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Would the Bundesbank Have Prevented the Great Inflation in the United States?*

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Abstract

Policy counterfactuals based on estimated structural VARs routinely suggest that bringing Alan Greenspan back in the 1970s' United States would not have prevented the Great Inflation. We show that a standard policy counterfactual suggests that the *Bundesbank*—which is near-universally credited for sparing West Germany the Great Inflation—would also *not* have been able to prevent the Great Inflation in the United States.

The implausibility of this result sounds a cautionary note on taking the outcome of SVAR-based policy counterfactuals at face value, and raises questions on the reliability of such exercises.

Keywords: Bayesian VARs; time-varying parameters; stochastic volatility; identified VARs; Great Inflation; policy counterfactuals.

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The start of inflation occurred under the Bretton Woods system of fixed exchange rates. [...] Once the fixed exchange rate system ended, Japan, Germany, Switzerland, and Austria reduced their inflation rates. Others permitted inflation to continue or increase. [...] The start of the Great Inflation—the sustained increase in the price level—was a monetary event. Monetary policy could have mitigated or prevented the inflation but failed to do so.

—Allan Meltzer¹

In the 1970s and 80s there were few central banks whose policy responses to inflation provided a sufficient tightening of policy in the face of inflation to anchor public beliefs around low and stable inflation. [...] [A]n exception to the general picture was the Bundesbank which kept stable and positive real interest rates over this period with the result that German inflation remained low and stable even though it was subject to the same international cost shocks as the other countries [...].

—Timothy Besley²

[D]ue to the vigorous action by the Bundesbank, Germany experienced much lower inflation rates than did the United States. In fact, after its peak in 1981, when the inflation rate stood at 6.3 percent, the German inflation rate swiftly declined, reaching values of around 2 percent at the end of 1985 [...].

—Otmar Issing³

1 Introduction

A standard result produced by structural VAR-based studies of the U.S. Great Moderation is that imposing over the entire post-WWII sample the structural monetary policy rule associated with the more recent, and more stable, period—in the literature jargon, ‘bringing Alan Greenspan back in time’—would not have prevented the Great Inflation, and, more generally, would only have exerted a limited impact on U.S. post-WWII macroeconomic dynamics. This result has been obtained based on either Markov-switching⁴ or time-varying parameters VARs,⁵ and based on several alternative identification schemes—specifically, Cholesky, as in Primiceri (2005); sign restrictions, as in the work of Fabio Canova and his co-authors; and based on the alternative identification scheme of Sims and Zha (2006). Because of the comparatively wide range of VAR specifications and identification schemes conditional on which it has been produced, the result that ‘bringing Alan Greenspan back in time’

¹See Meltzer (2005).

²See Besley (2008).

³See Issing (2005).

⁴See e.g. Sims and Zha (2006).

⁵See e.g. Primiceri (2005), Gambetti, Pappa, and Canova (2006), and Canova and Gambetti (2008).

would only have exerted a limited impact on U.S. post-WWII macroeconomic dynamics is regarded as a robust outcome of the structural VAR methodology, and is routinely taken to imply that sheer ‘luck’ (that is, shocks), has played a dominant role in shaping U.S. post-WWII macroeconomic fluctuations.⁶

With a few exceptions—see in particular DeLong (2003) and Bernanke (2004)—such result is typically not questioned.⁷ The reason for this is quite obvious, although never explicitly mentioned in the literature: during the 1970s, Alan Greenspan was not Chairman of the FED,⁸ and as a result there is simply *no way* of knowing whether, facing those very same shocks, he would have been able to spare the U.S. economy the Great Inflation. There is however at least one important exception to this logic:⁹ the *Bundesbank* is near-universally credited, within both academia and central banking, for preventing the Great Inflation in West Germany. As a consequence, we would logically expect that policy counterfactuals based on estimated structural VARs for the United States and West Germany would suggest that—in the very same way as the *Bundesbank* was able to successfully counter the 1970s’ inflationary impulses for West Germany—it would have been able to stare inflation down if it had been put in charge of U.S. monetary policy.

In this paper I perform the policy counterfactual of ‘bringing the *Bundesbank* to the United States’ based on three alternative identification strategies: sign restrictions, Cholesky, and an alternative strategy conceptually in line with Sims and Zha (2006). Results based on sign restrictions suggest that imposing the *Bundesbank*’s estimated structural monetary policy rule in the post-WWII United States would have exerted a limited impact on overall macroeconomic dynamics, and, crucially, it would *not* have prevented the Great Inflation, with counterfactual U.S. inflation peaking at 9.9 per cent in 1981Q1 (when German inflation was instead running at 4.2 per cent). Further, between March 1973 (when the German government relieved the *Bundesbank* from its obligation to defend the parity *vis-à-vis* the U.S. dollar, thus allowing it to pursue a vigorous counter-inflationary policy unimpeded by such exter-

⁶To be fair, the discussion in the literature is sometimes more nuanced. For example, a point that is often made is that, in principle, the FED could have prevented the Great Inflation, by implementing a very aggressive monetary policy, but that the cost in terms of output would have been extremely high. Also, Sims and Zha (2006), for example, acknowledge that when taking into account the uncertainty around the parameter estimates ‘[...] *one can tell a story consistent with the view that the Burns policy, had it persisted (instead of ending around 1977, as the model estimates it did), would have failed to end inflation.*’

⁷More generally, doubts about the reliability of SVAR-based policy counterfactuals are seldom expressed. An exception is represented by Christiano (1998)’s discussion of Sims (1998).

⁸Indeed, during those years he was either working in the private sector, as a macroeconomic forecaster, or working for the U.S. Government in a number of jobs (e.g., as Chairman of the Council of Economic Advisers) which, however, were all outside of the Federal Reserve System.

⁹We say ‘at least’ because, as stressed (e.g.) by Meltzer’s initial quotation, West Germany was not the only country to escape the 1970s largely unscathed: Japan, Austria, and especially Switzerland, too, were equally successful under this respect. Quite obviously, the very same logic underlying the present work could equally be applied to those three countries.

nal constraint) and the end of the Great Inflation, the counterfactual path for U.S. inflation is systematically and markedly higher than West Germany's actual inflation path for those years. Results based on the identification scheme in the spirit of Sims and Zha (2006) are slightly weaker, pointing towards some impact on inflation, which however stays almost uniformly higher than actual German inflation, reaching a peak of 8.5 per cent in 1981Q1. Results based on Cholesky point towards a non-negligible impact on inflation in the second half of the 1970s. Also in this case, however, counterfactual U.S. inflation stays almost uniformly higher than actual German inflation during those years by a non-negligible extent, reaching a peak of 8.0 per cent in 1981Q1. Further, I argue that results based on the two latter identification schemes should be seen with suspicion, and should therefore be significantly discounted, for two key reasons.

First, as it is well-known—see, first and foremost, the discussion in Canova and Pina (2005)—identification schemes based on the imposition of zero restrictions on impact are in general incompatible with DSGE models, whose impact matrices of the structural shocks at $t=0$ contain zero entries only under very special circumstances (basically, for a DSGE model's structural impact matrix to exhibit such zero entries, the model has to be specifically 'engineered' for that purpose). This is a crucial point because, as shown by Canova and Pina (2005), the imposition of inertial restrictions which are false in the data generation process (henceforth, DGP) can lead to a dramatic distortion of the inference, for example giving rise to estimated 'price puzzles' which are not in the original DGP.

Second, I show that the two alternative schemes adopted herein generate indeed implausible patterns for inflation's impulse-response functions (henceforth, IRFs) to an identified monetary policy shock. This is the case especially for Cholesky, which implies a dramatic, and statistically significant price puzzle for a large portion of the sample period, so that a monetary contraction ultimately ends up *increasing* the price level, rather than decreasing it. The scheme in the spirit of Sims and Zha (2006), on the other hand, still implies a price puzzle based on median estimates, but for no portion of the sample period it is possible to reject the null hypothesis that a monetary contraction has *no* impact on the price level at the 5 per cent significance level (it is worth stressing, however, that the notion that a monetary contraction has no impact whatsoever on the price level should also be regarded as pretty questionable ...). In the light of Canova and Pina (2005), one possible interpretation for these IRFs is they are simply the result of imposing inertial restrictions which are false in the DGP.

Overall, results suggest therefore that the *Bundesbank* would not have been able to prevent the Great Inflation in the United States. The results produced by these counterfactuals are therefore qualitatively the same as those obtained by 'bringing Alan Greenspan back in time' within the structural VAR-based literature on the Great Moderation. The key difference is that, whereas in the case of Alan Greenspan (or, more generally, of FED officials who have been in charge of U.S. monetary policy over the most recent years) we have no way of knowing how they would have performed

had they been in charge of U.S. monetary policy in the 1970s, this is obviously not the case for the *Bundesbank*. West Germany's central bank was indeed there, and its monetary policy is widely credited for sparing West Germany the Great Inflation. The notion that, if it had been put in charge of post-WWII U.S. monetary policy, it would have been unable to successfully counter the 1970s' inflationary upsurge in the United States is therefore quite hard to believe. As a logical corollary, these results raise doubts on the reliability of policy counterfactuals based on estimated structural VARs.

1.1 Relationship with the literature

Since Sims (1980) introduced the VAR methodology into macroeconomics, monetary policy counterfactuals have been one of its most prominent applications. SVAR-based counterfactuals have been used for example by Sims (1998) to explore the role played by monetary policy in the Great Depression, and by the previously mentioned authors to assess the role played by (supposedly) improved monetary policy in fostering the generalised fall in macroeconomic volatility associated with the Great Moderation.

