Monetary Policy Shocks, Cholesky Identification, and DNK Models: An Empirical Investigation for the U.S.*

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Abstract

The identification of monetary policy shocks in structural VARs is often achieved by assuming delayed impacts on inflation and output, i.e. a Cholesky economy. Alternatively, standard Dynamic New-Keynesian (DNK) models typically allow for immediate effects. We show that a DNK model estimated with U.S. data predicts a significant and persistent reaction of inflation and output to an unexpected move of the policy rate. However, when using such estimated DNK as Data Generating Process to feed Cholesky-SVARs in a Monte Carlo exercise, we find that Cholesky-SVARs (erroneously) predict muted macroeconomic responses. Intriguingly, this "in lab" evidence replicates the Cholesky-SVAR impulse responses estimated with actual U.S. data in the great moderation sample.

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1 Introduction

The macroeconomic effects of a monetary policy shocks are often estimated with structural vector autoregressions (SVARs). Several authors have found that, conditional on a stable macroeconomic sample like the "great moderation", SVARs tend to return very mild responses of inflation and output (see, among others, Christiano, Eichenbaum, and Evans (1999), Hanson (2004), Boivin and Giannoni (2006), Mojon (2008), Castelnuovo and Surico (2009)). Figure 1 recalls this evidence. A trivariate VAR estimated with 1984:I-2008:II U.S. data suggests that, in response to a monetary policy shock identified with a Cholesky scheme, the reaction of inflation and the output gap is basically nil at all horizons.[1] Zero or weak reactions in this sample are also obtained with a Factor Augmented VAR approach, which incorporates information coming from large datasets (Boivin and Giannoni (2006), Consolo, Favero, and Paccagnini (2009), Boivin, Kiley, and Mishkin (2010)).[2] A possible interpretation of this evidence is the reduced influence exerted by monetary policy shocks on the economy because of financial innovations occurred in the early 1980s, which might have enabled firms and consumers to better tackle shocks to nominal rates. Another interpretation suggests that the U.S. systematic monetary policy may have fought deviations of inflation and output from the policy targets more successfully since the mid-1980s.

This paper shows that mild-to-zero SVAR reactions, like those depicted in Figure

[1] Giordani (2004) shows that, if a measure of potential output is omitted from the SVAR, the estimated responses are doomed to be biased. Our vector includes a measure of the output gap constructed with the Congressional Budget Office's estimates of the U.S. potential output.

[2] Different results are typically obtained when dealing with samples including the 1970s (e.g. Christiano, Eichenbaum, and Evans (2005)). However, Mojon (2008) shows that such evidence may be induced by shifts in the mean of the inflation process occurred in the 1970s and 1980s. When controlling for such shifts, the impulse responses of inflation and output to a monetary policy shock turn out to be very similar to those obtained with the great moderation sample. Moreover, SVARs estimated with samples including the 1970s often return the "price puzzle", i.e. a positive reaction of inflation to a monetary policy shock. Possibly, such reaction is an artifact driven by omitted factors (see, among others, Bernanke, Boivin, and Eliasz (2005), Forni and Gambetti (2009), and Castelnuovo and Surico (2009)).

1, are *fully compatible* with a monetary policy whose shocks actually exert a *significant* impact on macroeconomic aggregates. The story goes as follows. A popular strategy to identify a monetary policy shock is to assume a recursive (triangular, or Cholesky) structure of the contemporaneous relationships of the variables included in the vector. This strategy is handy, in that it does not require the researcher to take a position on the identification of other shocks (see Christiano, Eichenbaum, and Evans (1999) for an extensive discussion on this issue). In fact, most of the current DNK frameworks admit an *immediate* reaction of inflation and output to a monetary policy impulse. In contrast, the Cholesky-SVAR model imposes *lagged* reactions. The aim of this paper is exactly that of empirically assessing the consequences of this *timing discrepancy.* To hit this target, we first estimate a standard Dynamic New-Keynesian (DNK) model for the U.S. economy, which features an immediate effect of monetary policy surprises on the macroeconomic environment. Then, we employ this estimated framework as our Data Generating Process (DGP) to produce pseudo-data with which we feed Cholesky-SVARs. Our goal is to assess to which extent the (wrong) "zero restrictions" lead to distorted impulse responses.

We find robust evidence of substantial distortions of the SVARs' impulse responses. While the estimated DNK model predicts a *statistically significant* drop in output and inflation in response to a monetary policy shock, SVARs estimated on pseudo-data return, on average, *muted* reactions of these two variables. The estimated distortion of the responses is sizeable, with deviations with respect to the true (DNK based) responses of about 100% and 95% as for (respectively) four-quarter ahead inflation and output reactions. Intriguingly, such reactions replicate the *actual* U.S. data-based SVAR evidence discussed above. Our findings suggest that *muted Cholesky-SVAR responses* of inflation and output to a monetary policy shock are fully consistent with *effective* monetary policy shocks. Given the popularity of the recursive identification scheme, and of the "zero short-run restrictions" in general, this result seems to be of interest for a wide array of macroeconomic applications. Therefore, empirical evidence which hinges upon Cholesky (and, in general, zero) restrictions should be interpreted very carefully.

Before moving to our analysis, we note connections with some closely related literature. Fernández-Villaverde, Rubio-Ramírez, Sargent, and Watson (2007) derive a necessary condition to ensure the existence of the VAR representation of a DSGE model (i.e. to check if the DSGE model is "invertible").[3] Notice that a DNK model may admit a VAR representation with infinite lags, e.g. typically, models with time delays. Ravenna (2007) discusses under which conditions a finite VAR representation exists, and shows that truncated VARs may provide misleading indications when the true DGP is an infinite order VAR. Further discussions on the distortions coming from the truncation bias, mainly on the identification of the technology shock and the dynamic reaction of hours to it, are offered by Christiano, Eichenbaum, and Vigfusson (2006) and Chari, Kehoe, and McGrattan (2008).[4] With respect to these contributions, we consider a DGP that enjoys a finite order VAR(2) representation, i.e. no truncation bias is at work, at least in population. However, the impulse responses which we estimate in our "in lab" exercise are severely distorted due to the timing discrepancy between DNK and SVARs. Interestingly, our Cholesky-SVARs responses produced "in lab" turn out to be remarkably close to those depicted in Figure 1, which we estimated with actual U.S. data.[5] Hence, our evidence suggests that Cholesky-SVAR muted responses are

[3] A VAR is non-invertible if its innovations do not map into the shocks of the economic model even in population and under the correct identification scheme. Non-invertibilities typically arise when some relevant state variables of the model are not included in the VAR (for instance, because they are not observable). The relevance of non-invertibility is, of course, an empirical issue - see Sims (2009).

[4] A somewhat related contribution is Benati and Surico (2009), who show that SVARs may display heteroskedasticity in a world in which, by construction, the DGP is homoskedastic but a policy break occurs. Benati (2010) shows that counterfactuals based on SVAR models may deliver dramatically different indications as regards the role of systematic monetary policy with respect to those obtained with a DNK model.

[5] Obviously, the timing-discrepancy issue may be by-passed with the employment of DNK models

not necessarily sign of monetary policy ineffectiveness. Indeed, they are fully consistent with a DGP in which monetary policy exerts a significant impact on inflation and the business cycle.

The papers closest to ours are probably Canova and Pina (2005) and Carlstrom, Fuerst, and Paustian (2009). Canova and Pina (2005) set up a Monte Carlo exercise in which they consider two calibrated DGPs (a limited participation model and a sticky price-sticky wage economy) to estimate a variety of short-run "zero restrictions" VAR identification schemes. They find substantial differences between the predictions coming from the structural models and those implied by the estimated SVARs. With respect to Canova and Pina (2005), we deal with an *estimated* DGP, whose calibration is then, by construction, the best one to replicate the U.S. macro dynamics in our sample. Moreover, we show that the predictions of SVARs estimated with artificial data line up with the (arti)facts generated with Cholesky-SVARs estimated with actual U.S. data. Consequently, we offer an alternative interpretation to the mild SVAR's responses plotted in Figure 1. Carlstrom, Fuerst, and Paustian (2009) propose a theoretical investigation on the consequences of the timing discrepancy between DNK and Cholesky-SVARs as for the macroeconomic reactions to a monetary policy shock. They show that, a-priori, "anything goes", i.e. conditional on given calibrations of the DNK model, Cholesky-SVARs may return a variety of predictions, including price and output puzzles, responses in line with the true DNK reactions, muted responses, and so on. With our analysis, we basically give empirical support to their main point, i.e. the imposition of the wrong zero restrictions actually leads to severely distorted SVAR-

featuring lagged transmission of the policy impulses. However, several considerations are in order. First, the microfoundations of the transmission lags in the DNK are questionable. Second, as stressed by Carlstrom, Fuerst, and Paustian (2009), such DNKs have VAR exact representations often requiring infinite lags, which naturally raise a truncation bias issue that may harm the precision of the estimated SVAR impulse responses. Third, Cholesky-SVAR's reactions in line with those produced by DNK models with lagged transmission would hardly line up with our evidence presented in Figure 1 and that proposed by the contributions cited in the Introduction. Further considerations may be found in Carlstrom, Fuerst, and Paustian (2009).

impulse response as for as the great moderation sample is concerned. Again, our results offer an alternative interpretation to the facts depicted in Figure 1, i.e. muted responses are not necessarily due to financial innovations and/or an hawkish systematic monetary policy, in that they are also consistent with monetary policy shock's misspecification in SVARs.

The paper develops as follows. Section 2 presents and estimates the new-Keynesian model we take as our DGP. Section 3 sets up our Monte Carlo experiment, with which we contrast the impulse responses generated with our estimated DNK with those coming from the SVARs in a controlled environment. An interpretation of our results, based both on some matrix-algebra on the DNK-SVAR mapping as well as a battery of simulations, is provided in Section 4. Section 5 presents our robustness checks, which verify the solidity of our results to a variety of perturbations of the baseline framework. Section 6 concludes.

