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Abstract

We employ a non-recursive identification scheme to identify the effects of a monetary policy shock in a Structural Vector Autoregressive (SVARs) model for the U.S. post-WWII quarterly data. The identification of the shock is achieved via heteroskedasticity, and different on-impact macroeconomic responses are allowed for (but not imposed) in each volatility regime. We show that the impulse responses obtained with the suggested non-recursive identification scheme are quite similar to those conditional on a recursive VAR estimated with pre-1984 data. In contrast, recursive vs. non-recursive identification schemes return different short-run responses of output and investment during the Great Moderation. Robustness checks dealing with a different definition of investment, an alternative break-point, and federal funds futures rates as an indicator of the monetary policy stance are documented and discussed.

JEL classification: C32, C50, E52

Keywords: Structural break, recursive and non-recursive VARs, identification, monetary policy shocks, impulse responses

1 Introduction

Since the seminal contribution by Sims (1980), Structural Vector Autoregressions (SVARs henceforth) have widely been employed by macroeconomists to establish stylized facts and discriminate among competing models. A lot of effort has been devoted to study the effects of monetary policy shocks in the United States (see, among others, Christiano, Eichenbaum and Evans (1999,2005)). Typically, exogenous variations of the federal funds rate have been identified by estimating fixed coefficient-VARs and appealing to the Cholesky-identification scheme. In other words, researchers have exploited long samples and applied a scheme which imposes a recursive structure on the contemporaneous relationships of the macroeconomic variables of interest. The underlying assumptions behind such identification scheme are: i) some macroeconomic variables (e.g., real GDP, inflation) are "slow moving", i.e., they are assumed to react to monetary policy shocks with a lag; ii) the systematic monetary policy component immediately reacts to macroeconomic shocks that affect the equilibrium value of such slow moving variables.

Fixed coefficient-recursive SVARs are potentially quite powerful, because of the number of degrees of freedom and the fact that they do not require the econometrician to identify macroeconomic shocks other than the one of interest. However, some researchers have found evidence inconsistent with the assumption of a lower-triangular economic system (see Del Negro, Schorfheide, Smets, and Wouters (2007) on the immediate reaction of output to a monetary policy shock, on the contemporaneous response of prices, Normandin and Phaneuf (2004) on both, and Gertler and Karadi (2014) as regards the on-impact reactions of a variety of interest rates related to different maturities). Moreover, most DSGE macroeconomic models typically feature no lags in the monetary policy transmission mechanism (see, e.g., the popular model by Smets and Wouters (2007), or the textbook version of the new-Keynesian business cycle framework by Galí (2008)).[1] As a matter of fact, however, recursive schemes are still quite popular among VAR macroeconomists. The reason is simple. More often than not, the non-recursive schemes implied by DSGE models are unfeasible due to insufficient information coming from the reduced-form variance-covariance matrix.[2] Moreover, fixed coefficient-

[1] Notable exceptions are Rotemberg and Woodford (1997), Christiano, Eichenbaum, and Evans (2005), Boivin and Giannoni (2006), and Altig, Christiano, Eichenbaum, and Linde (2011).

[2] Of course, such non-recursive schemes become feasible if the econometrician imposes the full set of cross-equation restrictions due to rational expectations. In this case, however, the need of estimating a VAR is unclear, given the knowledge of the true data-generating process by the econometrician.

VARs estimated over the post-WWII U.S. period are questionable in light of the huge evidence pointing to heteroskedasticity (see, among others, McConnell and Perez-Quiros (2000), Stock and Watson (2002), Sims and Zha (2006), Smets and Wouters (2007), Justiniano and Primiceri (2008), Canova, Gambetti, and Pappa (2008), and Canova (2009), Castelnuovo (2012)).

This paper's contribution is twofold. First, we apply the heteroskedasticity-based non-recursive identification strategy recently developed by Bacchiocchi and Fanelli (2015) to identify the effects of macroeconomic shocks that exploits the information coming from different volatility regimes in the data. The key idea is that breaks in the reduced form error covariance matrix can be associated with changes in the on-impact response of the variables to the shocks which in turn reflect in instabilities in the identified impulse response functions across volatility regimes.[3] This methodology generalizes in one important dimension the proposals by Rigobon (2003) and Lanne and Lütkepohl (2008), who focus on variations in the size of the structural shocks but assume impulse vectors to remain fixed across volatility regimes.[4] We employ our Structural VAR with break (SVAR-WB henceforth) to model a vector of seven U.S. macroeconomic variables for the post-WWII period. Our identification scheme exploits the change in the variance of the reduced form VAR errors detected in the mid-1980s, i.e., the 'Great Moderation'.[5] As previously pointed out, this choice is justified by the vast literature documenting heteroskedasticity in the U.S. (McConnell and Perez-Quiros (2000), Stock and Watson (2002), Sims and Zha (2006), Smets and Wouters (2007), Justiniano and Primiceri (2008), Canova, Gambetti, and Pappa (2008), and Canova (2009)). Second, we contrast the impulse responses produced by our non-recursive SVAR-WB with those obtained with a recursive SVAR-WB. This comparison is informative given the fact that the recursiveness assumption is still the most widely adopted one in the applied macroeconomic arena (for two reference papers, see Christiano, Eichenbaum and Evans (1999, 2005)).

Our results read as follows. First, we provide formal evidence of instability in the U.S. post-WWII macroeconomic impulse responses to a monetary policy shock in 1984Q1. Such evidence can be easily interpreted in light of the switch from the Great

[3] To be clear, our SVARs are not unstable in a statistical sense. Here we use the term 'instability' to refer to changes in the (regime-specific) impulse responses we analyze.

[4] Following Uhlig (2005), throughout the paper we term 'impulse vector' the column vector of the matrix of the SVAR which captures the on-impact response of the variables to an identified structural shock.

[5] The term 'Great Moderation' was coined by Stock and Watson (2002) to indicate the substantial reduction in the volatility of the U.S. real GDP growth rate and inflation occurred in the mid-1980s.

Inflation to the macroeconomic Great Moderation.[6] Second, we show that recursive restrictions imply responses that are extremely (and somewhat surprisingly) similar to those produced with a non-recursive scheme for the Great Inflation period. On the contrary, these two alternative identification schemes lead to substantially different predictions on the macroeconomic effects of monetary policy shocks as for the post-1984 phase. In particular, the response of output and investment to a one-standard deviation monetary policy shock is estimated to be larger and significantly negative when our non-recursive scheme is put at work. Other results are instead shown to be robust no matter whether the identification scheme in place is the recursive or the non-recursive one. The response of the long-term interest rate is shown to be clearly positive in the pre-break sample, but much milder, and mostly negative, during the Great Moderation. This last result confirms the one by Bagliano and Favero (1998), who work with different subsamples and a non-recursive scheme (less general than ours) and find a negative short run correlation between the federal funds rate and the long-term interest rate conditional on policy shocks in the Great Moderation period.

A list of robustness checks deals with important factors in our empirical analysis. First, a recent paper by Barakchian and Crowe (2013) points to 1988Q4 as a relevant break-date when it comes to understanding the effects of monetary policy shocks in two different policy regimes. In particular, they point to a change in the policy conduct by the Federal Reserve, which may have acted in a more forward-looking fashion since 1988. Second, following Justiniano, Primiceri and Tambalotti (2010, 2011), we deal with a different definition of investment, which comprises also durable consumption. The results of these two robustness checks largely confirm our baseline empirical findings. Third, we consider federal funds futures contracts to sharpen our identification of the monetary policy shocks. As pointed out by Barakchian and Crowe (2013) (and the literature cited therein), federal funds futures rates are likely to be informative as regards private sector's expectations over future policy moves. Then, they can be used to work out measures of policy shocks which are possibly more informative than those obtained with the standard 'federal funds rate only' approach. Given the limited availability of federal funds futures contracts (the first month these contracts are available is December 1988), we are unfortunately forced to abandon our identification-via-heteroskedasticity approach and focus on the post-1988 volatility regime only. Still,

[6] This result is robust to the employment of recursive and non-recursive identification schemes, and it is valid irrespective of whether the variables included in the SVARs-WB are modeled as highly persistent stationary time series or as non-stationary cointegrated time series (results available upon request).

we find that a recursive (Cholesky) SVAR produces quantitatively and, to some extent, qualitatively different responses to VARs featuring the standard federal funds rate, the futures rate for the current month only, or a factor computed by considering six different measures of futures rates as in Barakchian and Crowe (2013). We see the outcome of this third set of robustness checks as supportive of the employment of futures contracts in an identification-via-heteroskedasticity approach in future occasions, when more data will become available and different volatility regime will render our identification methodology feasible.

The paper is organized as follows. Section 2 illustrates the methodology used to identify the macroeconomic effects of monetary policy in our reference SVAR-WB. Section 3 presents and discusses a battery of results obtained with a standard vector of seven U.S. macroeconomic series. Section 4 documents and discusses our robustness checks. Section 5 relates our contribution to the existing methodological literature. Section 6 concludes.

2 The SVAR-WB: Identification analysis and implementation strategy

In this section we introduce the SVAR-WB and summarize the methodology we use to identify the macroeconomic effects of monetary policy shocks (Section 2.1). We then discuss the identification restrictions we impose on a SVAR-WB which includes seven U.S. macroeconomic variables, which is the model we use to quantify the effects of monetary shocks in a non-recursive economy (Section 2.2).

2.1 Representation and identification conditions

To fix ideas and notation, we briefly start from a reference fixed parameter-SVAR. Let $\boldsymbol{z}_t = (z_{1,t}, ..., z_{n,t})'$ be the $n \times 1$ vector of observable variables. We assume that the reference model for $\boldsymbol{z}_t$ is given by the SVAR:

$$\boldsymbol{z}_t = \boldsymbol{\Pi} \boldsymbol{w}_t + \boldsymbol{u}_t \quad , \boldsymbol{u}_t = \boldsymbol{C} \boldsymbol{e}_t \quad , \boldsymbol{e}_t \sim \mathrm{WN}(\boldsymbol{0}_n \ , \boldsymbol{I}_n), \quad t = 1, ..., T. \tag{1}$$

In system (1), $\boldsymbol{u}_t$ is the n-dimensional White Noise process of reduced form errors (disturbances) with covariance matrix $\boldsymbol{\Sigma}_u = E(\boldsymbol{u}_t \boldsymbol{u}_t')$, $\boldsymbol{w}_t = (\boldsymbol{z}_{t-1}', \boldsymbol{z}_{t-2}', ..., \boldsymbol{z}_{t-k}', \boldsymbol{d}_t')'$ is the vector of VAR regressors, k is the VAR lag order and $\boldsymbol{d}_t$ is a b-dimensional subvector collecting deterministic components. The reduced form parameters are contained in $\mathbf{\Pi} = (\boldsymbol{A}_1, ..., \boldsymbol{A}_k, \boldsymbol{\Psi})$ and $\mathbf{\Sigma}_u$, where $\boldsymbol{A}_j$, $j = 1, ..., k$ are $n \times n$ matrices, $\boldsymbol{e}_t$ is the n-dimensional vector of orthogonal structural shocks, $\boldsymbol{\Psi}$ collects the loadings of the deterministic components, and $\boldsymbol{C}$ is the $n \times n$ matrix which maps the structural shocks onto the VAR disturbances. We denote 'reduced form parameters' the elements in $\mathbf{\Pi}$ and $\mathbf{\Sigma}_u$, and 'structural parameters' the elements in $\boldsymbol{C}$.

Next, we assume that it is known that at time T_B, where $1 << T_B << T$, the matrix $\mathbf{\Sigma}_u$ changes. In our setup, also the matrix $\mathbf{\Pi}$ is allowed to change. The date T_B corresponds to the first observation in the second regime. We focus on the case of a single break for simplicity, consistently with the developments in the next empirical sections. However, our methodology can in principle be extended to a number of break dates larger than one, along the lines discussed in Bacchiocchi and Fanelli (2015). T_B (and the other possible break dates) might be also inferred from the data.

The baseline specification in eq. (1) is replaced with

$$\boldsymbol{z}_t = \mathbf{\Pi}(t)\boldsymbol{w}_t + \boldsymbol{u}_t \ , \ \boldsymbol{u}_t = \boldsymbol{C}(t)\boldsymbol{e}_t \quad , \ \boldsymbol{e}_t \sim \mathrm{WN}(\mathbf{0}_n \ , \ \boldsymbol{I}_n) \tag{2}$$

where $\mathbf{\Pi}(t)$ and $\mathbf{\Sigma}_u(t)$ are given by

$$\mathbf{\Pi}(t) = \mathbf{\Pi}_1 \times \mathbf{1}\,(t < T_B) + \mathbf{\Pi}_2 \times \mathbf{1}(t \geq T_B) \tag{3}$$

$$\mathbf{\Sigma}_u(t) = \mathbf{\Sigma}_{u,1} \times \mathbf{1}\,(t < T_B) + \mathbf{\Sigma}_{u,2} \times \mathbf{1}(t \geq T_B). \tag{4}$$

In eq.s (3)-(4), $\mathbf{1}\,(\cdot)$ is the indicator function, $\mathbf{\Pi}_1$ and $\mathbf{\Sigma}_{u,1}$ are the matrices of reduced form parameters in the pre-break regime and $\mathbf{\Pi}_2$ and $\mathbf{\Sigma}_{u,2}$ are the reduced form parameters in the post-break regime, respectively. We temporarily leave the $\boldsymbol{C}(t)$ matrix in eq. (2) unspecified. Our main assumption is that $\mathbf{\Sigma}_{u,1} \neq \mathbf{\Sigma}_{u,2}$, i.e., the data are characterized by two volatility regimes. We allow, but not necessarily require, the condition $\mathbf{\Pi}_1 \neq \mathbf{\Pi}_2$ to be met.