In spite of such counterfactuals having been, and being used, to address fundamental economic issues, however, their vulnerability, in principle, to the Lucas (1976) critique has been known since Sargent (1979), who pointed out that

‘[u]sers of [VARs] must recognize that the range of uses of these models is more limited than the range of uses that would be possessed by a truly structural simultaneous equations model. [...] One use to which [they] cannot be put is to evaluate the effect of policy interventions in the form of changes in the feedback rule governing a monetary or fiscal policy variable, say, the money supply or monetary base. [...] The reason it is not appropriate is to be found in the dynamic economic theory alluded to above and described by Lucas and Sargent (1979). That body of theory delivers a set of cross-equations restrictions which imply that when one equation [...] describing a policy authority's feedback rule changes, in general, all of the remaining equations will also change.’

The debate between Sargent and Sims on the vulnerability of SVAR-based counterfactuals to the Lucas critique,¹⁰ however, was entirely conducted ‘verbally’ (that is, without making explicit reference to any structural macroeconomic model which might have allowed to check how serious the problem was conditional on the postulated structure), and it essentially died out around the end of the 1980s. In recent years two papers based on estimated DGSE models have produced results illustrating the potential unreliability of SVAR-based policy counterfactuals.

Benati and Surico (2009) estimated a standard New Keynesian model for the pre- and post-October 1979 United States, imposing in estimation that the *only* source of

¹⁰See e.g. Sargent (1984), on the one hand, and Sims (1982) and Sims (1986), on the other.

changes across regimes is the move from passive to active monetary policy. One of the results they obtained based on the estimated structure is that policy counterfactuals based on the theoretical structural VAR representations of the model under the two regimes fail to capture the truth as defined by the DSGE model itself. In particular, substituting the SVAR's interest rate rule corresponding to the indeterminacy regime into the SVAR for the determinacy regime causes a volatility decrease, rather than an increase, for all series.

Benati (2010) performs a systematic investigation of the reliability of SVAR-based policy counterfactuals based on a battery of estimated New Keynesian models, showing that the size of the errors made by SVAR-based policy counterfactuals—compared to the authentic, DSGE-based counterfactuals—is potentially substantial, thus casting doubts, in principle, on their reliability. Further, he shows that the extent of the (un)reliability of the SVAR-based counterfactual depends not only on the magnitude of the policy shift, but also—and crucially—on key structural characteristics of the economy, such as the extent of forward-, as opposed to backward-looking behavior in price-setting and in the IS curve. Since such features are, in general, unknown, Benati's (2010) results imply that the reliability of SVAR-based counterfactuals cannot simply be assumed, and, within the context of a specific application, it can rather only be ascertained with a reasonable degree of confidence by estimating structural models. Eschewing the estimation of structural macroeconomic models, and making instead inference based on the notion of imposing a minimal set of restrictions on the estimated moving-average representation of the data, was however the entire point of structural VAR econometrics. What these results show is that, for one specific application of this methodology—performing policy counterfactuals—sidestepping the issue of structural estimation of macroeconomic models is not without consequences, as it becomes impossible to tell to which extent the results generated by the counterfactual are (or are not) reliable.

The obvious advantage of using estimated structural models in order to assess the reliability of SVAR-based counterfactuals is that this approach produces very sharp results: conditional on a specific structure, and for given values of the structural parameters, it is indeed possible to *exactly* compute how large the approximation error generated by the SVAR-based counterfactual actually is—compared with the result produced by the authentic, DSGE-based counterfactual—for any hypothetical policy shift. Basing the analysis on DSGE models, however, also presents a downside, as results may crucially depend on the specific characteristic of the DGPs that are being used. Benati (2010) attempted to minimise this risk by using a battery of estimated models, but clearly this does not represent a bulletproof guarantee.

The alternative strategy which is pursued in the present work is to use a 'quasi-natural experiment', that is a real-world situation/event for which we are reasonably certain that a specific aspect of macroeconomic dynamics in country A during sample period B was due to the impact of the monetary policy rule which was in place during that period. The comparative advantage of using such an approach is that it is not

necessary to postulate any DGP: as long as we are reasonably confident that monetary policy truly was the key underlying cause of what happened, we can just implement a SVAR-based counterfactual and see whether the results it produces are in line with those we expect. So the bottom line is that the present paper should be regarded, from a methodological point of view, as ‘complementary’ to Benati (2010).

The paper is organised as follows. The next section discusses the reduced-form specification for the time-varying parameters VAR with stochastic volatility we will use throughout the paper, and the three alternative identification strategies, whereas (standard) technical aspects of the Bayesian inference (in particular, our choices for the priors, and the Markov chain Monte Carlo algorithm we use to simulate the posterior distribution of the hyperparameters and the states conditional on the data) are relegated to an appendix. Section 3 presents results from the counterfactuals in which we ‘bring the Bundesbank to the post-WWII United States’, by imposing over the entire U.S. post-WWII sample period the structural monetary rules estimated for West Germany’s central bank. Section 4 draws some implications of these results for macroeconomics, whereas section 5 concludes.

2 Methodology

2.1 A Bayesian time-varying parameters VAR with stochastic volatility

In what follows we work with the following time-varying parameters VAR(p) model:

$$Y_t = B_{0,t} + B_{1,t}Y_{t-1} + \dots + B_{p,t}Y_{t-p} + \epsilon_t \equiv X_t'\theta_t + \epsilon_t \quad (1)$$

where the notation is obvious, and Y_t (which is an $N \times 1$ vector) is defined as either

$Y_t \equiv [\pi_t, y_t, m_t, r_t]'$, or $Y_t \equiv [\pi_t, y_t, m_t, r_t, neer_t]'$ (in these specific orders), with r_t , π_t , y_t , m_t , and $neer_t$ being a short-term interest rate (specifically, the Federal Funds rate for the United States, and a call money rate for West Germany), GDP deflator inflation, and the rates of change of real GDP, nominal M2, and the nominal effective exchange rate (henceforth, NEER), respectively (for a description of the data, see Appendix A).¹¹ The overall sample periods are 1959:2-2008:1 for the United States, and 1960:2-1990:25 for West Germany.¹² For reasons of comparability with other papers in the literature¹³ we set the lag order to $p=2$. Following, e.g., Cogley and

¹¹GDP deflator inflation and the rates of growth of real GDP, nominal M2, and the NEER have been computed as the annualised quarter-on-quarter rates of growth of the relevant series.

¹²The first 8 years of data are however used to calibrate the Bayesian priors, based on a time-invariant version of the same VAR used in estimation.

¹³See e.g. Primiceri (2005), Gambetti, Pappa, and Canova (2006), and Canova and Gambetti (2008).

Sargent (2002), Cogley and Sargent (2005), Primiceri (2005), and Gambetti, Pappa, and Canova (2006) the VAR's time-varying parameters, collected in the vector θ_t , are postulated to evolve according to

$$p(\theta_t | \theta_{t-1}, Q) = I(\theta_t) f(\theta_t | \theta_{t-1}, Q) \quad (2)$$

with $I(\theta_t)$ being an indicator function rejecting unstable draws—thus enforcing a stationarity constraint on the VAR—and with $f(\theta_t | \theta_{t-1}, Q)$ given by

$$\theta_t = \theta_{t-1} + \eta_t \quad (3)$$

with $\eta_t \sim N(0, Q)$. The VAR's reduced-form innovations in (1) are postulated to be zero-mean normally distributed, with time-varying covariance matrix Ω_t which, following established practice, we factor as

$$\text{Var}(\epsilon_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})' \quad (4)$$

The time-varying matrices H_t and A_t are defined as:

$$H_t \equiv \begin{bmatrix} h_{1,t} & 0 & \dots & 0 \\ 0 & h_{2,t} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & h_{N,t} \end{bmatrix} \quad A_t \equiv \begin{bmatrix} 1 & 0 & \dots & 0 \\ \alpha_{2,1,t} & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ \alpha_{N,1,t} & \alpha_{N,2,t} & \dots & 1 \end{bmatrix} \quad (5)$$

with the $h_{i,t}$ evolving as geometric random walks,

$$\ln h_{i,t} = \ln h_{i,t-1} + \nu_{i,t} \quad (6)$$

For future reference, we define $h_t \equiv [h_{1,t}, h_{2,t}, \dots, h_{N,t}]'$. Following Primiceri (2005), we postulate the non-zero and non-one elements of the matrix A_t —which we collect in the vector $\alpha_t \equiv [\alpha_{2,1,t}, \alpha_{3,1,t}, \dots, \alpha_{N,N-1,t}]'$ —to evolve as driftless random walks,

$$\alpha_t = \alpha_{t-1} + \tau_t, \quad (7)$$

and we assume the vector $[u_t', \eta_t', \tau_t', \nu_t']'$ to be distributed as

$$\begin{bmatrix} u_t \\ \eta_t \\ \tau_t \\ \nu_t \end{bmatrix} \sim N(0, V), \text{ with } V = \begin{bmatrix} I_4 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & Z \end{bmatrix} \text{ and } Z = \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \sigma_N^2 \end{bmatrix} \quad (8)$$

where u_t is such that $\epsilon_t \equiv A_t^{-1} H_t^{\frac{1}{2}} u_t$.¹⁴ Finally, following, again, Primiceri (2005) we adopt the additional simplifying assumption of postulating a block-diagonal structure

¹⁴As discussed in Primiceri (2005, pp. 6-7), there are two justifications for assuming a block-diagonal structure for V_t . First, parsimony, as the model is already quite heavily parameterized. Second, 'allowing for a completely generic correlation structure among different sources of uncertainty would preclude any structural interpretation of the innovations'.

for S , too—namely

$$S \equiv \text{Var}(\tau_t) = \begin{bmatrix} S_1 & 0_{1 \times 2} & \dots & 0_{1 \times (N-1)} \\ 0_{2 \times 1} & S_2 & \dots & 0_{2 \times (N-1)} \\ \dots & \dots & \dots & \dots \\ 0_{(N-1) \times 1} & 0_{(N-1) \times 2} & \dots & S_{N-1} \end{bmatrix} \quad (9)$$

with $S_1 \equiv \text{Var}(\tau_{21,t})$, $S_2 \equiv \text{Var}([\tau_{31,t}, \tau_{32,t}]')$, ..., and $S_{N-1} \equiv \text{Var}([\tau_{N,1,t}, \tau_{N,2,t}, \dots, \tau_{N,N-1,t}]')$, thus implying that the non-zero and non-one elements of A_t belonging to different rows evolve independently. As discussed in Primiceri (2005, Appendix A.2), this assumption drastically simplifies inference, as it allows to do Gibbs sampling on the non-zero and non-one elements of A_t equation by equation.

