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DIPARTIMENTO DI ECONOMIA

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ISSN 2279-6916 Working papers
(Dipartimento di Economia Università degli studi Roma Tre) (online)

Working Paper n° 161 2012

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Per ciascuna pubblicazione vengono soddisfatti gli obblighi previsti dall'art. l del D.L.L. 31.8.1945, n. 660 e successive modifiche.

Copie della presente pubblicazione possono essere richieste alla Redazione.

esemplare fuori commercio
ai sensi della legge 14 aprile 2004 n.106

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Francesco Giuli - Massimiliano Tancioni

Price-setting, Monetary Policy and the Contractionary Effects of Productivity Improvements[1]

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Abstract

This paper adds to the large literature on the effects of technology shocks empirically and theoretically. Using a SVEC model, we first show that not only hours but also investment decline temporarily following a technology improvement. This result is robust with respect to important data and identification issues addressed in the literature. We then show that the negative response of inputs is consistent with an estimated monetary DSGE model in which the presence of strategic complementarity in price setting, in addition to nominal rigidities, lowers the sensitivity of prices to marginal costs, and monetary policy does not fully accommodate the shock.

JEL CLASSIFICATION: C110, C320, E220, E320, E520
KEYWORDS: Technology shocks, Inputs dynamics, Structural Vector Error Correction model, New-Keynesian DSGE model, Bayesian inference

[1] The authors would like to thank Giuseppe Ciccarone, Enrico Marchetti and a referee for helpful comments and seggestions.

1 Introduction

A recent and large body of literature has challenged the empirical relevance of the concept of technology-driven business cycles. The shift of interest from the analysis of the sample correlations among macroeconomic time-series to the analysis of their conditional counterparts has identified a counter-cyclical behavior of factor inputs following a technology shock. This result is apparently at odds with the predictions of a broad class of business cycle models that envisage technology shocks as one of the main determinants of the observed pro-cyclical dynamics of factor inputs.

This paper develops on this literature from both an empirical and a theoretical perspective. First, using a Structural Vector Error Correction (SVEC) model we show that both hours and investment negatively respond to a positive technology shock and that this result is robust with respect to the main control dimensions addressed in the literature. Second, we demonstrate that the negative response of inputs at the typical business cycle frequencies is consistent with an estimated New Keynesian DSGE model in which: *i)* the presence of relevant strategic complementarities in price setting, in addition to nominal rigidities, lowers the sensitivity of prices to marginal costs; *ii)* monetary policy does not fully accommodate the shock.

The idea that technology improvements can have contractionary effects, which dates back to Hansen and Wright (1992), is supported by several empirical studies mainly focusing on the emergence of a negative conditional correlation between productivity and hours worked in Structural Vector Autoregressions (SVARs) identified with long-run restrictions (Galì, 1999; Francis and Ramey 2005). With the exception of Basu *et al.* (2006), who use a "purified" measure of technology in two-variables VAR specifications, and of Giuli and Tancioni (2012), who estimate a monetary DSGE model with nominal and real frictions characterized by a particularly flat NKPC, the evidence of an additional negative short-term response in investment has not instead generally been established in the empirical and theoretical literature on business cycles.

The evidence on the contractionary effects of productivity improvements is however highly debated among macroeconomists. An important issue is whether hours should be considered as stationary or nonstationary in empirical trials (Christiano *et al.*, 2004). More in general, this issue relates to the identifiability of technology shocks within the long-run SVAR approach when low frequency movements in productivity (Fernald, 2007) and hours (Canova *et. al*, 2010) are present.

The empirical evaluation of DSGE models also reaches conflicting conclusions. Basing the calibration of a monetary model on an impulse response matching strategy, Altig *et al.* (2005, 2011) obtain a positive short-term response of both factor inputs[2]. Del Negro *et al.* (2005) and Smets and Wouters (2007) estimate NK-DSGE models with nominal and real frictions and obtain that, whereas the response of hours is negative, that of investment is positive[3].

From the theoretical point of view, different explanations of the contractionary effects of technology shocks have been put forward. Galì (1999) proposes a sticky price model where monetary authorities adopt a partially exogenous money supply rule so that, following a productivity improvement, the weak response of real balances constrains the demand expansion, leading to a reduction in the use of labor. Francis and Ramey (2005) show that a negative response in hours

[2] In the 2005 version of this paper, Altig *et al.* also obtain a counterfactual increase in inflation after a neutral technology shock, due to a highly accommodative monetary policy response to the productivity improvement. A strong response of money growth is needed in order to account for the rise in economic activity obtained with the benchmark SVAR.

[3] Del Negro *et al.*'s (2005) baseline specification adopts a monetary policy rule that responds to technology shocks. Smets and Wouters (2007) assume instead that the monetary authority targets flexible price output. In both cases the policy rule accommodates the technology shock.

(but not in investment) is obtained also in a flexible price model with real demand rigidities modelled in the form of consumption habits and capital adjustment costs. This is also Smets and Wouters's (2007) preferred interpretation for the negative response in hours. Lindé (2009) shows that the negative correlation between output, hours and investment can emerge in a baseline RBC model in which the permanent technology shock is autocorrelated in growth rates. Under this hypothesis, the temporary contraction in inputs is due to the interaction of wealth and intertemporal substitution effects stemming from the expected increase in productivity. Schmitt-Grohé and Uribe (2011) show that a flexible price model in which the common stochastic trend is driven by both neutral and investment-specific productivity shocks is also consistent with a temporary contraction of inputs following an investment-specific shock[4]. Basu *et al.* (2006) take into account these different explanations and conclude that standard sticky price models, in which monetary policy follows a non-fully accommodative rule, can account for the negative response in both hours and investment better than the alternative explanations. However, they do not support their argument with an analytical monetary model[5]. Giuli and Tancioni (2012) partly confirm Basu *et al.*'s conclusions, even if they show that strong strategic complementarities in price-setting are needed in order to obtain reasonable estimates of the frequency of price re-optimization.

Overall, there is no clear consensus on the robustness of the empirical results, and the competing theoretical explanations still lack substantial empirical testing in a comparative perspective.

Our investigation improves on the empirical and theoretical literature in two respects. First, by showing that the short-term response of investment to a positive technology shock is negative, we widen the focus of the debate on the contractionary effects of technology shocks from hours to investment. Second, by employing an estimated formal model we provide a theoretical interpretation of our results and evaluate the empirical relevance of some of the alternative explanations summarized above.

The analysis is organized in two stages. In the first one we estimate a SVEC model using unprocessed data for productivity and considering hours as stationary. The SVEC is specified so as to approximate a fairly general NK-DSGE model subject to permanent supply shocks. Because of the explicit consideration of the stationary relations among nonstationary variables, the SVEC representation favours the separation between permanent and transitory components, thus improving the identification of the technology shock. The SVEC is identified by imposing theory-based long-run restrictions on the cointegration space and on the long-run effects matrix. The cointegrating vectors are the theory-based stationary ratios among real and monetary variables, and the long-run effects matrix is identified by imposing the standard hypothesis that only technology shocks can have permanent effects on labor productivity.

The SVEC analysis confirms the existence of short-term contractionary effects of productivity improvements. This provides new evidence able to question the ability of technology shocks to explain the unconditional pro-cyclicality of investment and hours. Moreover, the negative response of inflation and the hump-shaped negative response in the nominal interest rate signal that the

[4] The temporary contraction in inputs appears driven by the short-term negative response of both types of productivity to the investment-specific productivity shock, which is interpreted as indicating the operation of technological diffusion delays. A similar argument, based on the wealth and intertemporal substitution effects inplied by the presence of technological diffusion delays, or by expected increases in productivity, has been proposed by Rotemberg (2003) and Beaudry and Portier (2007). Note however that the diffusion process is not theoretically specified in Schmitt-Grohé and Uribe's (2011) model. A VEC representation describes the joint law of motion of the two sources of productivity growth, and gives the RBC model a particularly flexible dynamics.

[5] Since their conclusion refers to Basu's (1998) model, in which the policy rule responds to lagged inflation and the lagged output gap, it is not clear whether the negative effects on inputs would persist under more standard contemporaneous rules.

monetary authority does not fully accommodate the shock. From robustness checks we obtain that, contrary to Fernald (2007) and Canova *et al.* (2010), under the SVEC specification the consideration of trend breaks in productivity and long cycles in hours is not strictly needed. We also show that the use of alternative identification strategies does not alter the main conclusions of our investigation.

The second stage of our analysis provides a theoretical interpretation of the SVEC evidence to be confronted with the data and with alternative explanations. We set-up and estimate a monetary DSGE model that can encompass the different empirical results and the different theoretical interpretations provided by the literature. Standard monetary DSGE models are generally characterized by the presence of real rigidities in the form of consumption habits, capital adjustment costs and nominal rigidities in price and wage-setting. In addition to these hypotheses, we assume that capital is firm-specific (Altig *et al.*, 2005, 2011; Woodford, 2005; Sveen and Weinke, 2005, 2007) and the demand elasticity among differentiated goods is endogenous (Eichenbaum and Fisher, 2007; Smets and Wouters, 2007). Under these additional hypotheses, the slope of the new Keynesian Phillips curve (NKPC) depends not only on the frequency with which firms are allowed to reset their prices, but also on the degree of strategic complementarities in price setting (Woodford, 2005). This additional element lowers the slope of the NKPC, hence weakening the sensitivity of price inflation to variations in the marginal cost. The economic rationale for this result is that, since capital must be accumulated by the firm, marginal costs are firm-specific and the incentive to cut prices following a productivity improvement is partially counterbalanced by the expected increase in marginal costs due to the expected increase in demand.

The importance of the aggregate demand response to productivity improvements highlights the role played by monetary policy. It is well known that, for a wide class of NK models, a monetary policy rule that responds to the theory-consistent output gap can approximate the optimal policy, i.e., the one that would minimize the volatility of the target variables around their natural levels. The implementation of this rule in real life operations requires however knowledge of the natural rate of interest, or of the level of potential output, which is not within a monetary authority's information set. For this reason, we consider two alternative contemporaneous rules - one targeting output deviations from its trend (i.e., an "empirical" rule) and the other one the theory-based output gap - and let the data speak on which of them is the most empirically relevant.

The theoretical model is estimated by adopting a Bayesian approach, counterfactually elicidating a prior parameterization for which the model does not replicate the SVEC-based evidence on the negative conditional correlation between productivity and investment. We show that the dynamics of the estimated NK-DSGE model are qualitatively similar to those produced by the SVEC. Our estimates also show that neither real rigidities in consumption and investment, nor intertemporal substitution effects are sufficient to explain the empirical evidence. They instead support a New Keynesian interpretation. On the one hand, the evidence in favour of the empirical rule indicates that the policy response to productivity improvements is not fully accommodative. On the other hand, a flat slope of the NKPC signals the presence of relevant rigidities in price-setting which cannot be attributed exclusively to nominal rigidities, as this would imply a degree of price stickiness which is at odds with the evidence on the frequency of price optimization at the firm level. Firm-specific capital and endogenous demand elasticity are crucial to obtain a plausible estimate of the degree of price stickiness.The paper is organized as follows. Section 2 presents the hypotheses and the results of the SVEC analysis. Section 3 presents a monetary DSGE model with firm-specific capital and endogenous demand elasticity. Section 4 provides details of the Bayesian estimates of the model. Section 5 discusses the results in the light of the different theoretical explanations advanced in the literature. Section 6 concludes.

2 SVEC-based evidence

The empirical literature on the productivity-employment puzzle reaches conflicting conclusions on whether hours worked rise or fall after a productivity improvement. A controversial issue is whether hours should be assumed as stationary or nonstationary in empirical trials. Christiano *et al.* (2004) criticize Galì's (1999) results by showing that the productivity-employment puzzle emerges because hours worked are there incorrectly considered as nonstationary and thus enter the SVARs in first differences[6]. Fernald (2007) shows that the puzzle persists even if hours are entered in levels, when trend breaks in productivity are taken into account. From a similar perspective, Canova *et al.* (2010) demonstrate that, once low frequency movements in hours are removed, per capita hours fall in response to a technology improvement and that this result is robust to the potential sources of bias addressed in the critical literature on the SVAR approach[7].

Closely related to this debate, that basically focuses on the identifiability of technology shocks within the long-run SVAR approach, is the methodology detailed in Basu *et al.* (2006), which gets around these identification difficulties by using VARs in which a "direct" measure of technology is considered in the place of average productivity. Employing this alternative strategy, Basu *et al.* (2006) obtain that the short-term responses of both hours and investment are negative conditional to productivity improvements. However, even though this approach has the advantage of getting rid of the estimation biases induced by aggregation problems and by the presence of low-frequency components in hours and productivity, this comes at the cost of adopting a quite complex methodology for the derivation of the technology measure[8].

The fact that the negative response of inputs is found in minimal scale SVARs only if *i*) hours enter the VAR in first differences (Christiano *et. al.*, 2004), *ii*) productivity and/or hours are corrected by controlling for break dates and long cycles (Fernald, 2007; Canova *et al.*, 2010) or *iii*) productivity is replaced by a "purified" technology measure (Basu *et al.*, 2006), indicates that the imposition of long-run restrictions on a highly persistent series (such as hours) may lead to a problematic identification of the technology shock.

In this section we show that, by adopting a SVEC representation of a larger set of variables, we can provide empirical evidence that robustly confirms Basu *et al.*'s (2006) conclusions even considering unprocessed data on productivity. The choice of a SVEC specification has two major advantages. First, with respect to standard SVARs, it provides a more adequate approximation of a large class of DSGE models that predict long-run balanced growth and differential dynamic adjustments in real and monetary variables. Second, the explicit consideration of the stationary relations described by the cointegrating (CI) vectors in the SVEC improves the identifiability of the technology shock, since the presence of linear relations that satisfy the stationarity requirements enhances the separation between permanent and transitory components (Harvey and Stock, 1988; King *et al.*, 1991).

