflation	−	+
Nominal interest rate	−	+

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

5. THE BAYESIAN SVAR MODEL

In this section, we describe the empirical VAR model, the prior and the posterior distributions, and the identification scheme based on sign restrictions.

Our analysis is based on the following standard VAR model:

$$Z_t = \sum_{j=1}^{P} \beta_j Z_{t-j} + \varepsilon_t, \tag{25}$$

where the variance of ε_t is equal to Σ and the $T \times N$ data matrix Z_t contains the endogenous variables. We adopt a Bayesian approach to the estimation of Equation (25). Following Kadiyala and Karlsson (1997) and Sims and Zha (1998), we employ a Normal Inverted Wishart prior:

$$p\left(\Sigma\right) \backsim IW\left(\Sigma^0, T^0\right) \text{ and } p\left(\bar{\beta}/\Sigma\right) \backsim N\left(\beta^0, \Sigma \otimes \Psi^0\right), \tag{26}$$

where $\bar{\beta}$ is the vector of coefficients, β^0 is the prior mean for the VAR coefficients, Ψ^0 controls the tightness around this prior, Σ^0 is the prior scale matrix for the Inverse Wishart (IW) distribution, and T^0 denotes the prior degrees of freedom. Essentially, the prior in Equation (26) is a generalization of the Minnesota prior discussed in Litterman (1986) and assumes that the variables included in the VAR follow a random walk or an AR(1) process. 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 (26) does not assume a diagonal, fixed, and known covariance matrix, making it more suitable for VARs designed for structural analysis.

As described in Banbura et al. (2007) and commonly used in the literature, we impose the prior by adding dummy observations to the data matrix Z_t. That is, the prior in Equation (26) is implemented by adding dummy observations Y^0 and X^0 of length T_d to the system in Equation (25). It can be shown that $\beta^0 = (X^{0\prime}X^0)^{-1}(X^{0\prime}Y^0)$ and $\Sigma^0 = (Y^0 - X^0\beta^0)'(Y^0 - X^0\beta^0)$.

These dummy observations are defined as

$$Y^0 = \begin{pmatrix} \frac{diag\left(\beta_1^0\sigma_1 \ldots \beta_N^0\sigma_N\right)}{\varpi} \\ 0_{N\times(P-1)\times N} \\ \ldots\ldots\ldots\ldots\ldots \\ diag\left(\sigma_1 \ldots \sigma_N\right) \\ \ldots\ldots\ldots\ldots\ldots \\ 0_{1\times N} \end{pmatrix}, \text{ and } X^0 = \begin{pmatrix} \frac{J_P \otimes diag\left(\sigma_1 \ldots \sigma_N\right)}{\varpi} & 0_{NP\times 1} \\ 0_{N\times NP} & 0_{N\times 1} \\ \ldots\ldots\ldots\ldots\ldots & \\ 0_{1\times NP} & \xi \end{pmatrix},$$

where $\beta_1^0, \beta_2^0, \ldots, \beta_N^0$ denote the prior mean for each VAR coefficient and $0_{k\times j}$ is a matrix of zeros with dimension $k \times j$. Note that the parameter ϖ controls for the tightness of the prior on the VAR coefficients, such that a large number for ϖ corresponds to a loose prior. The parameter ξ controls the prior on the intercept, such that a small number makes the prior uninformative. Finally, following common practice, the parameters $\sigma_1, \sigma_2, \ldots, \sigma_N$ are scaling parameters and are approximated using the variance of univariate autoregressions for each variable in the VAR. The conditional posterior for the VAR parameters has the following form:

$$(27) \qquad g\left(\Sigma\right) \backsim IW\left(\hat{\Sigma}, T_d + 2 + T - K\right) \text{ and } g\left(\bar{\beta}/\Sigma\right) \backsim N\left(\hat{B}, \Sigma \otimes \left(X^{*\prime}X^{*}\right)^{-1}\right),$$

where $\hat{B} = (X^{*\prime}X^{*})^{-1}(X^{*\prime}Y^{*})$ and $\hat{\Sigma} = (Y^{*} - X^{*}\hat{B})'(Y^{*} - X^{*}\hat{B})$, T is the length of the time series, K is the number of coefficients in each VAR equation, and the terms Y^{*} and X^{*} denote the left- and the right-hand side of Equation (25) with the data Z_t augmented by dummy observations Y^0 and X^0. We use Gibbs sampling to draw 500,000 samples from this posterior. We discard the first 400,000 iterations as burn-in and retain every 10th draw of the remaining 100,000 draws for inference.[7]