2 DNK as DGP

2.1 The standard DNK framework

We work with a standard DNK model (see e.g. King (2000), Woodford (2003a), Carlstrom, Fuerst, and Paustian (2009)). The log-linearized version of the model is the following:

$$(1+\beta)\pi_t = \beta E_t \pi_{t+1} + \pi_{t-1} + \kappa y_t + \varepsilon_t^{\pi}, \tag{1}$$

$$R_t - E_t \pi_{t+1} = \sigma(E_t y_{t+1} - y_t) + P(\rho_a - 1)a_t, \tag{2}$$

$$R_t = \tau_R R_{t-1} + (1-\tau_R)(\tau_\pi \pi_t + \tau_y y_t) + \varepsilon_t^{R}, \tag{3}$$

Eq. (1) is an expectational new-Keynesian Phillips curve (NKPC) in which π_t stands for the inflation rate, β represents the discount factor, y_t identifies the output gap, whose impact on current inflation is influenced by the slope-parameter κ, and ε_t^{π} represents the "cost-push" shock. Firms set prices optimally conditional on the Calvo-lottery. Full indexation to past inflation à la Christiano, Eichenbaum, and Evans (2005), which implies the presence of past inflation in the NKPC, is assumed. Eq. (2) is obtained by log-linearizing households' Euler equation. Output fluctuations are driven both by expectations on future realizations of the business cycle and by the *ex-ante* real interest rate, whose impact is regulated by the degree of risk aversion σ. The convolution $P \equiv \sigma(1+\nu)(\sigma+\nu)^{-1}$ involves the inverse of the Frisch labor elasticity ν, and a_t identifies the technological shock. Eq. (3) is a standard Taylor rule postulating the systematic, inertial reaction of the policy rate to movements in inflation and the output gap. A monetary policy shock ε_t^R allows for a stochastic evolution of the policy rate.

The model is closed with the following stochastic processes:

$$\begin{bmatrix} \varepsilon_t^{\pi} \\ a_t \\ \varepsilon_t^R \end{bmatrix} = \boldsymbol{F} \begin{bmatrix} \varepsilon_{t-1}^{\pi} \\ a_{t-1} \\ \varepsilon_{t-1}^R \end{bmatrix} + \begin{bmatrix} u_t^{\pi} \\ u_t^a \\ u_t^R \end{bmatrix}, \boldsymbol{F} \equiv \begin{bmatrix} \rho_{\pi} & 0 & 0 \\ 0 & \rho_a & 0 \\ 0 & 0 & \rho_R \end{bmatrix}, \tag{4}$$

where the martingale differences, mutually independent processes $\boldsymbol{u}_t$ are distributed as

$$\begin{bmatrix} u_t^{\pi} \\ u_t^a \\ u_t^R \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{\pi}^2 & 0 & 0 \\ 0 & \sigma_{\pi}^2 & 0 \\ 0 & 0 & \sigma_R^2 \end{bmatrix} \right). \tag{5}$$

While being small-scale, the model (1)-(5) is not a "straw man". Several authors (among others, Lubik and Schorfheide (2004), Boivin and Giannoni (2006), Benati and Surico (2008), Benati and Surico (2009), Canova (2009)) have successfully replicated different features of the U.S. macroeconomic data with the AD/AS model presented above (or versions close to it). Moreover, our robustness checks (Section 5) consider a version of the model which features partial price indexation to past inflation in the

NKPC and lagged output in the IS schedule. Obviously, a better identification of the forces driving the U.S. macroeconomic dynamics might be provided by models à la Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007), which feature a larger variety of shocks and frictions. We postpone an exercise with bigger-scale models to future research. However, we believe the framework (1)-(5) may already provide empirically relevant indications on the degree of distortions affecting impulse responses to monetary policy shocks identified in Cholesky-SVARs (under the null of a DSGE structure like the one we work with).

2.2 Model estimation

We estimate the model (1)-(5) with Bayesian methods (see An and Schorfheide (2007) and Canova (2007) for a presentation, and Canova and Sala (2009) for a comparison between this methodology and alternatives). We concentrate on U.S. data spanning the sample 1984:I-2008:II. This sample roughly coincides with the great moderation, a period beginning in the mid-1980s (McConnell and Perez-Quiros (2000)). Our sample ends in 2008:II, i.e. it excludes the acceleration of the financial crises began with the bankruptcy of Lehman Brothers in September 2008, which triggered non-standard policy moves by the Federal Reserve (Brunnermeier (2009)). We employ three observables, which we demean prior to estimation. The output gap is computed as log-deviation of the real GDP with respect to the potential output estimated by the Congressional Budget Office. The inflation rate is the quarterly growth rate of the GDP deflator. For the short-term nominal interest rate we consider the effective federal funds rate expressed in quarterly terms (averages of monthly values) . The source of the data is the Federal Reserve Bank of St. Louis' website.

The vector $\boldsymbol{\xi} = [\beta, \sigma, \kappa, \nu, \tau_\pi, \tau_y, \tau_R, \rho_a, \rho_\pi, \rho_R, \sigma_a, \sigma_\pi, \sigma_R]^T$ collects the parameters characterizing the model. Given the structure we focus on, some parameters are hardly identified. Following Carlstrom, Fuerst, and Paustian (2009), we set $\beta = 0.99$, $\kappa = 0.1275$, and $\nu = 1$, i.e. a very standard calibration.[6] The remaining priors are collected in Table 1. Notice that such priors are fairly uninformative, above all as regards the autoregressive parameters, which are important drivers of the possible biases arising when imposing the (wrong) Cholesky-factorization to identify the monetary policy shock (Carlstrom, Fuerst, and Paustian (2009)). Some details on the Bayesian algorithm are relegated in the Technical Appendix.

Our posterior estimates are reported in Table 1. Basically, all the estimated parameters assume very conventional values. One interesting result is the similarity between the estimates regarding the persistence of the technological shock ρ_a, whose posterior mean is equal to 0.89, and the degree of interest rate smoothing τ_R, whose posterior mean is 0.84. Carlstrom, Fuerst, and Paustian (2009) put in evidence how these two parameters (in particular their relative value) may induce distortions in the SVAR's impulse responses (we get back to this issue in Section 4). Figure 2 compares the actual series we aim at tracking with the DNK's one step ahead predictions, which confirm the very good descriptive power of the DNK model.

3 Impulse responses: DNK vs. Cholesky-SVARs

We compare the impulse responses to a monetary policy shock produced with the estimated DNK vs. those stemming from Cholesky-SVARs estimated with artificial data generated by our DNK framework. Our algorithms works as follows.

For $k = 1$ to K, we

1. sample a realization of the vector $\boldsymbol{\xi}^k$ from the estimated posterior densities;

2. compute the DNK model-consistent impulse responses conditional on $\boldsymbol{\xi}^k$ to an un-

[6] Robustness checks performed by perturbing this baseline calibration confirmed the solidity of our results. Further robustness checks are reported in Section 5.

expected nominal interest rate hike, and store them in the $[3xHxK]$ $\boldsymbol{DNK\_IRFs}$ matrix, which accounts for the $[3x1]$ vector of macroeconomic indicators $[\pi_t, y_t, R_t]^T$, the $h = [1, ..., H]$ steps ahead of the impulse responses of interest, and the $k = [1, ..., K]$ draws of the vector of structural parameters $\boldsymbol{\xi}$;

3. estimate the Cholesky-SVAR impulse responses to a normalized monetary policy shock hike with the artificial data $\boldsymbol{x}^k_{ps,[3:T]}$ (ordering: inflation, output gap, nominal rate) generated with the DNK model conditional on $\boldsymbol{\xi}^k$, and store them in the $[3xHxK]$ $\boldsymbol{SVAR\_IRFs}$ matrix.[7]

We run this algorithm by setting the number of repetitions $K = 10,000$, the horizon of the impulse response functions $H = 15$, and the length of the pseudo-data sample $T = 98$. This sample numerosity coincides with that of the actual data sample (1984:I-2008:II) we employed to estimate both our DNK model and the Cholesky-SVAR whose responses are plotted in Figure 1. Monetary policy shocks are normalized to induce an on-impact equilibrium reaction of the nominal rate equivalent to 25 quarterly basis points.

Figure 3 contrasts the impulse response obtained with the DNK model with those stemming from the Cholesky-SVAR. This figure is extremely informative. First, the estimated DNK predicts a *statistically significant* reaction of both inflation and the output gap (according to the estimated 90% credible set). In particular, the unexpected interest rate hike induces an immediate recession, with the output level getting back to potential after some quarters. Such recession leads to a persistent deflationary phase, which has its maximum expression after three quarters, but lasts more than three years. Evidently, our estimated model supports the U.S. monetary policy's ability to *significantly* influence inflation and the business cycle.

[7] Given that the DNK model has a finite VAR(2) representation, our Cholesky-SVARs are estimated with two lags. We relax this assumption in Section 4.

Interestingly, a quite different picture arises when turning to our Cholesky-SVARs. On average, our SVARs return muted responses of inflation and output to a monetary policy shock, and even the 68% credible sets contain the zero value for all the horizons of interest. In terms of message, the similarity between these SVAR responses and those reported in Figure 1 is impressive, i.e. a monetary policy shock identified with the Cholesky recursive scheme induces no reactions of inflation and output. This evidence suggests that SVAR's muted responses of inflation and output to a monetary policy shock estimated with actual U.S. data may very well be due to the Cholesky-induced missidentification of the monetary policy shock, which returns zero responses when, in fact, monetary policy is effective. In other words, *muted SVAR responses* to a (misspecified) monetary policy shock are *fully consistent* with *significant macroeconomic reactions* to a (correctly identified) shock.

Is the distortion induced by the Cholesky-decomposition *quantitatively* relevant? To answer this question we compute, per each variable j, horizon h, and draw k the percent-deviation of the SVAR response with respect to the DNK-consistent one. In particular, we compute

$$DIST(j,h,k) = 100\left[\frac{SVAR\_IRFs(j,h,k)}{DNK\_IRFs(j,h,k)} - 1\right],$$

where $j \in \{\pi, y\}$. We focus on the second and fourth quarter-ahead responses of inflation and output. We do so to assess the size of the bias in the "very short run" as well as that after one year, the latter being an horizon typically of interest for policymakers.[8] Notice that, for $h = 2$ and $h = 4$, $DNK\_IRFs(j,h,k)$ are negative as regards inflation and output. Then, for a given variable and a given horizon, a negative realization of $DIST$ indicates either a SVAR reaction with the correct sign but that

[8] The *on-impact* reaction, which corresponds to the very first quarter in our analysis, calls for a Cholesky-induced bias *by construction*, due to the imposition of delayed effects of a monetary policy shock on inflation and output.

underestimates the true (DNK) reaction, or a SVAR reaction with the wrong sign (a "price puzzle" or an "output puzzle").