In the following section we propose a benchmark SVEC and then evaluate the robustness of

[6] The hypothesis of stationary hours is consistent with the predictions of a general class of DSGE models (Christiano *et al.*, 2005; Dedola and Neri, 2004). On the other hand, the use of differenced hours, irrespective of the predictions of the interpretative model being considered, is justified by the finding of a (near) unit root in per capita hours (Galì, 1999; Francis and Ramey, 2005).

[7] Cooley and Dwyer (1998), Chari *et al.* (2005) and Erceg *et al.* (2005) show that SVAR-based results can be seriously affected by the use of long-run restrictions in small samples. Fry and Pagan (2005) show that the use of low-dimensional VARs may lead to truncation biases.

[8] This measure is obtained using a bottom-up growth accounting method, first estimating a purified Solow residual by controlling for capacity utilization in Hall-style regressions and then obtaining the aggregate technology as a weighted sum of the industry residuals. This methodology requires to use industry-level annual data (so that the information at the higher frequencies is lost), the estimation of theory-based proxies for unobserved utilization and the use of a band-pass filter to isolate the frequencies of interest in the hours series.

the results with respect to alternative specifications, identification schemes and the use of break date controls.

2.1 Data and the VEC model

The VEC model is estimated using U.S. quarterly time-series for hourly productivity (y_t), inflation (π_t), labor supply (h_t), the short-term nominal interest rate (r_t), consumption per hour (c_t) and non-residential investment per hour (i_t). The sample period is 1954:3 - 2007:2. A detailed description of the data and data manipulations is provided in Table A.1 in the Appendix.

From the ADF and KPSS tests we obtain that real variables are all $I(1)$ in levels, irrespective of how the deterministic components are specified. The tests are inconclusive with respect to price inflation and the nominal interest rate, that result $I(1)$ according to the ADF unit root test and $I(0)$ according to the KPSS test for stationarity. The hours to population ratio is $I(0)$ at the standard 5% significance level when a constant term is included for both the ADF and KPSS tests, and $I(1)$ under the alternative specifications for the deterministic components. The test results are summarized in Table B.1 in the Appendix.

Considering that interpretative models would predict stationary hours around a constant term, and on the basis of the very weak decay of the autocorrelation function for inflation and the interest rate, we assume that the labor input measure is $I(0)$ and the monetary variables are $I(1)$. The dependence of results on this latter hypothesis is evaluated in the robustness checks.

A convenient structural formulation of the m-dimensional VEC representation for the endogenous variables $\mathbf{x}_t' = \begin{bmatrix} y_t & \pi_t & h_t & r_t & c_t & i_t \end{bmatrix}$ can be specified by assuming no contemporaneous correlations among variables:

$$\mathbf{\Gamma}(L)\,\Delta\mathbf{x}_t = \mathbf{\Pi}\mathbf{x}_{t-1} + \mathbf{B}\boldsymbol{\varepsilon}_t \tag{1}$$

where $\mathbf{\Gamma}(L) = \mathbf{\Gamma}_0 - \mathbf{\Gamma}_1 L - ... - \mathbf{\Gamma}_{p-1}L^{p-1}$ are structural coefficients matrices and $\mathbf{\Gamma}_0 = \mathbf{I}_m$. Under this hypothesis, $\mathbf{B}$ contains the contemporaneous structure of the system, i.e., the contemporaneous correlations among variables and errors. The long-run relation matrix $\mathbf{\Pi}$, in the presence of cointegration, is a reduced rank matrix and can be decomposed as $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$, where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $m \times r$ full-column rank matrices containing, respectively, the loading coefficients and the r cointegrating vectors. The vector of disturbances $\boldsymbol{\varepsilon}_t \sim (\mathbf{0}, \mathbf{I}_m)$ contains the orthonormal structural innovations. The system of linear equations relating the estimated reduced-form errors $\mathbf{u}_t$ to the structural shocks is thus $\mathbf{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t$, which implies $\mathbf{\Omega} = \mathbf{u}\mathbf{u}' = \mathbf{B}\mathbf{B}'$.

2.2 Long-run components and CI space

In order to control for residual autocorrelation and high order memory, we impose four lags on the starting VAR, a lag order that is higher than suggested by the information criteria[9]. The evident break in monetary policy in the Volker period, the presence of long cycles in per capita hours (Canova *et al.* 2010) and the upward behavior of the consumption to output ratio beginning in the late nineties are taken into account by considering four deterministic components entering the long-run relations of the VEC. The first one is a period dummy, d_1, that identifies the Volker period, the second and the third ones, d_2 and d_3, identify the two hours break dates (1970:4 and 1995:1, respectively) that are evident in the data and have been addressed in the literature (Canova *et al.*, 2010), the fourth one is a (segmented) trend, st_1, accounting for the trending behavior observed in the consumption to output ratio since 1997.

[9] The Schwartz and Akaike information criteria suggest one and three lags, respectively. Standard autocorrelation tests indicate that the choice of a fourth order memory for the levels VAR ensures serially uncorrelated errors.

Considering a VEC structure with unrestricted constants and structural breaks in the CI space, the LR trace test indicates the presence of four stationary components at the 95% significance level. The results are basically unaffected for lower and higher lag order specifications of the VAR. Five stationary components are obtained considering the 90% significance level[10]. According to this evidence, the system is driven by two permanent components and four transitory shocks. The rank test results are summarized in Table B.2 in the Appendix.

We assume that the permanent component observed in the three real variables y_t, c_t, i_t is due to the technological stochastic trend (King *et al.*, 1991; Pesaran and Smith, 1995; Garratt *et al.,* 2003), and that the permanent component observed in the monetary variables r_t and π_t is due to the way the central bank adjusts its policy target (Vlaar, 2004)[11]. Among other checks, in the robustness analysis we will evaluate the effects of considering inflation and the nominal interest rates as stationary, as predicted by standard NK-DSGE models.

In terms of the variables' ordering, the first CI relation in $\boldsymbol{\beta}'$ defines stationary hours adjusted for long cycles, i.e., we impose a CI relation in which only hours and the two break dummies enter the corresponding cointegrating vector $(h_t - \beta_{18}d_2 - \beta_{19}d_3)$. The second CI relation defines the Fisher interest parity, i.e., the stationary real interest rate adjusted for the Volker period $(r_t - \beta_{22}\pi_t - \beta_{27}d_1)$. The last two CI relations define the stationary "great ratios" of the economy, i.e. $c_t - \beta_{31}y_t - \beta_{310}st_1$ and $i_t - \beta_{41}y_t$, the former being adjusted for the observed segmented trend. The estimated coefficients of the great ratios are all significant but only marginally consistent with the hypothesis of balanced growth $(\beta_{31} = \beta_{41} = -1)$.

2.3 Identification of the SVMA representation

The forecast error impulse response functions (IRFs) and variance decompositions (FEVDs) are obtained from the structural vector moving average (SVMA) representation of the SVEC:

$$\mathbf{x}_t = \mathbf{C}(1)\sum_{i=1}^{t}\mathbf{B}\boldsymbol{\varepsilon}_i + \mathbf{C}^0(L)\mathbf{B}\boldsymbol{\varepsilon}_t + \widetilde{\mathbf{x}}_0 \tag{2}$$

where $\mathbf{C}(1)$ is the long-run effects matrix and $\mathbf{C}^0(L)$ is a convergent infinite order polynomial for the impact and interim multipliers of the shocks. The permanent components are identified by adopting the standard hypothesis that only technology shocks have permanent effects on productivity (Shapiro and Watson, 1989; Blanchard and Quah, 1989; Galì, 1999; Francis and Ramey, 2005)[12]. This provides one exclusion restriction on the long-run effects of inflation shocks on productivity (the element c_{12} of the $\mathbf{C}(1)\mathbf{B}$ matrix is zero). The assumption of a lower triangular structure for the $(m-r)\times(m-r)$ upper left block of $\mathbf{C}(1)\mathbf{B}$ separates the real from the nominal permanent component in the system. This hypothesis is consistent with the predictions of a broad class of theoretical business cycles models.[13].

The orthogonality among permanent and transitory components ensures that the dynamic effects of a technology shock on $\mathbf{x}_t$ do not depend on the identification of the transitory components

[10]When structural breaks are present, standard critical values of the trace test are not appropriate. For this reason, we use the percentiles of the asymptotic distribution of the test simulated by Johansen *et al.* (2000) for the case of known structural breaks. The same result is obtained by considering the long-run dummies as exogenous variables and using MacKinnon *et al.*'s (1999) critical values for the case $k = 4$.

[11]This assumption is justified by the fact that, in the absence of inflation biases, the long-run output gap is zero and long-run inflation is determined by the non-stationarity of the monetary authority's policy target.

[12]Further details on the identification strategy are provided in the Appendix.

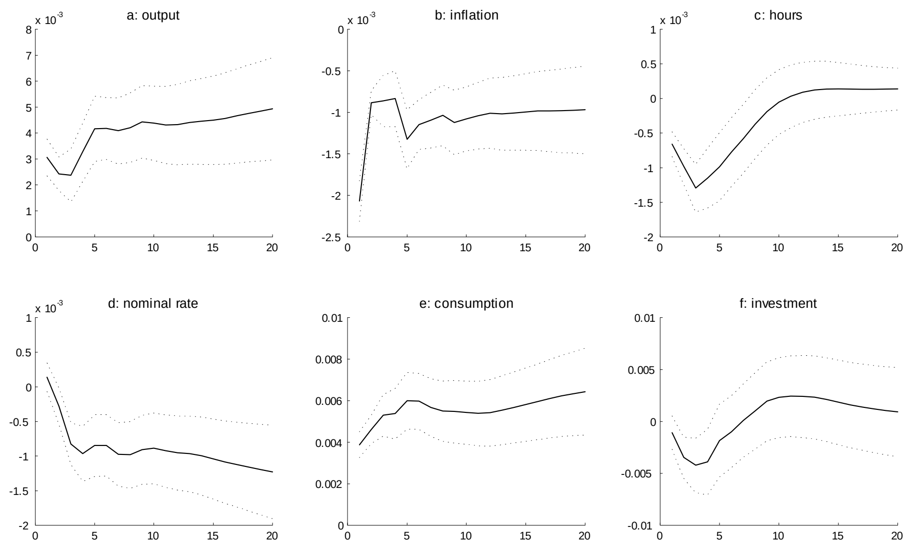
[13]The theoretical literature could suggest to include of a further zero restriction for the long-run effects of productivity shocks on hours (Francis and Ramey, 2005). We do not take account of such a restriction on the grounds that, in the presence of permanent productivity shocks, its validity is limited to a specification of utility where income and substitution effects exactly cancel out in the long-run.

(King *et al.* 1991). For this reason, and since we are only interested in the effects of technology shocks, the transitory components are left unidentified, i.e., we do not impose restrictions on the contemporaneous effects matrix $\mathbf{B}$[14].

2.4 SVEC-based impulse responses and variance decomposition

Figure 1 depicts the impulse responses to a one standard deviation productivity shock. The solid lines denote the impulse response point estimates; dotted lines define the 90% confidence intervals.

Figure 1 - Impulse responses to a productivity improvement



Notes: Dotted lines define 90% confidence interval regions

The results of the IRF analysis can be summarized as follows.

1. The long-run responses of real variables (output, consumption and investment) are positive, confirming the standard theoretical prediction that supply shocks are expansionary in the long-run. This feature is consistent with the nonstationary properties of the data and the long-run identification strategy imposing a technology-driven common stochastic trend among the real variables.

2. The IRFs of the monetary variables are consistent with the theoretical predictions of standard monetary models. Inflation and interest rate responses are significantly negative and the response of the nominal rate denotes gradual accommodation, confirming the well-documented inertia displayed by monetary policy. The reduction in inflation indicates that the monetary policy does not fully accommodate the increase in productivity.

[14] The results are unaffected if exact identification of the transitory components is obtained by restricting the $m \times r$ right block of the impact effects matrix with conventional exclusion restrictions or theory-based cross-coefficients restrictions.

3. Whereas the short-term responses of output and consumption are consistent with the predictions of standard business cycle models, those of hours and investment are not. Hours decline immediately after a supply shock, peaking at nearly three quarters. The 90% error bands indicate that the negative response of hours is significant over approximately five quarters. Similarly, investment shows a hump-shaped short-term negative response; the impulse response point estimate crosses the zero line only after seven quarters and denotes a slow convergence to its positive long-run value. According to the 90% confidence intervals, the negative response is significant over approximately four quarters.

4. Since consumption grows on impact more than output, there are signals that interpretations of the productivity-employment puzzle based on flexible price models with a relevant rigidity in consumption (Francis and Ramey, 2005; Smets and Wouters, 2007) are not supported by the data.

The FEVDs, reported in Table 1, confirms the idea that technology shocks are important, but not the main driver of economic fluctuations. The percentage of variance explained by the technology shock after four quarters is 30% for productivity, 40% for consumption, 19% for hours and only 8% for investment. After 40 quarters, technology shocks explain 85%, 80%, 14% and 9% of the variability of the same variables.

Table 1 - Forecast error variance decomposition

	Variables					
Periods	y_t	π_t	h_t	r_t	c_t	i_t
1	0.312	0.480	0.177	0.007	0.356	0.031
4	0.296	0.431	0.188	0.081	0.415	0.082
8	0.470	0.412	0.170	0.106	0.499	0.057
12	0.577	0.396	0.156	0.119	0.568	0.045
16	0.648	0.388	0.146	0.130	0.616	0.042
20	0.703	0.382	0.141	0.142	0.659	0.041
40	0.855	0.359	0.136	0.184	0.798	0.092

Notes: Fraction of FEV attributed to a productivity shock

These values, that are slightly above the findings of Basu *et al.* (2006), signal that the importance of the productivity shock in determining the variability of real variables increases with time, even if it remains quite low at business cycle frequencies. In particular, the technology shock is unable to explain the business-cycle variations in investment, and its relevance for the short-run variability of hours is only moderate. The overall picture which emerges is that, even if technology shocks are the main determinant of the long run behavior of real variables, they cannot explain the unconditional pro-cyclicality observed in the data at the typical business cycle frequencies. Other sources of fluctuations are responsible for the short- and the medium-run dynamics.