One crucial hypothesis in the recent literature on the identification of SVARs through changes in volatility is that the variation in $\mathbf{\Sigma}_u$ *is not associated* with a change in $\boldsymbol{C}$, i.e. $\boldsymbol{C}(t) = \boldsymbol{C}$ for $t = 1, ..., T$, given eq. (4). Under this condition, one can uniquely identify the elements of $\boldsymbol{C}$ (up to sign changes) by exploiting the simultaneous factorization of the matrices $\mathbf{\Sigma}_{u,1}$ and $\mathbf{\Sigma}_{u,2}$:

$$\mathbf{\Sigma}_{u,1} = \boldsymbol{P}\boldsymbol{P}' \quad , \quad \mathbf{\Sigma}_{u,2} = \boldsymbol{P}\boldsymbol{V}\boldsymbol{P}' \tag{5}$$

where $\boldsymbol{P}$ is a $n \times n$ non-singular matrix and $\boldsymbol{V} = \mathrm{diag}(v_1, ..., v_n) \neq \boldsymbol{I}_n$ is a diagonal matrix with elements $v_i > 0$, $i = 1, ..., n$. Identification can be achieved by setting $\boldsymbol{C} = \boldsymbol{P}$, where the choice $\boldsymbol{C}=\boldsymbol{P}$ is unique except for sign changes if all v_i's are distinct, see Lanne and Lütkepohl (2008, 2010). In this case, as also noticed by Rigobon (2003) in the context of simultaneous systems of equations, no theory-driven restriction is needed to identify $\boldsymbol{C}$. However, as previously pointed out, one has to assume the coefficients of the matrix of the contemporaneous relationships to be fixed. We relax this assumption by *allowing for changes in the* $\boldsymbol{C}$ *matrix across volatility regimes* via the following specification:

$$\boldsymbol{C}(t)=\boldsymbol{C}+\boldsymbol{Q}\times\mathbf{1}\,(t\geq T_B) \tag{6}$$

in which $\boldsymbol{Q}$ is a $n\times n$ matrix whose elements capture the changes (if any) of the coefficients of $\boldsymbol{C}$ from the pre- to the post-break regime, and the matrix $(\boldsymbol{C}+\boldsymbol{Q})$ is assumed to be invertible. The so-defined SVAR gives rise to the set of restrictions

$$\begin{aligned}\boldsymbol{\Sigma}_{u,1} &= \boldsymbol{C}\boldsymbol{C}' &&, \quad t=1,...,T_B-1 &(7)\\ \boldsymbol{\Sigma}_{u,2} &= (\boldsymbol{C}+\boldsymbol{Q})(\boldsymbol{C}+\boldsymbol{Q})' &&, \quad t=T_B,...,T. &(8)\end{aligned}$$

In this parametrization, the hypothesis $\boldsymbol{\Sigma}_{u,1}\neq\boldsymbol{\Sigma}_{u,2}$ implies $\boldsymbol{Q}\neq 0_{n\times n}$, i.e. the change in the covariance matrix is automatically associated with a change in the structural parameters.[7]

Eq.s (7)-(8) are not sufficient to identify the shocks of the SVAR with a break. To see this, observe that eq.s (7)-(8) provide $n(n+1)$ symmetry-induced restrictions, while $\boldsymbol{C}$ and $\boldsymbol{Q}$ contain $2n^2$ elements. In absence of further restrictions, $n(n-1)$ parameters in $\boldsymbol{C}$ and $\boldsymbol{Q}$ are unidentified. We thus consider a set of linear restrictions on $\boldsymbol{C}$ and $\boldsymbol{Q}$ that we write in explicit form

$$\begin{pmatrix} vec(\boldsymbol{C}) \\ vec(\boldsymbol{Q}) \end{pmatrix}=\begin{pmatrix} \boldsymbol{S}_C & \boldsymbol{S}_I \\ \mathbf{0}_{n^2\times a_C} & \boldsymbol{S}_Q \end{pmatrix}\begin{pmatrix} \boldsymbol{\varphi} \\ \boldsymbol{q} \end{pmatrix}+\begin{pmatrix} \boldsymbol{s}_C \\ \boldsymbol{s}_Q \end{pmatrix} \tag{9}$$

and by which the SVAR in eq. (2) can be identified.[8] In eq. (9), $\boldsymbol{\varphi}$ is a $a_C\times 1$ vector which collects the unrestricted (free) structural parameters of the matrix $\boldsymbol{C}$, $\boldsymbol{S}_C$ is a

[7]The converse, instead, is not generally true because it is possible to find examples in which $\boldsymbol{Q}\neq 0_{n\times n}$ but $\boldsymbol{\Sigma}_{u,1}$=$\boldsymbol{\Sigma}_{u,2}$. Consider, as an example, the case

$$\boldsymbol{C}:=\begin{pmatrix} c_{11} & -c_{12} \\ c_{12} & c_{22} \end{pmatrix} \quad , \quad \boldsymbol{Q}:=2c_{12}\begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix}.$$

[8]The upper triangular structure of the matrix $\boldsymbol{S}=\begin{pmatrix} \boldsymbol{S}_C & \boldsymbol{S}_I \\ \mathbf{0}_{n^2\times a_C} & \boldsymbol{S}_Q \end{pmatrix}$ that governs the restrictions is not mandatory. Indeed, it can be easily shown that given a set of generic linear restrictions, using the QR-decomposition, it can be transformed into an upper triangular structure (upper trapezoidal matrix) as in the definition of S.

$n^2 \times a_C$ known selection matrix, $\boldsymbol{s}_C$ is a $n^2 \times 1$ known vector and $a_C \leq \frac{1}{2}n(n-1)$, $\boldsymbol{q}$ is a $a_Q \times 1$ vector which collects the unrestricted (free) elements of the matrix $\boldsymbol{Q}$, $\boldsymbol{S}_Q$ is a $n^2 \times a_Q$ known selection matrix and $\boldsymbol{s}_Q$ is a $n^2 \times 1$ known vector. Finally, $\boldsymbol{S}_I$ is a known selection matrix by which it is possible to impose cross-restrictions on the elements of $\boldsymbol{C}$ and $\boldsymbol{Q}$. Obviously, $\boldsymbol{S}_I$ will be zero in the case of no cross-restrictions.

Throughout the paper we denote the system described by eq.s (2)-(4), eq. (6) and eq. (9) with the acronym 'SVAR-WB'. The necessary and sufficient rank condition that ensures that the SVAR-WB is identified (locally) are discussed in detail in Bacchiocchi and Fanelli (2015).[9] We briefly report the rank condition here, given its crucial role in our approach.

Let the matrices $\boldsymbol{C}_0$ and $(\boldsymbol{C}_0+\boldsymbol{Q}_0)$ be non-singular, where $\boldsymbol{C}_0$ and $\boldsymbol{Q}_0$ are the counterparts of $\boldsymbol{C}$ and $\boldsymbol{Q}$ once the vectors $\boldsymbol{\varphi}$ and $\boldsymbol{q}$ in eq. (9) have been replaced by their 'true' values $\boldsymbol{\varphi}_0$ and $\boldsymbol{q}_0$. Then, the SVAR-WB is locally identified if and only if

$$rank\left\{(\boldsymbol{I}_2 \otimes \boldsymbol{D}_n^+)\begin{pmatrix} (\boldsymbol{C}_0 \otimes \boldsymbol{I}_n) & \boldsymbol{0}_{n^2\times n^2} \\ (\boldsymbol{C}_0 + \boldsymbol{Q}) \otimes \boldsymbol{I}_n & (\boldsymbol{C}_0 + \boldsymbol{Q}_0) \otimes \boldsymbol{I}_n \end{pmatrix}\begin{pmatrix} \boldsymbol{S}_C & \boldsymbol{S}_I \\ \boldsymbol{0}_{n^2\times a_C} & \boldsymbol{S}_Q \end{pmatrix}\right\} = a_C + a_Q \tag{10}$$

where $\boldsymbol{D}_n^+ = (\boldsymbol{D}_n'\boldsymbol{D}_n)^{-1}\boldsymbol{D}_n'$ is the Moore-Penrose inverse of the duplication matrix $\boldsymbol{D}_n$ (i.e. $\boldsymbol{D}_n$ is such that $\boldsymbol{D}_n vech(\boldsymbol{\Sigma}_{u,1}) = vec(\boldsymbol{\Sigma}_{u,1})$), and $\boldsymbol{v}_0 = (\boldsymbol{\varphi}_0', \boldsymbol{q}_0')'$ is a 'regular point'.[10] The necessary order condition is

$$(a_C + a_Q) \leq n(n+1) \tag{11}$$

and this condition can be interpreted by observing that the number of free elements specified in $\boldsymbol{C}$ and $\boldsymbol{Q}$ can not exceed the total number of free elements in the covariance matrices $\boldsymbol{\Sigma}_{u,1}$ and $\boldsymbol{\Sigma}_{u,2}$.

[9] It is worth stressing that in our context it is not possible to apply, or easily generalize, the conditions for global identification of SVARs discussed in Rubio-Ramírez, Waggoner, and Zha (2010). Indeed, the necessary and sufficient conditions for global identification provided by Rubio-Ramírez, Waggoner, and Zha (2010) refer to exactly identified models, while we have in mind a more general setup (Rubio-Ramírez, Waggoner, and Zha (2010) discuss only sufficient conditions for more general cases). Second, and more importantly, the restrictions implied by eq.s (7)-(9) are not consistent with the class of identifying restrictions considered by Rubio-Ramírez, Waggoner, and Zha (2010). Hence, we confine our analysis to the concept of local identification, see Bacchiocchi and Fanelli (2015) for details.

[10] This means that the rank condition in eq. (10) does not change within a neighborhood of $\boldsymbol{v}_0$. The full-column rank condition in eq. (10) can be verified ex-post by replacing $\boldsymbol{\gamma}$ and $\boldsymbol{q}$ with their maximum likelihood estimates. Alternatively, Bacchiocchi and Fanelli (2012) discuss an algorithm that can be used to check the rank condition prior to estimation.

The SVAR-WB is just-identified when the rank condition in eq. (10) holds and the number of restrictions on $\boldsymbol{C}$ and $\boldsymbol{Q}$ is $(a_C + a_Q) = n(n+1)$, and is over-identified (with testable over-identification restrictions) when the rank condition in eq. (10) holds with $(a_C + a_Q) < n(n+1)$. In both cases, the (population) orthogonalized IRFs are given by

$$\boldsymbol{\Gamma}_{1,h} = \left(\gamma_{1,l,m,h}\right) = \boldsymbol{G}'(\boldsymbol{A}_1^*)^h \boldsymbol{G}\boldsymbol{C}_0 \ , \ \ h = 0, 1, 2, ... \tag{12}$$

on the 'pre-break' regime, and

$$\boldsymbol{\Gamma}_{2,h} = \left(\gamma_{2,l,m,h}\right) = \boldsymbol{G}'(\boldsymbol{A}_{\mathbf{2}}^*)^h \boldsymbol{G}(\boldsymbol{C}_0 + \boldsymbol{Q}_0) \ , \ \ h = 0, 1, 2, ... \tag{13}$$

on the 'post-break' regime, where $\boldsymbol{G}$ is a selection matrix of conformable dimensions and

$$\boldsymbol{A}_i^* = \begin{pmatrix} & \boldsymbol{\Pi}_i & \\ \boldsymbol{I}_{n(k-1)} & & \mathbf{0}_{n(k-1)\times n} \end{pmatrix} \ , \quad i = 1, 2$$

are the reduced form VAR companion matrices in the pre- and post-break regimes, respectively. Note that given our assumption on $\boldsymbol{\Pi}_{\mathbf{1}}$ and $\boldsymbol{\Pi}_{\mathbf{2}}$, $\boldsymbol{A}_{\mathbf{1}}^*$ and $\boldsymbol{A}_{\mathbf{2}}^*$ may be different or equal in eq.s (12)-(13). In our setup, the element $\gamma_{i,l,m,h} = \frac{\partial z_{l,t}}{\partial e_{m,t-h}}$ of the matrix $\boldsymbol{\Gamma}_{i,h}$ captures the response of variable $z_{l,t}$ to a structural shock $e_{m,t}$ at horizon h (h=0,1,2,...), in the volatility regime characterized by the covariance matrix $\boldsymbol{\Sigma}_{u,i}$, $i = 1, 2$.

In presence of stationary variables, the IRFs in eq.s (12)-(13) can be estimated consistently by replacing the matrices $\boldsymbol{C}_0$, $\boldsymbol{Q}_0$ and $\boldsymbol{A}_i^*$, $i = 1, 2$ ($\boldsymbol{A}_1^*$ and $\boldsymbol{A}_2^*$ have all their eigenvalues inside the unit circle) with their maximum likelihood estimates, see Bacchiocchi and Fanelli (2012, 2015). The same can be done if $\boldsymbol{z}_t$ contains non-stationary cointegrated variables, provided the unit roots driving the system are properly imposed in the Vector Error Correction representation of the system as suggested in, e.g., Lütkepohl and Reimers (1992), Amisano and Giannini (1997), Phillips (1998), and Vlaar (2004). A detailed discussion on cointegrated SVARs-WB can be found in Section 5 in Bacchiocchi and Fanelli (2015, Supplementary Material). Confidence bands for the IRFs in eq.s (12)-(13) can be computed accordingly, possibly using bootstrap confidence bands as in e.g. Kilian (1998).

Summing up, the methodology we follow in this paper allows for a mapping from the reduced-form residuals to the structural shock(s) of interest which admits, but does not necessarily impose, heteroskedasticity in the residuals to translate into changes in the contemporaneous structural relationships in our SVAR. This implies that a given shock (say a monetary policy shock) of a given size (common between two different regimes), can very well generate regime-dependent impulse responses. In Section 5 we frame the SVAR-WB methodology within the literature on identification of SVARs and compare it with other identification-by-heteroskedasticity methods. The next Section discusses how we specify the matrices $\boldsymbol{C}$ and $\boldsymbol{Q}$ to identify the monetary policy shock in a SVAR-WB which contains seven macroeconomic variables of interest.

2.2 Identification restrictions: Discussion

The SVAR-WB introduced in the previous section provides more flexible conditions for the identification of the structural shocks relative to the case of fixed parameter SVARs. As it will be shown below, specifications for the $\boldsymbol{C}$ matrix that would lead to unidentified systems in the case of fixed parameter SVARs are now possible. Such flexibility is essentially guaranteed by the use of more information stemming from the different volatility regimes detected in the data. Bacchiocchi and Fanelli (2012, 2015) discuss possible specifications of the matrices $\boldsymbol{C}$ and $\boldsymbol{Q}$ that can be used to identify monetary policy shocks in small-scale VARs. Here we extend the analysis to the case of a large system, which will be estimated on U.S. quarterly data next.

Consider the vector $\boldsymbol{z}_t$ of seven U.S. macroeconomic variables which includes non-durable personal consumption (NDCONS), durable personal consumption (DCONS), fixed-private investments (INVEST), gross domestic product (GDP), inflation (INFL), federal funds rate (FFR), and 10 year-Treasury Bill rate (10YR). A SVAR-WB for $\mathbf{z}_t$:=($NDCONS_t$, $DCONS_t$, $INVEST_t$, GDP_t, $INFL_t$, FFR_t, $10YR_t$)' will be estimated in Section 3 on U.S. quarterly data.[11] We assume that two heteroskedasticity regimes are detected from the data, with T_B being the break-date. Recall that the matrix $\boldsymbol{C}$ captures the contemporaneous structural relationships that characterize the variables, while the matrix $\boldsymbol{Q}$ captures possible post-break changes in these relationships. Thus, while the specification of $\boldsymbol{C}$ is driven by the theory, the specification of $\boldsymbol{Q}$ reflects the investigator's view about possible changes in the instantaneous effects of the shocks but can not neglect the statistical properties of the data.

Identification restrictions, non-recursive SVAR-WB: $\boldsymbol{C}$ matrix. We first discuss the identifying restrictions on $\boldsymbol{C}$. Since the idea here is to investigate the effects of monetary policy shocks, let's consider such shocks first. A safe assumption is that of

[11] The source of the data is the Federal Reserve Bank of St. Louis. The first four time series are all expressed in real and per-capita terms, and are considered in logs. The inflation rate is computed as the quarterly growth rate of the GDP deflator. The interest rates are quarterly rates. All series are expressed in percent terms.

the possibly immediate impact of a monetary policy shock on the federal funds rate (the monetary policy instrument in our vector) as well as on a "fast moving" variable like the long-term Treasury Bill rate. Given the emphasis placed by the Federal Reserve on the control of the inflation rate in the U.S., we allow for the possibility of an immediate impact of this variable as well. However, lags in the transmission of monetary policy shocks to real activity are well known (Svensson (1997)). Hence, we assume that "slow moving variables" such as consumption (both durable and non-durable) and investment are non immediately affected by exogenous variations in the nominal interest rate. Of course, moves in the policy rate may contemporaneously affect, say, exchange rates (both nominal and real), net exports, and therefore real GDP. While not modeling measures of external pressures such as exchange rates and net exports, we allow for a contemporaneous variation of real GDP after a monetary policy shock. For the remaining impulse vectors in the $\boldsymbol{C}$ matrix, which are related to non-monetary policy shocks we do not focus on in this paper, we follow the extant literature and assume a triangular structure as in Christiano, Eichenbaum and Evans (1999, 2005), the only exception being the contemporaneous systematic response of monetary policy to durable consumption, which we assume to be zero. This last assumption is justified by the fact that U.S. policymakers do not typically refer to durable consumption as a variable they systematically respond to. Overall, these considerations lead to the following structure for the matrix $\boldsymbol{C}$:

$$\boldsymbol{C} := \begin{pmatrix} * & & & & & & \\ * & * & & & & & \\ * & * & * & & & & \\ * & * & * & * & & * & \\ * & * & * & * & * & * & \\ * & & * & * & * & * & \\ * & * & * & * & * & * & * \end{pmatrix} \begin{array}{c} \text{NDCONS} \\ \text{DCONS} \\ \text{INVEST} \\ \text{GDP} \\ \text{INFL} \\ \text{FFR} \\ \text{10YR} \end{array} \tag{14}$$

where we have reported the names of the variables alongside the rows to improve readability. In eq. (14), asterisks ('$*$') denote unrestricted (free) coefficients and empty entries correspond to zeros. The number of free parameters in $\boldsymbol{C}$ in eq. (14) is $a_C = 29$. It is important to notice that, in a "conventional" framework, a SVAR based on $\boldsymbol{u}_t = \boldsymbol{C}\boldsymbol{e}_t$ with $\boldsymbol{C}$ as in eq. (14) would be unidentified because the order condition would not be satisfied.