Figure 4 displays the histograms of the distribution of the quarter-specific percentage deviations. All the objects of interest are affected by substantial distortions. The distributions are clearly shifted leftward with respect to the zero value, so indicating underestimation of the true effects of a monetary policy shock, or wrongly signed responses. The 68% interval suggests that these distortions are important also once sample uncertainty is accounted for, with the possible exception of the bias affecting the four-quarter ahead output gap response. To fix ideas, Table 2 collects figures documenting these distortions. The posterior means (of the "DIST" distributions) are all above 95%. The uncertainty surrounding these figures is large, but clearly support the idea of distorted SVAR responses.

4 Why do we get distorted IRFs?

4.1 Investigating the role of the timing discrepancy

Why do we get distorted SVAR-IRFs in our "in lab" exercise? The fundamental reason is the different *timing assumptions* underlying the impact of a monetary policy shock on contemporaneous macroeconomic variables entertained by the DNK model and the Cholesky-SVAR structure. In fact, while the first one allows for an *immediate* impact of the policy shock on inflation and output, the Cholesky-SVAR imposes a *delayed* reaction. This difference, apparently of negligible importance, turns out to be quite relevant from an empirical standpoint.

To better understand the relevance of this timing issue, we exploit Carlstrom *et al*'s (2009) theoretical results. Consider the set of unique decision rules (under equilibrium determinacy) consistent with the rational expectation assumption and the structure of the DNK model:

$$\begin{bmatrix} \pi_t \\ y_t \\ R_t \end{bmatrix} = \boldsymbol{\Gamma} \begin{bmatrix} \pi_{t-1} \\ y_{t-1} \\ R_{t-1} \end{bmatrix} + \boldsymbol{B} \begin{bmatrix} \varepsilon_t^{\pi} \\ a_t \\ \varepsilon_t^{R} \end{bmatrix}, \boldsymbol{\Gamma} \equiv \begin{bmatrix} a_1 & 0 & e_1 \\ a_2 & 0 & e_2 \\ a_3 & 0 & e_3 \end{bmatrix}, \boldsymbol{B} \equiv \begin{bmatrix} b_1 & c_1 & d_1 \\ b_2 & c_2 & d_2 \\ b_3 & c_3 & d_3 \end{bmatrix} \tag{6}$$

where $\boldsymbol{\Gamma}$ and $\boldsymbol{B}$ collect convolutions of the structural parameters $\boldsymbol{\xi}$ of the DNK model.[9] Given that the third column of $\boldsymbol{B}$ does not display, in general, zeros, the monetary policy shock ε_t^R *immediately* affects *all* the variables of the system.

It is easy to show that the system (6) has a VAR(2) representation, which reads:

$$\begin{bmatrix} \pi_t \\ y_t \\ R_t \end{bmatrix} = \boldsymbol{A}_1 \begin{bmatrix} \pi_{t-1} \\ y_{t-1} \\ R_{t-1} \end{bmatrix} + \boldsymbol{A}_2 \begin{bmatrix} \pi_{t-2} \\ y_{t-2} \\ R_{t-2} \end{bmatrix} + \boldsymbol{B} \begin{bmatrix} u_t^{\pi} \\ u_t^{a} \\ u_t^{R} \end{bmatrix} \tag{7}$$

where $\boldsymbol{A}_1 = \boldsymbol{\Gamma} + \boldsymbol{BFB}^{-1}$ and $\boldsymbol{A}_2 = -\boldsymbol{BFB}^{-1}\boldsymbol{\Gamma}$. The variance-covariance matrix of $\boldsymbol{Bu}$ is given by $\boldsymbol{B\Omega B}^T$, where $\boldsymbol{\Omega}$ is a diagonal matrix of full rank 3 with the variances of the shocks positioned on the main diagonal. Without loss of generality, we set $\boldsymbol{\Omega} = \boldsymbol{I}_3$.

Of course, when conducting an econometric exercise, the fundamental shocks $\boldsymbol{u}_t$ are not observable, and must be inferred. To do so, the econometrician can estimate a reduced form VAR(2)

$$\begin{bmatrix} \pi_t \\ y_t \\ R_t \end{bmatrix} = \boldsymbol{A}_1 \begin{bmatrix} \pi_{t-1} \\ y_{t-1} \\ R_{t-1} \end{bmatrix} + \boldsymbol{A}_2 \begin{bmatrix} \pi_{t-2} \\ y_{t-2} \\ R_{t-2} \end{bmatrix} + \begin{bmatrix} \zeta_t^{\pi} \\ \zeta_t^{a} \\ \zeta_t^{R} \end{bmatrix},$$

where $\boldsymbol{\zeta}_t$ is a vector of *residuals* whose variance-covariance $VCV(\boldsymbol{\zeta}) = \boldsymbol{\Lambda}$ is a full (non diagonal) $[3x3]$ matrix.

To recover the unobserved structural monetary policy shock u_t^R, a researcher must impose some restrictions on the structure of the VAR, e.g. the simultaneous relationships among the variables included in the vector, the long-run impact of some economic shocks, or the sign of some conditional correlations. The most popular choice is to

[9] The column of zeros in $\boldsymbol{\Gamma}$ is due to the absence of lagged output in the IS equation (2). Our empirical results are robust to the introduction of past realizations of output in the aggregate demand schedule (see Section 5).

orthogonalize the residuals by imposing a Cholesky structure to the system, which assumes delayed effects of the "monetary policy shock" on the variables located before the nominal interest rate in the vector $[\pi_t, y_t, R_t]^T$. This is done by computing the unique lower triangular matrix $\widetilde{\boldsymbol{B}}$ such that

$$\widetilde{\boldsymbol{B}}\boldsymbol{\varphi_t} = \boldsymbol{\zeta}, \text{ with } \widetilde{\boldsymbol{B}} = \begin{bmatrix} \widetilde{b}_1 & 0 & 0 \\ \widetilde{b}_2 & \widetilde{c}_2 & 0 \\ \widetilde{b}_3 & \widetilde{c}_3 & \widetilde{d}_4 \end{bmatrix}, \text{ and } \boldsymbol{\varphi_t} = \begin{bmatrix} \varphi_t^{\pi} \\ \varphi_t^{a} \\ \varphi_t^{R} \end{bmatrix}. \tag{8}$$

The Cholesky "shocks" $\boldsymbol{\varphi_t}$, which are orthogonal and are assumed to have unitary variance, are then identified by computing the elements of the matrix $\widetilde{\boldsymbol{B}}$ such that

$$\widetilde{\boldsymbol{B}}\widetilde{\boldsymbol{B}}^T = \boldsymbol{\Lambda}.$$

This implies that the equivalence $\widetilde{\boldsymbol{B}}\widetilde{\boldsymbol{B}}^T = \boldsymbol{B}\boldsymbol{B}^T$ must hold. Solving the system, it is then possible to express the elements of $\widetilde{\boldsymbol{B}}$ in terms of the objects belonging to $\boldsymbol{B}$.

Hence, given the restriction

$$\widetilde{\boldsymbol{B}}\boldsymbol{\varphi}_t = \boldsymbol{B}\boldsymbol{u}_t$$

imposed by eqs. (7) and (8), one may express the Cholesky-"shocks" $\boldsymbol{\varphi_t}$ in terms of the DNK shocks $\boldsymbol{u}_t$ and the elements belonging to the matrix $\boldsymbol{B}$. Carlstrom, Fuerst, and Paustian (2009) derive the mapping going from the true DNK shocks to the Cholesky-SVAR monetary policy "shock", which reads

$$\varphi_t^R = \alpha_1 u_t^{\pi} + \alpha_2 u_t^{a} + \alpha_3 u_t^{R}, \tag{9}$$

where the α-weights are given by the expressions[10]

[10] The derivation of these weights is confined in the Technical Appendix.

$$
\begin{aligned}
\alpha_1 &= \frac{(c_2 d_1 - c_1 d_2)\sigma_R^2 \sigma_a}{\Phi \sigma_\pi}, \\
\alpha_2 &= \frac{(d_2 b_1 - d_1 b_2)\sigma_R^2 \sigma_\pi}{\Phi \sigma_a}, \\
\alpha_3 &= \frac{(b_2 c_1 - b_1 c_2)\sigma_\pi \sigma_a}{\Phi}, \\
\Phi &= \sqrt{(c_2 d_1 - c_1 d_2)^2 \sigma_R^4 + (d_2 b_1 - d_1 b_2)^2 \sigma_R^4 + (b_2 c_1 - b_1 c_2)^2 \sigma_\pi^2 \sigma_a^2 \sigma_R^2}.
\end{aligned} \tag{10}
$$

In general, the "shock" φ_t^R is a misspecified representation of the true monetary policy shock u_t^R. The standard Cholesky identification scheme recovers the true policy shock only under the restriction $d_1 = d_2 = 0$, whose relevance may be appreciated by looking back at the set of decision rules (6) (see the column vector $\boldsymbol{B}[:,3]$, i.e. the monetary policy impulse vector).

Unfortunately, these restrictions are *not* consistent with standard DNK models like the one we focus on in this paper. The calibration conditional on our estimated posterior means implies the following values for the matrices characterizing the set of decision rules (6):

$$
\boldsymbol{\Gamma} = \begin{bmatrix} 0.72 & 0.00 & -0.17 \\ -0.33 & 0.00 & -0.72 \\ 0.22 & 0.00 & 0.74 \end{bmatrix}, \text{ and } \boldsymbol{B} = \begin{bmatrix} 1.31 & -0.04 & -0.36 \\ -1.10 & -0.17 & -1.35 \\ 0.37 & -0.03 & 0.80 \end{bmatrix}.
$$

Notably, $\boldsymbol{B}[1,3] = d_1 = -0.36$, and $\boldsymbol{B}[2,3] = d_2 = -1.35$. As a consequence, while $\alpha_1 \approx 0$, $\alpha_2 = -0.99$, and $\alpha_3 = 0.13$. Consequently, the Cholesky scheme misspecifies the monetary policy shock. The stochastic element identified by the Cholesky-SVAR monetary policy "shock" is in fact a convolution of the true technology shock u_t^a, which enters the reduced form φ_t^R with a *negative* sign, and of the true monetary policy shock u_t^R, which enters it with a *positive* sign. This is basically the reason why we get muted responses out of our Cholesky-SVARs. A negative technology shock opens a positive output gap, which exerts a positive pressure on inflation and the policy rate. At the same time, a monetary policy shock (a policy tightening) would trigger a positive reaction of the policy rate, and a negative reaction of inflation and the output gap. Then, the reduced form shock φ_t^R actually captures the *joint* effects of these two structural shocks, so wrongly leading to muted reactions.