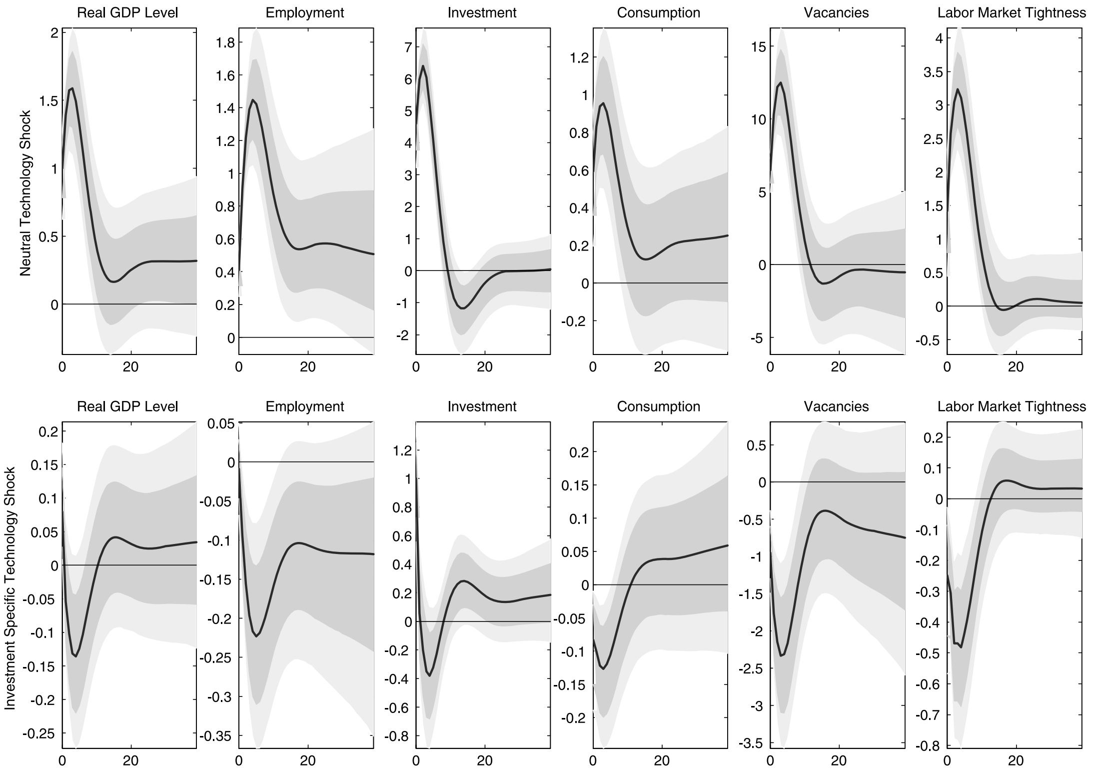
5.1. *Identification.* As mentioned, the structural analysis using the VAR model is based on the identification of two shocks: neutral and investment-specific technology shocks. Following Uhlig (2005) and Dedola and Neri (2007), we employ sign restrictions from the theoretical model, described in the previous section, 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 et al. (2008). Specifically, let $\Sigma = PDP'$ be the eigenvalue-eigenvector decomposition of the VAR's covariance matrix Σ, 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 VAR posterior.

6. FINDINGS

This section documents the findings. It uses the signs of the theoretical responses to constrain the first-period reaction of an SVAR model and determine the dynamics of labor input.

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

[7] An appendix that presents evidence on convergence of the Gibbs sampling algorithm is available upon request from the authors.



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 and the 5th, 16th, 84th, and 95th percentiles of the posterior distribution of the impulse responses.