2.2 Estimation

We estimate (1)-(9) *via* Bayesian methods. Appendix B discusses our choices for the priors (which are standard in the literature), and the Markov-Chain Monte Carlo algorithm (specifically, Gibbs-sampling) we use to simulate the posterior distribution of the hyperparameters and the states conditional on the data.

2.3 Assessing the convergence of the Markov chain to the ergodic distribution

Following Primiceri (2005), we assess the convergence of the Markov chain by inspecting the autocorrelation properties of the ergodic distribution's draws. Specifically, we consider the draws' inefficiency factors (henceforth, IFs), defined as the inverse of the relative numerical efficiency measure of Geweke (1992),

$$RNE = (2\pi)^{-1} \frac{1}{S(0)} \int_{-\pi}^{\pi} S(\omega) d\omega \quad (10)$$

where $S(\omega)$ is the spectral density of the sequence of draws from the Gibbs sampler for the quantity of interest at the frequency ω . We estimate the spectral densities *via* the lag-window estimator as described in chapter 10 of Hamilton (1994).

Figure 1 and 2 show results for West Germany and the United States, respectively, based on the four-variables VARs (results based on the five-variables VARs are qualitatively the same, and are available upon request). Specifically, the two figures show the draws' IFs for the models' hyperparameters—i.e., the free elements of the matrices Q , Z , and S —and for the states, i.e. the time-varying coefficients of the VAR (the θ_t), the volatilities (the $h_{i,t}$'s), and the non-zero elements of the matrix A_t . As the figures clearly show, the autocorrelation of the draws is uniformly very low (as stressed by Primiceri (2005, Appendix B), values of the IFs below or around twenty are generally regarded as satisfactory). In a handful of cases the IFs are slightly below one, thus pointing towards the presence of some negative serial correlation for those specific draws.

2.4 Identification strategies

The first identification strategy we use is based on imposing sign restrictions¹⁵ on the estimated reduced-form VAR on a period-by-period basis. Specifically, in the smaller VAR we identify four shocks—a monetary policy shock (ϵ_t^M), a supply shock (ϵ_t^S), a demand non-policy shock (ϵ_t^D), and a money demand shock (ϵ_t^{MD})—whereas in the larger one we identify an additional shock (ϵ_t^{NEER}) which can be given several alternative interpretations. For example, it might reflect either a shock to the foreign exchange risk premium, or the impact of a foreign monetary policy shock. The following table summarises the sign restrictions we impose on the estimated VAR. A ‘+’ and a ‘-’ mean ‘greater than or equal to zero’ and ‘smaller than or equal to zero’, respectively, whereas a ‘?’ means that the sign of this specific impact has been left unconstrained. Sign restrictions are imposed only on impact (that is, at zero). It can be trivially shown that these sign restrictions are sufficient to identify the shocks. We compute the time-varying structural impact matrix, $A_{0,t}$, via the procedure proposed by Rubio-Ramirez, Waggoner, and Zha (2005).¹⁶

Variable:	Shock:				
	ϵ_t^M	ϵ_t^D	ϵ_t^S	ϵ_t^{MD}	ϵ_t^{NEER}
<i>short rate</i>	+	+	?	+	-
<i>inflation</i>	-	+	-	-	-
<i>output growth</i>	-	+	+	-	-
<i>money growth</i>	-	+	?	+	?
<i>rate of change of NEER</i>	+	+	+	+	+

For robustness reasons we then consider two additional identification strategies. First Cholesky, as in Primiceri (2005), in spite of its well-known shortcomings, which we discuss in Section 3.2. (However, since the assumption that the NEER does not move for one quarter following a monetary policy shock is obviously untenable, we only apply Cholesky to the four-variables VAR.) Second, an alternative strategy based on ‘zero restrictions’ on impact in the spirit of Sims and Zha (2006). Specifically, we assume that, in the quarter of the shock, neither real GDP growth nor inflation react, whereas both the monetary aggregate and the NEER are allowed to react.

¹⁵Sign restrictions have been used in the studies of the U.S. Great Moderation of Gambetti, Pappa, and Canova (2006) and Canova and Gambetti (2008).

¹⁶Specifically, let $\Omega_t = P_t D_t P_t'$ be the eigenvalue-eigenvector decomposition of the VAR’s time-varying covariance matrix Ω_t , and let $\tilde{A}_{0,t} \equiv P_t D_t^{\frac{1}{2}}$. We draw an $N \times N$ matrix, K , from the $N(0, 1)$ distribution, we take the QR decomposition of K —that is, we compute matrices Q and R such that $K=Q \cdot R$ —and we compute the time-varying structural impact matrix as $A_{0,t}=\tilde{A}_{0,t} \cdot Q'$. If the draw satisfies the restrictions we keep it, otherwise we discard it and we keep drawing until the restrictions are satisfied, as in the Rubio-Waggoner-Zha code `SRestrictRWZalg.m` which implements their algorithm. (See at <http://home.earthlink.net/~tzha02/ProgramCode/SRestrictRWZalg.m>.)

2.5 Details of the counterfactual simulations

Based on either identification strategy we perform the counterfactual simulation in which we ‘bring the *Bundesbank* to the United States’ as follows. We start each counterfactual simulation conditional on the first p actual historical values of the vector Y_t for the United States. For each simulation $j=1, 2, \dots, 1,000$, at each quarter $t=p+1, p+2, \dots, T$ we draw two random numbers, κ_{US} , for the United States, and κ_{WG} , for West Germany, both defined over the domain $\{1, 2, 3, \dots, 1,000\}$. The two random numbers select two draws from the two countries’ ergodic distributions for their respective estimated structural VARs:

$$[\text{West Germany}] \quad Y_t^{WG} = B_{0,t}^{WG} + B_{1,t}^{WG}Y_{t-1}^{WG} + \dots + B_{p,t}^{WG}Y_{t-p}^{WG} + A_{0,t}^{WG}u_t^{WG} \quad (11)$$

$$[\text{United States}] \quad Y_t^{US} = B_{0,t}^{US} + B_{1,t}^{US}Y_{t-1}^{US} + \dots + B_{p,t}^{US}Y_{t-p}^{US} + A_{0,t}^{US}u_t^{US} \quad (12)$$

where $A_{0,t}^C$ and u_t^C , $C = \text{West Germany, United States}$, are the structural impact matrices and the structural disturbances for quarter t , respectively. We then pre-multiply (11) and (12) by $[A_{0,t}^{WG}]^{-1}$ and $[A_{0,t}^{US}]^{-1}$, respectively, thus obtaining

$$[\text{West Germany}] \quad [A_{0,t}^{WG}]^{-1}Y_t^{WG} = \tilde{B}_{0,t}^{WG} + \tilde{B}_{1,t}^{WG}Y_{t-1}^{WG} + \dots + \tilde{B}_{p,t}^{WG}Y_{t-p}^{WG} + u_t^{WG} \quad (13)$$

$$[\text{United States}] \quad [A_{0,t}^{US}]^{-1}Y_t^{US} = \tilde{B}_{0,t}^{US} + \tilde{B}_{1,t}^{US}Y_{t-1}^{US} + \dots + \tilde{B}_{p,t}^{US}Y_{t-p}^{US} + u_t^{US} \quad (14)$$

—where $\tilde{B}_{k,t}^C \equiv [A_{0,t}^C]^{-1}B_{k,t}^C$ —in which each structural shock gets ‘assigned’ to a specific equation. The identified monetary policy shocks in (13) and (14), respectively, uniquely identify the two countries’ monetary policy rules. At this point we simply take the German monetary rule from (13) and we impose it into (14), thus obtaining the counterfactual structural VAR for the United States for quarter t , which, conditional on $Y_{t-1}^{US}, \dots, Y_{t-p}^{US}$ and u_t^{US} generates counterfactual values for Y_t^{US}, \hat{Y}_t^{US} . We repeat this procedure 1,000 times for each quarter $t=p+1, p+2, \dots, T$, thus building up the distribution of the counterfactual U.S. series. Finally, we convert the quarter-on-quarter rates of growth of the GDP deflator, real GDP, M2, and the NEER into annual rates of growth by simply computing the convolutions of the quarter-on-quarter rates of growth at time t and in the previous three quarters. Specifically, letting x_t^A and x_t^Q be the annual and quarterly rates of growth of variable X in quarter t , we have $x_t^A = (1+x_t^Q) \cdot (1+x_{t-1}^Q) \cdot (1+x_{t-2}^Q) \cdot (1+x_{t-3}^Q) - 1$.

3 Would the *Bundesbank* Have Prevented the Great Inflation in the United States?

3.1 Results based on sign restrictions

Figures 3 and 4 show results from counterfactual simulations based on sign restrictions, based on the four-variables VARs.¹⁷ Specifically, Figure 3 shows the series' actual historical values together with the medians and the 16th and the 84th percentiles of the distributions of the simulated counterfactuals series, whereas Figure 4 shows the medians and the 16th and the 84th percentiles of the distributions of the difference between the counterfactual and the actual series. Finally, the first column of Figure 11 shows, for inflation and output growth, the medians and the 16th and the 84th percentiles of the distributions of the simulated counterfactuals series, together with West Germany's actual inflation and output growth series during those years. The key facts emerging from Figures 3, 4, and 11 can be summarised as follows.