The mapping going from the structural parameters $\boldsymbol{\xi}$ to the elements of the $\boldsymbol{B}$ matrix is highly non-linear, and a closed form solution to express the latter as a function of the former is not available. However, one may resort to numerical approximation to assess to what extent the calibration of the DNK model is responsible for the distortions affecting the VAR impulse responses. We then construct the empirical distributions of the α-coefficients by sampling 10,000 realizations of the structural parameters from their estimated posterior densities, and exploiting the closed forms (10).

Figure 5 plots these densities. Interestingly, the cost-push shock u_t^π enters the reduced form SVAR monetary policy shock with a negligible weight, close to zero. By contrast, the distribution of the weight α_2 assigned to the technology shock u_t^a is negative and "significantly" different from zero. Also the density of the loading α_3 of the shock u_t^R suggests values different from zero, but positive. According to Carlstrom, Fuerst, and Paustian (2009), the two effects (that of the technology shock and that of the monetary policy shock) are barely equivalent when the persistence of the technology shock and that of the monetary policy shock are similar, this similarity implying a comparable impact on agents' expectations.

To visually appreciate to what extent the monetary policy shock is misspecified, Figure 6 contrasts the (standardized) structural monetary policy shock u_t^R (red, circled line) and the reduced form φ_t^R (blue, solid line). Evidently, the two stochastic processes display a mild comovement, with a degree of correlation as low as 0.36. Realizations different in terms of sign and magnitudes occur frequently, suggesting the presence of a substantial misspecification induced by the Cholesky assumption.

4.2 Identifying the drivers of the distortions

Which are the structural parameters mainly responsible for this econometric misspecification? Figure 7 depicts the DNK- vs. SVAR-consistent impulse responses originated by calibrating the DNK model with our estimated posterior means.[11] The baseline scenario basically replicates the situation depicted in Figure 2. We then switch-off some selected structural parameters (one at a time) to isolate their participation to the IRFs. Given the emphasis placed on persistence parameters by Carlstrom, Fuerst, and Paustian (2009) in their empirical analysis, we concentrate on the degree of interest rate smoothing as well as the persistence of the DNK structural shocks. When setting $\tau_R = 0$, the effect of the monetary policy shock on inflation and output turns out to be dramatically dampened. Intuitively, this is due to the effect of interest rate smoothing on agents' expectations over the future paths of inflation and output (Woodford (2003b)). Such effect enhances the impact of a monetary policy shock on current (i.e. on impact) outcomes, so widening the gap between the DNK reactions and the "zeros" assumed when engaging in a Cholesky decomposition. The second row of Figure 7 makes it clear that the absence of interest rate smoothing, more than improving the Cholesky-SVAR's ability to correctly recover the true policy shock, dramatically harms monetary policy's strength. In other words, more than reducing the "artifact", it sweeps the "fact" away. Similarly to what previously found, also setting $\rho_R = 0$ leads to a weakened effect of the "true" monetary policy shock. As for the remaining persistence parameters, while imposing $\rho_\pi = 0$ leaves the situation basically unaltered, important effects come from simulating a scenario in which $\rho_a = 0$. In fact, both inflation and output SVAR reactions get the right sign and a shape very similar to the one predicted by the structural model. This finding lines up with the indications put forth by Carlstrom, Fuerst, and Paustian (2009), who find that the distortions in the

[11] The Cholesky-SVARs' population moments are computed by setting the sample size N=100,000.

reactions of inflation and output are positively correlated with the degree of persistence of the technology shock in this DNK model.

Wrapping up, the on impact distortions of the SVAR inflation and output is mainly induced by the effect of the persistence of the nominal interest rate (due to both interest rate smoothing and the persistence of the monetary policy shock) and the technological shock on the reduced-form dynamics of the system. Given that all these sources of persistence find solid empirical support in the U.S. data (see e.g. Clarida, Gali, and Gertler (2000) on the degree of interest rate smoothing, and Smets and Wouters (2007), and Justiniano and Primiceri (2008) on the persistence of the technological shock), we believe that the above documented distortions are a likely outcome as regards Cholesky-SVARs estimated with U.S. data.

5 Robustness checks

We perform some checks to verify the robustness of our results.[12]

- *"Hybrid" NKPC and IS curves.* In our baseline analysis we assume full indexation to past inflation à la Christiano, Eichenbaum, and Evans (2005) and absence of endogenous persistence in the IS curve. In fact, the degree of indexation of the U.S. firms is not necessarily full in the sample we focus on. Moreover, habit formation in consumption offers a rationale for the introduction of lagged realizations of the output gap in the aggregate demand schedule. It is then worth checking the robustness of our findings in a model that allows for partial indexation in the NKPC and lagged output in the IS schedule. We then replace eqs. (1) and (2)

[12] The posterior estimates of the models estimated in this Section are not shown for the sake of brevity, but are available upon request.

with the following schedules:

$$(1+\lambda\beta)\pi_t = \beta E_t \pi_{t+1} + \lambda \pi_{t-1} + \kappa y_t + \varepsilon_t^{\pi}, \tag{11}$$

$$R_t - E_t \pi_{t+1} = \sigma[\phi_y E_t y_{t+1} + (1-\phi_y) y_{t-1} - y_t] + P(\rho_a - 1) a_t, \tag{12}$$

where, following Christiano, Eichenbaum, and Evans (2005), the parameter λ in the modified NKPC (11) represents the fraction of firms resetting prices as a function of past inflation, while ϕ_y identifies the "degree of forward-lookingness" by the U.S. households. We assume λ and ϕ_y to be $Beta(0.5, 0.2)$ distributed, and estimate the model (3)-(5), (11)-(12). The estimated degree of indexation (posterior mean) reads 0.11 (90% credible set: $[0.01, 0.21]$), while the value of the coefficient regulating the weight of the forward looking component is estimated to be 0.75 (90% credible set of $[0.62, 0.87]$). These estimates are very similar to those put forward by Benati and Surico (2008) and Benati and Surico (2009).[13] The estimates of the remaining parameters of the model suggest values fairly in line with those presented in Table 2. We then employ this version of the estimated model as DGP, and re-run our "in lab" exercise. The result of this exercise, depicted in Figure 8, supports our main finding, i.e. the Cholesky-induced distortions still force SVARs impulse responses to be flat when, in fact, the true ones predict a persistent deflation and a substantial recession.[14]

- *Alternative business cycle measure.* Canova (1998) shows that different filtering techniques enjoy different abilities to extrapolate business cycle frequencies out of the U.S. real GDP series. Of course, heterogeneous business cycle representations may imply very different calibrations of business cycle models, so influencing

[13] Cogley and Sbordone (2008) model a time-varying trend inflation process jointly with a consistently derived supply curve. Given the relative stability of trend inflation during the great moderation, our point estimate may be considered as statistically comparable to Cogley and Sbordone's (2008).

[14] The posterior density of the autoregressive parameter ρ_R turns out to be substantially left skewed. This induces a substantial uncertainty in the model consistent impulse response functions. Then, we switch off the uncertainty surrounding this parameter and calibrate it with its posterior mean.

the computation of the moments of interest, conditional correlations included (for some Monte Carlo exercises, see Canova and Ferroni (2009)). To check the robustness of our results, we re-estimate our benchmark model with the measure of the business cycle recently proposed by Perron and Wada (2009), which is constructed by assuming a piecewise linear trend with a break in 1973:I for the post-WWII U.S. real GDP. Figure 9 suggests that our results are robust to the employment of the Perron-Wada filter.

- *Optimal selection of the number of lags of the SVARs.* Given that the DNK model has a finite VAR(2) representation, our SVARs are estimated with two lags. Of course, sample uncertainty may call for a different number of lags for some particular draws $\boldsymbol{x}_{ps,[3:T]}^{k}$. We then re-run our exercise by optimally selecting, per each estimated SVAR, the number of lags according to the Schwarz criterion. Figure 10 depicts the result of this robustness check, which suggests that the impact of sample uncertainty on optimal lag-selection in this context is negligible at best.

- *Measurement errors.* The estimation of the DNK model assumes a perfect match between the model-consistent latent factors and the three observables at hand. In fact, measurement errors are likely to be present. This might be a relevant issue in principle, in that measurement errors may contaminate the estimation of the structural shocks, so influencing (and possibly distorting) the estimation of the Cholesky-SVAR monetary policy shock. We then re-estimate the DNK model with mutually and serially uncorrelated measurement errors for each of the observables in our dataset. The prior distribution for each measurement error is an Inverse Gamma with 0.35 mean and 0.2 standard deviation. Figure 11 plots the responses conditional on the estimation with measurement errors. The responses of the DNK model, above all that of inflation, are clearly much less precisely estimated, an evidence pointing towards movements of inflation not fully captured by the structural model. Possibly, unmodeled movements of the low-frequency component of inflation may partly explain this result. Distortions in the estimation of the price deflator may also be a relevant component to interpret our findings. However, the main message of the paper remains, again, unaltered.

These robustness checks suggest the solidity of our main result, i.e. the consistency between Cholesky-SVARs' flat responses of inflation and output to a (misspecified) monetary policy shock and monetary policy effectiveness.