Identification restrictions, non-recursive SVAR-WB: $\boldsymbol{Q}$ matrix. We now discuss the specification of $\boldsymbol{Q}$. Changes in the norms regulating financial markets which occurred in the early 1980s, like the Depository Institutions Deregulation and Monetary Control Act in 1980, particularly the termination of regulation Q, and the Garn-St. Germain Act of 1982, have granted easier access to financial liquidity to households and firms. This may have had an impact on the effects of monetary policy shocks on short- and long-term rates, as well as on aggregates like consumption and investment. We then allow for a change in the impact of monetary policy shocks on the federal funds rate and the long-term interest rate, non-durable consumption (possibly financed by very short-term borrowings, whose interest rates is probably proxied by the federal funds rate) and investment (financed by longer-term borrowings, whose interest rate is proxied by the long-term interest rate). Moreover, given the change in the systematic monetary policy regime documented by Clarida, Galí, and Gertler (2000), among others, we also allow for a change in the contemporaneous interest rate-inflation relationship. Moving to other impulse vectors, given the relevance of inflationary shocks for the term structure of interest rates, we allow shocks to inflation to exert a different effect on the short- and long-term interest rate. We also allow for all elements of the main diagonal of the matrix $\boldsymbol{Q}$ to vary over regime, something that enables us to estimate regime-specific standard deviations for the structural shocks. In light of some recent evidence pointing to a change in the policy response to output fluctuations (Coibion and Gorodnichenko (2011)), we allow for a possible variation of the impact of real GDP shock on the federal funds rate. Finally, we allow non-durable consumption shocks to exert a different post-break effect on durable consumption, investment, and GDP, shocks to durable consumption to have a different impact on investment and GDP. Overall, these considerations lead to the following structure for the matrix $\boldsymbol{Q}$:

$$\boldsymbol{Q} := \begin{array}{cc} \begin{pmatrix} * & & & & & * & \\ * & * & & & & & \\ * & * & * & & & * & \\ * & * & & * & & & \\ & & & & * & * & \\ & & & * & * & * & \\ & & & & * & * & * \end{pmatrix} & \begin{array}{c} \text{NDCONS} \\ \text{DCONS} \\ \text{INVEST} \\ \text{GDP} \\ \text{INFL} \\ \text{FFR} \\ \text{10YR} \end{array} \end{array} \qquad (15)$$

Preliminary investigations led us to test and accept the restriction additional restriction $q_{5,6} = -c_{5,6}$, which implies that the monetary policy shock has no instantaneous impact on the inflation rate in the post-break regime, an assumption in line with the standard recursive approach. Fixed the matrix $\boldsymbol{C}$ as in eq. (14), the necessary order condition in eq. (11) requires that $a_Q \leq n(n+1) - a_C = 39$. In eq. (15) we have $a_Q = 18$.

Jointly, eq.s (14)-(15) allow us to specialize the relationship $\boldsymbol{u}_t = \boldsymbol{C}(t)\boldsymbol{e}_t = (\boldsymbol{C} + \boldsymbol{Q} \times \mathbf{1}\,(t \geq T_B))\,\boldsymbol{e}_t$ in the expression

$$
\underbrace{\begin{pmatrix} u_t^{NDCONS} \\ u_t^{DCONS} \\ u_t^{INVEST} \\ u_t^{GDP} \\ u_t^{INFL} \\ u_t^{FFR} \\ u_t^{10YR} \end{pmatrix}}_{\boldsymbol{u}_t} = \left\{ \underbrace{\begin{pmatrix} * & & & & & & \\ * & * & & & & & \\ * & * & * & & & & \\ * & * & * & * & & * & \\ * & * & * & * & * & * & \\ * & & * & * & * & * & \\ * & * & * & * & * & * & * \end{pmatrix}}_{\boldsymbol{C}} \right.
$$

$$
\left. + \underbrace{\begin{pmatrix} * & & & & & * & \\ * & * & & & & & \\ * & * & * & & & * & \\ * & * & & * & & & \\ & & & & * & * & \\ & & & * & * & * & \\ & & & & * & * & * \end{pmatrix}}_{\boldsymbol{Q}} \times \mathbf{1}\,(t \geq T_B) \right\} \underbrace{\begin{pmatrix} e_t^{NDCONS} \\ e_t^{DCONS} \\ e_t^{INVEST} \\ e_t^{GDP} \\ e_t^{INFL} \\ e_t^{FFR} \\ e_t^{10YR} \end{pmatrix}}_{\boldsymbol{e}_t}, \tag{16}
$$

which, provided the rank condition in eq. (10) is satisfied, implies an over-identified SVAR-WB for $\mathbf{z}_t$ featuring $n(n+1) - (a_C + a_Q) = 9$ (testable) over-identification restrictions. The interpretation of the reduced form disturbances u_t^x and structural shocks e_t^x, $x = \{NDCONS,\ DCONS,\ INVEST,\ GDP,\ INFL,\ FFR,\ 10YR\}$ in eq. (16) is straightforward.

Identification restrictions, recursive SVAR-WB: $\boldsymbol{C}$ and $\boldsymbol{Q}$ matrices. In the next section, the non-recursive SVAR-WB based on the specifications in eq. (16) will be contrasted empirically with a 'recursive' system based on the following triangular structure for $\boldsymbol{C}$ and $\boldsymbol{Q}$:

$$
\underbrace{\begin{pmatrix} u_t^{NDCONS} \\ u_t^{DCONS} \\ u_t^{INVEST} \\ u_t^{GDP} \\ u_t^{INFL} \\ u_t^{FFR} \\ u_t^{10YR} \end{pmatrix}}_{\boldsymbol{u}_t} = \left\{ \underbrace{\begin{pmatrix} * & & & & & & \\ * & * & & & & & \\ * & * & * & & & & \\ * & * & * & * & & & \\ * & * & * & * & * & & \\ * & * & * & * & * & * & \\ * & * & * & * & * & * & * \end{pmatrix}}_{\boldsymbol{C}} \right.
$$

$$+\underbrace{\begin{pmatrix} * & & & & & & \\ * & * & & & & & \\ * & * & * & & & & \\ * & * & * & * & & & \\ * & * & * & * & * & & \\ * & * & * & * & * & * & \\ * & * & * & * & * & * & * \end{pmatrix}}_{\boldsymbol{Q}} \times \mathbf{1}\left(t \geq T_B\right) \Bigg\} \underbrace{\begin{pmatrix} e_t^{NDCONS} \\ e_t^{DCONS} \\ e_t^{INVEST} \\ e_t^{GDP} \\ e_t^{INFL} \\ e_t^{FFR} \\ e_t^{10YR} \end{pmatrix}}_{\boldsymbol{e}_t}. \tag{17}$$

In the SVAR-WB defined by eq. (17), the structural parameters are allowed to change across the two volatility regimes without changing the triangular - Cholesky-type - structure underlying the mapping from e_t to u_t. The ordering of the variables in eq. (17) is justified by the usual considerations regarding "slow moving" variables (those ordered before the federal funds rate) vs. "fast moving" ones (the long term interest rate). The rank condition in eq. (10) is met and the SVAR-WB is exactly identified. Obviously, the efficiency of the structural parameter estimates can be improved by setting to zero in estimation the coefficients in $\boldsymbol{C}$ and $\boldsymbol{Q}$ that are not significant. In that case, the SVAR-WB in eq. (17) becomes automatically over-identified.

3 Empirical results

As anticipated, we model the vector $\mathbf{z}_t$:=($NDCONS_t$, $DCONS_t$, $INVEST_t$, GDP_t, $INFL_t$, FFR_t, $10YR_t$)'. We specify our reduced form VAR for $\mathbf{z}_t$ with equation-specific constants and four lags.[12] We consider the sample 1960Q1-2008Q2. The beginning of the sample corresponds approximately to the beginning of the phase of rising inflation in the post-WWII U.S. economic history. The end of the sample is justified by our decision to avoid dealing with the acceleration of the financial crisis and, above all, with the binding zero-lower bound (ZLB) that has kicked in since the end of 2008. The presence of the ZLB calls for a non-linear version of the model, which we do not develop here.

Our aim is to identify the macroeconomic effects of a monetary policy shock. We do so by working with the two SVARs-WB introduced in the previous section. Both these models are based on the (testable) hypothesis of a change in the error covariance matrix $\boldsymbol{\Sigma}_u$ at the beginning of the 1980s (see Section 3.1), and fulfill the identification

[12] A robustness check involving an equation-specific linear trend returned virtually identical results.

conditions discussed in the previous section. Throughout the paper, the SVAR-WB in eq. (16) will be termed 'non-recursive SVAR-WB' and will be analyzed in detail in Section 3.2. The SVAR-WB in eq. (17) will be termed 'recursive SVAR-WB' and will be analyzed in detail in Section 3.3. The plausibility of our identified monetary policy shock and a formal comparison between these two models will be discussed in Sections 3.4-3.5.

3.1 Evidence of a change in the VAR error covariance matrix

As shown in Section 2, the SVAR-WB approach hinges upon the exploitation of a structural break. The macroeconomic literature has recently documented a dramatic fall in the variances of the main macroeconomic indicators, which has been termed 'Great Moderation'. Kim and Nelson (1999) and Stock and Watson (2002) offer support for a break in the macroeconomic volatilities around 1984. McConnell and Perez-Quiros (2000) identify 1984Q1 as the break-date of the variance of the U.S. real GDP. Boivin and Giannoni (2006) also detect a break in the coefficients of a reduced-form VAR for the U.S. economy in the early 1980s. As in Justiniano and Primiceri (2008) and Blanchard and Riggi (2013), we take such date as a break-point in our sample, i.e., T_B =1984Q1.

We formally test the occurrence of the break in the reduced form parameters at time T_B =1984Q1 through a standard LR Chow-type test. We first focus on the joint null hypothesis that the VAR reduced form parameters are constant across the two regimes 1960Q1-1983Q4 and 1984Q1-2008Q2, i.e. $(\mathbf{\Pi}_1 = \mathbf{\Pi}_2) \wedge (\mathbf{\Sigma}_{u,1} = \mathbf{\Sigma}_{u,2})$ against the alternative $(\mathbf{\Pi}_1 \neq \mathbf{\Pi}_2) \vee (\mathbf{\Sigma}_{u,1} \neq \mathbf{\Sigma}_{u,2})$. The null hypothesis of stable parameters is clearly rejected. The LR statistic is equal to LR =-2[1213.20 - (602.89+953.90)]=687.18 and has a p-value of 0.000 (taken from the $\chi^2(231)$ distribution).[13] Obviously, also the LR Chow-type test for the null $\mathbf{\Sigma}_{u,1} = \mathbf{\Sigma}_{u,2}$ against the alternative $\mathbf{\Sigma}_{u,1} \neq \mathbf{\Sigma}_{u,2}$ (conditional on $\mathbf{\Pi}_1 = \mathbf{\Pi}_2$) leads us to strongly reject the null of stability (homoskedasticity).

Overall, even admitting that the LR Chow-type tests may be over-rejective in finite samples, we can safely conclude that the sub-periods 1960Q1-1983Q4 and 1984Q1-2008Q2 represent two distinct regimes characterized by different error covariance matrices. This evidence calls for the employment of models able to deal with breaks and provide information for the identification of monetary policy shocks, a task for which our SVAR-WB approach is clearly suited.

[13] Our estimates are 'quasi'-ML estimates because of the maintained assumption of a Gaussian likelihood. Thus, all LR tests discussed throughout the paper should be interpreted as 'quasi'-LR tests.

3.2 Non-recursive approach

Non-recursive SVAR-WB: Identification scheme. Identified T_B =1984Q1 as the relevant break-date, the specification in eq. (16) implies an over-identified SVAR-WB that meets the necessary and sufficient rank condition in eq. (10), and whose structure is not rejected by a LR test with a p-value of 0.14. The lower panel of Table 1 reports the ML estimates of $\boldsymbol{C}$ and $\boldsymbol{Q}$.

Non-recursive SVAR-WB: IRFs. Figure 1 depicts the impulse responses conditional on our non-recursive identification scheme. We comment on the pre-break-date responses first. An unexpected increase in the short-term policy rate trigger conventional macroeconomic reactions (see, e.g., Christiano, Eichenbaum, and Evans, 1999, 2005). In particular, all real aggregates react negatively, persistently, and significantly to such a monetary policy tightening. The reaction of durable spending comoves positively with non-durable spending, but with a much larger sensitivity with respect to the latter. This result is in line with some recent evidence by Erceg and Levin (2006), Barsky, House, and Kimball (2007), and Monacelli (2009). Investments comove with consumption and real GDP, with a sensitivity much larger than that of non-durable consumption and GDP, but very similar to the one of durable spending. The recessionary effects of a monetary policy tightening are associated to a persistent and significant deflationary phase. The long-term interest rate comoves positively with the short-term policy rate, it shows an on-impact positive and significant reaction, and a persistent decline towards its steady state value, which is reached after some quarters. Finally, an exogenous increase in the federal funds rate is followed by a positive (but insignificant) short-run response of inflation. This 'price puzzle' is a well-known regularity in the VAR literature (Eichenbaum, 1992). Interestingly, our results suggest that such regularity is not only present when recursive identification schemes are employed, but also when our non-recursive SVAR-WB is put at work.

Conditional on an increase in the federal funds rate of one-standard deviation, the post-break dynamics reveal a much more moderate reaction of the economic system. Still, significantly negative and persistent responses are found as regards all real activity indicators (non-durable and durable consumption, investment, and output), with investment displaying a much more accentuated response here with respect to the rest of the real GDP components. The reaction of inflation is statistically non-significant, and no price puzzle is detected. This result confirms that the 'price puzzle' evidence is likely to be a product of the high correlation between inflation and the federal funds rate in the 1970s, as stressed by the previous analysis by Hanson (2004), Boivin and Giannoni (2006), Castelnuovo and Surico (2010), and Boivin, Kiley, and Mishkin (2010). The response of the long-term rate turns out to be somewhat different as for its dynamics, and it is also imprecisely estimated.

3.3 Recursive approach

Recursive SVAR-WB: Identification scheme. The upper panel of Table 1 reports the ML estimates of the matrices $\boldsymbol{C}$ and $\boldsymbol{Q}$ obtained under the scheme in eq. (17), considering only coefficients with associated 't-ratio' larger than one.