As the upper-left panel of Figure 4 shows, the difference between the counterfactual and the actual inflation series during the Great Inflation episode is, in general, not negligible, oscillating (based on median estimates) between nearly -6 and about 5 per cent. Such difference, however, does not exhibit any consistent pattern, either positive or negative, with the result that the counterfactual does not lead to any clear improvement or worsening of the U.S. inflationary performance. Indeed, as the upper-left panel of Figure 5 shows, results from this counterfactual clearly suggest that bringing the *Bundesbank* to the United States would *not* have prevented the Great Inflation, with counterfactual U.S. inflation peaking at 11.0 and 9.9 per cent in 1975Q1 and 1981Q1, respectively.

A comparison with West Germany's inflation's performance during those years is, under this respect, instructive. Following March 1973, the *Bundesbank's* tough counter-inflationary stance led to a swift decline in German inflation, which oscillated around 4 per cent between the second half of 1975 and mid-1983, and during subsequent years declined further, first dropping below 2 per cent in 1985Q1. Counterfactual U.S. inflation, by contrast, *rises* rapidly during the second half of the 1970s, and peaks at nearly 10 per cent in the early 1980s. A key point to stress is that the series plotted in the top-left panel of Figure 9—both West Germany's actual inflation series, and the U.S. counterfactual inflation series—have been generated *conditional on the very same structural monetary rule*, with the only difference that, in the case of the United States, such rule has been embedded in the estimated structural VAR for the U.S.. What can therefore account for the stark difference between actual German inflation and counterfactual U.S. inflation? Several non-mutually exclusive

¹⁷Since, in general, results based on the five-variables VARs are qualitatively the same as, and quantitatively very close to, those based on the four-variables VARs, for reasons of space throughout the entire paper we only discuss the latter set of results. The entire set of results based on the five-variables VARs is however available from the author upon request.

explanations are possible. *First*, it may be the case that the structural shocks which had been buffeting the two economies during those years were fundamentally different in nature, with those impacting upon the German economy being significantly more benign than those hitting the United States. *Second*, structural features of the two economies unrelated to monetary policy were radically different, with the U.S. economy, in particular, being significantly more prone to inflationary outbursts than the German one. *Third*, the policy counterfactual has simply failed to capture the truth: if the *Bundesbank* had been in charge of U.S. monetary policy during those years, it would have prevented the Great Inflation in the United States exactly as it actually prevented it in West Germany, but the SVAR-based counterfactual wrongly suggests that it would have not. Which of these explanations is most plausible?

As discussed by Benati and Goodhart (2011), the notion that West Germany and Switzerland, countries traditionally associated with ‘hard-money, low-inflation’ policies, had somehow ‘got lucky’ during the 1970s, whereas countries such as the U.S. and the U.K., which according to a host of narrative evidence,¹⁸ pursued during those years markedly sub-optimal policies, were afflicted by a bout of chronic bad luck is pretty hard to believe. On the other hand, it is not clear *which* specific structural characteristics of the U.S. economy unrelated to monetary policy made the United States so prone to inflationary outbursts during the 1970s, but not during the two decades and a half which followed the Volcker disinflation. Further, a key point to be stressed is that over such a long period of time (the Great Inflation started in the mid-1960s, and ended in the first half of the 1980s) average inflation *should* be regarded, to a first approximation, as under the control of the monetary authority. This leaves us with what is, in my own view, the most plausible explanation: the SVAR-based counterfactual has simply failed to capture the truth. Again, an important point to stress is that this explanation has not been ‘pulled out of thin air’: on the contrary, as previously discussed in Section 1.1, *(i)* such counterfactuals have been known for more than three decades to be questionable as a matter of principle, and *(ii)* DSGE-based evidence produced by Benati and Surico (2009) and especially Benati (2010) suggests that the problem may well be practically relevant.

Let’s now turn to the results based on the two alternative identification schemes.

3.2 Results based on the two alternative identification strategies

Figures 5-6 and 8-9 show results from the counterfactual simulations based on the alternative identification strategy in the spirit of Sims and Zha (2006), and based on Cholesky, respectively, whereas the second and third columns of Figure 11 compare the counterfactual U.S. series for inflation and output growth to West Germany’s actual inflation and output growth series. Based on either identification scheme, results

¹⁸See e.g. DeLong (1997) for the United States, and Nelson and Nikolov (2004) and Batini and Nelson (2005) for the United Kingdom.

are slightly weaker than based on sign restrictions, with counterfactual inflation peaking at 10.3 and 11.1, respectively, in 1975Q1; sharply increasing, once again, during the second half of the 1970s; and peaking again at 8.4 and 8.0, respectively, in 1981Q1, before falling rapidly around the time of the Volcker disinflation. In particular, during the second half of the 1970s the counterfactual inflation paths generated by these two alternative strategies are systematically lower than those produced by the sign restrictions methodology. As a consequence, whereas in the case of sign restrictions West Germany's actual inflation path was consistently below the one standard deviation lower percentile of the distribution of counterfactual U.S. inflation, this is no longer always the case for the two alternative identification schemes, with some quarters in which West Germany's actual inflation is inside the one standard deviation confidence interval.

The results based on these two alternative identification schemes should however be seen with suspicion, and should therefore be significantly discounted, for two key reasons.

First, as extensively discussed by Canova and Pina (2005), identification schemes based on inertial restrictions (that is, zero restrictions on impact, as in the present case) are in general incompatible with DSGE models, whose impact matrices of the structural shocks at $t=0$ are typically 'full'—that is, they contain zero entries only under very special circumstances. In particular, for a DSGE model's structural impact matrix at $t=0$ to contain zero entries, the model has to be specifically 'tailored' for that purpose. (This is especially relevant at the quarterly frequency which is used herein, whereas at the monthly frequency the assumption of, e.g., no impact of a monetary policy shock on inflation and unemployment within the month, as in Sims and Zha (2006), is more plausible.) This is a very important point, because, as shown by Canova and Pina (2005), the imposition of inertial restrictions which are false in the DGP can produce significantly distorted results, for example giving rise to entirely spurious estimated 'price puzzles' (that is, price puzzles which are not in the true DGP).

Second, the two alternative identification schemes used herein generate indeed implausible IRFs to an identified monetary policy shock.¹⁹ Specifically, Cholesky (see Figure 7) implies a dramatic, and statistically significant price puzzle for a large portion of the sample period, so that a monetary contraction ultimately ends up *increasing* the price level, rather than decreasing it. The scheme in the spirit of Sims and Zha (2006)—see Figure 10—still implies a price puzzle based on median estimates, but for no portion of the sample period it is possible to reject the null hypothesis that a monetary contraction has *no* impact on the price level at the 5 per cent significance level. (An important point to stress, however, is that the notion that a monetary contraction exerts no impact on the price level should also be regarded

¹⁹In computing the IRFs, we take into account of the uncertainty originating from future time-variation in the VAR *via* Monte Carlo integration, as in Benati (2008) and Benati and Mumtaz (2007).

as questionable.) In the light of Canova and Pina (2005)’s analysis, one obvious, possible interpretation for these IRFs is they are simply the result of imposing inertial restrictions which are false in the DGP.

3.3 Implications

Overall, results—in particular, those based on the most plausible (or least implausible ...) identification scheme, sign restrictions—suggest therefore that the *Bundesbank* would not have been able to prevent the Great Inflation in the United States. The results produced by these counterfactuals are therefore qualitatively the same as those obtained by ‘bringing Alan Greenspan back in time’ within the structural VAR-based literature on the Great Moderation, with the key difference being that, instead of performing the counterfactual within a single country across time periods, we have performed it across countries on a quarter-by-quarter basis. However, whereas in the case of Alan Greenspan (or, more generally, of FED officials who have been in charge of U.S. monetary policy over the most recent years) we have no way of knowing how they would have performed had they been in charge of U.S. monetary policy in the 1970s, this is clearly not the case for the *Bundesbank*. West Germany’s central bank was indeed there, and its monetary policy is widely credited for sparing West Germany the Great Inflation. The notion that, if it had been put in charge of post-WWII U.S. monetary policy, it would have been unable to successfully counter the 1970s’ inflationary upsurge in the United States is therefore quite hard to believe. As a logical corollary, these results raise doubts on the reliability of policy counterfactuals based on estimated structural VARs.

One qualification to this conclusion is the following.²⁰ When moving an evolving monetary policy rule across periods within a single country—which is what has been done in the SVAR-based literature on the U.S. Great Moderation—it may be possible to argue that, as long as the regime changes are recurrent, the SVAR-based policy counterfactual should still be reasonably accurate, because the time-varying VAR embeds a learning process which mimics/captures the real-world learning process on the part of economic agents about the evolution of monetary policy. Within the present context, however, such a presumption is clearly unwarranted, because the ‘*Bundesbank* regime’ is not among the regimes experienced by U.S. economic agents over the post-WWII era. This implies that, being such a regime entirely ‘alien’ to the post-WWII United States, the corresponding SVAR-based policy counterfactual *should* logically be expected to fail simply because of the Lucas (1976) critique. At the same time, however, it may be argued that policy counterfactuals pertaining to one of the post-WWII U.S. recurrent regimes may not suffer from the Lucas (1976) critique to the same extent, simply because such regime comes from a distribution of possible regimes about which the U.S. public had a reasonably good knowledge. As a consequence, the failure of the ‘*Bundesbank* counterfactual’ which has been docu-

²⁰I wish to thank a referee for making this point.

mented in this paper may not necessarily imply that the ‘Greenspan counterfactual’ should be regarded as equally unreliable.