6 Conclusions

This paper shows that flat impulse responses produced with a Cholesky-SVAR estimated with U.S. 1984:I-2008:II data are fully consistent with monetary policy shocks exerting a substantial effect on inflation and output. We estimate a Dynamic New-Keynesian (DNK) model with Bayesian techniques, and verify that the model–consistent impulse responses predict significantly negative, persistent reactions of inflation and output to a monetary policy shock. Then, we feed SVARs with pseudo-data produced with the estimated DNK model, and show that the Cholesky-SVAR "shock" implies distorted estimates of the monetary policy impulse. In particular, SVARs impulse responses wrongly predict muted macroeconomic reactions to an unexpected nominal rate hike. The misspecification of the policy shock finds its foundations in the timing discrepancy existing between the structural DNK model, which allows immediate macroeconomic reactions to a policy shock, and the Cholesky-SVARs, which wrongly impose delays in the transmission mechanism. In light of the widespread employment of the recursiveness assumption for the identification of the monetary policy shock in SVARs, and the use of "zero restrictions" in general, researchers should interpret the predictions coming from the Cholesky-impulse responses with great care. Importantly, our estimated DNK, as stressed in the paper, tracks the U.S. series we model remarkably well. However, a better identification of the forces driving the U.S. macroeconomic dynamics might be provided by models à la Christiano, Eichenbaum, and Evans (2005) and Smets and Wouters (2007), which feature a larger variety of shocks and frictions. We plan to undertake a similar exercise with such larger-scale models in the close future.

Which are the implications of our study? To be clear, our results do *not* call for a rejection of the SVAR approach. Vector autoregressions are clearly useful to establish stylized facts when different, competing models are *a-priori* equally sensible. As Fernandéz-Villaverde, Rubio-Ramírez, Sargent, and Watson (2007, page 1025) put it, "Despite pitfalls, it is easy to sympathize with the enterprise of identifying economic shocks from VAR innovations if one is not dogmatic in favor of a particular fully specified model." The identification of such shocks, however, should be implemented in the most careful manner. Two possibly complementary ways to tackle this issue are available. First, as regards model calibration, one call follow Sims (1989) and Cogley and Nason (1995), who impose the same restrictions on SVARs estimated with actual data and on those estimated with pseudo-data generated with a business cycle model, so rendering the comparison of the two structures' dynamics more consistent from a logical standpoint (for a recent application of this strategy, see Blanchard and Riggi (2009)). Second, a "sign restriction" approach, which constraints some dynamics of the SVAR to line up with common indications across different structural models, or conventional wisdom, can be exploited to achieve macroeconomic shocks' identification. Indeed, the differences between conditional correlations arising under the Cholesky vs. sign restriction identification schemes may be dramatic (see, among others, Canova (2007), Chapter 4, and Castelnuovo and Surico (2009)). A non-exhaustive list of recent applications with sign restrictions include Canova and de Nicoló (2002), Franchi (2004), Peersman (2005), Canova and Pina (2005), Uhlig (2005), and Rubio-Ramírez, Waggoner, and Zha (2009).

Canova and Paustian (2010) propose an algorithm which exploits sign restrictions to validate business cycle models. We believe that sign-restrictions should become the new *status quo* for the identification of monetary policy shocks in SVARs.

7 Technical Appendix

7.1 Bayesian estimation

To perform our Bayesian estimations we employed DYNARE, a set of algorithms developed by Michel Juillard and collaborators. DYNARE is freely available at the following URL: http://www.dynare.org/.

The simulation of the target distribution is basically based on two steps.

- First, we initialized the variance-covariance matrix of the proposal distribution and employed a standard random-walk Metropolis-Hastings for the first $t \leq t_0 = 20,000$ draws. To do so, we computed the posterior mode by the "csminwel" algorithm developed by Chris Sims. The inverse of the Hessian of the target distribution evaluated at the posterior mode was used to define the variance-covariance matrix C_0 of the proposal distribution. The initial VCV matrix of the forecast errors in the Kalman filter was set to be equal to the unconditional variance of the state variables. We used the steady-state of the model to initialize the state vector in the Kalman filter.

- Second, we implemented the "Adaptive Metropolis" (AM) algorithm developed by Haario, Saksman, and Tamminen (2001) to simulate the target distribution. Haario, Saksman, and Tamminen (2001) show that their AM algorithm is more efficient than the standard Metropolis-Hastings algorithm. In a nutshell, such algorithm employs the history of the states (draws) so to "tune" the proposal distribution suitably. In particular, the previous draws are employed to regulate the VCV of the proposal density. We then exploited the history of the states sampled up to $t > t_0$ to continuously update the VCV matrix C_t of the proposal distribution. While not being a Markovian process, the AM algorithm is shown to possess the correct ergodic properties. For technicalities, see Haario, Saksman, and Tamminen (2001).

We simulated two chains of 1,000,000 draws each, and discarded the first 90% as burn-in. To scale the variance-covariance matrix of the chain, we used a factor so to achieve an acceptance rate belonging to the [23%,40%] range. The stationarity of the chains was assessed via the convergence checks proposed by Brooks and Gelman (1998). The region of acceptable parameter realizations was truncated so to obtain equilibrium uniqueness under rational expectations.

7.2 Derivation of the weights α_s

The Cholesky-SVAR reduced form shock φ_t^R is a linear combination of the structural shocks of the DNK model. We derive the loadings of such linear combination by generalizing the derivation reported in the Appendix of Carlstrom, Fuerst, and Paustian (2009) to the case of non-unitary variances of the structural shocks of the DNK model.

The loadings are derived as follows. Given that the Cholesky shock is orthogonal to contemporaneous movements, we can write $E_{t-1}(\pi_t \varphi_t^R) = E_{t-1}(y_t \varphi_t^R) = 0$. The relationship linking the Cholesky-SVAR monetary policy "shock" to the true structural shocks is given by $\varphi_t^R = \alpha_1 u_t^\pi + \alpha_2 u_t^a + \alpha_3 u_t^R$, with $E_{t-1}(u_i u_j) = 0$ for $i \neq j$. The variance of the Cholesky shock φ_t^R is unitary by assumption.

By exploiting the decision rules (7), the features of the stochastic shocks u_s, and the definition of φ_t^R, we can derive the following expressions:

$$
\begin{aligned}
b_1\alpha_1\sigma_\pi^2 + c_1\alpha_2\sigma_a^2 + d_1\alpha_3\sigma_R^2 &= 0, \\
b_2\alpha_1\sigma_\pi^2 + c_2\alpha_2\sigma_a^2 + d_2\alpha_3\sigma_R^2 &= 0, \\
\alpha_1^2\sigma_\pi^2 + \alpha_2^2\sigma_a^2 + \alpha_3^2\sigma_R^2 &= 1.
\end{aligned}
$$

After some manipulations, one may obtain the following expressions:

$$
\begin{aligned}
\alpha_1 &= \frac{(c_2d_1 - c_1d_2)\sigma_R^2\sigma_a}{\Phi\sigma_\pi}, \\
\alpha_2 &= \frac{(d_2b_1 - d_1b_2)\sigma_R^2\sigma_\pi}{\Phi\sigma_a}, \\
\alpha_3 &= \frac{(b_2c_1 - b_1c_2)\sigma_\pi\sigma_a}{\Phi}, \\
\Phi &= \sqrt{(c_2d_1 - c_1d_2)^2\sigma_R^4 + (d_2b_1 - d_1b_2)^2\sigma_R^4 + (b_2c_1 - b_1c_2)^2\sigma_\pi^2\sigma_a^2\sigma_R^2},
\end{aligned}
$$

which are reported in the main text (see eqs. (10)).

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$Param.$	$Interpretation$	$Priors$	$Posterior\ Means$ $_{[5h,95th]}$
β	Discount factor	$Calibrated$	0.99 [−]
σ	Risk aversion	$Normal(3,1)$	4.07 [2.88,5.25]
υ^{-1}	Frisch elasticity	$Calibrated$	1 [−]
κ	Slope of the NKPC	$Calibrated$	0.1275 [−]
τ_π	T. Rule, Inflation	$Normal(1.5,0.3)$	2.12 [1.79,2.46]
τ_y	T. Rule, Output gap	$Gamma(0.3,0.2)$	0.40 [0.25,0.56]
τ_R	T. Rule, Inertia	$Beta(0.5,0.285)$	0.84 [0.80,0.88]
ρ_a	AR tech. shock	$Beta(0.5,0.285)$	0.89 [0.85,0.94]
ρ_π	AR cost-push shock	$Beta(0.5,0.285)$	0.67 [0.52,0.84]
ρ_R	AR mon. pol. shock	$Beta(0.5,0.285)$	0.42 [0.27,0.57]
σ_a	Std. tech. shock	$InvGamma(1.5,0.2)$	2.64 [1.86,3.40]
σ_π	Std. cost-push. shock	$InvGamma(0.35,0.2)$	0.23 [0.18,0.28]
σ_R	Std. mon. pol. shock	$InvGamma(0.35,0.2)$	0.12 [0.11,0.14]

Table 1: **Bayesian estimates of the benchmark model.** 1984:I-2008:II U.S. data. Prior densities: Figures indicate the (mean,st.dev.) of each prior distribution. Posterior densities: Figures reported indicate the posterior mean and the [5th,95th] percentile of the estimated densities. Details on the estimation procedure provided in the text.