2.5 Robustness

The robustness of our results can be evaluated in several ways. Here we focus on three major aspects of the analysis: *i*) the importance of considering price inflation and the nominal interest rate as cointegrated $I(1)$ processes; *ii*) the long-run identification strategy chosen for the baseline specification *iii*) the relevance of taking into account structural breaks, in particular the use of controls for long cycles in hours worked. Figure 2 compares the IRFs to a one standard deviation productivity shock which obtain when these aspects are considered with the IRFs produced by the baseline SVEC of Section 2.2. Our results are shown to be qualitatively robust in the these control dimensions.

2.5.1 Price inflation and the interest rate as stationary processes

The baseline SVEC was specified considering two permanent and four stationary components. Based on ADF, KPSS and trace tests, we assumed that all variables but hours worked are $I(1)$ and thus that four components are stationary. Given the evidence on stationary hours, the remaining three stationary components were interpreted in terms of the two great ratios and the Fisher interest parity[15]. In order to evaluate the dependence of results on the inclusion of the last relation, we re-estimate and simulate the SVEC assuming that both inflation and the interest rate are stationary, as predicted by the monetary DSGE models under standard hypotheses on the monetary policy reaction rule and on the persistence on non-technology shocks. In this case, the long-run behavior of the system is driven by the technology (real) permanent component only, whose identification is provided by the zero restrictions on the long run effects matrix implied by the five transitory components in the model (the last five columns of $\mathbf{C}(1)\mathbf{B}$ are zero vectors) and by the orthogonality between the permanent and the transitory components[16].

In comparison with the baseline specification, the IRFs are only marginally affected by the hypothesis of stationarity for price inflation and the nominal interest rate (Check I in Figure 2). The short-term responses of hours and investment remain negative and significant, even if for investment this evidence is observed over a slightly shorter period. Unsurprisingly, the major differences are observed for the IRFs of inflation and the interest rate which display negative but slightly less persistent responses.

2.5.2 An alternative long-run identification strategy

In order to evaluate the sensitivity of results to different long-run identification schemes, we employ a six variable VAR with four lags which includes differenced output together with the consumption and the investment to output ratios: $\mathbf{x}_t' = \begin{bmatrix}\Delta y_t & \pi_t & h_t & r_t & c_t - y_t & i_t - y_t\end{bmatrix}$. In order to control for long cycles in hours, we use a filtered series in which intercept shifts are removed using the dummy variable method reported in Canova *et al.* (2010). The consumption to output ratio is adjusted in order to remove the trending behavior observed in the data[17]. It should be noted that under this peculiar VAR representation, which is similar to that employed by Christiano *et al.* (2005) and by Altig *et al.* (2005, 2011), inflation and nominal interest are considered as stationary and exact balanced growth is assumed.

The identification of the productivity shock can be obtained in two ways: *i)* following Blanchard and Quah (1989), by imposing a lower triangular long-run effects matrix providing the 15 restrictions needed for exact identification and leaving $\mathbf{B}$ unrestricted; *ii)* by imposing five exclusion restrictions only on the first row of the long-run response matrix $\mathbf{C}(1)$, i.e $c_{12}...c_{16} = 0$, to identify the technology shock, and imposing orthogonality between the first and the remaining

[15]However, the tests were inconclusive with respect to inflation and the interest rate, since the KPSS test, contrary to the ADF test, signalled that these two variables can be considered as stationary.

[16]The zero restrictions on the $m \times r$ right block of $\mathbf{C}(1)\mathbf{B}$ are implied by the five cointegrating vectors π_t, $h_t - \beta_{28}d_2 - \beta_{29}d_3$, r_t, $c_t - \beta_{41}y_t - \beta_{410}st_1$ and $i_t - \beta_{51}y_t$. Exact identification of the transitory components would require the imposition of ten further restrictions on the contemporaneous effects matrix $\mathbf{B}$.

[17]This is obtained by: *i*) regressing h_t and $c_t - y_t$ on a constant and on the dummies used to control for the break dates in the CI vectors of the baseline SVEC; *ii*) adding the estimated constants to the regression residuals.

shocks of the system. This second option can be implemented by means of the instrumental variables method detailed in Shapiro and Watson (1989) and Francis and Ramey (2005)[18].

Under both alternative long-run identification schemes, the IRFs show that results are qualitatively in line with those obtained using the baseline SVEC. The major differences are obtained in the IRFs of the nominal rate and of investment: the former is positive on impact, the latter shows a higher persistence of the negative effects. Since results are basically the same under the two alternative long-run identification schemes and in order to improve the readability of the graphs, only the IRFs of the former are reported in Figure 2 (Check II).

2.5.3 Removal of break date controls

The baseline SVEC in section 2.2 and the SVAR of the robustness check detailed in the previous section are specified by using control dummies for break date corrections. By removing these controls, we can check to what extent our results depend on their inclusion. This is particularly relevant for the control dummies for hours, since their removal allows us to compare our results with those of the recent literature on the contractionary effects of technology shocks on labor input, according to which SVAR-based results are affected by the presence of break dates and long cycles in productivity and hours (Fernald, 2007; Canova *et al.*, 2010).

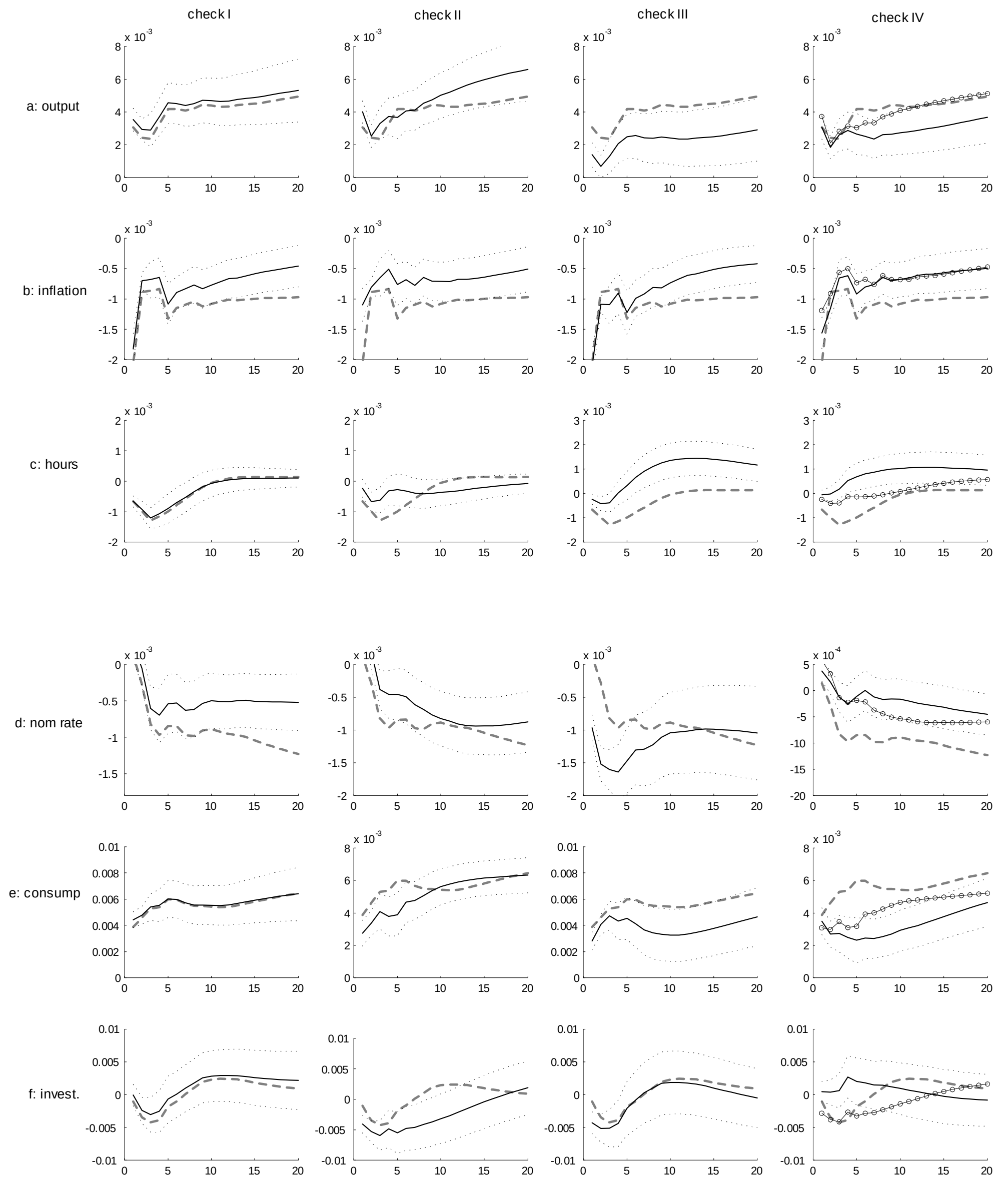
The IRFs to a productivity improvement when break dates and segmented trends are excluded from the baseline SVEC show that both hours and investment continue to negatively respond to the shock, even though the negative effect on hours is reduced in size and its persistence is shortened (Check III in Figure 2). Unlike the SVEC, the SVAR-based results are instead sensitive to the corrections: the short-term responses of both hours and investment become positive, as in Christiano *et al.* (2005) and Altig *et al.* (2005, 2011), and badly estimated (Check IV/a in Figure 2). If the *adjusted* consumption to output ratio is reintroduced into the SVAR, the IRFs of hours and investment become negative again (Check IV/b in Figure 2).

The main reason for this outcome is that with the SVEC representation we do not impose exact balanced growth between variables, i.e., we do not fix $\beta_{31} = \beta_{41} = -1$. The choice of estimating the cointegrating vectors improves the data-consistency of the long-run restrictions imposed on the stationary ratios. This is particularly important when considering the consumption to output ratio: if the observed trending behavior is not removed, or is controlled by relaxing the balanced growth hypothesis, the imposition of the long-run constraint leads to a bias in the estimation of the technology shock. Basically, neglecting the high persistence in the consumption to output ratio leads to a problematic identification of the permanent components, i.e., to the same difficulty addressed in the literature on the productivity-employment puzzle using bivariate SVARs.

These results indicate that, when using a SVAR, it should be verified that all the variables (or their ratios) subject to long-run restrictions satisfy the stationarity condition. Also, they only marginally confirm Fernald's (2007) and Canova *et al.*'s (2010) findings, signalling that the SVEC specification is more robust than standard two-variables SVARs with respect to the presence of structural breaks and low frequency components in the productivity and hours series.

[18] The identification of the technology shock is obtained by estimating the first equation of the VAR with the contemporaneous values and $p-1$ lags of $\Delta\pi_t$, Δh_t, $\Delta\ r_t$ and with the contemporaneous values and p lags of $\Delta(c_t - y_t)$ and $\Delta(i_t - y_t)$. p and $p+1$ lags of the level variables, respectively, are used as instruments. The shock of the first equation is then included as a regressor in the remaining five equations of the VAR in order to capture the contemporaneous correlation between the technology shock and the other variables. Note that, for the purpose of identification and simulation of the technology shock only, this is equivalent to the use of a mixed long-run and short-run identification strategy in which the remaining 10 restrictions for exact identification are imposed on the contemporaneous effects matrix $\mathbf{\Gamma}_0$.

Figure 2 - Impulse responses to a productivity improvement: robustness checks



Notes: Dashed grey line:benchmark specification. Dotted lines define 90% confidence interval regions Check I: SVEC with stationary inflation and interest rate; Check II: Alternative long-run identification Check III: Removal of break date corrections (SVEC); Check IV/a,b: Removal of break date corrections (SVAR; bulleted line for CheckIV/b).

3 The model and its (stationary) log-linear representation

In this section we provide the linearized version of a cash-in-advance sticky price/wage NK-DSGE model that can encompass the alternative theoretical explanations on the contractionary effects of technology improvements and reproduce the contrasting empirical results. This basically requires to consider the main factors that can constrain the aggregate demand response to a productivity improvement, and to allow for intertemporal substitution effects by assuming that technology shocks are permanent and autocorrelated in growth rates. In addition to standard nominal and real rigidities, the model is characterized by the presence strategic complementarity in price setting emerging from the hypotheses of firm-specific capital and endogenous demand elasticity. Our theoretical apparatus is thus developed along the lines of Altig *et al.* (2005, 2011), Sveen and Weinke (2005) and Woodford (2005) in order to model firm-specific capital accumulation, and Smets and Wouters (2007) and Eichenbaum and Fisher (2007) for the endogenous demand elasticity specification.

The model economy is populated by maximizing households and firms, whereas monetary and fiscal authorities follow exogenous policy rules. Final sector firms operate in a perfectly competitive environment as simple aggregators of the differentiated goods produced by intermediate sector firms. These combine labor and capital services employing a Cobb-Douglas production technology, which is subject to permanent productivity shocks which give rise to a common stochastic trend and to long-run stationary ratios among real variables. This feature makes the model consistent with the non-stationary and co-trending behavior of the data addressed by the SVEC analysis.

Each intermediate firm rents differentiated labor services from the households and makes an investment decision to adjust its capital stock to the desired level taking into account a capital adjustment cost. Intermediate sector firms can re-optimize their prices only infrequently, according to a random duration Calvo-lottery. Households maximize a separable utility function defined over consumption and leisure. Their preferences exhibit persistence of external consumption habits and are assumed to be log-linear in consumption and CRRA in leisure in order to guarantee balanced growth. The presence of differentiated labor services implies some monopoly power in labor supply, and wages are set in staggered contracts according to a Calvo-scheme.