Finally, a possible alternative interpretation of the results discussed in this paper would be to see the *Bundesbank*’s failure to prevent the Great Inflation in the United States as a definitive vindication of the notion that the U.S. Great Inflation *truly* was due to ‘bad luck’, that is to a sequence of large adverse shocks. Although, in principle, this is certainly a possibility, for the reasons I previously discussed in Section 3.1 I personally find such interpretation as distinctly unappealing, because it would automatically imply that West Germany has been comparatively ‘lucky’ during the 1970s, which, as extensively discussed by Benati and Goodhart (2011), is quite hard to believe. By the same token, a possible alternative interpretation might be to argue that there might have been other key differences between the U.S. and the German economy, beyond the ones implied by the conduct of monetary policy. Again, as I previously discussed in Section 3.1, first, it is not clear *which* specific structural characteristics of the U.S. economy unrelated to monetary policy made the United States so prone to inflationary outbursts during the 1970s, but not during the two decades and a half which followed the Volcker disinflation; and second, it is important to stress that over such a long period of time (the Great Inflation started in the mid-1960s, and ended in the first half of the 1980s) average inflation *should* be regarded, to a first approximation, as fully under the control of the monetary authority.

4 Conclusions

Since the structural VAR methodology came to essentially dominate applied macroeconomic research, around mid-1980s, policy counterfactuals have been one of its main applications. As we have discussed, the outcome of such counterfactuals is seldom questioned, and the results they produce are usually taken at face value. In this paper we have shown that standard structural VAR methodology, when applied to a specific policy counterfactual—‘bringing the *Bundesbank* to the post-WWII United States’—produces a result which the vast majority of macroeconomists would likely find extremely hard to believe: the very same central bank which burnished its ‘hard-money’, anti-inflation reputation by successfully countering the 1970s’ inflationary impulses in West Germany would not have been able to deliver a comparable performance had it been put in charge of U.S. monetary policy. The fact that (i) such counterfactual is a ‘standard’ one—in the specific sense that, instead of being performed within a single country and across time, it is performed across countries—and (ii) it has been produced based on ‘off-the-shelf’ methods (in terms of both estimation and identification), sounds a cautionary note on taking the outcome of SVAR-based policy counterfactuals at face value, and raises questions on their reliability.

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A The Data

A.1 United States

Quarterly seasonally adjusted series for the GDP deflator (‘GDPCTPI: Gross Domestic Product: Chain-type Price Index, Seasonally Adjusted, Quarterly, Index 2000=100’) and real GDP (‘GDPC96: Real Gross Domestic Product, 3 Decimal, Seasonally Adjusted Annual Rate, Quarterly, Billions of Chained 2000 Dollars’) are both from the U.S. *Department of Commerce, Bureau of Economic Analysis*, and are both available since 1947:1. A monthly series for the Federal Funds rate (‘FEDFUNDS: Effective Federal Funds Rate, Monthly, Percent’) from the *Board of Governors of the Federal Reserve System* is available since July 1954, and has been converted to the quarterly frequency by taking averages within the quarter. A monthly seasonally adjusted series for M2 (‘M2SL: M2 Money Stock, H.6 Money Stock Measures, Seasonally Adjusted, Monthly, Billions of Dollars’), available since January 1959, is from the *Board of Governors of the Federal Reserve System* and has been converted to the quarterly frequency by taking averages within the quarter. Finally, a monthly seasonally adjusted series for the nominal effective exchange rate computed based on unit labor costs (series’ code is 111..NEUZF...), available since January 1957, is from the *IMF’s IFS*, and it has been converted to the quarterly frequency by taking averages within the quarter. The overall sample period is from 1959:1 to 2008:1.

A.2 West Germany

Quarterly seasonally adjusted series for the GDP deflator and real GDP are both from the *IMF’s IFS*, and are both available since 1960:1 (series’ codes are 13499BIRZF... and 13499BVRZF... respectively). A monthly seasonally unadjusted series for the call money rate from the *IMF’s IFS*, available since January 1957, has been converted to the quarterly frequency by taking averages within the quarter (series’ code is 13460B..ZF...). A quarterly seasonally adjusted series for M2, available since 1948:4, is from the *Bundesbank*. Finally, a monthly seasonally adjusted series for the nominal effective exchange rate computed based on unit labor costs (acronym is 134..NEUZF...), available since January 1960, is from the *IMF’s IFS*, and it has been converted to the quarterly frequency by taking averages within the quarter. The overall sample period is from 1960:1 to 1990:1.

B Details of the Markov-Chain Monte Carlo Procedure

We estimate (1)-(9) *via* Bayesian methods. The next two subsections describe our choices for the priors, and the Markov-Chain Monte Carlo algorithm we use to simulate the posterior distribution of the hyperparameters and the states conditional

on the data, while the third section discusses how we check for convergence of the Markov chain to the ergodic distribution.

B.1 Priors

For the sake of simplicity, the prior distributions for the initial values of the states— θ_0 , α_0 , and h_0 —which we postulate all to be normal, are assumed to be independent both from one another, and from the distribution of the hyperparameters. In order to calibrate the prior distributions for θ_0 , α_0 and h_0 we estimate a time-invariant version of (1) based on the first 8 years of data, from 1959:3 to 1966:4, and we set

$$\theta_0 \sim N \left[\hat{\theta}_{OLS}, 4 \cdot \hat{V}(\hat{\theta}_{OLS}) \right] \quad (\text{B1})$$

As for α_0 and h_0 we proceed as follows. Let $\hat{\Sigma}_{OLS}$ be the estimated covariance matrix of ϵ_t from the time-invariant VAR, and let C be the lower-triangular Choleski factor of $\hat{\Sigma}_{OLS}$ —i.e., $CC' = \hat{\Sigma}_{OLS}$. We set

$$\ln h_0 \sim N(\ln \mu_0, 10 \times I_4) \quad (\text{B2})$$

where μ_0 is a vector collecting the logarithms of the squared elements on the diagonal of C . We then divide each column of C by the corresponding element on the diagonal—let's call the matrix we thus obtain \tilde{C} —and we set

$$\alpha_0 \sim N[\tilde{\alpha}_0, \tilde{V}(\tilde{\alpha}_0)] \quad (\text{B3})$$

where $\tilde{\alpha}_0$ —which, for future reference, we define as $\tilde{\alpha}_0 \equiv [\tilde{\alpha}_{0,11}, \tilde{\alpha}_{0,21}, \dots, \tilde{\alpha}_{0,61}]'$ —is a vector collecting all the non-zero and non-one elements of \tilde{C}^{-1} (i.e, the elements below the diagonal), and its covariance matrix, $\tilde{V}(\tilde{\alpha}_0)$, is postulated to be diagonal, with each individual (j,j) element equal to 10 times the absolute value of the corresponding j -th element of $\tilde{\alpha}_0$. Such a choice for the covariance matrix of α_0 is clearly arbitrary, but is motivated by our goal to scale the variance of each individual element of α_0 in such a way as to take into account of the element's magnitude.

Turning to the hyperparameters, we postulate independence between the parameters corresponding to the three matrices Q , S , and Z —an assumption we adopt uniquely for reasons of convenience—and we make the following, standard assumptions. The matrix Q is postulated to follow an inverted Wishart distribution,

$$Q \sim IW(\bar{Q}^{-1}, T_0) \quad (\text{B4})$$

with prior degrees of freedom T_0 and scale matrix $T_0\bar{Q}$. In order to minimize the impact of the prior, thus maximizing the influence of sample information, we set T_0 equal to the minimum value allowed, the length of θ_t plus one. As for \bar{Q} , we calibrate it as $\bar{Q} = \gamma \times \hat{\Sigma}_{OLS}$, setting $\gamma = 3.5 \times 10^{-4}$, the same value used by Cogley and Sargent (2005).

The three blocks of S are assumed to follow inverted Wishart distributions, with prior degrees of freedom set, again, equal to the minimum allowed, respectively, 2, 3 and 4:

$$S_1 \sim IW(\bar{S}_1^{-1}, 2) \quad (\text{B5})$$

$$S_2 \sim IW(\bar{S}_2^{-1}, 3) \quad (\text{B6})$$

$$S_3 \sim IW(\bar{S}_3^{-1}, 4) \quad (\text{B7})$$

As for \bar{S}_1 , \bar{S}_2 and \bar{S}_3 , we calibrate them based on $\tilde{\alpha}_0$ in (B3) as $\bar{S}_1=10^{-3} \times |\tilde{\alpha}_{0,11}|$, $\bar{S}_2=10^{-3} \times \text{diag}(|\tilde{\alpha}_{0,21}|, |\tilde{\alpha}_{0,31}|)'$ and $\bar{S}_3=10^{-3} \times \text{diag}(|\tilde{\alpha}_{0,41}|, |\tilde{\alpha}_{0,51}|, |\tilde{\alpha}_{0,61}|)'$. Such a calibration is consistent with the one we adopted for Q , as it is equivalent to setting \bar{S}_1 , \bar{S}_2 and \bar{S}_3 equal to 10^{-4} times the relevant diagonal block of $\tilde{V}(\tilde{\alpha}_0)$ in (B3). Finally, as for the variances of the stochastic volatility innovations, we follow Cogley and Sargent (2002, 2005) and we postulate an inverse-Gamma distribution for the elements of Z ,

$$\sigma_i^2 \sim IG\left(\frac{10^{-4}}{2}, \frac{1}{2}\right) \quad (\text{B8})$$

B.2 Simulating the posterior distribution

We simulate the posterior distribution of the hyperparameters and the states conditional on the data *via* the following MCMC algorithm, combining elements of Primiceri (2005) and Cogley and Sargent (2002, 2005). In what follows, x^t denotes the entire history of the vector x up to time t —i.e. $x^t \equiv [x'_1, x'_2, \dots, x'_t]'$ —while T is the sample length.