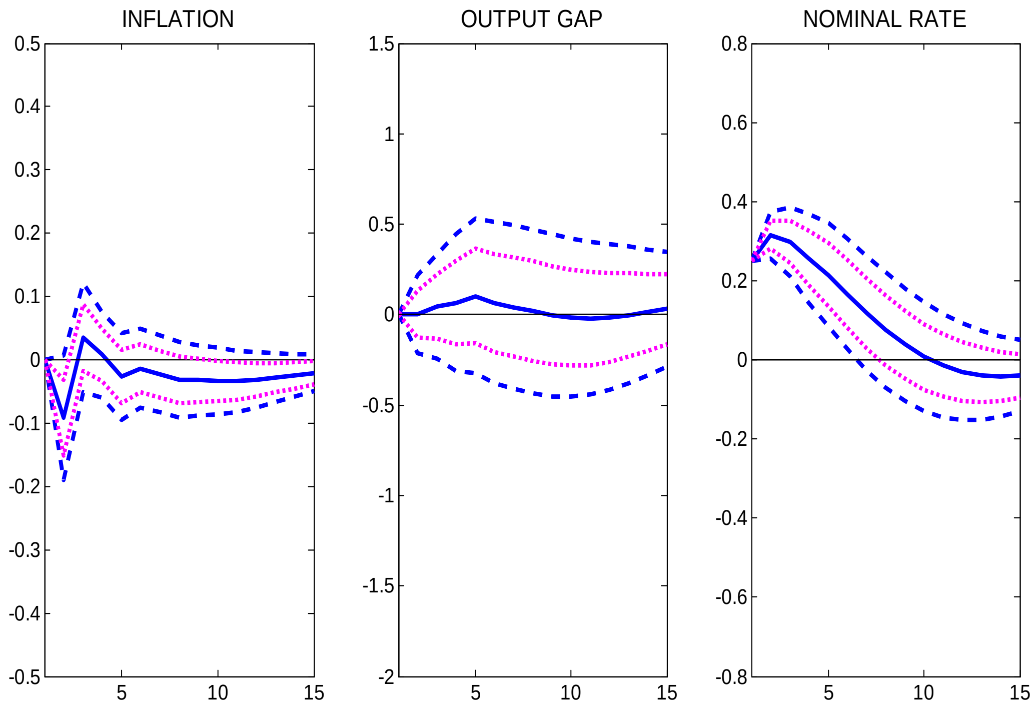

Figure 1: **SVAR impulse response functions to a monetary policy shock.** Sample: 1984:I-2008:II. Variables: Quarterly GDP inflation, CBO output gap, quarterly federal funds rate - source: FREDII. Identification of the monetary policy shock via Cholesky decomposition (lower triangular matrix, ordering: inflation, output gap, federal funds rate). Solid blue line: Mean response; Dashed blue lines: 90% confidence bands; Magenta dotted lines: 68% confidence bands (analytically computed). VAR estimated with a constant, a linear trend, and three lags.

	INFLATION	OUTPUT GAP
2nd qtr. ahead	-101.80	-98.33
	$[-142.17,-60.04]$	$[131.99,-54.58]$
4th qtr. ahead	-100.41	-95.69
	$[-175.25,-25.18]$	$[-200.60,44.91]$

Table 2: **DNK vs. SVAR impulse response functions: Estimated Distortions.** The Table reports the means and [5th,95th] percentiles of the distribution of the percentage deviations of the VAR response with respect to the DNK responses.

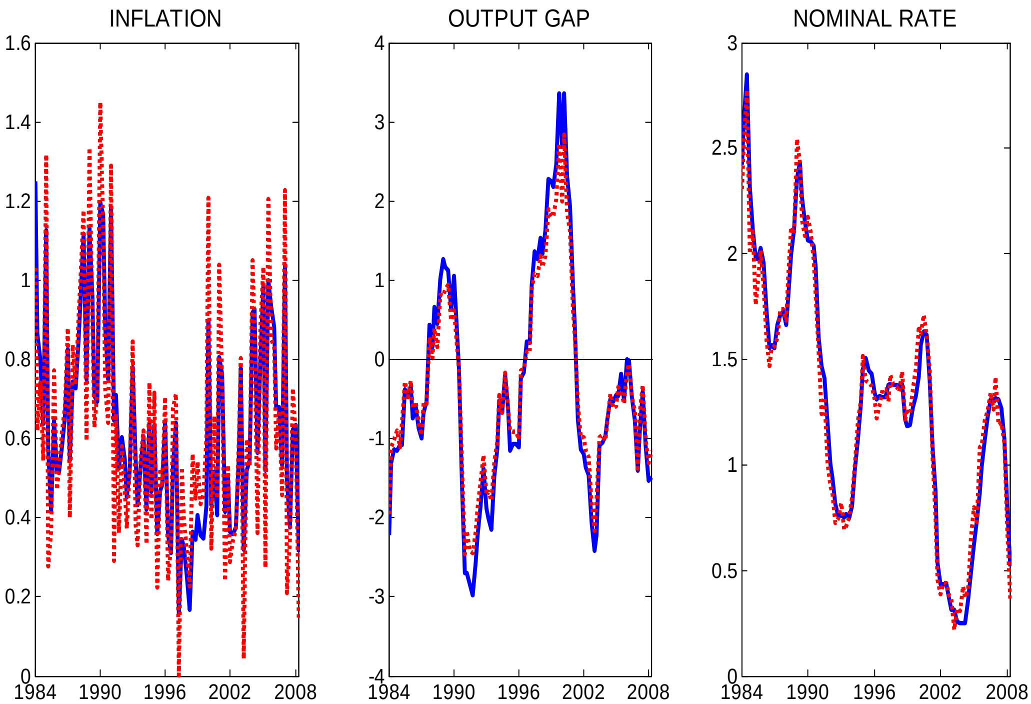

Figure 2: **Actual series vs. DNK's one-step ahead forecasts.** Solid blue line: Actual series; Dotted red lines: DNK's predictions.

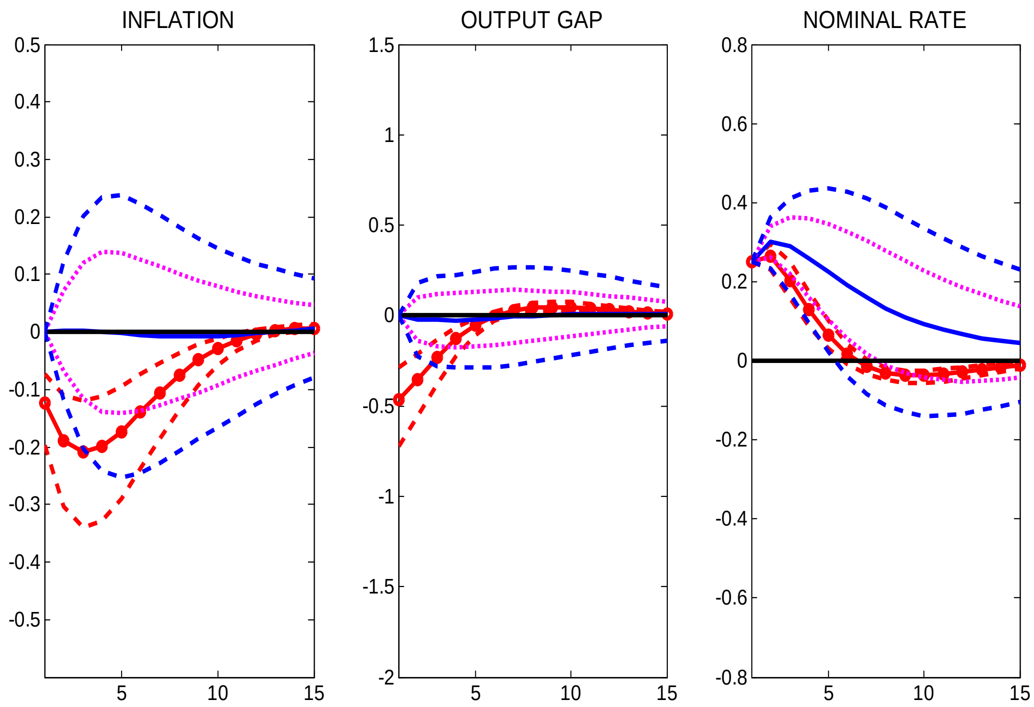

Figure 3: **DNK and VAR impulse response functions to a monetary policy shock.** Circled red lines: DNK Bayesian mean impulse responses; Dashed red lines: 90% credible sets. Solid blue line: VAR mean impulse responses; Dashed blue lines: 90% confidence bands; Magenta dotted lines: 68% confidence bands. Moments computed the impulse response function distributions simulated by drawing 10,000 realizations of the vector of parameters of the DNK model, which is also used to generate the pseudo-data to feed the SVARs. Identification of the monetary policy shock via Cholesky decomposition (lower triangular matrix, ordering: inflation, output gap, nominal rate). VAR estimated with two lags.

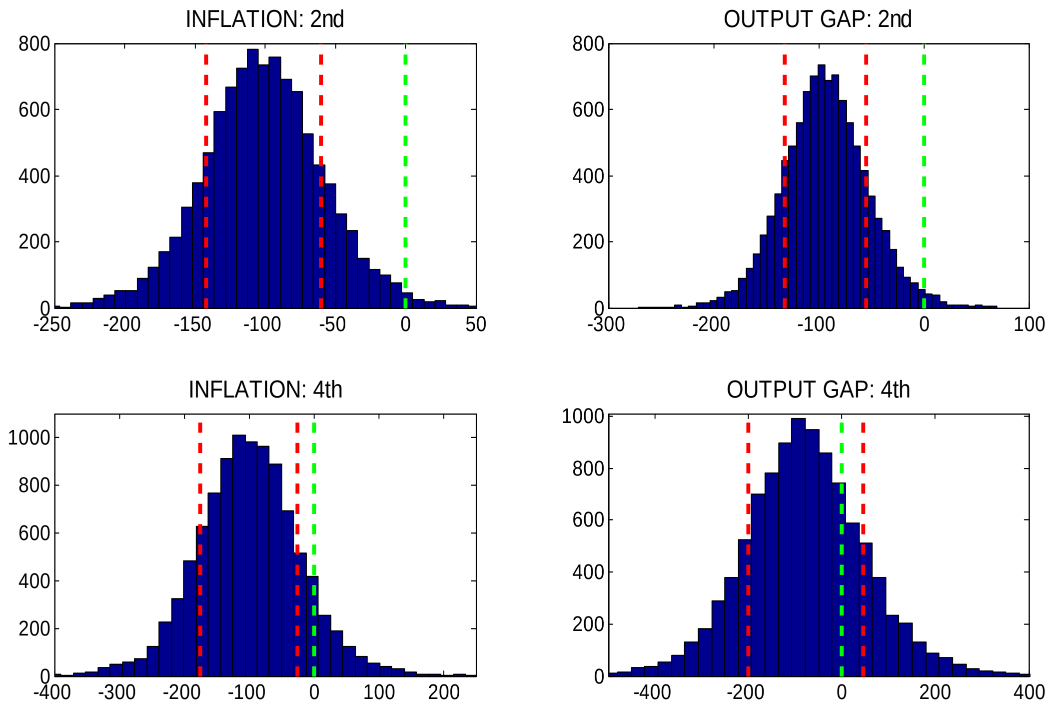

Figure 4: **Estimated distortions of the SVAR's impulse responses**. Distortions computed as percentage deviation of the SVAR responses with respect to the DNK (true) response. Computation of the densities based on 10,000 draws of the structural parameters of the DNK model.