The linearized model is expressed in stationary form[19]. The stationary representation is needed since we deal with the hypothesis of non-stationary technology shocks which induce a common stochastic trend in the real variables (Juillard *et al.*, 2008). To obtain model stationarity, we scale the real variables with respect to the stochastic technology level Z_t by imposing the transformation $X_t = \hat{X}_t Z_t$, where the "hat" superscript indicates that level variables are expressed in terms of stationary ratios. The model, then, is log-linearized around the steady state of the scaled (thus stationary) variables. Lower case letters with a "hat" denote log-deviations in the corresponding detrended variables.

3.1 Supply side

The linearized aggregate production function is:

$$\hat{y}_t = \alpha \hat{k}_{t-1} + (1-\alpha)\, h_t - \alpha \log g_t^z \tag{3}$$

where we assume that firms produce their output $\hat{y}_t$ combining, in a Cobb-Douglas production function, their accumulated (thus firm-specific) capital endowment $\hat{k}_{t-1}$ with hired labor services

[19] More details are provided in a technical appendix which is available upon request from the authors.

h_t. The parameter α $(1-\alpha)$ denotes the capital (labor) share in production. The term $\log g_t^z$ is the growth rate in the labor-augmenting technology, which is assumed to follow a first-order autoregressive process $\log g_t^z = (1-\rho_z)\log\gamma_z + \rho_z \log g_{t-1}^z + \varepsilon_t^z$, where γ_z is the deterministic long-run growth rate. Under this specification, the evolution of the technology level has a non-stationary second-order autoregressive representation, since $\log Z_t = \log Z_{t-1} + \log g_t^z$ can be rewritten as $\log Z_t = (1-\rho_z)\log\gamma_z + (1+\rho_z)\log Z_{t-1} - \rho_z \log Z_{t-2} + \varepsilon_t^z$. The choice of such a flexible specification for the technology process is motivated by the need to separate the model-specific dynamics from the dynamics potentially emerging from a fairly general specification of the stochastic components. In fact, when technology is autocorrelated in growth rates, even flexible prices models can be made consistent with the contractionary effects of positive technology shocks, due to the operation of wealth and intertemporal substitution effects (Lindé, 2009).

We assume that firms face convex adjustment costs of changing their fixed asset holdings, which become productive with one period lag. By log-linearizing the capital adjustment cost function we obtain the following law of motion for capital:

$$\hat{k}_t = \frac{(\delta+\gamma_z-1)}{\gamma_z}\hat{\imath}_t + \frac{(1-\delta)}{\gamma_z}\hat{k}_{t-1} + \frac{(\delta-1)}{\gamma_z}\log g_t^z \tag{4}$$

where $\hat{\imath}_t$ is the stationary log-deviation of gross investment and the parameter δ denotes capital depreciation[20].

3.2 Pricing behavior of firms

The aggregate price dynamics π_t, i.e., the pricing behavior of the monopolistically competitive firms, is described by the following specification of the NKPC:

$$\pi_t = \iota_p \pi_{t-1} + \beta E_t(\pi_{t+1} - \iota_p \pi_t) + \kappa \widehat{mc}_t + \log u_t^\pi \tag{5}$$

where β is the discount factor, $\widehat{mc}_t = \hat{w}_t^r - \hat{y}_t + h_t$ is the log-linearized real marginal cost ($\hat{w}_t^r$ is the real wage), κ is the reduced-form NKPC slope coefficient and the stochastic term $\log u_t^\pi$ denotes a cost-push disturbance which is assumed to follow the stationary first-order autoregressive process $\log u_t^\pi = \rho_\pi \log u_{t-1}^\pi + \varepsilon_t^\pi$. The backward looking component in (5) emerges from the hypothesis of partial indexation (of degree ι_p).

Equation (5) is compatible with a large class of models. The adoption of the firm-specific or the rental capital specification (FSK or RK, respectively) and of constant or endogenous demand elasticity (CDE or EDE, respectively) only affects the convolution of parameters defining the reduced-form slope coefficient κ (Eichenbaum and Fisher, 2007). Under RK and CDE, the slope coefficient is given by $\kappa_{RK} = \frac{(1-\beta\theta_p)(1-\theta_p)}{\theta_p}$, where θ_p defines the random fraction of firms that are not allowed to reset their price. Under FSK, the NKPC slope coefficient can be written as $\kappa_{FSK} = \kappa_{RK}\Lambda$, where Λ is a function of the model's parameters. The computation is of Λ is not straightforward and can be obtained only using the undetermined coefficients method. Sveen and Weinke (2005) and Woodford (2005) provide the useful approximation $\Lambda \simeq \frac{1-\alpha}{1-\alpha+\alpha\epsilon}$ in terms of the capital share in production and the elasticity of substitution ϵ, where the equality holds in the case of constant capital (Woodford, 2005). Note that, with respect to the standard rental capital specification, the multiplicative term Λ reduces the slope of the curve for any model parameterization. The economic rationale for the flatter slope of the NKPC under FSK (i.e., reduced price sensitivity to changes in the marginal cost) is that, since firms operate with

[20] Note that the steady-state growth parameter γ_z enters the coefficients of the dynamic relations of the model since it is the deterministic (thus expected) component in the long-run behavior of real variables.

a predetermined (firm-specific) stock of capital, their marginal cost increases with the level of output. As compared to a situation in which capital services can be chosen period by period in a rental capital market, this implies that re-optimizing firms facing a positive productivity shock are induced to cut prices by a smaller amount, since they anticipate that price reductions eventually lead to higher marginal costs due to increased demand and output at the firm level.

Another theoretical hypotheses that can also induce strategic complementarity in price setting, is the EDE assumption (Eichenbaum and Fisher, 2007; Smets and Wouters, 2007). In such a case, the coefficient relating inflation to the marginal cost in the EDE model (k^{EDE}), irrespective of the RK or FSK specification, is reduced by the factor $\left(\frac{1}{(\epsilon-1)}\phi_k+1\right)^{-1}$, where ϕ_k is the percentage change in the demand elasticity evaluated in the steady state due to a one percent change in the relative price of the good (Kimball, 1995). The relation between the CDE and the EDE specifications of the reduced-form NKPC slope coefficient is thus approximated by the following equation:

$$\kappa^{EDE} = \kappa^{CDE}\frac{1}{\frac{1}{\epsilon-1}\phi_k+1}$$

The fact that both the FSK and the EDE models differ from the baseline rental capital model only for the size of the NKPC slope coefficient makes the different model specifications observationally equivalent when considering a specification in which the reduced-form coefficient κ enters the NKPC. This allows us to estimate the model in a form that is consistent with that adopted by Altig *et al.* (2005, 2011), i.e., without specifying whether capital is firm-specific or rental, and whether the elasticity of substitution among differentiated goods is constant or endogenous. From the estimated value of κ, given assumptions about ϵ and ϕ_k, we can infer the degree of price duration in each model[21].

3.3 Pricing behavior of wage setters

Concerning the pricing behavior of monopolistically competitive wage setters, the following real wage equation holds:

$$\begin{aligned}\hat{\pi}_t^w &= \beta E_t\left[\hat{\pi}_{t+1}^w + (\pi_{t+1}-\iota_w\pi_t) + \log g_{t+1}^z\right] - \log g_t^z - (\pi_t - \iota_w\pi_{t-1}) + \\ &\quad +\kappa^w\left(\widehat{mrs}_t - \hat{w}_t^r - \log\chi_t\right) + \log u_t^{\pi^w}\end{aligned} \tag{6}$$

where $\hat{\pi}_t^w = \hat{w}_t^r - \hat{w}_{t-1}^r$ is real wage growth, $\widehat{mrs}_t = \frac{\gamma_z}{\gamma_z-\lambda}\left[\widehat{c}_t - \frac{\lambda_c}{\gamma_z}\left(\widehat{c}_{t-1} - \log g_t^z\right)\right] + \eta h_t$ denotes the (real) marginal rate of substitution between consumption $\widehat{c}_t$ and labor and λ_c is the degree of habit persistence in consumption. $\kappa^w = \frac{(1-\beta\theta_w)(1-\theta_w)}{\theta_w}\frac{1}{1+\epsilon_H\eta}$ is the reduced-form slope coefficient, where the parameter θ_w denotes the degree of nominal wage stickiness, and the parameters η and ϵ_H are the inverse Frish labor elasticity and the elasticity of substitution among differentiated labor services, respectively. The stochastic wage-push disturbance $\log u_t^{\pi^w}$ is assumed to follow the first-order autoregressive process $\log u_t^{\pi^w} = \rho_{\pi^w}\log u_t^{\pi^w} + \varepsilon_t^{\pi^w}$. Even in this case, the backward looking component in (6) is due to the partial indexation to past inflation (of degree ι_w).

[21] To do so, we employ a modified version of Christiano's matlab routines, to which we add the EDE hypothesis and omit the firm-specific labor specification. Details of these modifications are provided in the technical appendix.

3.4 Demand-side

Concerning the demand-side of the economy, the dynamics of consumption $\hat{c}_t$ resulting from the corresponding Euler equation is described by:

$$\begin{aligned} \hat{c}_t &= \frac{\lambda_c/\gamma_z}{1+\lambda_c/\gamma_z}\left(\hat{c}_{t-1} - \log g_t^z\right) + \left(1 - \frac{\lambda_c/\gamma_z}{1+\lambda_c/\gamma_z}\right) E_t\left(\hat{c}_{t+1} + \log g_{t+1}^z\right) + \\ &\quad - \frac{1-\lambda_c/\gamma_z}{1+\lambda_c/\gamma_z}\left[\left(r_t - E_t\pi_{t+1} - \rho\right) - E_t\left(\Delta \log \chi_{t+1}\right)\right] \end{aligned} \tag{7}$$

where r_t and ρ are the current and the steady state nominal interest rates. Current consumption thus depends on the expected real interest rate and on a weighted average of past and future consumption, with weights depending on the degree of external habit persistence λ_c. The term $\log \chi_t$ denotes a consumption preference shock and is assumed to follow the stationary first-order autoregressive process $\log \chi_t = \rho_\chi \log \chi_{t-1} + \varepsilon_t^\chi$.

The investment dynamics depends on the firm's choices over capital accumulation, defined by the log-linear capital Euler equation:

$$\begin{aligned} \hat{k}_t &= \frac{1}{(1+\beta)}\hat{k}_{t-1} + \frac{\beta}{(1+\beta)}E_t\hat{k}_{t+1} + \frac{1-\beta\gamma_z^{-1}(1-\delta)}{\epsilon_\psi\gamma_z(1+\beta)}E_t\widehat{ms}_{t+1} + \\ &\quad - \frac{1}{\epsilon_\psi\gamma_z(1+\beta)}\left(r_t - E_t\pi_{t+1} - \rho\right) - \frac{1}{(1+\beta)}\log g_t^z + \\ &\quad + \frac{\beta}{(1+\beta)}\log g_{t+1}^z + \frac{1}{\epsilon_\psi\gamma_z(1+\beta)}\left[\beta\gamma_z^{-1}(1-\delta)E_t\log\zeta_{t+1} - \log\zeta_t\right] \end{aligned} \tag{8}$$

where $\beta = (1+\rho)^{-1}$ and $\widehat{ms}_{t+1} = \hat{w}_{t+1}^r + h_{t+1} - \hat{k}_t + \log g_{t+1}^z$ is the expected stationary log-deviation of the return on capital, which under firm-specific capital is expressed in terms of the firm's marginal savings on labor costs. Current installed capital thus depends on its past and expected future values, expected marginal savings and expected real interest rates. Moreover, the dynamics of investment/capital is affected by a stationary first-order autoregressive disturbance $\log\zeta_t = \rho_\zeta \log\zeta_{t-1} + \varepsilon_t^\zeta$ to the convex capital adjustment cost function, whose steady-state elasticity is $\epsilon_\psi > 0$.

3.5 Model closure

The model is closed by considering the aggregate resource constraint and the policy reaction function. The log-linear constraint is given by:

$$\hat{y}_t = (1 - \psi - g^y)\,\hat{c}_t + \psi\hat{\imath}_t + g^y\hat{g}_t \tag{9}$$

where $\psi = \frac{\alpha(\delta+\gamma_z-1)}{\frac{\epsilon}{\epsilon-1}\gamma_z(\rho+\delta)}$ is the steady-state investment to output ratio. The term $\hat{g}_t$ is an AR(1) measurement error capturing the evolution of public expenditure and the other exogenous components affecting the aggregate resource constraint. In order to account for the relevant changes in US net exports, we follow Smets and Wouters (2007) and assume that exogenous expenditure is also affected by the technology shock, i.e.: $\hat{g}_t = \rho_g\hat{g}_{t-1} + \varepsilon_t^g + \rho_{z,g}\varepsilon_t^z$. The coefficient g^y denotes the long-run value of the public expenditure to GDP ratio.

Two alternative monetary policy reaction rules are considered. The first one targets inflation deviations from a non-zero policy target π^* and output growth deviations from the deterministic long-run rate of growth $\Delta y_t - \log\gamma_z = \Delta\hat{y}_t + \log g_t^z - \log\gamma_z$. The second targets inflation deviations and the theory-based output gap $\hat{y}_t - \hat{y}_t^p$, where $\hat{y}_t^p$ is the level of output that would prevail in the absence of nominal rigidities. The policy instrument is adjusted gradually, giving rise to interest rate smoothing, whose degree is defined by ρ_r:

$$r_t = \rho + \rho_r r_{t-1} + (1-\rho_r)\left[\phi_\pi (\pi_t - \pi^*)\right] + \phi_y \left(\Delta\hat{y}_t + \log g_t^z - \log\gamma_z\right) + \log u_t^r \qquad (10)$$
$$r_t = \rho + \rho_r r_{t-1} + (1-\rho_r)\left[\phi_\pi (\pi_t - \pi^*)\right] + \phi_y \left(\hat{y}_t - \hat{y}_t^p\right) + \log u_t^r \qquad (11)$$

The parameters ϕ_π and ϕ_y define the strength of the policy reaction to inflation and output deviations from the respective targets. The stochastic term $\log u_t^r = \varepsilon_t^r$ denotes an *i.i.d.* monetary policy error.