(a) *Drawing the elements of θ_t* Conditional on Y^T , α^T , and H^T , the observation equation (1) is linear, with Gaussian innovations and a known covariance matrix. Following Carter and Kohn (2004), the density $p(\theta^T|Y^T, \alpha^T, H^T, V)$ can be factored as

$$p(\theta^T|Y^T, \alpha^T, H^T, V) = p(\theta_T|Y^T, \alpha^T, H^T, V) \prod_{t=1}^{T-1} p(\theta_t|\theta_{t+1}, Y^T, \alpha^T, H^T, V) \quad (\text{B9})$$

Conditional on α^T , H^T , and V , the standard Kalman filter recursions nail down the first element on the right hand side of (B9), $p(\theta_T|Y^T, \alpha^T, H^T, V) = N(\theta_T, P_T)$, with P_T being the precision matrix of θ_T produced by the Kalman filter. The remaining elements in the factorization can then be computed via the backward recursion algorithm found, e.g., in Kim and Nelson (2000), or Cogley and Sargent (2005, appendix B.2.1). Given the conditional normality of θ_t , we have

$$\theta_{t|t+1} = \theta_{t|t} + P_{t|t}P_{t+1|t}^{-1}(\theta_{t+1} - \theta_t) \quad (\text{B10})$$

$$P_{t|t+1} = P_{t|t} - P_{t|t}P_{t+1|t}^{-1}P_{t|t} \quad (\text{B11})$$

which provides, for each t from $T-1$ to 1, the remaining elements in (1), $p(\theta_t|\theta_{t+1}, Y^T, \alpha^T, H^T, V) = N(\theta_t|\theta_{t+1}, P_{t|t+1})$. Specifically, the backward recursion starts with a draw from $N(\theta_T, P_T)$, call it $\tilde{\theta}_T$. Conditional on $\tilde{\theta}_T$, (B10)-(B11) give us $\theta_{T-1|T}$ and $P_{T-1|T}$, thus allowing us to draw $\tilde{\theta}_{T-1}$ from $N(\theta_{T-1|T}, P_{T-1|T})$, and so on until $t=1$.

(b) *Drawing the elements of α_t* Conditional on Y^T, θ^T , and H^T , following Primiceri (2005), we draw the elements of α_t as follows. Equation (1) can be rewritten as $A_t \tilde{Y}_t \equiv A_t(Y_t - X_t' \theta_t) = A_t \epsilon_t \equiv u_t$, with $\text{Var}(u_t) = H_t$, namely

$$\tilde{Y}_{2,t} = -\alpha_{21,t} \tilde{Y}_{1,t} + u_{2,t} \quad (\text{B12})$$

$$\tilde{Y}_{3,t} = -\alpha_{31,t} \tilde{Y}_{1,t} - \alpha_{32,t} \tilde{Y}_{2,t} + u_{3,t} \quad (\text{B13})$$

$$\tilde{Y}_{4,t} = -\alpha_{41,t} \tilde{Y}_{1,t} - \alpha_{42,t} \tilde{Y}_{2,t} - \alpha_{43,t} \tilde{Y}_{3,t} + u_{4,t} \quad (\text{B14})$$

—plus the identity $\tilde{Y}_{1,t} = u_{1,t}$ —where $[\tilde{Y}_{1,t}, \tilde{Y}_{2,t}, \tilde{Y}_{3,t}, \tilde{Y}_{4,t}]' \equiv \tilde{Y}_t$. Based on the observation equations (B12)-(B14), and the transition equation (7), the elements of α_t can then be drawn by applying the same algorithm we described in the previous paragraph separately to (B12), (B13) and (B14). The assumption that S has the block-diagonal structure (9) is in this respect crucial, although, as stressed by Primiceri (2005, Appendix D), it could in principle be relaxed.

(c) *Drawing the elements of H_t* Conditional on Y^T, θ^T , and α^T , the orthogonalised innovations $u_t \equiv A_t(Y_t - X_t' \theta_t)$, with $\text{Var}(u_t) = H_t$, are observable. Following Cogley and Sargent (2002), we then sample the $h_{i,t}$'s by applying the univariate algorithm of Jacquier, Polson, and Rossi (1994) element by element.²¹

(d) *Drawing the hyperparameters* Finally, conditional on Y^T, θ^T, H^T , and α^T , the innovations to θ_t, α_t , the $h_{i,t}$'s are observable, which allows us to draw the hyperparameters—the elements of Q, S_1, S_2, S_3 , and the σ_i^2 —from their respective distributions.

Summing up, the MCMC algorithm simulates the posterior distribution of the states and the hyperparameters, conditional on the data, by iterating on (a)-(d). In what follows we use a burn-in period of 50,000 iterations to converge to the ergodic distribution, and after that we run 10,000 more iterations sampling every 10th draw in order to reduce the autocorrelation across draws.²²

²¹For details, see Cogley and Sargent (2005, Appendix B.2.5).

²²In this we follow Cogley and Sargent (2005). As stressed by Cogley and Sargent (2005), however, this has the drawback of ‘increasing the variance of ensemble averages from the simulation’.

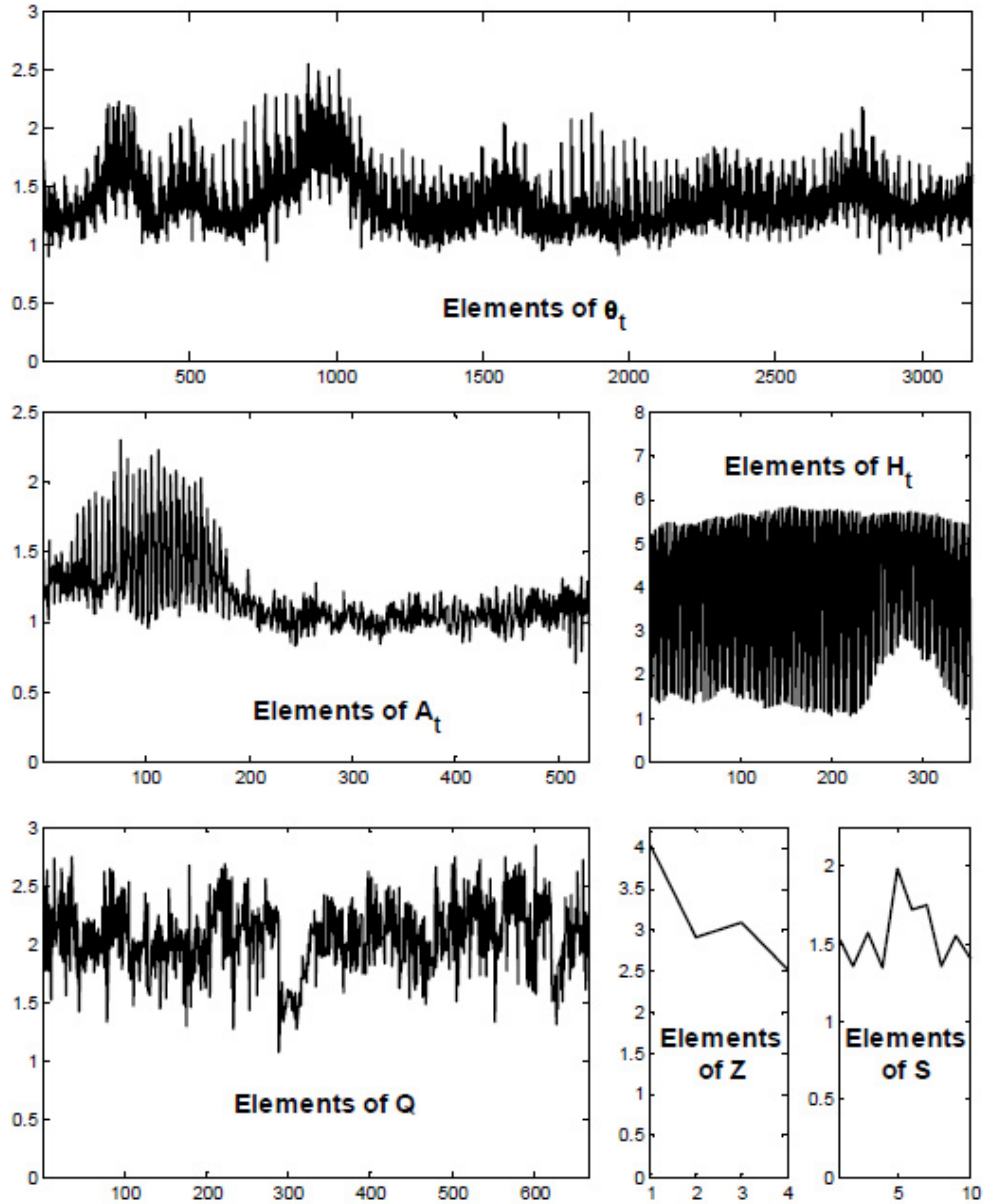


Figure 1 Checking for the convergence of the Markov chain: inefficiency factors for the draws from the ergodic distribution for the hyperparameters and the states (West Germany)