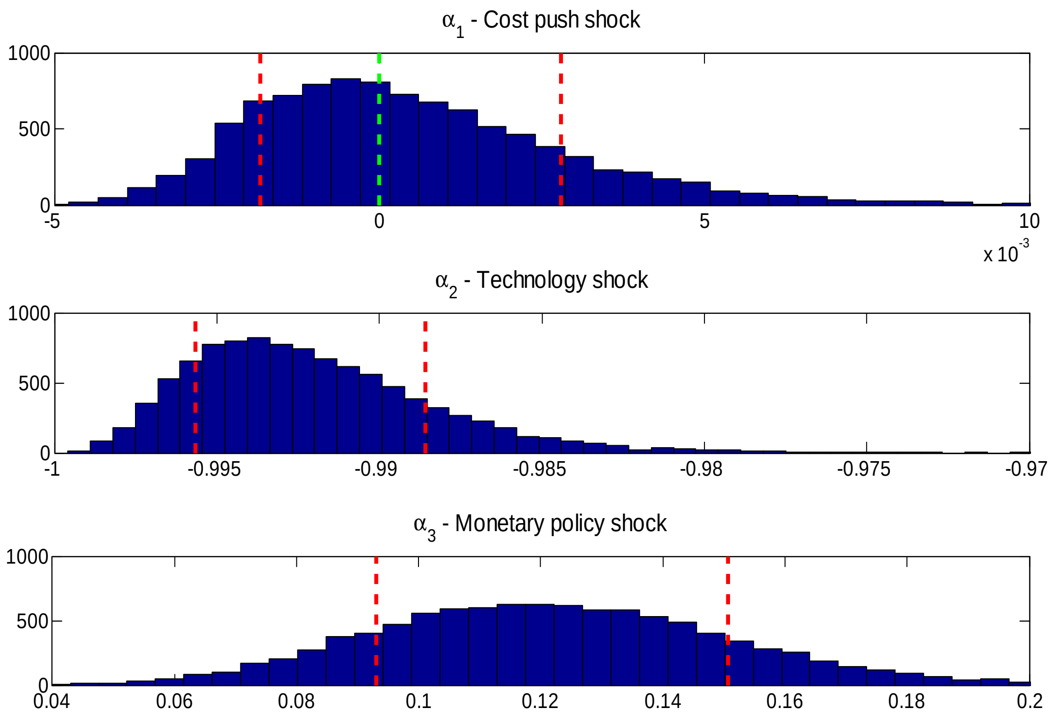

Figure 5: **Densities of the weights of the true structural shocks in the Cholesky-monetary policy "shock".** Computation of the densities based on 10,000 draws of the structural parameters of the DNK model. The mapping from the structural parameters to the coefficients plotted in the Figure is described in the text.

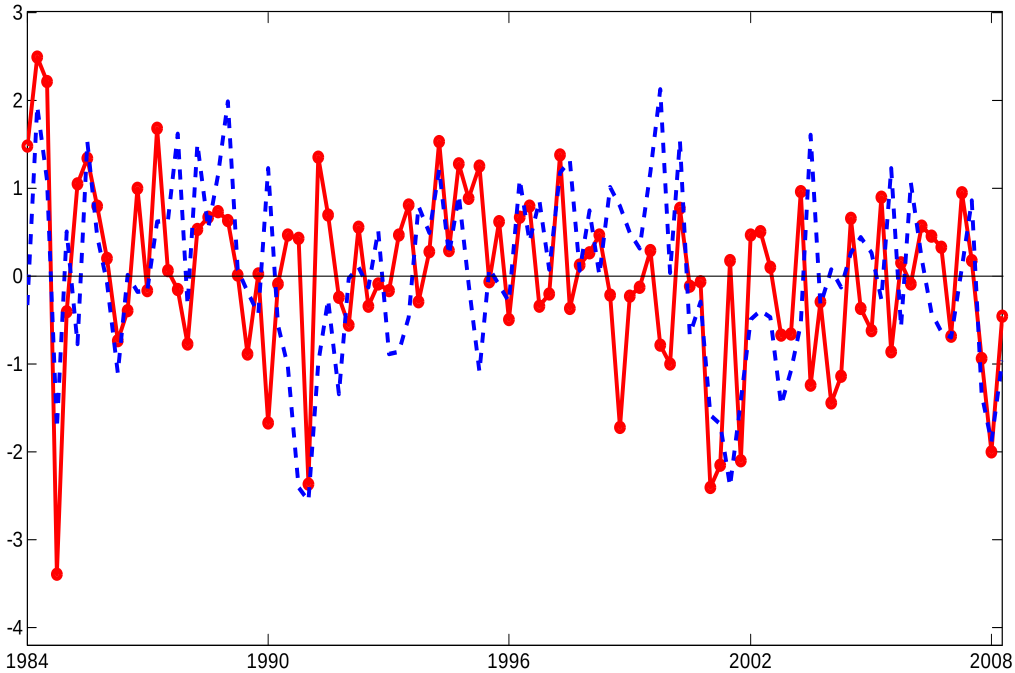

Figure 6: **DNK vs. Cholesky-SVAR monetary policy standardized shocks.** Red circled line: DNK monetary policy shock (smoothed estimates, parameters calibrated at their posterior modes); Blue dotted line: Cholesky-SVAR monetary policy shock (conditional on the smoothed estimates of our DNK model's shocks, and constructed as explained in the text, see eq. (9)).

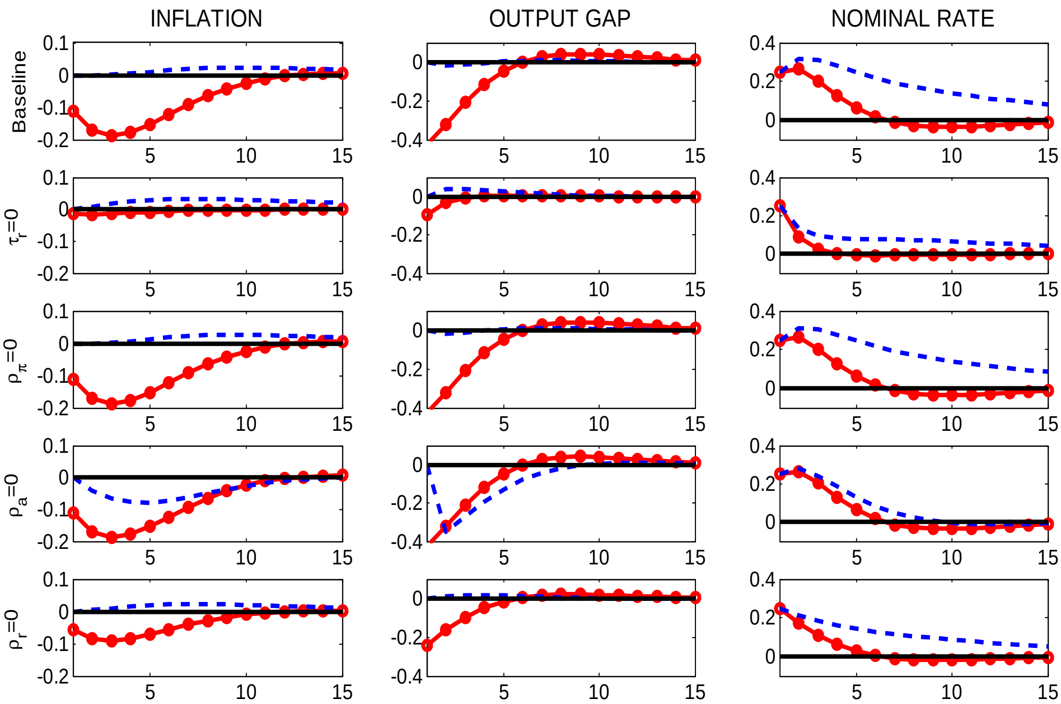

Figure 7: **DNK- vs. Cholesky-SVAR-consistent impulse response functions: Alternative calibrations.** Populations moments computed by setting N=100,000.

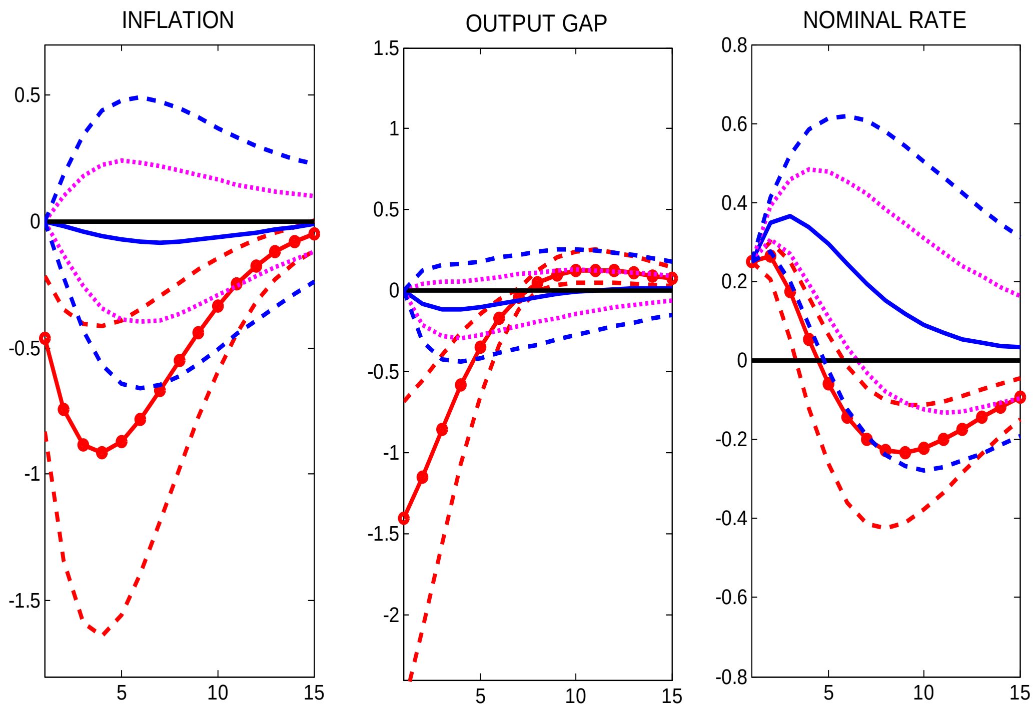

Figure 8: **Partial price indexation & hybrid IS curve model.** Circled red lines: DNK Bayesian mean impulse responses; Dashed red lines: 90% credible sets. Solid blue line: VAR mean impulse responses; Dashed blue lines: 90% confidence bands; Magenta dotted lines: 68% confidence bands. Moments computed the impulse response function distributions simulated by drawing 10,000 realizations of the vector of parameters of the DNK model, which is also used to generate the pseudo-data to feed the SVARs. Identification of the monetary policy shock via Cholesky decomposition (lower triangular matrix, ordering: inflation, output gap, nominal rate). VARs estimated with two lags.