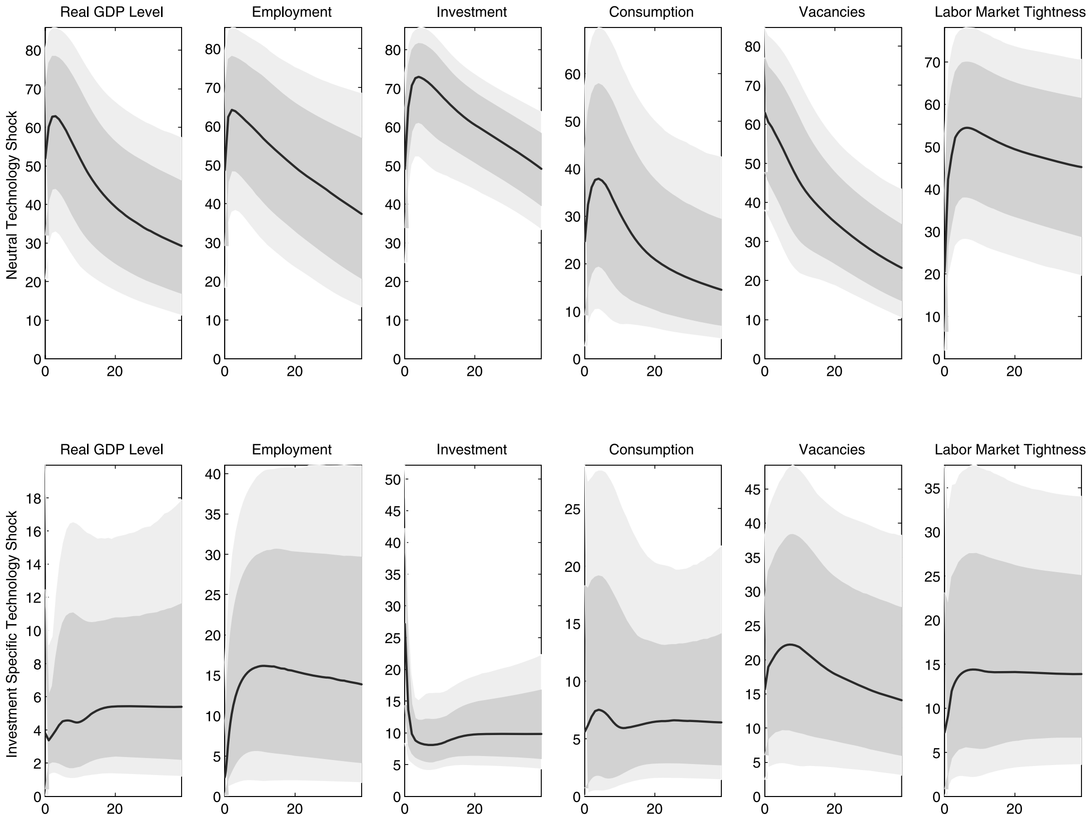
FIGURE 3

EMPIRICAL IMPULSE-RESPONSE FUNCTIONS TO A NEUTRAL AND INVESTMENT-SPECIFIC TECHNOLOGY SHOCK

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, labor market tightness, and employment. The data for real GDP, investment, consumption and employment are from the FRED database.[8] The data for hiring and labor market tightness are from Shimer (2007). The data are quarterly, seasonally adjusted, and cover the period 1951:Q1 2006:Q3. We specify an SVAR in levels with two lags but, as detailed below, results are robust to higher lags order. We present results based on the model with flexible prices, derived by setting $\phi_p = 0$, since it includes a lower number of variables and the identifying restrictions rely solely on the responses of hiring, labor market tightness, and consumption. However, as shown below, the qualitative results hold for the model with staggered price setting that uses a larger data set, which includes series for marginal cost, inflation, and the nominal interest rate and imposes additional restrictions on the responses of inflation and the nominal interest rate.

Figure 3 plots the estimated impulse responses to a positive neutral and investment-specific technology shock. Each plot shows the median and 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 labor market tightness, which is statistically significant, as the 16th percentile is above zero for approximately the initial two and a half years. As expected from theory, as in Fisher (2006),

[8] The FRED mnemonics for the variables are GDPC96, PNFI, PCECC96, and CE16OV, respectively.



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 and the 5th, 16th, 84th, and 95th percentiles of the posterior distribution of the impulse responses.

FIGURE 4

FORECAST ERROR VARIANCE DECOMPOSITIONS

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) and Christiano et al. (2004), the median response of labor 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, labor market tightness, and labor input, the impact reaction is significantly different from zero for about five years, whereas in the case of real GDP and investment, the 16th percentile reaches zero after approximately 12 quarters. It is interesting to note that the response of employment in the SVAR is much larger than in the theoretical model. This is related to the weak propagation mechanism of employment (or unemployment) in search and matching models of the labor market, as pointed out in Shimer (2005). Gertler and Trigari (2009) suggest that staggered wage setting helps in magnifying the response of employment in reaction to shocks. Enriching the theoretical model with staggered wage setting to produce a stronger response of employment would certainly be a useful extension for future research.

To understand the extent to which the movements of each variable are explained by the shocks, 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, whereas their importance almost halves at low frequencies. Similarly, neutral technology shocks are the main contributors to short-run fluctuations in investment, consumption, vacancies, labor 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 stabilizes 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 Zanetti (2008) obtained by estimating a standard real business cycle model. 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.