Recursive vs. non-recursive SVAR-WB: IRFs. Figure 2 displays the IRF point estimates obtained with the recursive scheme over those obtained with the non-recursive one employed in the previous Section. Interestingly, the top panels in Figure 2 reveals that the recursive and non-recursive schemes deliver very similar responses for the pre-break period. Differently, the Great Moderation period is associated to stronger responses by real activity indicators such as nondurable consumption, investment, and output when the non-recursive scheme is employed. In particular, the on-impact responses of GDP and investment, which are zero by construction in the recursive case, are instead negative according to the non-recursive scheme. A look at Figure 1 reveals that such responses are significantly negative at a 95% confidence level. Consistently with a large number of DSGE models (see, e.g., Smets and Wouters (2007), Benati and Surico (2009), Canova (2009), Castelnuovo (2012)), we find monetary policy shocks to trigger a response of real activity within a quarter. It is important to recall here that, by construction, such on impact non-zero response is just a-priori excluded when a standard recursive scheme is employed, something which can lead to biased impulse responses (Castelnuovo (2016)).

3.4 Plausibility of our non-recursive identification scheme: A discussion

A discussion on the monetary policy shocks identified with our non-recursive identification procedure is in order. Our methodology does not impose any zero-restrictions to identify monetary policy shocks on variables like real GDP and inflation. Monetary policy shocks are often identified in VAR analysis by assuming that they do not exert an immediate impact on quantities as well as prices. Differently, demand and supply shocks are allowed to have an immediate impact on the policy instrument, typically a short-term interest rate. Restrictions of this type have been popularized by, among others, Christiano, Eichenbaum, and Evans (1999, 2005). Admittedly, if variables like consumption, investment, output, and inflation are genuinely "slow-moving" and react to monetary policy shocks with a delay up to a quarter, missing the imposition of such zero-restrictions may result in a lack of relevant information in our non-recursive identification scheme. However, we note that the zero-restrictions imposing a lag in the response of macroeconomic aggregates are not undisputed in the literature. In fact, they are not consistent with micro-founded models relying on standard assumptions on the timing of the formation of rational expectations, which allows immediate effects of monetary policy shocks on the components of real GDP and inflation (see, e.g., Smets and Wouters (2007)). Moreover, as anticipated in our Introduction, recent contributions have found support for an immediate response of output and inflation to monetary policy shocks (see, Del Negro, Schorfheide, Smets, and Wouters (2007) for output, and Faust, Swanson, and Wright (2004) for inflation, Normandin and Phaneuf (2004) for both). Moreover, interest rates other than the federal funds rate are likely to react to monetary policy shocks within a quarter (Bagliano and Favero (1998), Gertler and Karadi (2014)). Hence, it seems of interest to work with identification schemes alternative to the recursive one, which is what we do in this paper.

It is important to check the sensibility of our estimates of the monetary policy shocks. Figure 3 contrasts our estimates of the policy shocks conditional on our non-recursive model with four alternative measures of policy shocks, i.e., the one obtained with our recursive framework admitting a break, the one obtained with a standard recursive SVAR à la Christiano, Eichenbaum, and Evans (1999, 2005) which assumes no breaks in the VAR coefficients, the monetary policy shocks estimated by Smets and Wouters (2007), a measure of policy shocks proposed by Romer and Romer (2004), and the new measure of shocks based on federal funds futures rates recently proposed by Barakchian and Crowe (2013). Smets and Wouters (2007) model monetary policy shocks as stochastic deviations from a Taylor rule in an estimated medium-scale micro-founded DSGE framework featuring a variety of nominal and real frictions. Such framework has become a reference for researchers in central banks and policy institutions. Romer and Romer (2004) identify policy innovations in two steps. First, they use a narrative approach to identify changes in the Federal Reserve's target interest rate occurring during FOMC's meetings. Then, they regress this measure of policy changes on the Fed's real-time forecasts of past, current, and future inflation, output growth, and unemployment. In doing so, they isolate the innovations of these policy changes that are orthogonal to the information set possessed by the Federal Reserve, i.e., the monetary policy shocks. Barakchian and Crowe (2013) stress the importance of using federal funds futures data to effectively proxy the stance of monetary policy in the United States. Given the different information carried out by different series of futures rates, they cleverly propose to use six different series of futures rates (ranging from the series of futures rate related to the current month to the one having a five-month horizon) in a combined fashion in order to construct a factor potentially retaining all the relevant information coming from these six different rates. We document more extensively the role of federal funds futures in the next Section. However, we anticipate that, given that federal funds futures rates are available only starting from December 1988, our identification-via-heteroskedasticity approach cannot be put at work when futures are embedded in the VAR. Hence, we display the shock as estimated by Barakchian and Crowe (2013) in their paper.

A look at these six measures of policy shocks confirms that our methodology has the potential to meaningfully isolate exogenous variations in the federal funds rate. These six series clearly comove, with their local peaks typically anticipating recessions or occurring in correspondence to economic downturns. The correlation between the estimates of the policy shocks obtained with our non-recursive model and the recursive one (both admitting a break in 1984Q1) reads 0.82, while that of the former with the estimates provided by a fixed coefficient-recursive SVAR, the model by Smets and Wouters (2007), and Romer and Romer (2004) approach reads 0.76, 0.53, and 0.39, respectively. Interestingly, the correlation between our reference measure and Barakchian and Crowe's (2013) new shock reads -0.18. Notice that this negative correlation refers to a much shorter sample starting in 1988.[14] We interpret this negative correlation in favor of such a new shock as potentially carrying different information with respect to the set of other shocks analyzed here. The next Section will deal with the role played by futures rates for the identification of the monetary policy shock.

Granger-causality tests based on bivariate VARs modeling the policy shocks estimated with our non-recursive identification scheme and, alternatively, one of the other five measures of policy shocks clearly reject any anticipatory effects in any direction. Again, this is consistent with the fact that these measures of policy shocks, while being quantitatively somewhat different, tend to comove and carry common information

[14] The quarterly version of the Barakchian and Crowe (2013) new shock is obtained by taking within-quarter averages of their monthly realizations. The correlation between our baseline shock and the standard monetary policy shock measure one extracts from a Cholesky VAR without break reads 0.39 in the sample 1988Q1-2008Q2.

regarding the exogenous variations of the federal funds rate in the post-WWII U.S. period. We see this validation check as supportive for our non-recursive identification proposal, at least as far as the identification of monetary policy shocks is concerned.[15]

3.5 Recursive vs. non-recursive schemes: Statistical comparison

A natural question at this point is: Which identification scheme should we trust more? Under exact identification, the likelihoods of the estimated recursive and non-recursive SVARs-WB would be the same. However, the specification of the non-recursive SVARs-WB in the lower panel of Table 1 is designed to produce an over-identified (testable) model. Similarly, the recursive SVARs-WB reported in the upper panel of Table 1 has been estimated by considering only coefficients with associated 't-ratio' larger than one. It seems therefore "natural" to select the two estimated models in terms of their likelihoods and standard information criteria.

Table 2 compares the LR test for the over-identification restrictions associated with the two estimated models, and the AIC (Akaike), BIC (Schwartz) and HQ (Hannan-Quinn) information criteria. The model selected by the data is the non-recursive SVAR-WB.

4 Robustness checks

Our baseline exercise hinges upon a number of working hypothesis. First, the structural break occurs in 1984. Second, the federal funds rate is the reference indicator of the monetary policy stance in the United States. Third, the federal funds rate is the most informative indicator as regards the U.S. monetary policy conduct. We discuss these working hypothesis one at a time and we propose robustness checks to changes in such hypothesis below.

Break in 1984 vs. 1988. As discussed in Section 3, our choice of a structural break in 1984 is based both on some of the extant literature on the Great Moderation and on a statistical test. Other contributions in the literature, however, points to changes in inventory management to justify a break in volatility in 1984 (see, e.g., Blanchard and

[15] The aim of this Section is to show that the monetary policy shocks obtained with our methodology appear to be sensible when contrasted with other, more conventional measure of policy innovations. For a comparison of the different macroeconomic effects associated to monetary policy shocks identified with a number of approaches recently pursued by the literature, see Coibion (2012).

Simon (2001)). An alternative break-point is proposed by a recent study by Barakchian and Crowe (2013). As convincingly argued in this study, the U.S. monetary policy may have become more forward looking since 1988. Hence, more than the shift in volatility of the economy from high to low after 1984, the true break in the monetary policy conduct to consider if one wants to correctly estimate the consequences of a change in the transmission of the monetary policy shocks in the U.S. is actually sometime in 1988. Following Barakchian and Crowe (2013), we consider 1988Q4 as the reference date for this alternative break.

Figure 4 plots the impulse responses to the monetary policy shocks identified via our methodology and conditional on the 1988Q4 break. A number of findings arise. First, in general, the point estimates we obtain are similar to those of our baseline exercise. This implies that our procedure is robust to reasonable perturbations of the break-date, at least as far as this empirical application is concerned. Second, and interestingly enough, the precision of our point estimates is higher, above all as regards the pre-break period, when this different break-date is considered. This result suggests that investigations conducted in order to understand the role played by monetary policy shocks under different systematic monetary policy regimes should consider a break in 1988 as seriously as the commonly employed break in 1984. Third, the responses of durable consumption and investment turn out to be similar not only quantitatively but also qualitatively. To the extent that these two aggregates should respond in a similar fashion to macroeconomic shocks, this result speaks in favor of the 1988 break as a possible alternative to the standard, mid-1980s one. An analysis along this line is proposed by Barakchian and Crowe (2013).

Are the on-impact responses under the non-recursive vs. recursive identification schemes equivalent when considering the 1988Q4 break-point? Figure 5 confirms that, even when this break-date is used as a reference for our identification-via-heteroskedasticity approach, some non-zero responses are detected. In particular, investment and real GDP are still found to respond negatively and contemporaneously to an unexpected hike of the policy rate. Interestingly, however, the magnitude of the response appears to be dampened with respect to the one found with the analysis relying on the 1984Q4 break-point. Again, this result suggests that the 1988Q4 break-date proposed by Barakchian and Crowe (2013) may be informative to unveil the macroeconomic effects of a monetary policy shock in the post-WWII U.S. economy.[16]

[16] Details on the estimated contemporaneous coefficients are provided in an Appendix available upon request.

Nondurable consumption as investment. Our baseline exercise models durable consumption and investment in a separate fashion. On the one hand, this approach enables us to run an unconstrained version of the model in which these two variables are free to respond differently to the same shock. Differences in the responses of these variables may be related to, for instance, differences in the interest rates paid on loans activated to purchase a durable good (like, say, a car) vs. a productive investment (like, say, a warehouse). In fact, the costs on loans related to different goods and services may be differently sensitive to changes in the reference policy rate. However, it is well known that durable consumption behaves very much like business fixed investment. Because of this reason, estimated DSGE models typically include durable consumption in the definition of investment. Examples in the literature include, among others, Justiniano, Primiceri and Tambalotti (2010, 2011). We then estimate a version of the model in which the aggregate "investment" is defined as in Justiniano, Primiceri and Tambalotti's (2010, 2011) papers. Given that durable consumption is not anymore an independent variable in our SVAR, one implication of this exercise is that the system features only six variables. Consequently, the structure of the matrices $\boldsymbol{C}$ and $\boldsymbol{Q}$ is also different with respect to the one employed in our baseline. When running this exercise, we maintain a structure as close as possible to the baseline one.[17] Figure 6 plots the impulse responses obtained by considering this different definition of investment. The response of investment in this restricted case resembles, both qualitatively and quantitatively, the reaction of investment in the unrestricted, baseline scenario. This implies that the response of this "aggregate" definition of investment is largely driven by business fixed-investment. More importantly for our analysis, Figure 7 proposes the comparison involving our non-recursive scheme vs. the standard recursive one. Interestingly, even in presence of this alternative definition of investment, the difference in the response of this aggregate under the two different identification schemes is still present. Again, the driver of this difference is the fact that, when left free to take a non-zero value on impact, investment does so with our non-recursive scheme, something which is just not possible under the standard recursive one.

Federal funds futures - futures rate for the current month. Our analysis relies on the employment of the federal funds rate as the reference rate for the U.S. monetary policy stance. As pointed out above, this is a standard choice in VAR analysis (see, e.g., Christiano, Eichenbaum and Evans (1999, 2005)). However, some contributions in the literature have advocated the use of federal funds futures prices to

[17] Details are provided in an Appendix available upon request.

better capture the beliefs of the private sector about future monetary policy moves (see, among others, Rudebusch (1998), Bagliano and Favero (1999), Kuttner (2001), Söderström (2001), Faust, Swanson, and Wright (2004), and Barakchian and Crowe (2013)). As stressed by Barakchian and Crowe (2013), the simplest signal of the policy stance is the futures rate for the current month. It is then of interest to check what happens to our results if we replace the federal funds rate with such measure of policy stance. Unfortunately, this comes at a big cost for our analysis. Our methodology relies on heteroskedasticity to identify monetary policy shocks in non-recursive models. However, federal funds futures prices are available only starting from December 1988. Hence, no useful break-date can be used to discriminate the high volatility scenario of the 1970s and early 1980s from the moderate volatility one beginning sometime during the 1980s. Said so, a feasible exercise is to compare the impulse responses obtained by estimating a Cholesky-VAR with the federal funds rate with those computed by estimating the model with the futures rate for the current month. To enhance comparability, the recursive formulation with the federal funds rate is estimated for this subsample only, i.e., without appealing to the identification-via-heteroskedasticity approach previously entertained in this paper.

Figure 8 plots the impulse responses obtained with the Cholesky-VAR model with the federal funds rate and those estimated with the model with the federal funds futures rate for the current month. A few differences arise from a quantitative standpoint. In particular, the short-run response of consumption (both durable and non-durable), investment, and real GDP turn out to be milder when the futures rate is employed. This suggests that the use of futures rates may provide additional information for the identification of monetary policy shocks. We elaborate further on this point below.

Federal funds futures - factor analysis. A possible drawback of the previous analysis is that it focuses on a single maturity. However, as stressed by Barakchian and Crowe (2013), there are several reasons to focus on a range of maturities. First, combining the information from different maturities is likely to reduce the noise affecting each specific contract. Second, given the persistence of the Federal Reserve's policy rate decisions, a policy change in the current period may influence federal funds futures rates several months ahead. In spite of the availability of contracts for more than one year into the future, we follow Barakchian and Crowe (2013) and consider federal funds futures for the current month up to five months ahead which are available since December 1988. Two are the possible strategies to synthesize the information coming from these different futures rates. The first one, proposed by Barakchian and Crowe (2013), is to extract the common shocks in the contract prices at different horizons after identifying such shocks on the basis on some timing assumptions regarding the way in which private sectors form expectations over future policy moves. The second one, *de facto* inspired by the very same paper, is to compute the common factor of the six federal funds futures available for the period December 1988-June 2008 and use such factor in our VAR. Given that this second strategy relies on the same identification assumptions entertained so far as regards the econometric VAR model, we replace the federal funds rate with this factor and re-estimate our Cholesky-VAR.[18]

Figure 8 plots the impulse responses obtained with the Cholesky-VAR with the factor employed as indicator of the monetary policy stance. Interestingly, some differences emerge with respect to the baseline recursive case in the model with the federal funds rate. First, the long-term interest rate displays a larger reaction from a quantitative standpoint. Second, and intriguingly, on top of the recurrent "price puzzle", this model predicts also an "output puzzle" and an "investment puzzle", i.e., a short-run positive response of both variables. As regards the price puzzle, this is exactly what happens in Barakchian and Crowe's (2013) paper, where a statistically significant increase in the level of prices is found. The different short-run responses of investment and GDP point to a different information content of the federal funds futures factor with respect to the federal funds rate or the federal funds futures for the current month *per se*.