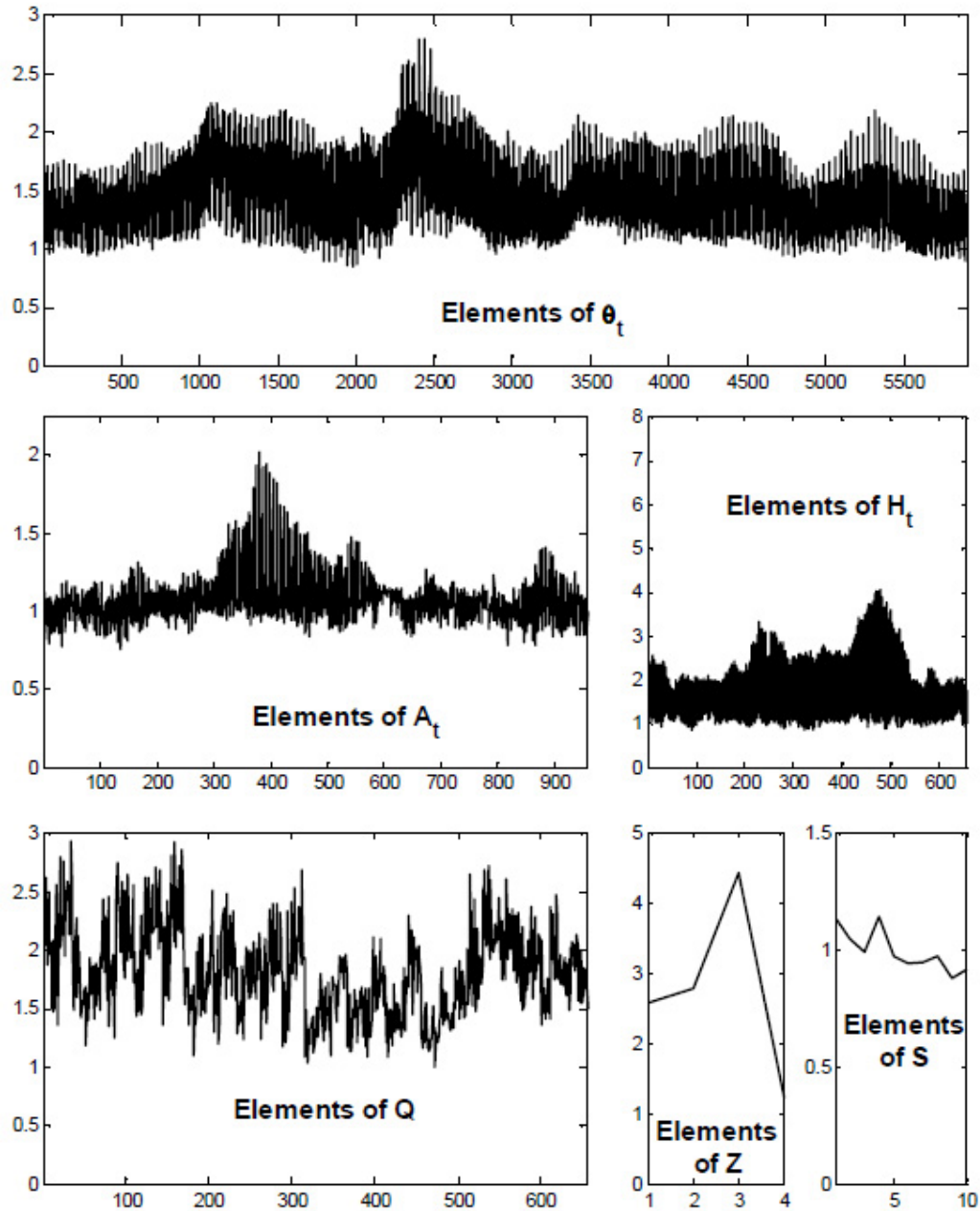


Figure 2 Checking for the convergence of the Markov chain: inefficiency factors for the draws from the ergodic distribution for the hyperparameters and the states (United States)

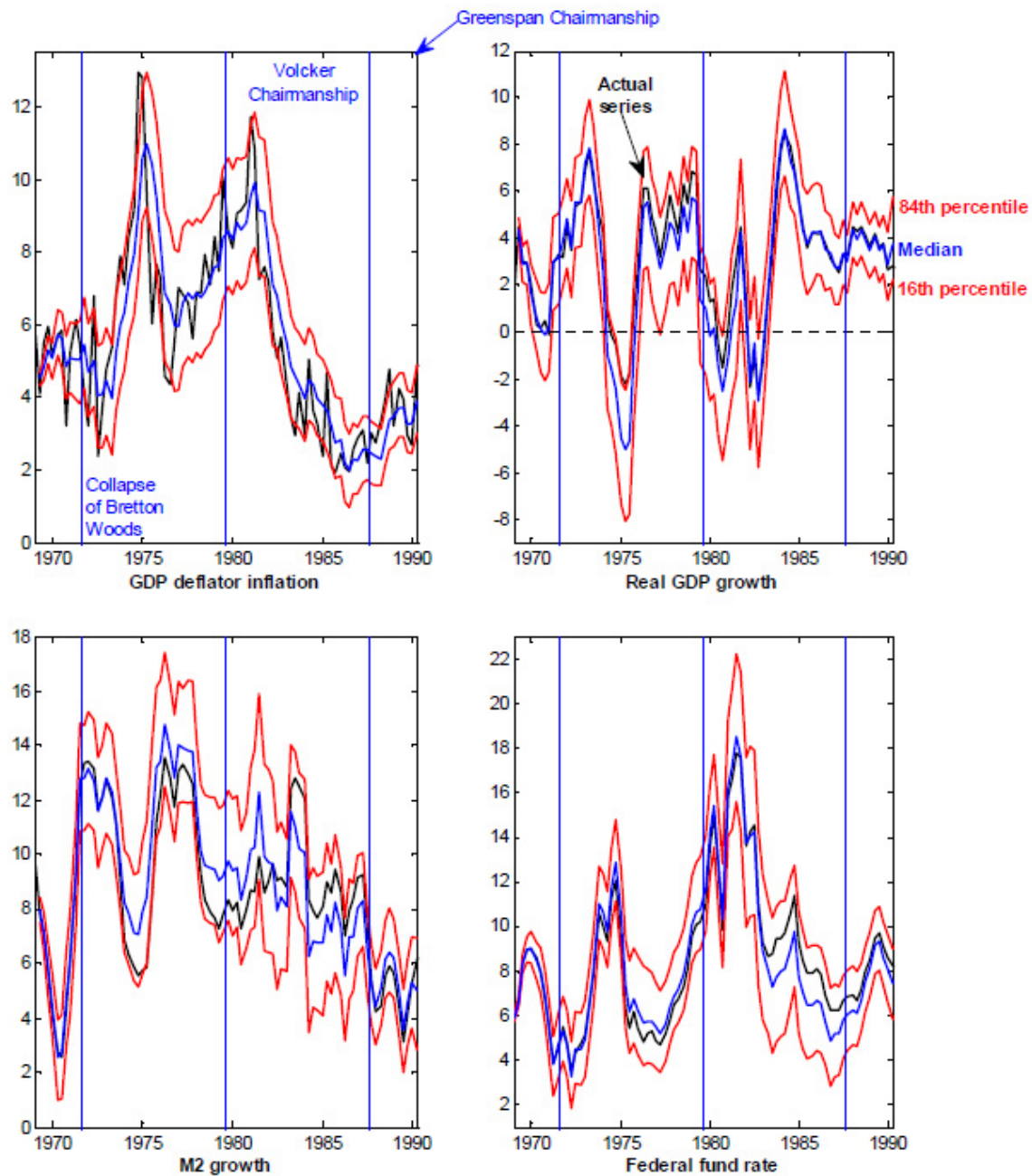


Figure 3 Bringing the *Bundesbank* to the United States: results from counterfactual simulations based on sign restrictions (based on the four-variables VARs)