Considering a productivity improvement, a policy rule targeting potential output would result more accommodative than a policy rule targeting the long-term growth rate. In fact, under the empirical rule (10) the authorities underestimate the actual growth rate of natural output, resulting in a not fully accommodative interest rate response. However, there are at least two reasons that can justify the use of an empirical rule: first, targeting the theory-based output gap requires perfect knowledge of the natural level of output which - by definition - is unobservable. In other words, we have to consider how policy makers - in real life operations - form their opinions about the natural output, which is hardly within a monetary authoritiy's information set. Second, given that real-time data on potential output are subject to relevant imperfections, under model uncertainty and when technology evolves according to a random walk with drift process, the estimated long-term deterministic growth component γ_z might represent the best prediction for output growth. In the estimation process, we will evaluate the relevance of both the empirical and the theory-based monetary policy reaction functions, and let the data decide about which model - thus rule - is to be preferred.

The linearized system is composed of four behavioral equations (7), (8), (5) and (6), the production function (3), the permanent inventory equation (4), the aggregate resource constraint (9) and a Taylor rule (10 or 11). Four definition equations for $\hat{w}_t^r$, $\widehat{ms}_t$, $\widehat{mrs}_t$, $\widehat{mc}_t$ complete the economic system.

4 Bayesian estimation and simulation

The strategy adopted for the parameterization of theoretical models is a key issue in the face of the conflicting SVAR-based evidence discussed in section 2. Some recent and influential contributions supporting the pro-cyclicality of investment and hours worked (Christiano *et al.*, 2005; Altig *et al.*, 2005, 2011) use monetary DSGE models parameterized through estimators that minimize the weighted distance between the theoretical and the SVAR-based impulse responses. In our view, results obtained using a matching estimator applied to a model with particularly flexible dynamic properties, cannot be considered conclusive, since they do not add much to the evidence implied by the SVAR-based impulse responses. This consideration leads us to use a calibration strategy for our model that does not rely upon our SVECM evidence, but which is based on a Bayesian direct estimate of model's parameters. This section provides some details of the estimation methodology and of the evaluation of the empirical relevance of the two alternative specifications of the monetary policy rule. Note that, by estimating a reduced form slope coefficient of the NKPC, we do not impose any prior assumptions about the CDE/EDE or the RK/FSK specifications of the model.

4.1 The posterior distribution and model comparison

The scope of the Bayesian estimators is to obtain the posterior distribution for model parameters conditioning on prior beliefs for models M_j $(j = 1, 2, ...)$, structural parameters $\boldsymbol{\theta}_j$, and sample information. The methodology thus nests the formalized prior distribution $P(\boldsymbol{\theta}_j, M_j)$ for the j-th model's parameter vectors $\boldsymbol{\theta}_j \in \Theta$, and the conditional distribution $P(\mathbf{Y}_T \mid \boldsymbol{\theta}_j, M_j)$, where $\mathbf{Y}_T = \{\mathbf{y}_t\}_{t=1}^{T}$ contains sample information, to obtain the posterior density $P(\boldsymbol{\theta}_j \mid \mathbf{Y}_T, M_j)$.

The consideration of the two alternative policy rules corresponds to the evaluation of two different model structures $(j = A, B)$, one adopting the empirical policy rule (10), the other one the theory-based rule (11). The empirical relevance of the two policy options can be evaluated by estimating the two competing models M_A and M_B with parameter vectors $\boldsymbol{\theta}_A$ and $\boldsymbol{\theta}_B$ and deriving the Bayes factor from the log-marginal likelihoods. Following Schorfheide (2000), we employ the Laplace approximation method to obtain the log-marginal likelihood and adopt Jeffrey's (1961) scale of evidence for assessing the log-Bayes factor indications[22].

4.2 Data, priors and estimated posterior distributions

4.2.1 Data

We use the same US data sources as the SVEC analysis briefly described in section 2.3. The sample is thus composed of quarterly data for the sample period 1954:3 - 2007:2. Following Del Negro *et al.* (2005) and Smets and Wouters (2007), seven quarterly time series are considered: the log-differences of real GDP Δy_t, real consumption Δc_t, real investment Δi_t and real wage Δw_t, the log-levels of hours h_t, of GDP price inflation π_t and of the federal funds rate r_t. The vector of observables is thus:

$$\mathbf{x}_t' = \begin{bmatrix} \Delta y_t & \Delta c_t & \Delta i_t & \Delta w_t & h_t & \pi_t & r_t \end{bmatrix}$$

Since we express the models in log deviations around the stochastic growth path ($\log Z_t$), the measurement equations linking the model variables to observables are the following:

$$\begin{array}{l} \Delta y_t = \widehat{y}_t - \widehat{y}_{t-1} + \log g_t^z \\ \Delta c_t = \widehat{c}_t - \widehat{c}_{t-1} + \log g_t^z \\ \Delta i_t = \widehat{i}_t - \widehat{i}_{t-1} + \log g_t^z \\ \Delta w_t = \widehat{w}_t - \widehat{w}_{t-1} + \log g_t^z \\ h_t = h_t + h \\ \pi_t = \pi_t + \log g^p \\ r_t = r_t - \log(\beta) + \log \gamma_z + \log g^p \end{array} \tag{12}$$

where $\log g_t^z = (1 - \rho_z) \log \gamma_z + \rho_z \log g_{t-1}^z + \varepsilon_t^z$.

4.2.2 Prior distributions

Priors are defined based on the results obtained in previous analyses and economic reasoning. However, it is worth highlighting that we counterfacually impose a common prior parameterization (i.e. $\boldsymbol{\theta}_A = \boldsymbol{\theta}_B$) such that the estimates are initialized over a parameter space for which both

[22] The posterior mode is estimated with the Sims' optimizer and numerical integration is performed employing 500,000 M-H replications. The fraction of the drops in the initial parameter vector estimates is set at 30%. The scale parameter for the variance of the jump distribution is calibrated so as to obtain an acceptance rate of nearly 25%. This value guarantees that the M-H algorithm considers the entire support of the posterior distributions. For the application of the Bayesian method we use the open-source software Dynare for Matlab. Further details on Bayesian estimation and model selection are provided in the Appendix.

M_A and M_B do not replicate the SVEC-based evidence on the persistent contractionary effects of productivity improvements on investment[23].

We impose five dogmatic priors on the 32-dimensional parameter vector $\boldsymbol{\theta}$. We fix the discount factor $\beta = 0.998$, the steady state values for the elasticity of substitution among differentiated goods and labor services $\epsilon = \epsilon_H = 11$ and the parameters defining the degree of price and wage indexation to past inflation $\iota_p = \iota_w = 0$. The high value of β is chosen to facilitate a data-consistent estimate of the long-run growth parameter γ_z and the steady-state inflation parameter g^p, provided that $\rho = -\log(\beta) + \log(\gamma_z) + \log(g^p)$. Concerning the elasticity parameters ϵ and ϵ_H, the choice is based on conventional values adopted in the literature, consistent with a price/wage mark-up $\epsilon\left(\epsilon-1\right)^{-1}$ of 10%. The absence of dynamic indexation is assumed to enhance empirical identification and to allow an interpretation of results on the estimated NKPC slope in terms of the frequency of price adjustments[24]. In fact, since under dynamic indexation prices are changed each period according to past inflation, the Calvo price parameter looses its direct link with the frequency at which firms reset their prices. The empirical relevance of a fully dynamic indexation scheme will be evaluated as a robustness check.

All the remaining parameters are estimated. The shape of the prior distributions is chosen according to the following standards: the reference distribution for structural shocks is the inverted gamma which is consistently defined over the $\mathbb{R}^+$ range; for parameters theoretically defined in a $[0-1]$ range a beta distribution is assumed, while the normal distribution is adopted for priors on parameters theoretically defined over the $\mathbb{R}$ range.

For the parameter defining the steady-state value of productivity growth (γ_z) we adopt a tight prior defined by a normal distribution centered on its sample mean (nearly 1.005), with standard deviation equal to 0.001. An informative beta-distributed prior is also adopted for α and δ, whose prior means (standard deviations) are set at 0.36 and 0.025 (0.02 and 0.002), respectively. The prior distribution for the inverse labor supply Frish elasticity parameter is assumed to follow a normal distribution centered around $\eta = 1$, with standard deviation equal to 0.1. As for the real rigidities directly affecting investment and consumption, we assume that the parameter defining the convex capital adjustment cost ϵ_ψ follows a normal distribution with prior mean 3 and standard deviation 0.2, and the habit persistence parameter follows a Beta distribution with prior mean 0.5 and prior standard deviation 0.1.

For the reduced-form NKPC slope coefficient κ, we adopt a beta-distributed prior with mean 0.05 and prior standard deviation 0.02. Under the standard RK specification, this prior implies a Calvo parameter value $(\theta_p = 0.8)$, which is in line with the available macroeconometric evidence obtained with the standard NKPC specification (Galì and Gertler, 1999; Smets and Wouters, 2003; Eichenbaum and Fisher, 2007; Del Negro *et al.*, 2005). Under the FSK and EDE hypotheses, given the chosen value for the demand elasticity parameter $(\epsilon = 11)$ and considering the standard calibration of the curvature parameter of the Kimball aggregator $(\phi_\kappa = 10)$**,** the prior implies a Calvo parameter of about 0.5, in line with the microdata-based evidence produced by Bils and Klenow (2004), suggesting an average price duration of nearly two quarters. For the parameter defining the degree of nominal wage rigidity θ_w we adopt a beta-distributed prior with mean of 0.5 and prior standard deviation of 0.1.

The coefficients of the monetary policy reaction rule are assumed to follow a normal distribution centered on the standard prior mean values $\phi_\pi = 1.5$ and $\phi_y = 0.25$, with standard deviations equal to 0.1. The autoregressive coefficient ρ_r, defining the degree of interest rate

[23] The IRFs obtained under the prior parameterization are confronted with the posterior IRFs in Figure 3.

[24] Note that, the relation with marginal costs aside, inflation persistence depends on the size of the indexation coefficient ι_p (defining the backward component in the NKPC) and on the degree of persistence of the cost-push shock ρ_π. For this reason, these parameters are not variation-free.

smoothing, is beta-distributed with a prior mean of 0.5 and standard deviation of 0.1[25].

For the standard error of innovations we assume a prior mean of 0.01 with two degrees of freedom. These diffuse priors on perturbations reflect very imprecise opinions about the dimensionality of shocks. Even if we assume that all shocks but the monetary policy shock are serially correlated, we adopt differentiated priors for the autoregressive coefficients. For those defining the autocorrelation in differences, i.e., for the AR(2) non stationary technology process, we adopt a prior zero-mean normal distribution with a diffuse prior standard deviation of 0.2. For the autoregressive coefficients of the stationary stochastic components affecting capital adjustment costs and the aggregate resource constraint we adopt a beta distribution with a prior mean of 0.75 and standard deviation of 0.10. The autoregressive coefficient of the wage shock and the coefficient capturing the effects of productivity improvements on net exports are assumed to be beta-distributed with prior mean of 0.5 and standard deviation of 0.1. For the remaining autoregressive coefficients we assume a beta distribution with prior mean of 0.25 and standard deviation of 0.05. The choice of a low degree of autocorrelation for the stationary disturbances favors the separation between stationary and non-stationary components (Smets and Wouters, 2003). This choice enhances the identification of the economic (endogenous) as opposed to the stochastic (exogenous) sources of persistence[26]. These prior opinions on structural parameters are summarized in the first two columns of Tables 1 and 2.

4.2.3 Estimated posterior distributions

Tables 2a and 2b report the posterior mode and mean estimates of the 27-dimensional parameters vector $\widehat{\boldsymbol{\theta}}$ for models A and B. Table 2a presents the estimates of the 13 parameters defining the model structure; Table 2b presents the estimates of the 14 parameters defining the persistence and size of the 7 exogenous stochastic components. According to the estimated posterior standard deviations and the implied pseudo-t values, all parameter estimates appear significant at the standard level in both model specifications. The estimated autoregressive coefficient of the technology growth process, in line with Del Negro *et al.*'s (2005) estimates, indicates weak autocorrelation under both models, even if lower for M_A ($\widehat{\rho}_z = 0.11$) than for M_B ($\widehat{\rho}_z = 0.23$).

Concerning the stationary disturbances, we obtain a high degree of autocorrelation for the measurement error entering the aggregate resource constraint equation and for the stochastic process affecting capital adjustment costs. A moderate degree of autocorrelation is obtained for all the remaining shock processes. This is more evident for M_A, signalling that the first specification of the policy rule tends to tone-down the relevance of the stochastic sources of persistence.

The steady state value for productivity growth is estimated to be around 0.5% on a quarterly basis under both model specifications, a value that is strictly in line with productivity growth priors and sample evidence. The estimated mean values of the Cobb-Douglas coefficient and capital depreciation are basically aligned with the corresponding priors and sample information in M_A ($\hat{\alpha} = 0.33$ and $\hat{\delta} = 0.026$), but are relatively distant in M_B ($\hat{\alpha} = 0.30$ and $\hat{\delta} = 0.033$).

[25] The prior mean for the interest rate smoothing parameter is lower than that adopted in other applications. Our choice is justified by the need to initialize the estimates over a parameterization for which monetary policy is sufficiently accommodative, so as to rule out the emergence of contractionary effects of the supply shocks on investment.