This last result points to the potential usefulness of federal funds futures contracts for the identification of monetary policy shocks. Unfortunately, as stressed above, the identification via heteroskedasticity we pursue in this paper does not allow us to use federal funds futures contracts because of the lack of heteroskedasticity at a macroeconomic level in the period 1988Q4-2008Q2, which is the one for which futures contracts are available. Of course, the collapse of Lehman Brothers, occurred in September 2008, may very well represent an interesting break to exploit in order to put our machinery at work and analyze the period starting in 1988 with futures contracts. However, the zero-lower bound issue affecting VAR analysis conducted with the federal funds rate also

[18] This factor is computed by implementing a standard principal component analysis conditional on the six federal funds futures series available starting from December 1988. We first demean all series and divide them by their standard deviation. Then, we compute the six factors via which we can completely recover the variance of the futures rates. The first factor accounts for 97% of the total variance, hence we consider it as sufficient to capture the correlations in the data. We then move from monthly to quarterly frequencies by taking within-quarter averages, and - to ensure comparability with the federal funds rate - we rescale the so-computed quarterly factor by adding the sample mean of the federal funds rate in the sample 1988Q4-2008Q2 and multiplying it by the federal funds rate's standard deviation.

affects investigations relying on future contracts. Wrapping up, the results documented in Figure 8 corroborate previous findings which point to a different information content of futures contracts with respect to the federal funds rate as regards the monetary policy stance in the United States (see Barakchian and Crowe (2013) and the literature cited therein). We leave the elaboration of strategies aimed at combining futures contracts and identification via heteroskedasticity at a quarterly frequency to future research.

5 Relation to the methodological literature

The approach used in this paper is related to some recent works by Normandin and Phaneuf (2004), Lanne and Lütkepohl (2008, 2010) and Lanne, Lütkepohl, and Maciejowska (2010) on the identification of SVARs subject to different volatility regimes and, more generally, to the contributions of Rigobon and Sack (2003, 2004). Similarly to these authors, we exploit the presence of breaks in the VAR covariance matrix to identify the structural shocks of interest. Differently from these authors, however, we remove the assumption that structural breaks affect only the error covariance matrix and leave the impulse vectors unchanged. In our setup, a change in the VAR covariance matrix can be associated with a change in the structural parameters, hence the identification analysis of the macroeconomic effects of monetary policy shocks involves a mix of volatility-driven and theory-driven restrictions. Thus, while in Rigobon (2003), Rigobon and Sack (2003, 2004), Lanne and Lütkepohl (2008), Lanne, Lütkepohl, and Maciejowska (2010), Lütkepohl (2013), Herwartz and Lütkepohl (2014), Lütkepohl and Netšunajev (2014a, 2014b) and Lutkepohl and Velinov (2015) the SVAR is solely identified by the heteroskedasticity found in the data and the shocks normalized between two different regimes generate the very same impulse responses, the identification of our SVAR-WB via the rank condition in eq. (10) requires combining the information stemming from volatility regimes with theoretical restrictions on the matrices $\boldsymbol{C}$ and $\boldsymbol{Q}$.[19] Our SVAR-WB approach identifies one structural model with different identification structures and heteroskedasticity regime-dependent impulse responses. Moreover, our SVAR-WB is designed to deal with a few structural breaks that are best thought of as permanent and not as stochastically recurring (reversible) events. Differently, Lanne, Lütkepohl, and Maciejowska (2010) model the changes in the error covariance matrix through an underlying Markov switching process. Our SVAR-WB does not be-

[19] We refer to Bacchiocchi and Fanelli (2015) for a detailed discussion of why the identification conditions in eq.s (10)-(11) nest those developed by Rigobon (2003) and Lanne and Lütkepohl (2008).

long to the class of 'fully' time-varying VARs recently employed to model the evolution of the correlation among macroeconomic U.S. variables by Cogley and Sargent (2005a, 2005b), , Primiceri (2005), and Canova, Gambetti, and Pappa (2008), among others. With respect to these authors, we use identification schemes that allow for non-recursive contemporaneous relationships.[20]

A notable example of contributions in the literature dealing with a non-recursive scheme to identify the effects of a monetary policy shock is Sims and Zha (2006). Sims and Zha (2006) appeal to economic theory to impose zero-restrictions to the matrix modelling the contemporaneous relationships in their VAR. Such zero restrictions are imposed so to admit the immediate response of a sub-set of modeled variables in their vector to a monetary shock. Still, they are forced to set to zero the contemporaneous responses of other variables like unemployment and commodity prices. Given the high attention paid by the Federal Reserve to the labor market (unemployment) and inflation expectations (commodity prices), it seems to be of interest to dispose of a more flexible identification scheme. Our proposed identification scheme leaves the econometrician the possibility to model (and, indeed, test) a fully non-zero monetary policy shock-related impulse vector.

As shown in the previous Sections, our methodology enriches the set of available strategies to identify a monetary policy shock without appealing to a recursive scheme. An agnostic identification procedure consistent with a full impulse vector as for monetary policy shocks is represented by sign restrictions. Faust (1998), Canova and de Nicoló (2002) and Uhlig (2005) (among others) show how to deal with a set of restrictions imposed on moments generated by the estimated VAR (correlations, impulse responses) to identify a structural shock of interest. Sign restrictions have been shown to be quite powerful to discriminating among competing classes of structural models (Canova and Paustian (2011)) and identify the effects of structural shocks in general. However, the distinction between model uncertainty and parameter uncertainty has to be carefully drawn when computing dynamic responses to identified shocks (Fry and Pagan (2011)). Romer and Romer (2004) identify monetary policy shocks in a model-free fashion by performing a careful reading of the minutes reporting the discussions and monetary policy decisions by the FOMC. After identifying the series of the changes in the policy rate, they regress such series over a set of macroeconomic forecasts readily available to policymakers, therefore purging the identified series from the component

[20]For a recent paper dealing with overidentified, non-recursive, time-varying coefficients SVARs, see Canova and Forero (2015).

systematically reacting to economic conditions. Kliem and Kriwoluzky (2013) employ the shocks identified by Romer and Romer (2004) as instruments in a “proxy-VAR” approach à la Stock and Watson (2012). A similar approach is pursued by Gertler and Karadi (2014), who identify policy shocks which include shocks to forward guidance by appealing to high-frequency data on policy surprises on interest rates. Faust, Swanson, and Wright (2004) use the prices of federal funds future to identify monetary policy shocks. Del Negro and Schorfheide (2004) and Del Negro, Schorfheide, Smets, and Wouters (2007) employ structural, non-recursive DSGE models to form priors for the estimation of Bayesian VARs. Our approach is complementary to those listed above, in that it requires the imposition of a relatively small number of short-run zero restrictions but it requires neither the use of a-priori information on moments to be met for the identification of the shock to be in place, nor the employment of an auxiliary DSGE model, nor to undertake the reading and interpretation of minutes revealing information on policy decisions. Differently, it requires the imposition of a relatively small number of zero restrictions. Moreover, it naturally deals with structural breaks, something that these alternative identification schemes are not necessarily designed to deal with. Admittedly, given the role played by the data (heteroskedasticity) in our approach, this may come at the cost of confounding the effects of a monetary policy shock with those of a different structural shock. As shown in Section 3.4, however, the measure of monetary policy shocks obtained with our SVARs-WB turns out to be quite correlated with other measures present in the literature (among others, Romer and Romer’s (2004) and Smets and Wouters’ (2007)). At the very least, our IRFs offer a documentation of conditional responses of the U.S. economy to a shock which is consistent with an exogenous movement of the federal funds rate orthogonal to the rest of the system.

Finally, some authors, including Rudebusch (1998), Bagliano and Favero (1999), Kuttner (2001), Söderström (2001), Faust, Swanson, and Wright (2004), and Barakchian and Crowe (2013), have employed federal funds futures contracts to exploit private sector’s expectations over the future policy moves implemented by the Federal Reserve to identify monetary policy shocks and their effects. As discussed in the previous section, our analysis hinges upon the assumption of a break in volatility within the sample. Hence, given that federal funds futures rates are available starting from December 1988, the combination of futures contracts and identification-via-heteroskedasticity appears to be unfeasible if breaks like the Great Inflation-Great Moderation one (Blanchard and Simon (2001), McConnell and Perez-Quiros (2000)) or the study of the impact of monetary policy shocks before and after a policy break in the 1980s (Clarida, Galí, and

Gertler (2000), Lubik and Schorfheide (2004), Boivin and Giannoni (2006), Benati and Surico (2009), Barakchian and Crowe (2013)) is objectively unfeasible at the moment. However, as more data come along, we envision this combination as a promising one.

6 Conclusions

We have shown how to identify structural shocks in non-recursive SVARs featuring instabilities in the covariance matrix of the residuals and in the coefficients of the matrix responsible for the contemporaneous relationships of the modeled variables, denoted with SVAR-WB. After presenting our methodology in detail, we have exploited it to identify the effects of monetary policy shocks in the U.S. economy using post-WWII quarterly data. We have found that a non-recursive SVAR-WB implies impulse responses very similar to those coming from a standard Cholesky-type recursive SVAR when pre-1984 data are considered. Differently, non-recursive vs. recursive schemes tell different stories on the dynamics related to the Great Moderation. We have also provided statistical support in favor of the non-recursive scheme, and such an evidence seems to be consistent with the SVAR representation of the large majority of DSGE models employed by central banks and academic scholars to perform their empirical analysis. Our checks have shown that our results are robust to the employment of a different break-date (1988 as in Barakchian and Crowe (2013), instead of the commonly employed 1984) and a different definition of the aggregate investment which comprises durable consumption as in Justiniano, Primiceri, and Tambalotti (2010, 2011). Following Barakchian and Crowe (2013), we have also conducted some empirical exercises and proposed a discussion on the role that futures contracts may play for the identification of monetary policy shocks.

Our effort lines up with previous contributions by Rigobon (2003), Rigobon and Sack (2003, 2004), Normandin and Phaneuf (2004), Lanne and Lütkepohl (2008, 2010), Lanne, Lütkepohl, and Maciejowska (2010), Lütkepohl (2013), Herwartz and Lütkepohl (2014), Lütkepohl and Netŝunajev (2014a), Lütkepohl and Netŝunajev (2014b), and Lutkepohl and Velinov (2015) in showing that instabilities may represent relevant sources of information to identify structural shocks. Our analysis generalizes and adds to the above mentioned contributions the idea that the transmission mechanism of the shocks may change across volatility regimes. Hence, also the parameters relating the reduced form disturbances to the structural shocks are allowed to vary across heteroskedasticity regimes.

The detection of such instabilities is likely to be informative to calibrate models constructed for policy design. Our novel non-recursive identification scheme could be employed to implement an impulse-response function approach of the type pursued by a number of authors in the literature (Rotemberg and Woodford (1997), Christiano, Eichenbaum, and Evans (2005), Boivin and Giannoni (2006), Altig, Christiano, Eichenbaum, and Linde (2011), and Blanchard and Riggi (2013)). Our approach would indeed provide the econometrician with an auxiliary model whose restrictions are theoretically consistent with the ones associated to standard DSGE models admitting immediate responses of endogenous variables to a monetary policy shock. Indeed, our proposal is more general than that, in the sense that shocks other than the monetary policy one can be identified with our non-recursive scheme. We see the identification of shocks and time-dependent macroeconomic reactions to such shocks due to breaks as a promising and policy-relevant avenue for future research.

References

Altig, D., L. J. Christiano, M. Eichenbaum, and J. Linde (2011): "Firm-Specific Capital, Nominal Rigidities and the Business Cycle," *Review of Economic Dynamics*, 14(2), 225–247.

Amisano, G., and C. Giannini (1997): *Topics in Structural VAR Econometrics.* 2nd edn, Springer, Berlin.

Bacchiocchi, E., and L. Fanelli (2012): "Identification in Vector Autoregressive models with structural changes," University of Milan, DEMM, Working Paper n. 2012-16.

Bacchiocchi, E., and L. Fanelli (2015): "Identification in Structural Vector Autoregressive Models with Structural Changes with an Application to U.S. Monetary Policy," *Oxford Bulletin of Economics and Statistics*, forthcoming.

Bagliano, F. C., and C. A. Favero (1998): "Measuring monetary policy with VAR models: An evaluation," *European Economic Review*, 42, 1069–1112.

——— (1999): "Information from financial markets and VAR measures of monetary policy," *European Economic Review*, 43(4-6), 825–837.

Barakchian, S. M., and C. Crowe (2013): "Monetary policy matters: Evidence from new shocks data," *Journal of Monetary Economics*, 60(8), 950–966.

Barsky, R., C. House, and M. Kimball (2007): "Sticky price models and durable goods," *American Economic Review*, 97, 984–998.

Benati, L., and P. Surico (2009): "VAR Analysis and the Great Moderation," *American Economic Review*, 99(4), 1636–1652.

Blanchard, O., and M. Riggi (2013): "Why Are the 2000s so Different from the 1970s? A Structural Interpretation of Changes in the Macroeconomic Effects of Oil Prices," *Journal of the European Economic Association*, 11(5), 1032–1052.

Blanchard, O., and J. Simon (2001): "The Long and Large Decline in U.S. Output Volatility," *Brookings Papers on Economic Activity*, 1, 135–174.

Boivin, J., and M. Giannoni (2006): "Has Monetary Policy Become More Effective?," *Review of Economics and Statistics*, 88(3), 445–462.

Boivin, J., M. T. Kiley, and F. S. Mishkin (2010): "How Has the Monetary Transmission Mechanism Evolved over Time?," in B.M. Friedman and M. Woodford M. (eds): Handbook of Monetary Economics, Elsevier, Chapter 8, 369–422.

Canova, F. (2009): "What Explains the Great Moderation in the US? A Structural Analysis," *Journal of the European Economic Association*, 7(4), 697–721.

Canova, F., and G. de Nicoló (2002): "Monetary Disturbances Matter for Business Fluctuations in the G-7," *Journal of Monetary Economics*, 49, 1131–1159.

Canova, F., and F. J. P. Forero (2015): "A General Algorithm for Estimating Structural VARs," *Quantitative Economics*, forthcoming.

Canova, F., L. Gambetti, and E. Pappa (2008): "The Structural Dynamics of US Output and Inflation: What Explains the Changes?," *Journal of Money, Credit and Banking*, 40(23), 369–388.

Canova, F., and M. Paustian (2011): "Business cycle measurement with some theory," *Journal of Monetary Economics*, 58, 345–361.

Castelnuovo, E. (2012): "Estimating the Evolution of Money's Role in the U.S. Monetary Business Cycle," *Journal of Money, Credit and Banking*, 44(1), 23–52.

——— (2016): "Modest Macroeconomic Effects of Monetary Policy Shocks During the Great Moderation: An Alternative Interpretation," *Journal of Macroeconomics*, forthcoming.

Castelnuovo, E., and P. Surico (2010): "Monetary Policy Shifts, Inflation Expectations and the Price Puzzle," *Economic Journal*, 120(549), 1262–1283.

Christiano, L., M. Eichenbaum, and C. Evans (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113(1), 1–45.

Christiano, L. J., M. Eichenbaum, and C. Evans (1999): "Monetary Policy Shocks: What Have We Learned and to What End?," In: J.B. Taylor and M. Woodford (eds.): Handbook of Macroeconomics, Elsevier Science, 65–148.

Clarida, R., J. Galí, and M. Gertler (2000): "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 115, 147–180.

Cogley, T., and T. Sargent (2005a): "Drifts and Volatilities: Monetary Policies and Outcomes in the Post War U.S.," *Review of Economic Dynamics*, 8, 262–302.

——— (2005b): "The Conquest of U.S. Inflation: Learning and Robustness to Model Uncertainty," *Review of Economic Dynamics*, 8, 528–563.

Coibion, O. (2012): "Are the Effects of Monetary Policy Shocks Big or Small?," *American Economic Journal: Macroeconomics*, 4(2), 1–32.

Coibion, O., and Y. Gorodnichenko (2011): "Monetary Policy, Trend Inflation and the Great Moderation: An Alternative Interpretation," *American Economic Review*, 101, 341–370.