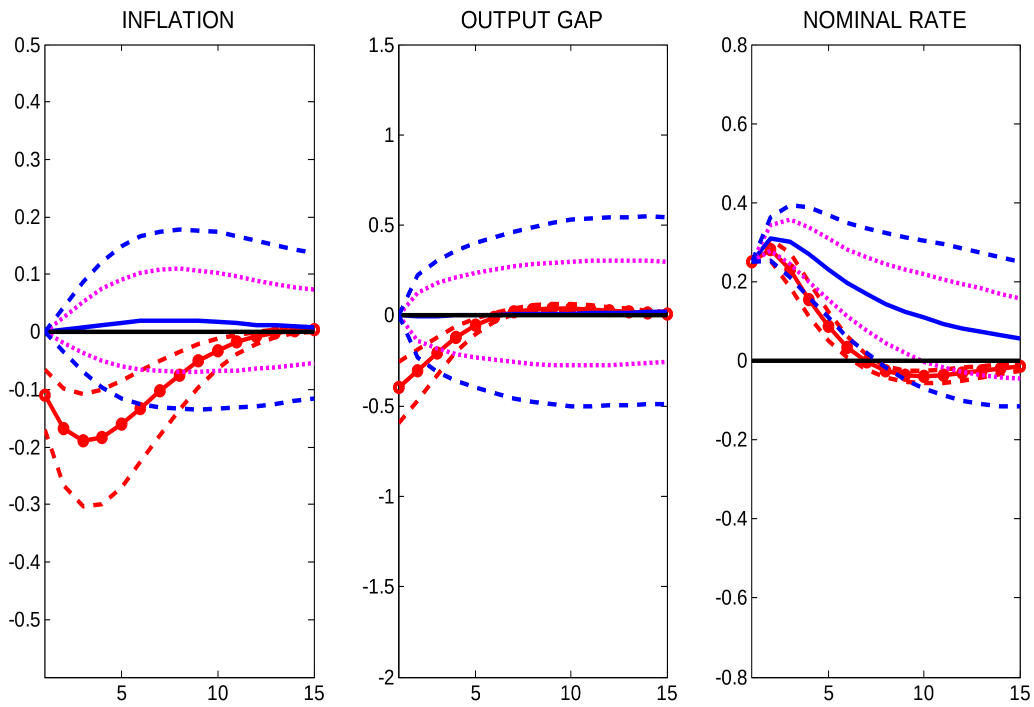

Figure 9: **Perron-Wada piecewise-linear output trend.** Circled red lines: DNK Bayesian mean impulse responses; Dashed red lines: 90% credible sets. Solid blue line: VAR mean impulse responses; Dashed blue lines: 90% confidence bands; Magenta dotted lines: 68% confidence bands. Moments computed the impulse response function distributions simulated by drawing 10,000 realizations of the vector of parameters of the DNK model, which is also used to generate the pseudo-data to feed the SVARs. Identification of the monetary policy shock via Cholesky decomposition (lower triangular matrix, ordering: inflation, output gap, nominal rate). VARs estimated with two lags. The output trend is piecewise-linear, with a break in 1973:I.

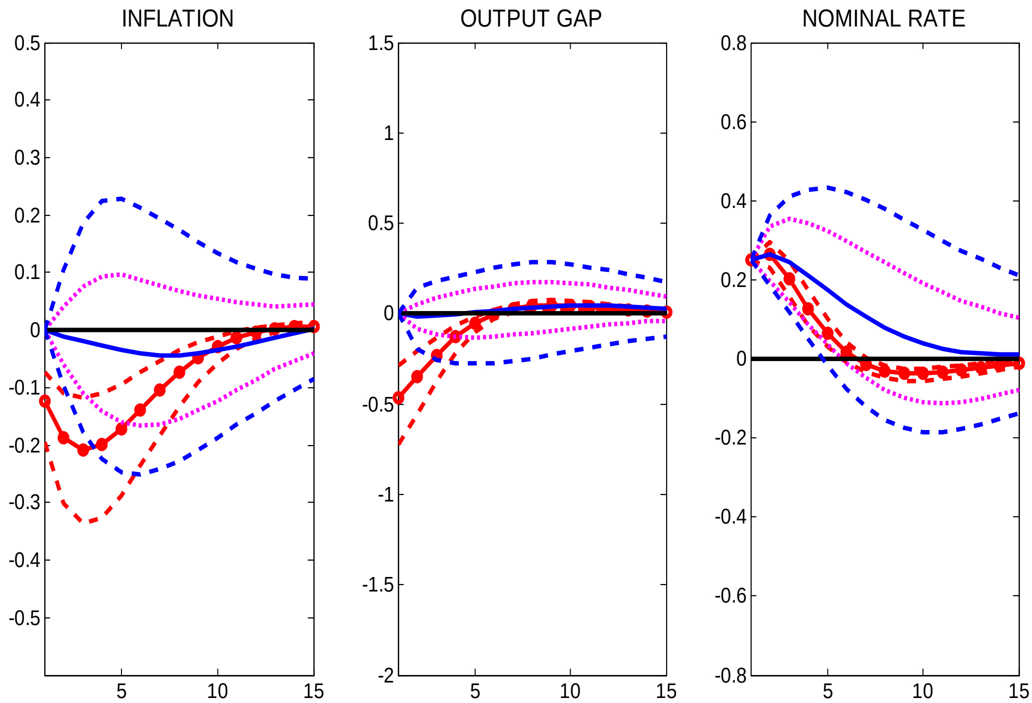

Figure 10: **Optimal lag-selection.** Circled red lines: DNK Bayesian mean impulse responses; Dashed red lines: 90% credible sets. Solid blue line: VAR mean impulse responses; Dashed blue lines: 90% confidence bands; Magenta dotted lines: 68% confidence bands. Moments computed the impulse response function distributions simulated by drawing 10,000 realizations of the vector of parameters of the DNK model, which is also used to generate the pseudo-data to feed the SVARs. Identification of the monetary policy shock via Cholesky decomposition (lower triangular matrix, ordering: inflation, output gap, nominal rate). Lags of the estimated VARs selected according to the Schwarz criterion.

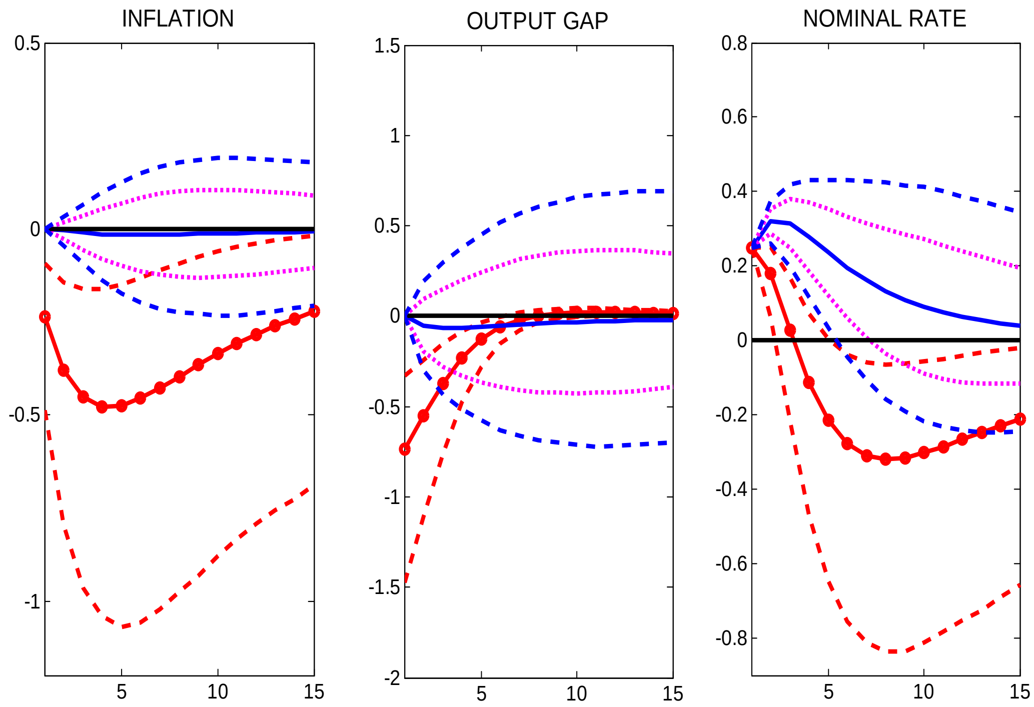

Figure 11: **Measurement errors in the estimation of the DNK framework.** Circled red lines: DNK Bayesian mean impulse responses; Dashed red lines: 90% credible sets. Solid blue line: VAR mean impulse responses; Dashed blue lines: 90% confidence bands; Magenta dotted lines: 68% confidence bands. Moments computed the impulse response function distributions simulated by drawing 10,000 realizations of the vector of parameters of the DNK model, which is also used to generate the pseudo-data to feed the SVARs. Identification of the monetary policy shock via Cholesky decomposition (lower triangular matrix, ordering: inflation, output gap, nominal rate). VARs estimated with two lags. Serially and mutually uncorrelated a-priori Inverse Gamma(0.35,0.2) distributed measurement errros modeled in the estimation.