[26] This is particularly relevant for the estimation of the sources of persistence of price dynamics. Smets and Wouters (2007), by assuming a higher prior value for the autoregressive coefficient (0.5), estimate a very high degree of stochastic persistence for price dynamics (nearly 0.9). On the basis of our preliminary checks, this increases the slope of the NKPC (reduces the estimated Calvo parameter), lowering the persistence explained by *economic* relations.

Even if distant from the prior, the estimated Calvo parameter on wage contracts (0.75 and 0.65 for M_A and M_B, respectively) is in line with the findings of other studies adopting an equivalent wage schedule (Del Negro *et al.* 2005). These different values reflect the different estimates of the NKPC slope coefficient under M_A and M_B. As shown by Canova and Sala (2009), there is a negative relation between the estimated degree of persistence in wage and price setting.

Similar considerations apply for the estimated real rigidities directly affecting the demand components: the habits persistence parameter, which is higher for M_A than for M_B ($\widehat{\lambda}_c = 0.81$; 0.68, respectively)[27], and the estimated capital adjustment cost parameter, which is higher for M_B than for M_A ($\epsilon_\psi = 3.3$; 3.9, respectively), is quite distant from the prior for both models, even if basically in line with the findings of previous studies (Del Negro *et al.*, 2005, Smets and Wouters, 2007).

Table 2a - Priors and posterior distribution of structural parameters

	Prior distribution		Posterior distribution							
	Models A and B		Model A				Model B			
	Distr	Mean St.Dev	Mode St.Dev	Mean	5%	95%	Mode St.Dev	Mean	5%	95%
γ_z	$\mathcal{N}$	1.004 0.001	1.005 0.001	1.005	1.004	1.006	1.004 0.000	1.004	1.003	1.005
γ^p	$\mathcal{N}$	1.009 0.001	1.009 0.001	1.009	1.008	1.010	1.009 0.001	1.009	1.008	1.010
g^y	$\mathcal{B}$	0.200 0.025	0.292 0.026	0.287	0.245	0.327	0.272 0.026	0.267	0.226	0.309
α	$\mathcal{B}$	0.360 0.015	0.326 0.012	0.329	0.309	0.349	0.301 0.013	0.304	0.283	0.325
δ	$\mathcal{B}$	0.025 0.002	0.026 0.002	0.026	0.023	0.029	0.033 0.002	0.033	0.028	0.036
η	$\mathcal{N}$	1.000 0.200	1.067 0.193	1.065	0.755	1.384	1.995 0.165	1.775	1.522	2.041
λ_c	$\mathcal{B}$	0.500 0.100	0.811 0.063	0.808	0.644	0.925	0.678 0.045	0.676	0.609	0.751
ϵ_ψ	$\mathcal{N}$	3.000 0.200	3.300 0.198	3.291	2.979	3.624	3.973 0.180	3.945	3.692	4.221
κ	$\mathcal{B}$	0.050 0.015	0.013 0.005	0.016	0.007	0.026	0.007 0.002	0.007	0.004	0.010
θ_w	$\mathcal{B}$	0.500 0.100	0.823 0.074	0.748	0.603	0.953	0.668 0.055	0.650	0.560	0.752
ρ_r	$\mathcal{B}$	0.500 0.100	0.515 0.053	0.486	0.393	0.581	0.723 0.030	0.721	0.671	0.772
ϕ_π	$\mathcal{N}$	1.500 0.100	1.640 0.105	1.655	1.434	1.870	1.620 0.086	1.622	1.483	1.769
ϕ_y	$\mathcal{N}$	0.250 0.100	0.735 0.064	0.740	0.639	0.856	0.120 0.016	0.124	0.099	0.151

Notes: $\mathcal{N}$: is the normal distribution; $\mathcal{B}$: is the beta distribution.

Posterior mean estimates obtained with 500000 Metropolis-Hastings replications.

[27] There are signals of weak identification problems for the economic source of persistence in consumption behavior. This is testified by the fact that higher (lower) habit persistence parameters can be obtained by fixing the autoregressive coefficient of the preference shock to lower (higher) values.

Table 2b - Priors and posterior distribution of shock processes

	Prior distribution Models A and B		Posterior distribution							
			Model A				Model B			
	Distr	Mean (St.Dev)	Mode (St.Dev)	Mean	5%	95%	Mode (St.Dev)	Mean	5%	95%
ρ_z	$\mathcal{N}$	0.000 (0.200)	0.110 (0.046)	0.110	0.038	0.185	0.242 (0.058)	0.235	0.137	0.326
ρ_ζ	$\mathcal{B}$	0.750 (0.100)	0.926 (0.011)	0.931	0.908	0.954	0.922 (0.014)	0.920	0.896	0.941
ρ_g	$\mathcal{B}$	0.750 (0.100)	0.920 (0.021)	0.922	0.889	0.956	0.938 (0.016)	0.936	0.909	0.963
$\rho_{z,g}$	$\mathcal{B}$	0.500 (0.100)	0.381 (0.083)	0.393	0.260	0.522	0.417 (0.087)	0.431	0.291	0.574
ρ_{π^w}	$\mathcal{B}$	0.500 (0.100)	0.468 (0.086)	0.531	0.346	0.713	0.488 (0.063)	0.501	0.398	0.605
ρ_π	$\mathcal{B}$	0.250 (0.050)	0.566 (0.044)	0.556	0.503	0.613	0.587 (0.034)	0.572	0.536	0.613
ρ_χ	$\mathcal{B}$	0.250 (0.050)	0.282 (0.055)	0.288	0.173	0.400	0.475 (0.057)	0.470	0.378	0.562
σ_z	$\mathcal{IG}$	0.010 (2)	0.011 (0.001)	0.011	0.010	0.012	0.010 (0.001)	0.010	0.009	0.011
σ_ζ	$\mathcal{IG}$	0.010 (2)	0.015 (0.001)	0.015	0.012	0.018	0.014 (0.001)	0.014	0.012	0.015
σ_g	$\mathcal{IG}$	0.010 (2)	0.016 (0.002)	0.017	0.014	0.020	0.017 (0.002)	0.018	0.014	0.022
σ_{π^w}	$\mathcal{IG}$	0.010 (2)	0.004 (0.000)	0.004	0.003	0.004	0.004 (0.000)	0.004	0.003	0.004
σ_π	$\mathcal{IG}$	0.010 (2)	0.002 (0.000)	0.002	0.002	0.002	0.002 (0.000)	0.002	0.002	0.002
σ_χ	$\mathcal{IG}$	0.010 (2)	0.046 (0.015)	0.055	0.016	0.084	0.030 (0.004)	0.031	0.024	0.038
σ_{u^r}	$\mathcal{IG}$	0.010 (2)	0.006 (0.001)	0.006	0.005	0.007	0.003 (0.000)	0.003	0.003	0.004

Notes: $\mathcal{N}$, $\mathcal{B}$ and $\mathcal{IG}$ are normal, beta and inverted gamma distributions, respectively.
Posterior mean estimates obtained with 500000 Metropolis-Hastings replications.

The posterior mean estimates for the other behavioral and policy parameters are close to our priors and to the results obtained in the related literature. Two exceptions deserve however some discussion. First, the estimated reduced form NKPC slope coefficient is lower than the prior mean value under both model specifications, indicating a particularly weak transmission mechanism from marginal costs to price inflation. This evidence is stronger under M_B, signalling a bigger role for the nominal and real rigidities affecting the slope of the NKPC ($\widehat{\kappa} = 0.016$ in M_A and 0.007 in M_B). The value obtained under M_A is basically the same as that obtained by Altig *et al.* (2005, 2011)[28]. Second, both estimated parameters defining the interest rate response to real activity in the two alternative monetary policy reaction functions depart from the common prior mean, but in opposite directions: $\widehat{\phi}_y$ is 0.74 under M_A and 0.12 under M_B. Interestingly, the degree of interest rate smoothing is slightly lower than the prior under M_A ($\widehat{\rho}_r = 0.48$) and is higher under M_B ($\widehat{\rho}_r = 0.72$)[29].

Overall, these differences signal that, under M_B, the estimates tend to highlight the sources of price persistence in the model. This result can be attributed to the fact that the higher stabilizing effects implied by the theory-based monetary policy reaction rule are counteracted by higher estimates of the economic and stochastic sources of persistence.

The Laplace approximation of the marginal likelihood is 5101.3 for Model A and 5079.4 for Model B. Using the Laplace approximation of the marginal likelihoods, the Bayes factor is

[28] Both $M_A$and M_B - based values lie well within the wide range of NKPC slope coefficient estimates reported in the literature. Schorfheide (2008) provides a survey of these findings.

[29] Giuli and Tancioni (2010) analyze the effect of a monetary rule that adjusts the interest rate according to a weighted average of trend output deviations and the theory-based output gap. In line with our results, their estimates favor the weight assigned to trend output.

$B_{A,B} = e^{[\log P(Y_T/M_A) - \log P(Y_T/M_B)]} = e^{63.2}$, a value which, according to Jeffrey 's (1961) scale of equivalence, indicates that the evidence in favor of Model A is decisive.

By estimating models A and B with full dynamic indexation, which is not supported by the data, results do not qualitatively change[30]. The main effect is a reduction of the estimated autocorrelation coefficients for the price and the wage push shock processes.

5 Model dynamics and theoretical indications

In this section we provide an evaluation of the dynamic properties of the estimated models using stochastic simulations based on posterior mean estimates. In discussing our results we focus on the economic mechanisms determining the sign and the persistence of the response of factor inputs to a positive technology shock.

5.1 Posterior impulse responses

Figure 3 shows the posterior IRFs to a positive technology shock and compares them with those obtained with the prior parametrization. At least three indications are worth highlighting.

First, the estimates for Model A, but not those for Model B, confirm the results obtained with the SVEC analysis presented in section 2. With M_A, the investment and hours responses are qualitatively in line with those obtained with the SVEC-based impulse response analysis. The investment response is negative in the short run and becomes positive only after some periods, when the demand constraint becomes less binding and the standard expansionary mechanisms may display their effects. The posterior hours response is also negative in the short and in the medium run, coherently with the productivity-employment puzzle. With M_B, both hours and investment respond positively to the productivity improvement even on impact.

Second, the negative short run interest rate reduction, which obtains under both model specifications, signals that the estimated monetary policy rules are fairly accommodating, but not enough to prevent a short-run decrease in inflation. The impulse resposes of inflation and the interest rate, however, are quite different from those obtained with the SVEC, in which a more persistent contraction of both monetary variables is observed. Differences are stronger as for the posterior IRFs obtained under M_B.

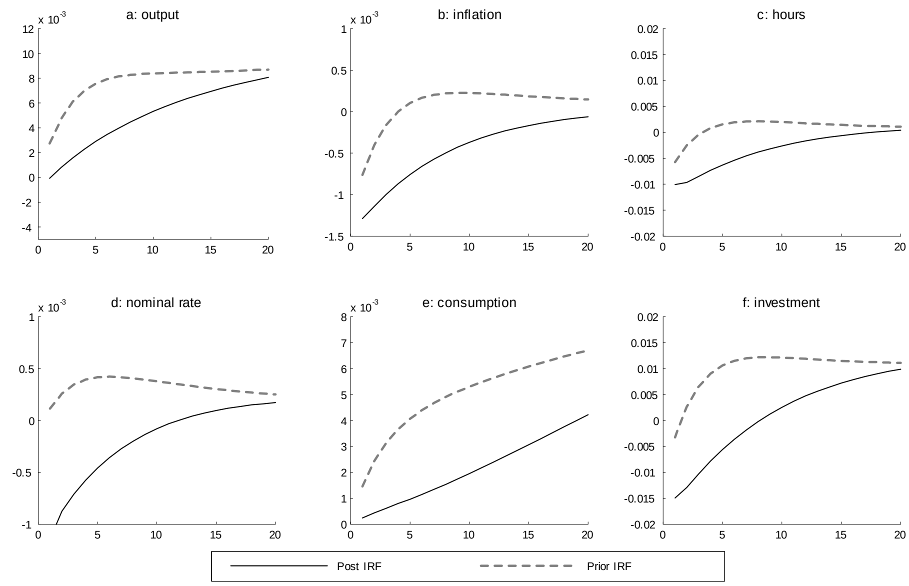
Third, consumption and output responses are standard under both model specifications: consumption rises in response to the expected permanent increase in productivity and output, driving the expansionary aggregate demand response. Unsurprisingly, the speed of convergenge towards the new steady state is higher under M_B than under M_A. Even if the consumption response is higher than the output response on impact, the shape of the IRF denotes high inertial behavior, especially under M_A[31].

[30] See also Giuli and Tancioni (2010).

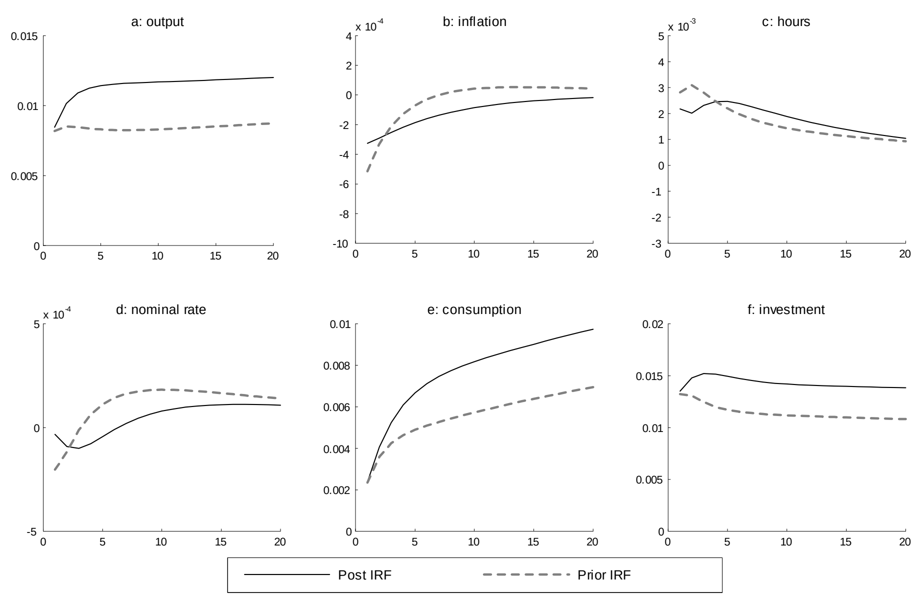
[31] This result, which is not fully in line with the SVEC-based evidence, only partially depends on the relatively high degree of habits persistence. We have verified that the consumption dynamics are only marginally affected when the habit persistence parameter is drastically reduced.