Del Negro, M., and F. Schorfheide (2004): "Priors for General Equilibrium Models for VARs," *International Economic Review*, 45, 643–673.

Del Negro, M., F. Schorfheide, F. Smets, and R. Wouters (2007): "On the Fit of New-Keynesian Models," *Journal of Business and Economic Statistics*, 25(2), 124–162.

Eichenbaum, M. (1992): "Comment on "Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy" by C.A. Sims," *European Economic Review*, 36(5), 1001–1011.

Erceg, C., and A. Levin (2006): "Optimal monetary policy with durable consumption goods," *Journal of Monetary Economics*, 53, 1341–1359.

Faust, J. (1998): "The Robustness of identified VAR Conclusions about Money," *Carnegie Rochester Conference Series on Public Policy*, 49, 207–244.

Faust, J., E. T. Swanson, and J. H. Wright (2004): "Identifying VARs based on high frequency futures data," *Journal of Monetary Economics*, 51, 1107–1131.

Fry, R., and A. Pagan (2011): "Sign Restrictions in Structural Vector Autoregressions: A Critical Review," *Journal of Economic Literature*, 49(4), 938–960.

Galí, J. (2008): *Monetary Policy, Inflation and the Business Cycle*. Princeton University Press. Princeton, New Jersey.

Gertler, M., and P. Karadi (2014): "Monetary Policy Surprises, Credit Costs and Economic Activity," NBER Working Paper No. 20224.

Hanson, M. (2004): "The "Price Puzzle" Reconsidered," *Journal of Monetary Economics*, 51, 1385–1413.

Herwartz, H., and H. Lütkepohl (2014): "Structural Vector Autoregressions with Markov Switching: Combining Conventional with Statistical Identification of Shocks," *Journal of Econometrics*, 183, 104–116.

Justiniano, A., and G. Primiceri (2008): "The Time-Varying Volatility of Macroeconomic Fluctuations," *American Economic Review*, 98(3), 604–641.

Justiniano, A., G. Primiceri, and A. Tambalotti (2011): "Investment Shocks and the Relative Price of Investment," *Review of Economic Dynamics*, 14(1), 101–121.

Justiniano, A., G. E. Primiceri, and A. Tambalotti (2010): "Investment Shocks and Business Cycles," *Journal of Monetary Economics*, 57(2), 132–145.

Kilian, L. (1998): "Small-sample confidence intervals for impulse response functions," *Review of Economics and Statistics*, 80, 218–230.

Kim, C., and C. Nelson (1999): "Has the U.S. Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle," *The Review of Economics and Statistics*, 81, 608–616.

Kliem, M., and A. Kriwoluzky (2013): "Reconciling Narrative Monetary Policy Disturbances with Structural VAR Model Shocks?," *Economics Letters*, 121(2), 247–251.

Kuttner, K. (2001): "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, 47(3), 523–544.

Lanne, M., and H. Lütkepohl (2008): "Identifying Monetary Policy Shocks via Changes in Volatility," *Journal of Money, Credit and Banking*, 40, 1131–1149.

——— (2010): "Structural Vector Autoregressions with Non Normal Residuals," *Journal of Business and Economic Statistics*, 28, 159–168.

Lanne, M. L., H. Lütkepohl, and K. Maciejowska (2010): "Structural Vector Autoregressions with Markov Switching," *Journal of Economic Dynamics and Control*, 34, 21–131.

Lubik, T., and F. Schorfheide (2004): "Testing for Indeterminacy: An Application to U.S. Monetary Policy," *American Economic Review*, 94(1), 190–217.

Lütkepohl, H. (2013): "Identifying Structural Vector Autoregressions via Changes in Volatility," *Advances in Econometrics*, 32, 169–203.

Lütkepohl, H., and A. Netšunajev (2014a): "Disentangling Demand and Supply Shocks in the Crude Oil Market: How to Check Sign Restrictions in Structural VARs," *Journal of Applied Econometrics*, 29, 479–496.

——— (2014b): "Structural Vector Autoregressions with Smooth Transition in Variances: The Interaction between U.S. Monetary Policy and the Stock Market," DIW Berlin-German Institute for Economic Research Discussion Paper No. 1388.

Lütkepohl, H., and H. Reimers (1992): "Impulse Response Analysis of Cointegrated Systems with an Application to German Money Demand," *Journal of Economic Dynamics and Control*, 16, 53–78.

Lutkepohl, H., and A. Velinov (2015): "Structural Vector Autoregressions: Checking Identifying Long-Run Restrictions via Heteroskedasticity," *Journal of Economic Surveys*, forthcoming.

McConnell, M., and G. Perez-Quiros (2000): "Output Fluctuations in the United States: What Has Changed Since the Early 1980s?," *American Economic Review*, 90, 1464–1476.

Monacelli, T. (2009): "New-Keynesian Models, Durable Goods, and Collateral Constraints," *Journal of Monetary Economics*, 56(2), 242–254.

Normandin, M., and L. Phaneuf (2004): "Monetary Policy Shocks: Testing identification Conditions under Time-Varying Conditional Volatility," *Journal of Monetary Economics*, 51, 1217–1243.

Phillips, P. (1998): "Impulse Response and Forecast Error Variance Asymptotics in Nonstationary VARs," *Journal of Econometrics*, 83, 21–56.

Primiceri, G. (2005): "Time-Varying Structural Vector Autoregressions and Monetary Policy," *Review of Economic Studies*, 72, 821–852.

Rigobon, R. (2003): "Identification through Heteroskedasticity," *Review of Economics and Statistics*, 85, 777–792.

Rigobon, R., and B. Sack (2003): "Measuring the Reaction of Monetary Policy to the Stock Market," *Quarterly Journal of Economics*, 118, 639–669.

Rigobon, R., and B. Sack (2004): "The Impact of Monetary Policy on Asset Prices," *Journal of Monetary Economics*, 51, 1553–1575.

Romer, C., and D. Romer (2004): "A New Measure of Monetary Policy Shocks: Derivation and Implications," *American Economic Review*, 94(4), 1055–1084.

Rotemberg, J., and M. Woodford (1997): "An Optimization-Based Econometric Framework for the Evaluation of Monetary Policy," NBER Macroeconomics Annual, 297–346.

Rubio-Ramírez, J. F., D. F. Waggoner, and T. Zha (2010): "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference," *Review of Economic Studies*, 77, 665–696.

Rudebusch, G. D. (1998): "Do Measures of Monetary Policy in a Var Make Sense?," *International Economic Review*, 39(4), 907–931.

Sims, C. (1980): "Macroeconomics and Reality," *Econometrica*, 48(1), 1–48.

Sims, C., and T. Zha (2006): "Were There Regime Switches in U.S. Monetary Policy?," *American Economic Review*, 96(1), 54–81.

Smets, F., and R. Wouters (2007): "Shocks and Frictions in US Business Cycle: A Bayesian DSGE Approach," *American Economic Review*, 97(3), 586–606.

Stock, J. H., and M. W. Watson (2002): "Has the Business Cycle Changed and Why?," in M Gertler and K. Rogoff (eds.): NBER Macroeconomic Annual, MIT Press, Cambridge, MA.

Stock, J. H., and M. W. Watson (2012): "Disentangling the Channels of the 2007-2009 Recession," *Brookings Papers on Economic Activities*, forthcoming.

Svensson, L. (1997): "Inflation Forecast Targeting: Implementing and Monitoring Inflation Targets," *European Economic Review*, 41, 1111–1146.

Söderström, U. (2001): "Predicting Monetary Policy with Federal Funds Futures Prices," *Journal of Futures Markets*, 214, 377–391.

Uhlig, H. (2005): "What are the Effects of Monetary Policy? Results from an Agnostic Identification Procedure," *Journal of Monetary Economics*, 52, 381–419.

Vlaar, P. (2004): "On the Asymptotic Distribution of Impulse Response Functions with Long-Run Restrictions," *Econometric Theory*, 20, 891–903.

Recursive SVAR-WB													
			$\hat{C}$							$\hat{Q}$			
0.49 (0.04)	0	0	0	0	0	0	−0.13 (0.04)	0	0	0	0	0	0
1.14 (0.26)	2.40 (0.17)	0	0	0	0	0	−1.03 (0.33)	−0.40 (0.22)	0	0	0	0	0
0.56 (0.20)	0.95 (0.17)	1.65 (0.12)	0	0	0	0	−0.26 (0.23)	−0.57 (0.20)	−0.58 (0.14)	0	0	0	0
0.43 (0.08)	0.42 (0.06)	0.13 (0.06)	0.54 (0.04)	0	0	0	−0.14 (0.09)	−0.28 (0.08)	0.10 (0.07)	−0.24 (0.05)	0	0	0
−0.10 (0.03)	0	0	0	0.28 (0.02)	0	0	0.05 (0.03)	−0.04 (0.02)	−0.02 (0.02)	0	−0.12 (0.02)	0	0
0.04 (0.03)	0.02 (0.02)	0.05 (0.03)	−0.07 (0.03)	0	0.24 (0.02)	0	−0.03 (0.03)	−0.02 (0.02)	−0.04 (0.03)	0.09 (0.03)	0	−0.16 (0.02)	0
0.04 (0.01)	0	0.04 (0.01)	−0.02 (0.01)	0	0.06 (0.01)	0.08 (0.01)	−0.01 (0.01)	0.01 (0.01)	−0.02 (0.01)	0.03 (0.01)	0.04 (0.01)	−0.03 (0.01)	−0.01) (0.01)
log-lik = -599.39			LR test:				$\chi(8)=$ **15.82**		p-value=**0.05**				

Non-recursive SVAR-WB													
			$\hat{C}$							$\hat{Q}$			
0.48 (0.03)	0	0	0	0	0	0	−0.14 (0.07)	0	0	0	0	−0.15 (0.11)	0
1.08 (0.26)	2.42 (0.17)	0	0	0	0	0	−0.97 (0.33)	−0.43 (0.22)	0	0	0	0	0
0.50 (0.19)	1.02 (0.18)	1.64 (0.12)	0	0	0	0	−0.34 (0.27)	−0.64 (0.20)	−0.63 (0.17)	0	0	−0.45 (0.29)	0
0.40 (0.08)	0.45 (0.06)	0.17 (0.05)	0.45 (0.08)	0	−0.30 (0.11)	0	−0.21 (0.13)	−0.30 (0.07)	0	−0.18 (0.06)	0	0	0
−0.06 (0.02)	−0.02 (0.01)	−0.01 (0.01)	−0.03 (0.02)	0.28 (0.02)	0.05 (0.05)	0	0	0	0	0	−0.12 (0.03)	−0.05 (0.05)	0
0.03 (0.02)	0	0.03 (0.02)	0.08 (0.05)	0.01 (0.01)	0.24 (0.03)	0	0	0	0	−0.02 (0.02)	0.02 (0.02)	−0.20 (0.02)	0
0.03 (0.01)	0.01 (0.01)	0.03 (0.01)	0.02 (0.01)	−0.01 (0.01)	0.06 (0.01)	0.08 (0.01)	0	0	0	0	0.05 (0.02)	−0.06 (0.02)	−0.01) (0.01)
log-lik = -598.30			LR test:				$\chi(9)=$ **13.63**		p-value=**0.14**				

Table 1: **Estimated parameters for the recursive and non-recursive SVAR-WB**, $T_B = 1984Q1$. Estimated values obtained via (Full Information) ML. Standard errors in brackets.

	Recursive	Non-Recursive
order of overidentification	8	9
log-likelihood	-599.4	-598.3
freely estimated parameters	48	47
LR test p-value	0.05	0.14
AIC	-13.191	-13.213
BIC	-11.079	-11.145
HQ	-12.864	-12.892

Table 2: **Recursive vs Non-recursive SVAR-WB: Log-likelihood, LR test and information criteria.**

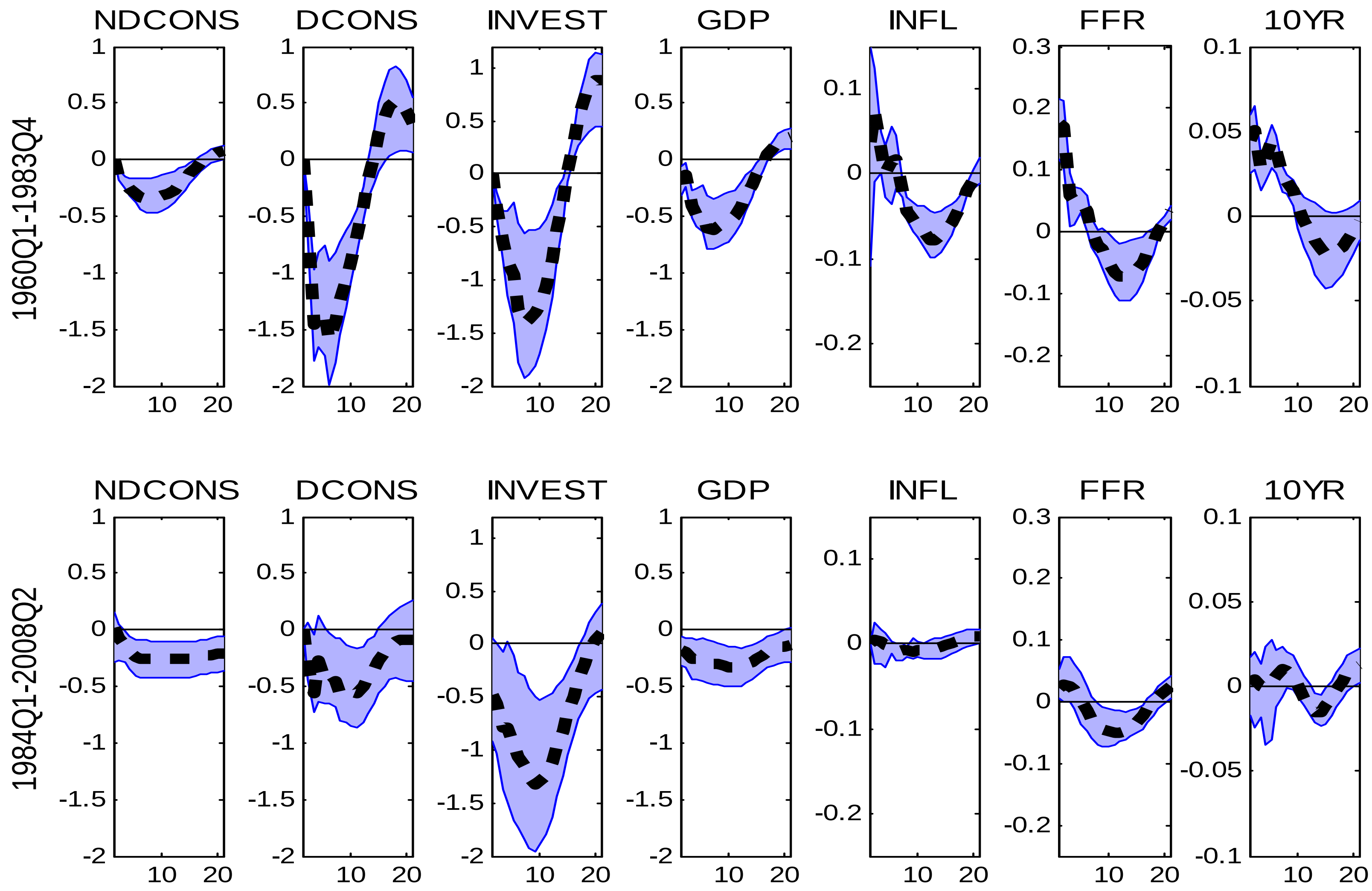

Figure 1: **SVAR-WB, Impulse response functions: Great Inflation versus Great Moderation.** Dashed-black lines: Median responses to a monetary policy shock (size: one standard deviation). Shaded-areas: 95-per cent confidence interval. Monetary policy shock identified with the non-recursive scheme discussed in Section 2. Ordering of the variables in the VAR: Non durable consumption, durable consumption, investment, gdp, inflation, federal funds rate, 10 year-Treasury Bill rate.