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 before and after 1980, if we use alternative variables in the SVAR, if we extend the length of sign restrictions, and if we use the restrictions from the model with staggered prices to identify shocks. Finally, we also enrich the theoretical framework with additional shocks and establish that the identification of a neutral technology shock is unique. We establish that the results hold to all the different perturbations to the benchmark specification.[9]

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.[10] In particular, as summarized in panel B of Table 2, we impose as additional restrictions that inflation and the nominal interest rate both fall on the first-period reaction to a neutral technology shock, although they increase in response to an investment-specific technology shock.[11] Figure 5 shows that the response of employment to a neutral technology shock is positive, and the response of the variables is similar to the estimated responses based on the model with flexible prices.[12]

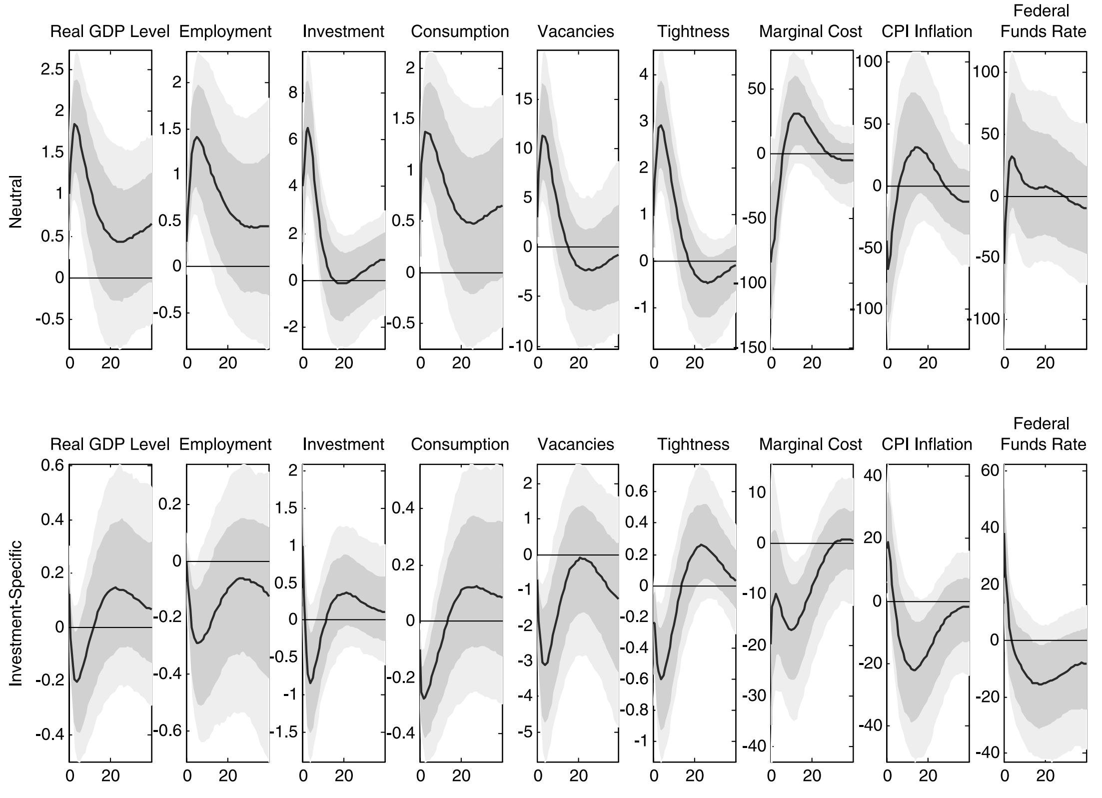
Finally, in order to test the robustness of our sign identification scheme we conduct a simple Monte Carlo experiment. We generate 5,000 samples of artificial data from the New

[9] An appendix, which details the robustness of the results, is available upon request from the authors.

[10] Inflation is defined as the quarterly growth rate of the CPI index, whereas 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 mnemonics are CPIAUCSL and FEDFUNDS, respectively. We proxy the marginal cost with the labor share using data on labor income from the U.S. Bureau of Economic Analysis's National Income and Product Accounts. Note that 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). An appendix that details the construction of the labor share and provides further details on the additional shocks is available upon request from the authors.

[11] A companion appendix details how the alternative shocks are implemented in the data and it also performs robustness analysis on the identification scheme.

[12] 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.