Figure 3 - Prior and posterior impulse responses to a productivity improvement

Model A



Model B



Notes: IRFs are computed at the posterior mean estimates (solid lines). Dotted grey lines define prior IRFs. Model A: empirical policy rule; Model B: theory-based policy rule

5.2 Theoretical indications

The literature suggests different theoretical explanations for the contractionary effects of productivity improvements. Our model specification allows us to consider some of them in a comparative perspective.

First, based on Model A estimates, we are induced to rule-out explanations based on intertemporal substitution effects due to expected increases in productivity implied by permanent technology shocks autocorrelated in growth rates (Lindè, 2009). The small size of the estimated autoregressive coefficient ρ_z, in the absence of relevant nominal and real frictions, is not sufficient to generate the negative response of hours and investment. In the flexible price version of our model, the contractionary effects on inputs are in fact observed only for values of ρ_z well above 0.8. This is also the value used by Lindè (2009) in its RBC model simulation. Considering the flexible price version of the model, the autoregressive coefficient is estimated to be near to 0.25, irrespective of the presence of real demand frictions (M_E and M_F in table E.1 in the Appendix).

Second, the estimates do not support explanations based on real rigidities directly affecting consumption and investment behavior (Francis and Ramey, 2005; Smets and Wouters, 2007). In the absence of nominal frictions, i.e., considering the flexible price - real rigidities version of the model, and given a standard calibration for the capital adjustment cost parameter ($\epsilon_\psi = 3$), a negative hours - but not investment - response to a positive technology shock can be observed on impact only for high degrees of habit persistence ($\lambda_c > 0.91$). By assuming $\epsilon_\psi = 10$, the threshold λ_c value for observing a negative impact response of hours is reduced to 0.85. Considering the flexible price/real frictions version of the model, λ_c and ϵ_ψ are estimated to be 0.14 and 3, respectively (M_F in table E.1 in the Appendix).

Third, as indicated by Model B's posterior IRFs, estimated real and nominal frictions, in the presence of an accommodative policy reaction function, cannot generate the negative response of inputs. Such a response can be obtained for hours, but not for investment, by increasing the degree of real demand frictions to values that are higher than those needed in the flexible price model, and by lowering the interest rate reaction to inflation to values close to one (or by assuming a backward-looking policy rule).

The reason for this result lies on the strongly pro-cyclical investment response implied by the sticky-price monetary model, where the mechanics of firms' investment behavior is the same as in standard frictionless models and ultimately depending on the Tobin's q dynamics stimulated by the productivity shock. The introduction of nominal frictions leads to the opening up of temporary positive gaps in the Tobin's q, leading to the positive response in investment. For reasonable model parameterizations and standard specifications of the policy rule, the NK model may imply that the incentive to invest is higher than in the flexible price economy, because the central bank's reactions operate in the same direction as increased expected capital returns. This is the basic reason why Galì and Gertler (2007) argue that, other things being equal, in a NK environment firms may invest more than they would under flexible prices.

Fourth, as indicated by Model A estimates, the low degree of accommodation of monetary policy and the flatness of the NKPC are the key factors explaining the negative response of hours and investment. In fact, when a technology shock hits the economy, the degree to which real activity follows its natural level depends on the resulting price cut. A small NKPC slope coefficent implies that, following a productivity improvement, the contraction of the marginal cost is followed by a weak reduction in prices. For low degrees of monetary policy accommodation of the shock, this implies that the aggregate demand response can be insufficient to meet the increase in productivity, leading to a reduction in the use of inputs. The lower is the degree of monetary policy accommodation of the shock, the more likely is the transitory drop in inputs use.

For these reasons, Basu *et al.*'s (2006) conclusion that standard NK monetary models can account for the contractionary effects of supply shocks is not fully legitimate, since *i)* the negative hours and investment responses to productivity improvements emerge only considering informational lags or empirical rules such as that adopted in Model A; *ii*) under a standard rental capital specification, the estimated slope of the NKPC would imply an excessively high degree of nominal frictions. This is not the case if strategic complementarities in price-setting, along with nominal rigidities, are considered. These points are analysed in greater detail in the next section.

5.2.1 Nominal, real rigidities and the slope of NKPC

As stressed in Section 3.1.2, a weak relation between marginal costs and price inflation is the result of both nominal and real rigidities, the latter defined in terms of strategic complementarity in price-setting. From the estimated parameterization, and in particular from the estimated value of the reduced-form coefficient κ, given assumptions about the demand elasticity coefficient ϵ and the coefficient defining its degree of endogeneity ϕ_κ,we can obtain the degree of nominal rigidity that emerge under alternative model specifications.

Considering the standard RK-CDE specification, the estimated slope coefficient implies a price Calvo parameter θ_p near to 0.88 (0.91 in Model B), consistent with a frequency of price optimization of 8 quarters (12 in Model B). These values are distant from those implied by the available firm-level evidence indicating an average frequency of roughly two quarters (Bils and Klenow, 2004). This micro-macro puzzle persists, but to a reduced extent, when the FSK-EDE specification is considered: in this case, given the prior assumptions on the demand elasticity coefficients ($\epsilon = 11$ and $\phi_\kappa = 10$), our estimates point to a sticky price parameter value of 0.7 (near to 0.8 under Model B). Table 3 shows the sensitivity of the NKPC slope coefficient to different values of ϵ and θ_p, given $\phi_\kappa = 10$.

Table 3 - The NKPC slope coefficient κ

	θ_p								
ϵ	0.5	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
3	0.0653	0.0482	0.0350	0.0248	0.0170	0.0111	0.0067	0.0036	0.0016
6	0.0791	0.0584	0.0425	0.0302	0.0208	0.0137	0.0084	0.0046	0.0021
11	0.0617	0.0457	0.0333	0.0237	0.0164	0.0108	0.0067	0.0037	0.0017
21	0.0381	0.0282	0.0206	0.0147	0.0102	0.0068	0.0042	0.0024	–
26	0.0316	0.0234	0.0171	0.0122	0.0085	0.0056	0.0035	0.0020	–
41	0.0209	0.0155	0.0113	0.0081	0.0056	0.0037	0.0024	–	–
RK	0.5010	0.3691	0.2675	0.1892	0.1292	0.0838	0.0504	0.0268	0.0113

Notes: θ_p is the Calvo parameter (nominal rigidity); ϵ is the demand elasticity parameter
κ is obtained with the undetermined coefficient method. Kimball curvature parameter ϕ_κ= 10.

Even though the degree of demand elasticity is clearly crucial in this specification, the parameters ϵ and ϕ_κ are unfortunately unobservable. The choice of a specific combination of real and nominal rigidities is hence not straightforward, as testified by the wide array of values adopted in the literature for the demand elasticity parameter, ranging from a value of 3, as in Smets and Wouters (2007), to a value of 101, as in the benchmark specification of Altig *et al.* (2005, 2011). Bowman (2003)'s recent estimates of the price mark-up, which point to a value close to 4% for the U.S. economy, would suggest to use a value of the elasticity parameter of nearly 26. On this basis, the implied price stickiness parameter is reduced to a value of 0.61 (0.72 under Model B). The implied frequency of price optimization is near to 2.6 periods (3.6 under Model B), a value that is slightly above Bils and Klenow's (2004) firm-level evidence and Altig *et al.*'s (2005, 2011) macro estimates[32].

Our results are in line with the estimates in Smets and Wouters (2007), who obtain a Calvo parameter of 0.66. However, given their assumptions on the demand elasticity coefficients ($\epsilon = 3$, and $\phi_\kappa = 10$) and their EDE model specification, the implied NKPC slope coefficient is near 0.028, a value which is above our estimate. The reason for this difference is that they estimate (and allow for) a very high persistence of the cost-push shock affecting the NKPC. This implies that the weak correlation between price inflation and marginal costs which is present in the data tends to be explained by the persistence of the stochastic component, determining persistent (and parallel) shifts of the NKPC. Our estimates are obtained without dynamic indexation and with a moderate degree of persistence of the shock ($\widehat{\rho}_\pi = 0.56$), which forces the explanation of the weak correlation between inflation and marginal costs on the slope of the NKPC. By considering a full dynamic indexation scheme for models A and B, the estimated NKPC slope coefficients are slightly reduced and the estimated degrees of persistence of the interest rate shock become negligible (M_C and M_D in table E.1 in the Appendix).

The importance of the real rigidities entailed by the FSK and EDE hypotheses is thus that, because of their effects on the relation between marginal costs and prices, low estimates of the NKPC slope are coherent with a degree of nominal stickiness that is close to the firm-level evidence on the frequency of price adjustments. By contrast, under a standard rental capital specification, a flat NKPC estimate implies unrealistically high degrees of price stickiness.

A flat NKPC is needed to obtain the negative short-term response of both hours and investment to productivity improvements. The economic mechanisms relating the FSK-EDE hypotheses with these contractionary effects hinge on the endogeneity of marginal costs with respect to the pricing behavior of firms, whose theoretical basis has been discussed in Section 3.1.1. The inertial behavior of inflation - reinforced by an insufficiently accommodative monetary policy - implies a weak demand response which leads to a reduction in the use of inputs in production.

5.2.2 Technology shocks and monetary policy

Our estimates show that the data support the hypothesis that monetary policy follows an empirical rule rather than a theory-based reaction rule. This, togheter with the flat slope of the NKPC, explains the negative short-term hours and investment responses. Clearly, this conclusion is conditional on the specific policy rules and models being tested and it cannot be generalized to the vast set of options which are present in the literature. What the data unambiguously tell us is that monetary policy does not fully accommodate the productivity improvement, since the observed reduction in the interest rate is not sufficient to prevent a short-run reduction in inflation. This is evident in both the SVEC and in model-based impulse responses[33].

The degree to which a rule targeting a measure of potential output does not fully accommodate the technology shock depends on the measure being used. The policy rule adopted in

[32] Since the estimated NKPC slope coefficient in the benchmark specification in Altig *et al.* (2005, 2010) is slightly lower than our estimates ($\kappa = 0.014$), the key element justifying the difference between our and their conclusions on the frequency of price optimization is that they assume a much higher demand elasticity coefficient ϵ.

[33] However, the medium-term behavior of both inflation and nominal interest rate envisaged by Model A is in line neither with the SVEC-based evidence, nor with the dynamics implied by Model B estimates, indicating a persistent drop in both monetary variables following the productivity improvement. This difference is related to the fact that in Model A the monetary policy rule is assumed to target actual output growth deviations from the long-run deterministic growth rate and not level deviations from trend.

Model A considers the long-run deterministic trend in potential output, which by definition does not respond to stochastic variations in technology. Consider a technological improvement that increases the potential and actual levels of output. Since our estimate of potential output is based on the trend in actual output, the general rise in economic activity leads to a positive *measured* output gap, counteracting the interest rate drop stimulated by the inflation deviation from the target. If the demand response is constrained by the presence of real and/or nominal rigidities, the *true* output gap is instead negative. As a consequence, the policy response suggested by the measured gap is the opposite of what the actual gap would indicate.

Since potential output is inherently unobservable, the consideration of different statistical measures can at best reduce, but not solve, this problem, as testified by the fact that the most common statistical measures of the output gap do not match the theoretical measures (Orphanides and van Norden, 2002). On the other hand, model-based measures are theory-specific and thus subject to the problems implied by model uncertainty. For these reasons, policy effectiveness resulting from targeting a misperceived output gap can be inferior to a policy rule responding to output deviations from the trend (Orphanides, 2003a, 2003b, 2007; Del Negro *et al.*, 2005).

6 Conclusions

This paper has addressed the contractionary effects of positive technology shocks. By employing a SVEC model, we show that the short-term response of both hours and investment to an identified productivity shock is negative and that this result is robust to important data and identification issues addressed in the literature. We have then provided a theoretical explanation of the SVEC-based results by showing that they are consistent with an estimated monetary DSGE model in which firm-specific capital and endogenous demand elasticity lower the price sensitivity to marginal costs (i.e. the slope of the NKPC) and monetary policy follows a not fully accommodative interest rate rule. These hypotheses ensure that the negative hours and investment responses are observed also for reasonable degrees of nominal stickiness.

Our results are consistent with those obtained by Basu *et al.* (2006), who use a purified measure of the Solow residual in VAR estimates, but they are in contrast with some of the conclusions in the literature, in particular those obtained using either unprocessed data in standard stationary SVAR representations or empirical NK-DSGE models with optimal or nearly optimal policy rules. With respect to the SVAR-based results, the reasons for these different outcomes are to be found in the use of the, in our opinion, more adequate SVEC representation of the joint data density. Such a representation, which is consistent with the non-stationary and co-trending properties of the data, improves the identifiability of the permanent productivity shock underlying the common trend among real variables, since the explicit (and flexible) consideration of the stationary ratios enhances the separation between permanent and transitory components.

With respect to the NK-DSGE model-based evidence, the contractionary effects of productivity improvements on inputs are due to the presence of relevant demand constraints produced, on the one hand, by a nearly flat NKPC (denoting a limited operation of the price adjustment mechanism) and, on the other hand, by a not fully accommodative conduct of monetary policy. The assumption of monetary authorities targeting flexible price output in other contributions prevents the emergence of the short-term contraction of investment. The data indicate that a weakly accommodative empirical rule should be preferred to a theory-based rule.