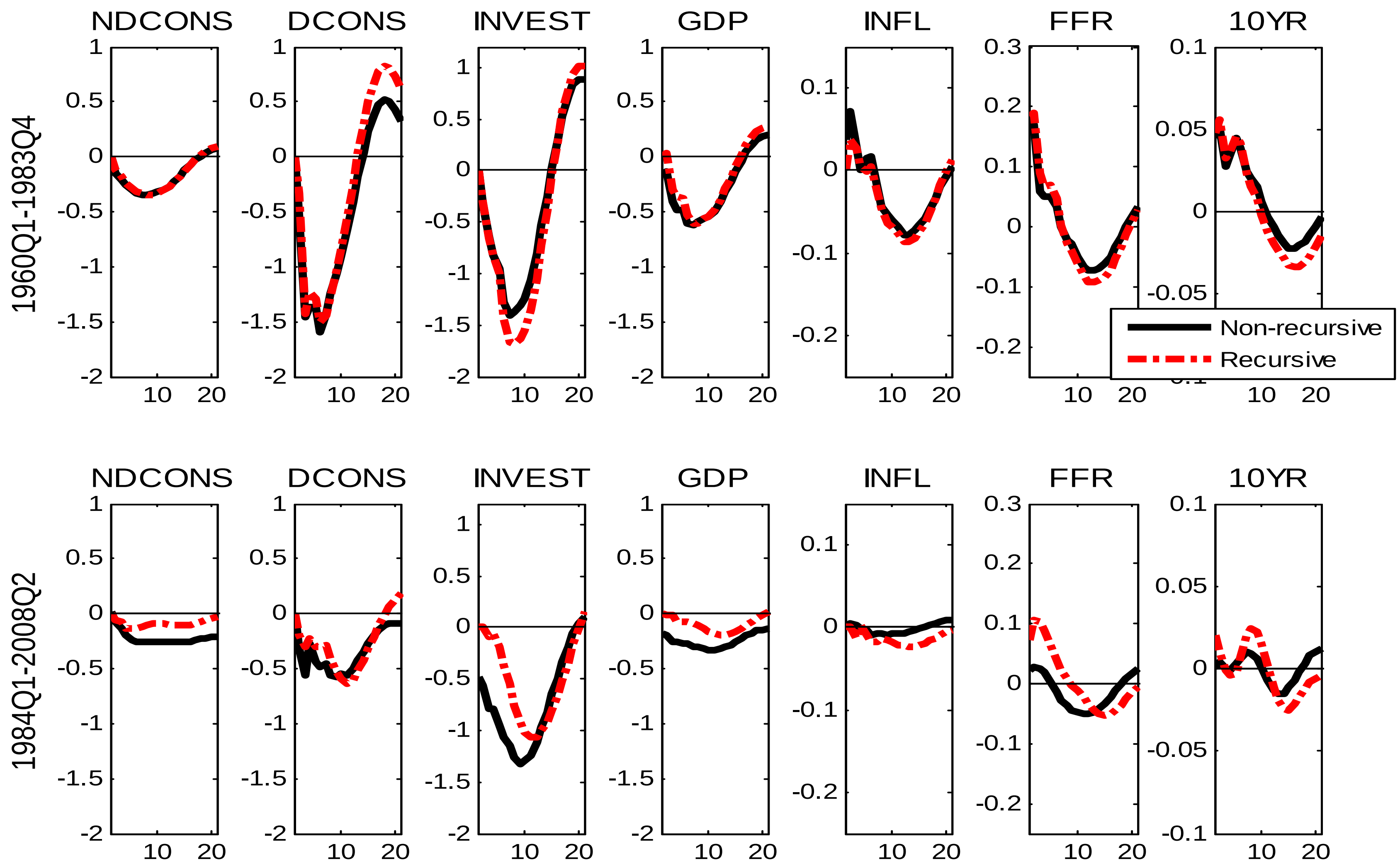

Figure 2: **Non-recursive vs. recursive SVAR-WB, Impulse response functions: Great Inflation versus Great Moderation.** Dashed-black (red) lines: Median responses to a monetary policy shock (size: one standard deviation) identified with a non-recursive (recursive) scheme. Monetary policy shock identified with the non-recursive scheme discussed in Section 2 (black line)/ recursive Cholesky-scheme (red line). Ordering of the variables in the VAR: Non durable consumption, durable consumption, investment, gdp, inflation, federal funds rate, 10 year-Treasury Bill rate.

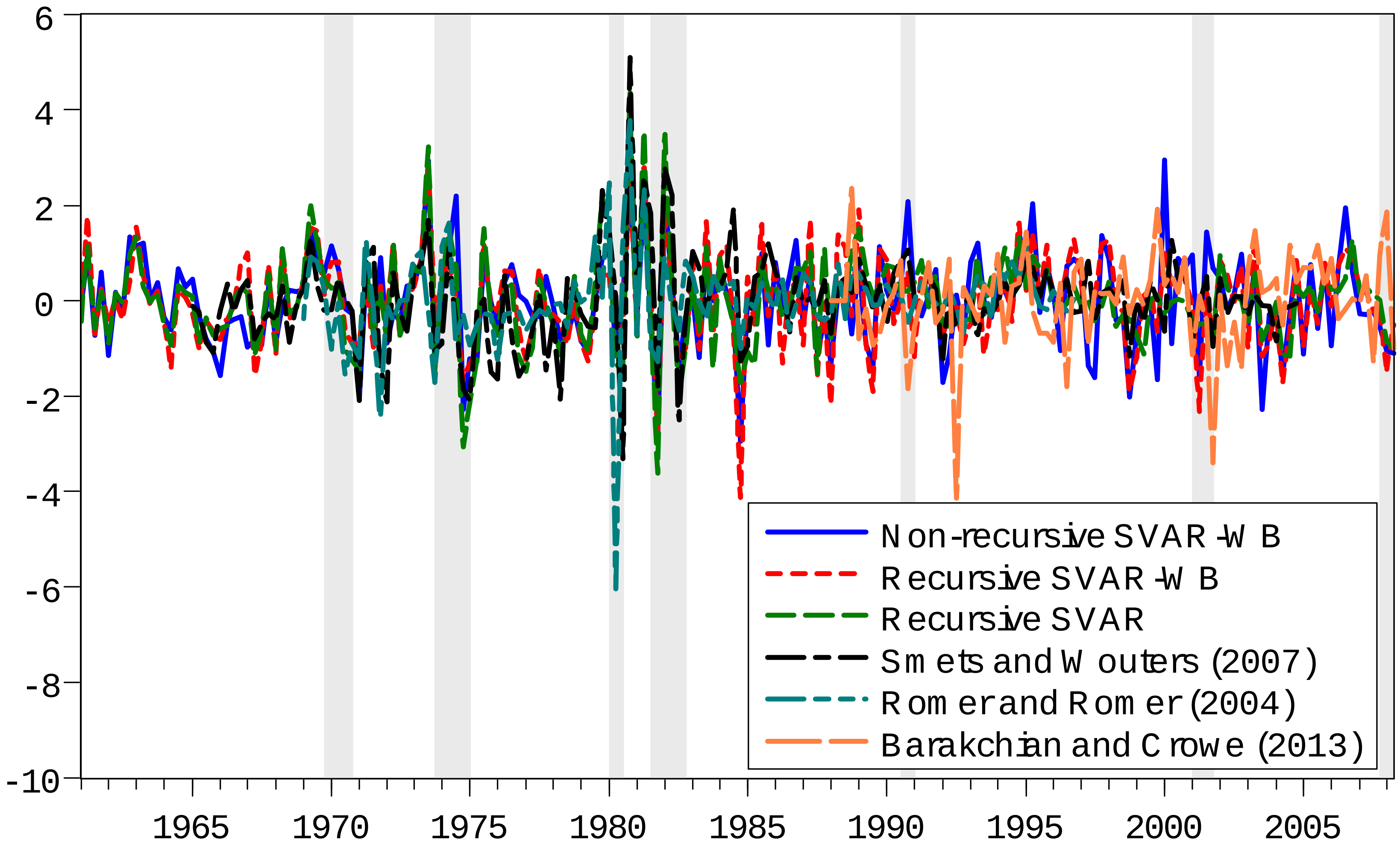

Figure 3: **Estimated policy shocks: Comparison.** Blue, solid line: Shocks conditional on our "BCF Non-Recursive VAR" model, which imposes no-zero restrictions. Red, dashed line: Shocks conditional on our "BCF CVAR" framework, which imposes a standard lower-triangular matrix on the contemporaneous relationships in the system. Green, dashed line (with longer dashes than the red ones): Shocks conditional on a standard fixed coefficient-Cholesky VAR. Black, dash-dotte line: Shocks estimated by Smets and Wouters (2007). Light green, dashed line: Shocks estimated by Romer and Romer (2004) (average of monthly cumulative values). Orange, dashed line: Barakchian and Crowe's (2013) shocks estimated by using a factor extracted by six futures rates and conditional on the information set available to the private sector before and after a FOMC policy decision. The BCF models allow for a break in 1984Q1. Vertical gray bars: NBER recessions. The measure of policy shocks by Romer and Romer (2004) is taken from Coibion (2012). All series displayed in this Figure are standardized.

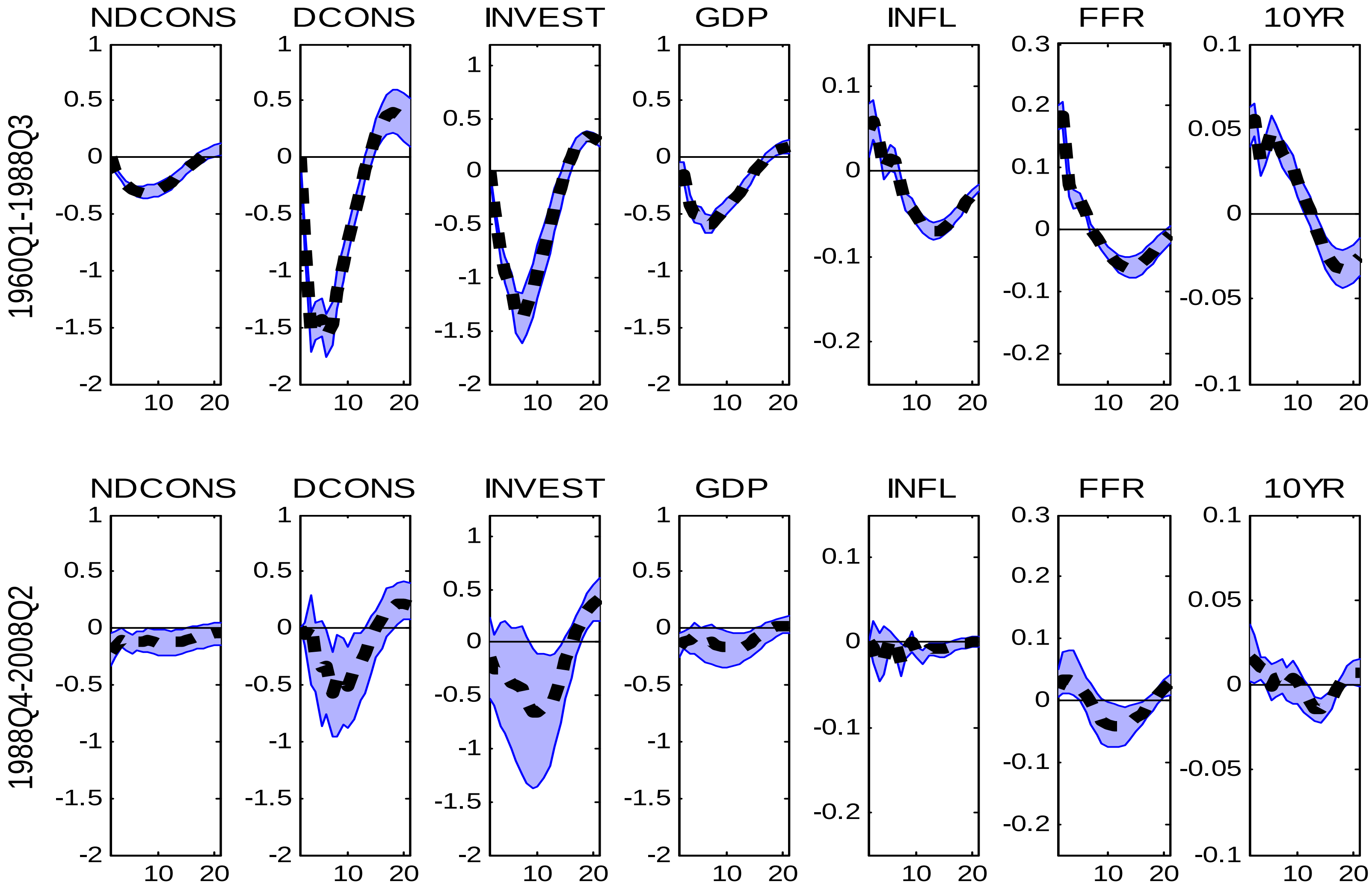

Figure 4: **SVAR-WB, Impulse response functions: Break in 1988Q4 as in Barakchian and Crowe (2013).** Dashed-black lines: Median responses to a monetary policy shock (size: one standard deviation). Shaded-areas: 95-per cent confidence interval. Monetary policy shock identified with the non-recursive scheme discussed in Section 2. Ordering of the variables in the VAR: Non durable consumption, durable consumption, investment, gdp, inflation, federal funds rate, 10 year-Treasury Bill rate.