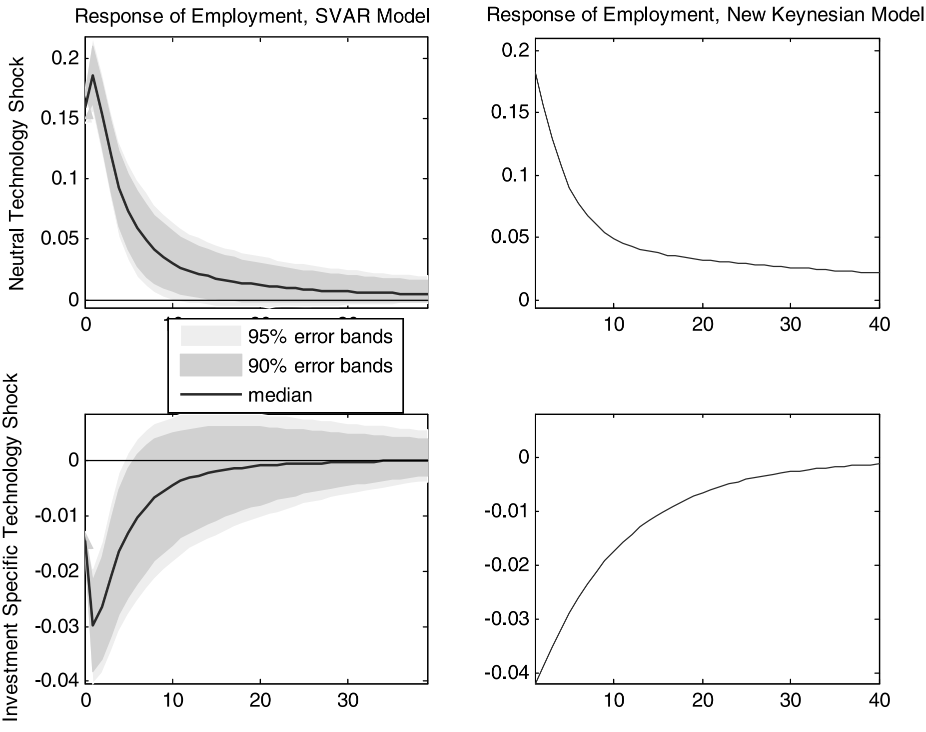
NOTES: The top row shows impulse responses from the SVAR model to a positive neutral technology shock. The bottom row shows impulse responses from the SVAR model to a positive investment-specific technology shock. Each plot shows the median and the 5th, 16th, 84th, and 95th percentiles of the posterior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

FIGURE 5

EMPIRICAL IMPULSE–RESPONSE FUNCTIONS TO A NEUTRAL AND INVESTMENT-SPECIFIC TECHNOLOGY SHOCK, MODEL WITH STAGGERED PRICES

Keynesian model using the mean value of the benchmark parameters ranges is shown in Table 1.[13] At each iteration we simulate 300 observations for the model's variables, discarding the first 50 observations to reduce the impact of initial conditions. The generated data are used to estimate the impulse response to neutral and investment-specific technology shocks using the VAR model and benchmark contemporaneous sign restrictions implied by the New Keynesian model. The left panels of Figure 6 show the distribution of the response of employment (across the Monte Carlo replications) to the neutral and investment-specific technology shocks estimated using the VAR model, and the right panels show the impulse response to these shocks in the theoretical model. The VAR responses match the model responses closely in terms of magnitude and persistence. The median response to the neutral technology shock in the VAR peaks at 0.19%, which is close to 0.18% suggested by the model, with both responses close to zero at the 35-quarter horizon. The VAR estimate of the response of employment to the investment-specific technology shock also captures the key features of the model's response. The median VAR response suggests a peak impact of −0.03%, which is close to the model's response estimated at −0.04%. These results suggest that the short-run identification scheme we employ is capable of recovering the structural response to the two technology shocks, which is in sharp contrast to the performance of the long-run identification schemes.

[13] Note that the autoregressive coefficients and the variances for all the shocks are set equal to 0.75 and 1, respectively.



NOTES: The left panels show the estimated responses of employment to a neutral (top) and investment-specific (bottom) technology shock using data simulated from the VAR model. The right panels show the responses of employment to a neutral (top) and investment-specific (bottom) technology shock using the theoretical models. Each plot shows the median and 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 6

EMPIRICAL AND THEORETICAL IMPULSE–RESPONSE FUNCTIONS TO A NEUTRAL AND INVESTMENT-SPECIFIC TECHNOLOGY SHOCK, MONTE CARLO EXPERIMENT

7. CONCLUSION

This article has investigated the dynamic response of labor input to neutral technology shocks. Neutral technology shocks are identified using the cyclical properties of benchmark DSGE models of the business cycle with flexible and staggered prices, characterized by labor market search frictions and investment-specific technology shocks. The identification procedure holds across models and additional shocks and is robust to plausible parameterizations. By imposing the signs of the theoretical responses on the first-period reaction of an SVAR model, the estimation supports an increase in labor 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 labor market variables, splitting the sample period, and extending the length of sign restrictions.

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