Our results thus provide additional evidence challenging the empirical relevance of standard flexible price models, which address neutral technology shocks as the main driver of the observed pro-cyclicality of productivity, investment and hours. The analysis also allows for a comparative evaluation of some of the different theoretical explanations of the contractionary effects of productivity improvements suggested by the literature. On this respect, our main conclusion is that both real and nominal rigidities, along with a weakly accommodative policy rule, are needed in order to explain the apparent puzzle within a NK-DSGE apparatus. The key real rigidities are however different from those directly affecting the dynamics of consumption and investment. Whereas habit persistence and capital adjustment costs may contribute to explain the observed persistence in the real variables and, for some model calibration, the negative response of hours, they are in fact unable to produce a negative investment response to technology improvements. The emergence of this phenomenon requires a weak relation between marginal costs and firms' pricing behavior that can be brought about by the additional real rigidities implied by the strategic complementarities generated by capital firm-specificity and endogenous demand elasticity.

7 Aknowledgements

Financial Support by the Italian Ministry of Education and Scientific Research (PRIN 2009) and by Sapienza University of Rome is acknowledged. We wish to thank Fabio Canova, Michel Juillard, Giuseppe Ciccarone, Francesco Nucci and Enrico Marchetti for useful comments on previous versions of the paper. Lawrence Christiano is thanked for making the Matlab routine used in the approximation of the NKPC slope coefficient available. We tahnk Frank Smets and Raf Wouters for sharing the data and codes used for the estimation of their DSGE model. Any remaining errors are our own responsibility.

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Appendix A. Sources of data and their transformations.

GDP (Y_t), personal consumption (C_t), private non residential investment (I_t) and wages (W_t) are taken from the US Department of Commerce - Bureau of Economic Analysis (BEA) database. Employment (N_t), hours worked by non farm civilian employees (H_t) and population aged 16 and older ($P16_t$) are taken from the Bureau of Labour Statistics (BLS). Inflation is approximated with the quarterly log-differences of the GDP price deflator (PY_t). The nominal rate is the Federal Funds Rate (FFR_t) and is taken from the FRB's database. Real GDP is expressed in chained 2000 dollars. Nominal consumption, investment and wages are deflated using the chained price GDP deflator. This choice makes our dataset fully consistent with that employed by Altig *et al.* (2005), Del Negro *et al.* (2005) and Smets and Wouters (2007). Moreover, it eliminates the positive trend in the investment share resulting from the almost flat dynamics of the investment relative price deflator. Hourly productivity, consumption, investment and wages are obtained by dividing the real variables by total quarterly hours worked (N_tH_t) . Labor supply is obtained by dividing total quarterly hours worked by total available time. The latter is given by the product between population 16 and older and a constant k approximating quarterly available time, obtained by considering 16 hours per day. The use of hours to population ratios as the labor supply measure is standard in the literature (Christiano *et al.* 2004, Galì and Rabanal, 2004, Chari *et al.* 2005 and Del Negro *et al.* 2005). All series are seasonally adjusted and entered in logs. The log quarterly nominal rate is obtained employing the transformation $r_t = \log(1 + R_t/400)$ to the original variable. Table A.1 below summarizes data sources and manipulations.

Table A.1 - Sources of data and their transformations

Variable	Source	Definition	Database Table/Code	Transformation
Y_t	BEA	Gross domestic product (GDP)	NIPA Table 1.1.5	$y_t = \log\left(\frac{Y_t}{N_tH_t}\right)$
C_t	BEA	Personal cons. expenditures	NIPA Table 1.1.5	$c_t = \log\left(\frac{C_t}{N_tH_t}\right)$
I_t	BEA	Non resid. investment	NIPA Table 1.1.5	$i_t = \log\left(\frac{I_t}{N_tH_t}\right)$
W_t	BEA	Wage and salary accruals	NIPA Table 1.1.2	$w_t = \log\left(\frac{W_t}{N_tH_t}\right)$
PY_t	BEA	Implicit price defl. for GDP 2000 = 100	NIPA Table 1.1.9	$\pi_t = \log\left(\frac{PY_t}{PY_{t-1}}\right)$
R_t	FRB	Effective Federal Funds Rate	FF	$r_t = \log\left(1 + \frac{R}{400}\right)$
H_t	BLS	Weekly hours of prod. workers	CES0500000007	$h_t = \log\left(\frac{N_tH_t}{k \times P16_t}\right)$
N_t	BLS	Non farm employees	CES000000000 CES900000000	-
$P16_t$	BLS	Civilian non inst. population 16 years and older	LNU00000000	-

Appendix B. Test for (non)stationarity and cointegration

Table B.1 below provides summary information for the results of the Augmented Dickey-Fuller (ADF) tests of nonstationarity and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests of stationarity for the variables used in the SVEC and the NK-DSGE estimations, discussed in Section 2.1.1. The order $(p - 1)$ specification of the tests is based on a two-step procedure. The lag lenght is specified first according to the Schwartz Bayesian Criterion (SBC). Then, on the basis of the results of the portamenteau statistic, it is augmented such that residuals are not autocorrelated. The test specification for the deterministic components considers the appropriate process under the alternative hypothesis of stationarity: a τ_μ specification is preferred for non zero mean variables and a τ_β specification for trending variables.

Table B.1 - ADF and KPSS test results for model variables

			Differences				Levels			
	Test spec (level)		ADF		KPSS		ADF		KPSS	
Variable	$p-1$	τ_β	test	5% cv	test	5% cv	test	5% cv	test	5% cv
y_t	0	τ_β	-14.3	-2.87	0.23	0.46	-2.18	-3.43	0.27	0.15
h_t	1	τ_μ	-7.38	-1.94	0.04	0.46	-3.03	-2.87	0.43	0.46
π_t	4	τ_μ	-12.5	-1.94	0.07	0.46	-2.24	-2.87	0.32	0.46
r_t	3	τ_μ	-10.8	-1.94	0.08	0.46	-2.77	-2.87	0.37	0.46
c_t	0	τ_β	-12.6	-2.87	0.07	0.46	-1.80	-3.43	0.17	0.15
i_t	0	τ_β	-9.47	-2.87	0.07	0.46	-2.37	-3.43	0.24	0.15

Notes: $p-1$ defines the selected order in ADF tests in the level specification; τ_μ: constant; τ_β: trend.

Table B.2 provides a summary of Johansen's trace tests results for the six variables VEC discussed in Section 2.1.2. The tests consider different lag order specifications of the starting VAR. The Schwartz Bayesian criterion (SBC) and the Akaike Information criterion (AIC) indicate one and two lags, respectively. The critical values are obtained from Johansen *et al.* (2000).

Table B.2 - Johansen's trace test results for different lag orders

	LR trace stat				Critical values		
Rank	$p=1^a$	$p=2^b$	$p=4^c$	$p=6$	90%	95%	99%
0	348.31	240.88	190.43	210.84	140.89	146.56	157.61
1	223.19	174.14	139.34	154.51	108.36	113.39	123.23
2	124.51	117.68	95.11	107.67	79.65	84.02	92.64
3	75.46	64.44	58.63	69.55	54.86	58.56	65.93
4	35.95	34.65	28.69	36.15	33.87	36.86	42.94
5	7.72	9.90	6.74	12.10	16.43	18.64	23.26

Note: p defines the lag order of the starting VAR.a: SBC; b: AIC; c: baseline VAR

Appendix C. Identification of the technology shock.

Consider the SVMA representation of the SVEC:

$$\mathbf{x}_t = \mathbf{C}(1)\sum_{i=1}^{t}\mathbf{B}\boldsymbol{\varepsilon}_i + \mathbf{C}^0(L)\mathbf{B}\boldsymbol{\varepsilon}_t + \widetilde{\mathbf{x}}_0 \tag{C.1}$$

where $\mathbf{C}(1) = \boldsymbol{\beta}\perp(\boldsymbol{\alpha}'\perp\boldsymbol{\Gamma}\boldsymbol{\beta}\perp)^{-1}\boldsymbol{\alpha}'\perp$, $\boldsymbol{\Gamma} = \mathbf{I}_m - \sum_{i=1}^{p-1}\boldsymbol{\Gamma}_i$ and $\boldsymbol{\alpha}\perp, \boldsymbol{\beta}\perp$ are the orthogonal complements of the loading coefficients and the long-run equilibrium matrices, respectively. $\mathbf{C}^0(L) = \sum_{j=0}^{\infty}\mathbf{C}_j^0 L^j$ is a convergent infinite order polynomial in the lag operator and $\widetilde{\mathbf{x}}_0 = \mathbf{C}(1)\mathbf{x}_0$ depends on initial conditions (Johansen, 1995).

Leaving out the coefficients attached to the lagged variables, the reduced-form VEC provides $m(m+1)/2 = 21$ nonredundant coefficients in the dispersion matrix $\boldsymbol{\Omega}$, while the SVEC has $m^2 = 36$ unknown structural coefficients in $\mathbf{B}$. Once errors are orthonormalized, the order conditions for identification require the imposition of $m\,(m-1)\,/2 = 15$ restrictions. Since the rank of the $m \times m$ total impact matrix $\mathbf{C}\,(1)$ is given by the number of permanent components in the system, which is $m - r = 2$, the last four columns of $\mathbf{C}\,(1)$, which correspond to the r transitory components in the model (the CI vectors), are zero vectors. However, given the reduced rank of $C\,(1)$, CI provides only $(m-r)\,r = 8$ constraints for the long-run response matrix $C\,(1)$, leaving $(m-r)\,(m-r-1)\,/2 = 1$ additional restriction to exactly identify the permanent shocks and $r\,(r-1)\,/2 = 6$ restrictions to exactly identify the transitory shocks.

Appendix D. Bayesian estimation and model selection.

The posterior density is obtained by employing the Bayes rule:

$$P\left(\boldsymbol{\theta}_j \middle|\, \mathbf{Y}_T, M_j\right) = \frac{P\left(\mathbf{Y}_T \mid \boldsymbol{\theta}_j, M_j\right) P\left(\boldsymbol{\theta}_j, M_j\right)}{P\left(\mathbf{Y}_T, M_j\right)} \tag{D.1}$$

where $P\left(\mathbf{Y}_T, M_j\right)$ is the marginal data density, which can be normalized since it does not depend on $\boldsymbol{\theta}_j$. Since the posterior density of interest is a complex nonlinear function of the deep parameters $\boldsymbol{\theta}_j$ its analytical calculation is not generally feasible. For this reason, we calculate the posterior distribution via numerical integration. Operationally, the Bayesian MCMC posterior estimates are obtained in a two-step procedure, first employing the Kalman smoother to approximate the conditional distribution and then the Metropolis-Hastings (M-H) algorithm to perform Monte Carlo integration. Bayesian model selection is based on the Bayes factor. Considering Bayes' theorem, the posterior distribution above can be expressed i terms of the posterior probabilities of the models, i.e.:

$$P(M_A, \mathbf{Y}_T) = \frac{P(\mathbf{Y}_T/M_A)P(M_A)}{P(\mathbf{Y}_T/M_A)P(M_A) + P(\mathbf{Y}_T/M_B)P(M_B)} \tag{D.2}$$

where $P(\mathbf{Y}_T/M_j) = \int P(\mathbf{Y}_T/\boldsymbol{\theta}_j, M_j)P(\boldsymbol{\theta}_j, M_j)d\boldsymbol{\theta}_j$, $j = A, B$, is the marginal distribution. The ratio between the posterior distributions of the two models gives the posterior odds ratio, which can be expressed as the priors ratio $P(M_A)/P(M_B)$ times the Bayes factor $P(\mathbf{Y}_T/M_A)/P(\mathbf{Y}_T/M_B)$. Since we do not have any prior preference for one of the two models, we assume $P(M_A) = P(M_B)$, so that the posterior odds is equivalent to the Bayes factor:

$$B_{A,B} = PO_{A,B} = \frac{P(\mathbf{Y}_T/M_A)}{P(\mathbf{Y}_T/M_B)} \tag{D.3}$$

Appendix E. Alternative DSGE model specifications: summary of estimation results.

Table E.1 provides a summary of results from the Bayesian estimation of the alternative model specifications briefly discussed in Section 5. The specifications being considered are: *i*) Models A and B under full dynamic indexation for prices and wages, i.e. with $\iota_p = \iota_w = 1$ (M_C and M_D, respectively); *ii*) the flexible price model version without real frictions, i.e. a monopolistic competition monetary RBC model (M_E); *iii*) the flexible price - real rigidities version of the model (M_F), where real rigidities are given by the habits persistence and the capital adjustment cost parameters.

All the alternative model specifications are estimated considering the sample information employed for M_A and M_B. Models C and D are estimated considering the prior distributions described in Section 4.2. The table reports the Laplace approximation of the marginal likelihood and the posterior mode estimates of the most important parameters for the conditional dynamics of hours and invesment. Results of M_A and M_B are reported for comparison.

Table E.1 - Alternative model specifications: summary of results

		Posterior mode estimates for selected parameters							
Model	Log marg..lik.	λ_c	ϵ_ψ	κ	ϕ_π	ϕ_y	ρ_r	ρ_z	ρ_π
M_A	5138.9	0.811	3.300	0.013	1.640	0.735	0.515	0.110	0.566
M_B	5075.8	0.678	3.973	0.007	1.620	0.112	0.723	0.242	0.587
M_C	5101.3	0.707	3.760	0.011	1.755	0.583	0.459	0.234	0.137
M_D	5079.4	0.684	4.065	0.006	1.729	0.117	0.611	0.242	0.125
M_E	4585.0	–	–	–	–	–	–	0.233	0.794
M_F	4580.8	0.142	3.008	–	–	–	–	0.261	0.795

Notes: Models M_C and M_D consider full dynamic indexation in M_A and M_B models, respectively. Models M_E and M_F denote the flexible price version without and with real demand frictions, respectively.