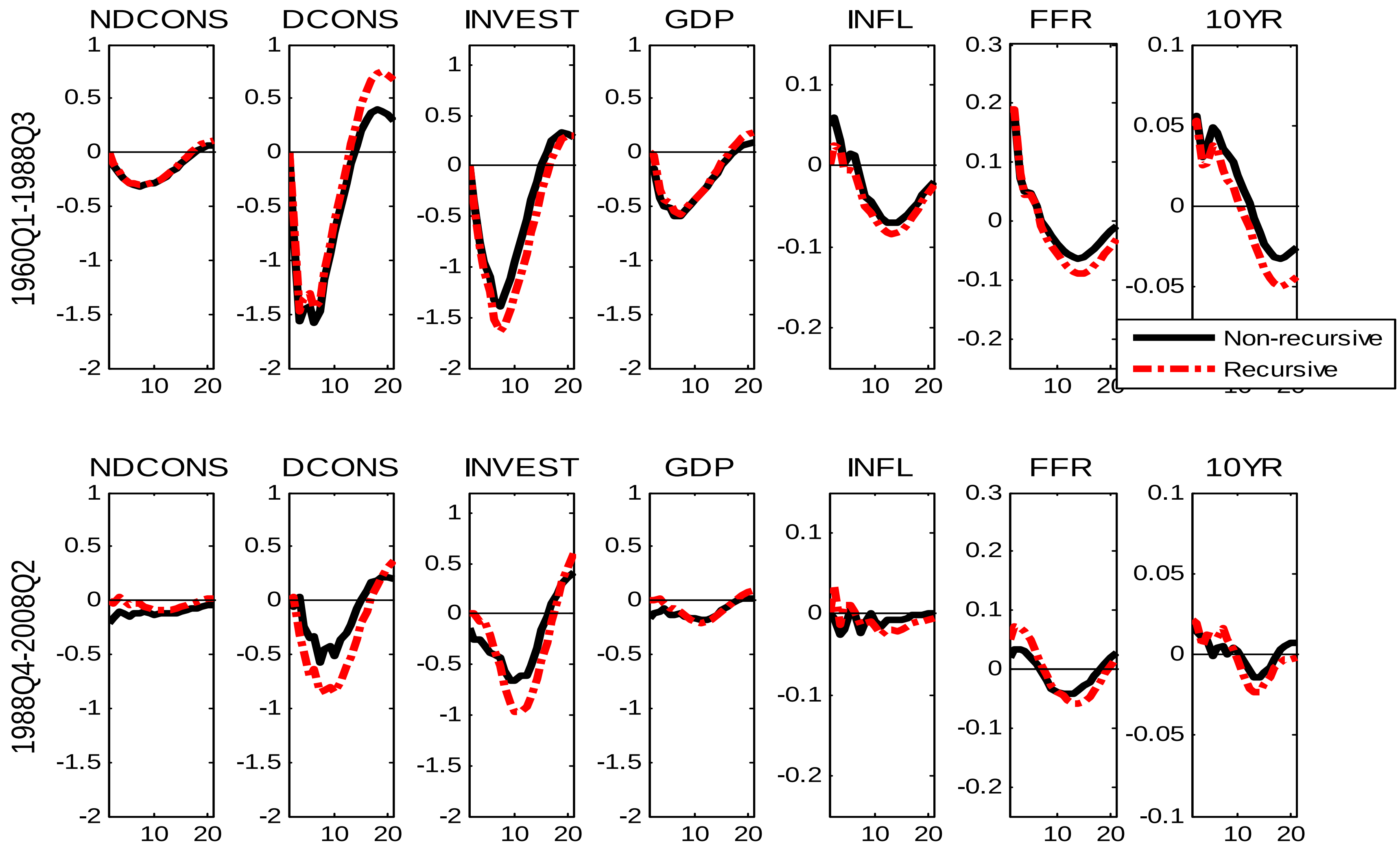

Figure 5: **Non-recursive vs. recursive SVAR-WB, Impulse response functions: Break in 1988Q4 as in Barakchian and Crowe (2013).** Dashed-black (red) lines: Median responses to a monetary policy shock (size: one standard deviation) identified with a non-recursive (recursive) scheme. Monetary policy shock identified with the non-recursive scheme discussed in Section 2 (black line)/ recursive Cholesky-scheme (red line). Ordering of the variables in the VAR: Non durable consumption, durable consumption, investment, gdp, inflation, federal funds rate, 10 year-Treasury Bill rate.

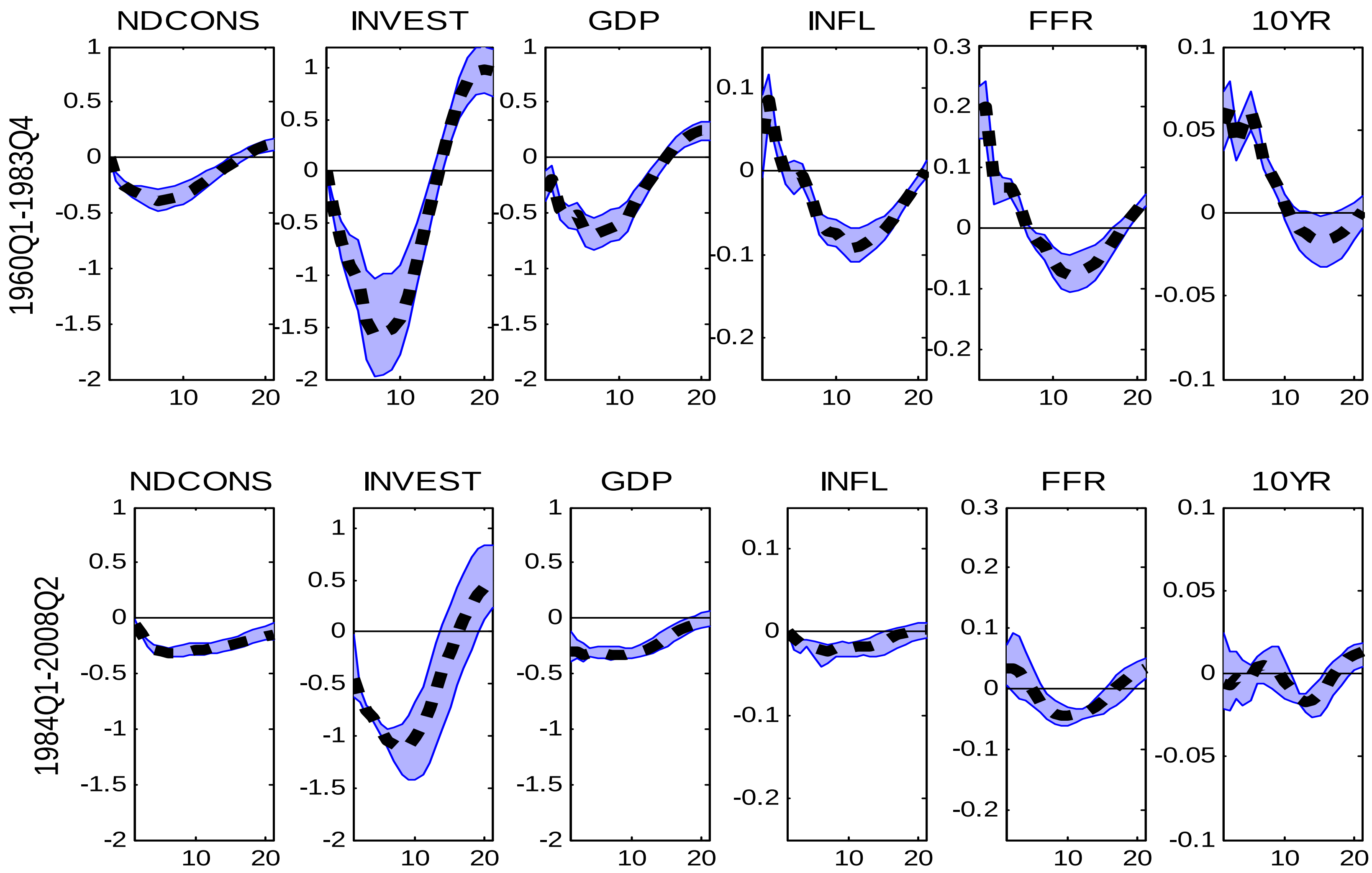

Figure 6: **SVAR-WB, Impulse response functions: Definition of investment as in Justiniano, Primiceri, and Tambalotti (2010, 2011).** Dashed-black lines: Median responses to a monetary policy shock (size: one standard deviation). Shaded-areas: 95-per cent confidence interval. Monetary policy shock identified with the non-recursive scheme discussed in Section 2. Ordering of the variables in the VAR: Non durable consumption, investment, gdp, inflation, federal funds rate, 10 year-Treasury Bill rate. Investment defined as the sum of durable consumption and investment (official series which excludes durable consumption).

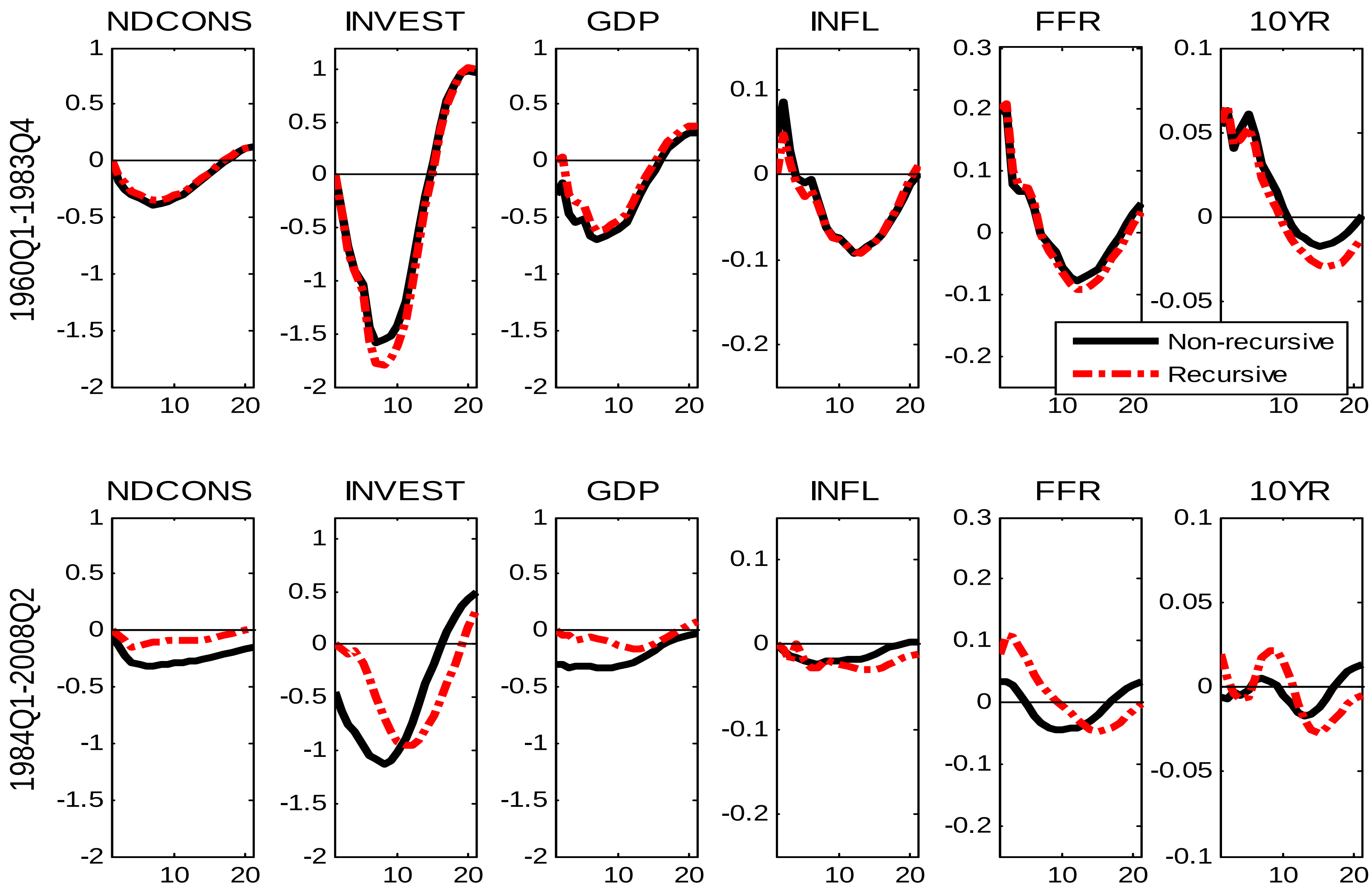

Figure 7: **Non-recursive vs. recursive SVAR-WB, Impulse response functions: Great Inflation versus Great Moderation: Definition of investment as in Justiniano, Primiceri, and Tambalotti (2010, 2011).** Dashed-black (red) lines: Median responses to a monetary policy shock (size: one standard deviation) identified with a non-recursive (recursive) scheme. Monetary policy shock identified with the non-recursive scheme discussed in Section 2 (black line)/ recursive Cholesky-scheme (red line). Ordering of the variables in the VAR: Non durable consumption, investment, gdp, inflation, federal funds rate, 10 year-Treasury Bill rate. Investment defined as the sum of durable consumption and investment (official series which excludes durable consumption).

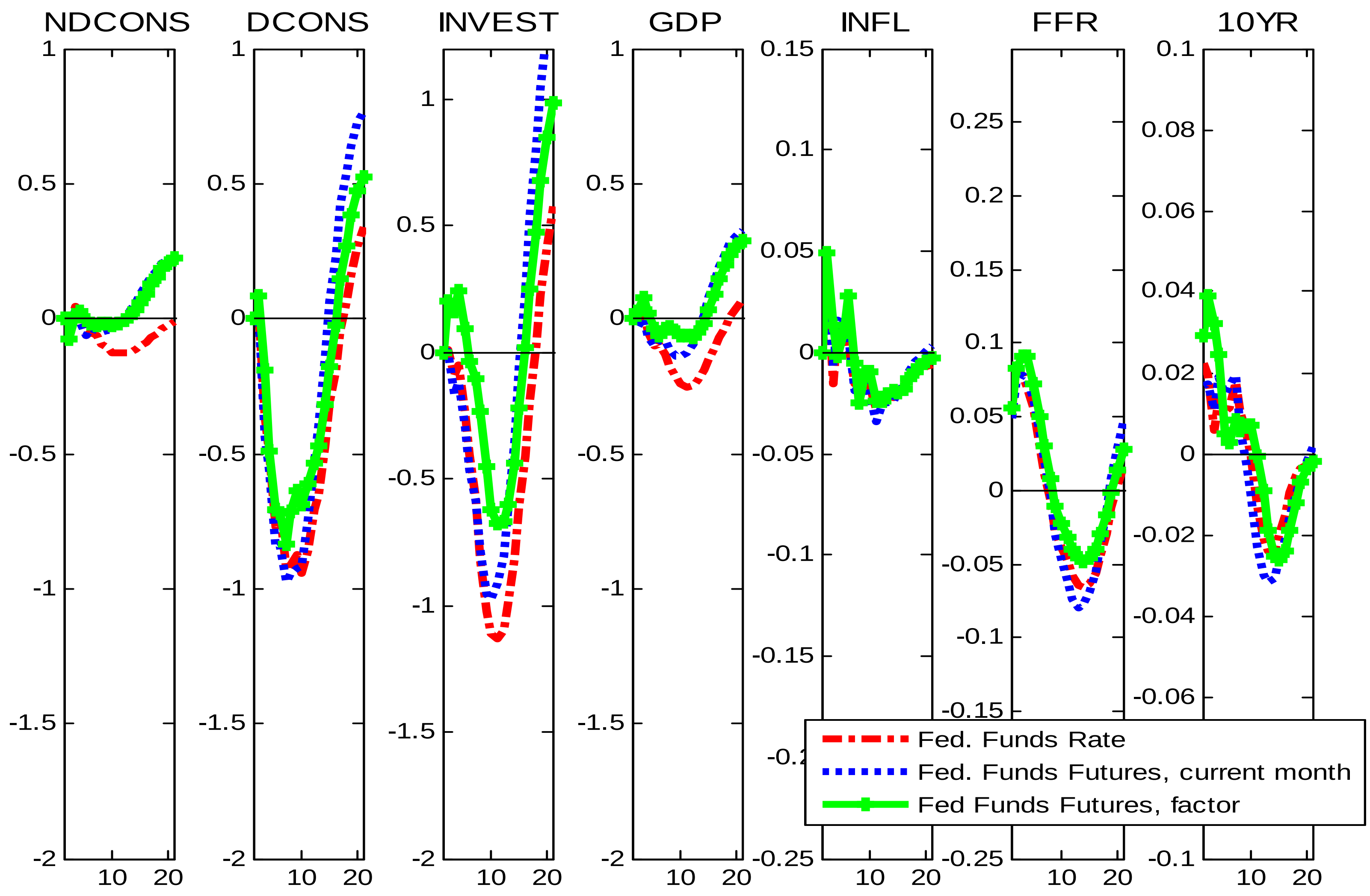

Figure 8: **Recursive SVAR, Impulse response functions: Fed Funds Futures.** Median responses to a monetary policy shock (size: one standard deviation) identified with a recursive scheme, sample: 1988Q4-2008Q2. Models featuring different indicators of the monetary policy stance. Red dash-dotted line: Model with the Federal Funds rate. Blue dotted line: Model with the Federal Funds Futures rate for the current month. Green line with pluses: Model with a factor computed with Federal Funds Futures, contracts going from the current month up to five month-ahead. Ordering of the variables in the VAR: Non durable consumption, durable consumption, investment, gdp, inflation, indicator of monetary policy stance, 10 year-Treasury Bill rate.