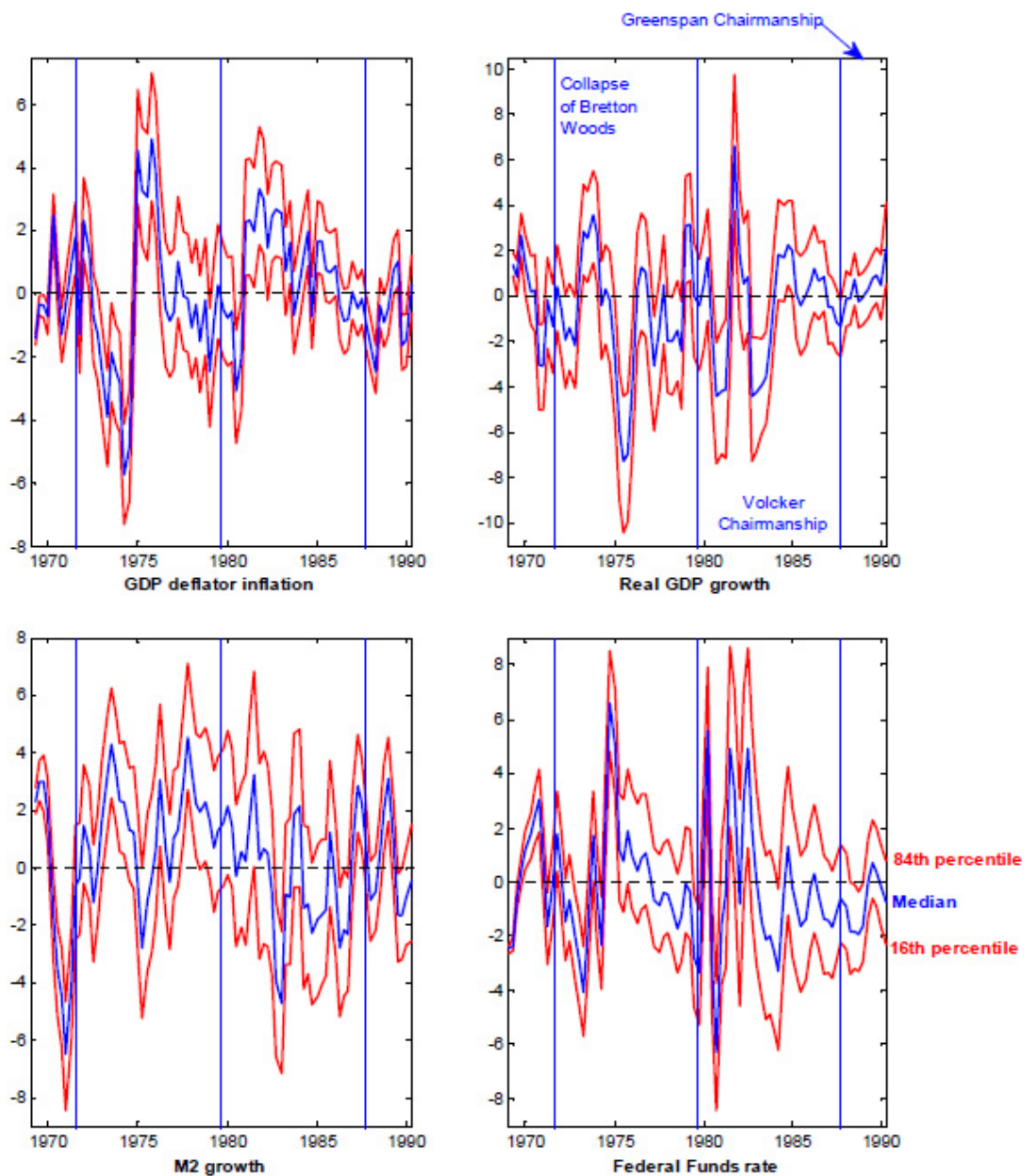


Figure 4 Bringing the *Bundesbank* to the United States: results from counterfactual simulations based on sign restrictions: difference between counterfactual and actual series (based on the four-variables VARs)

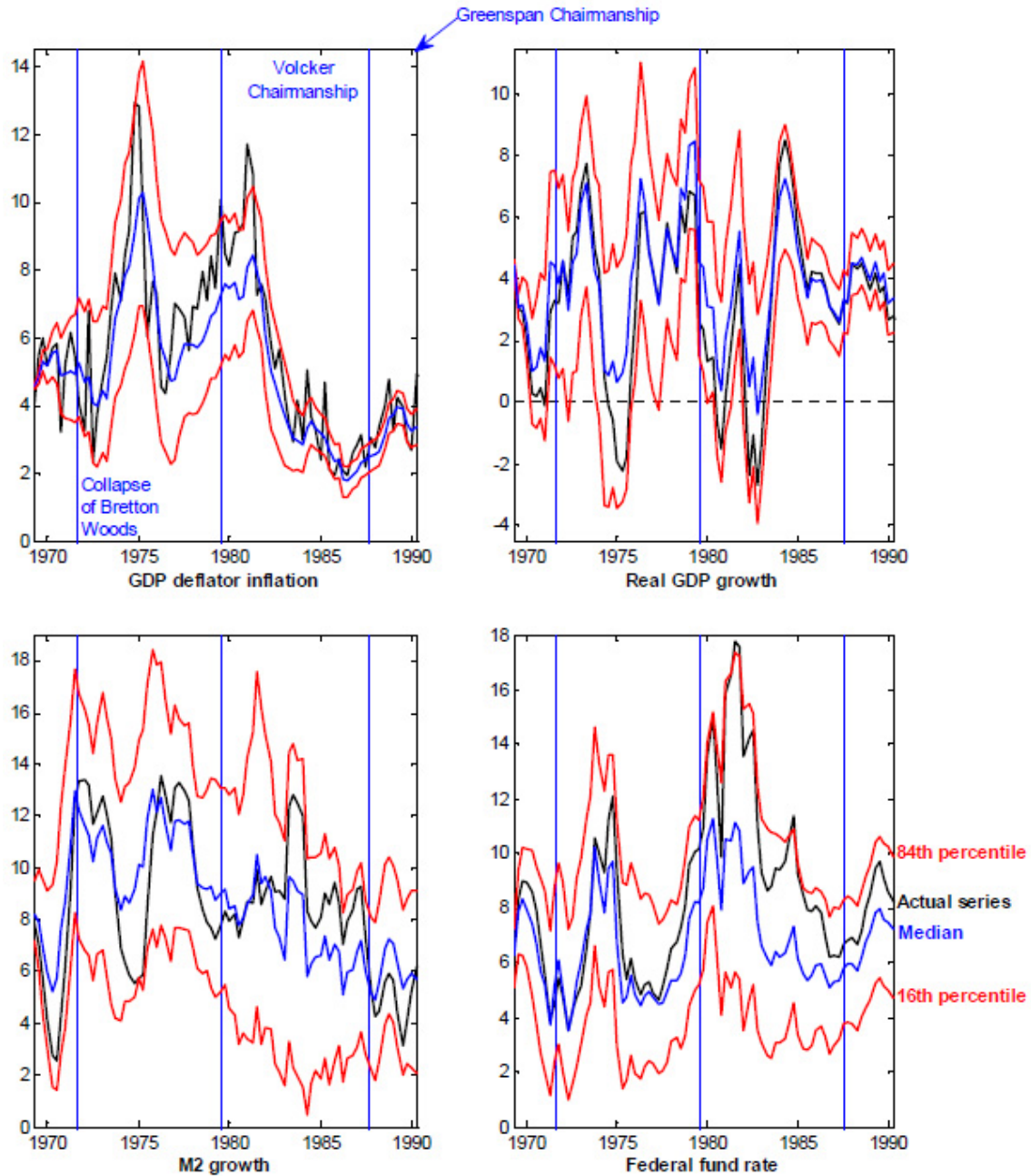


Figure 5 Bringing the *Bundesbank* to the United States: results from counterfactual simulations based on the identification scheme in the spirit of Sims and Zha (2006)(based on the four-variables VARs)

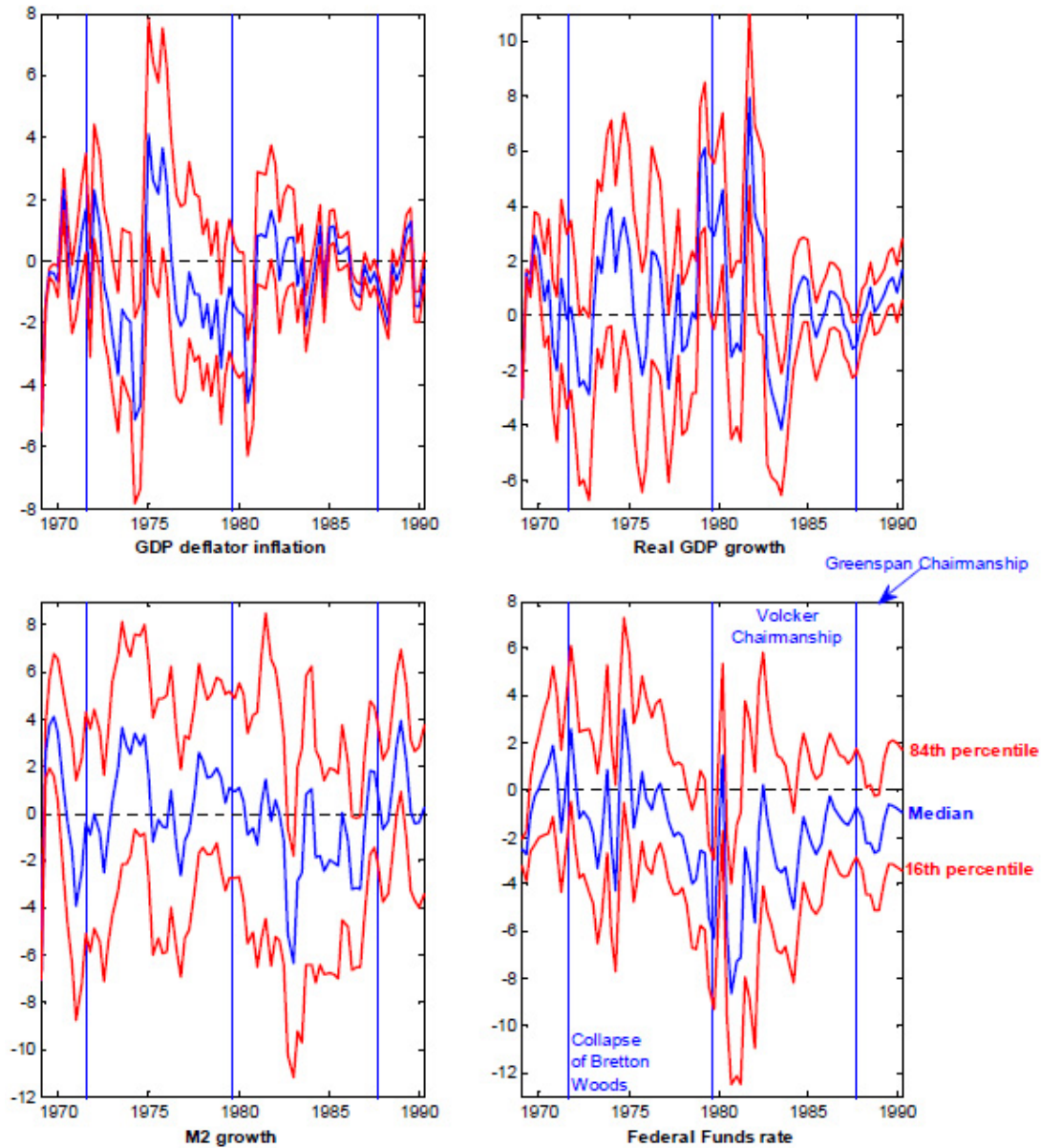


Figure 6 Bringing the *Bundesbank* to the United States: results from counterfactual simulations based on the identification scheme in the spirit of Sims and Zha (2006): difference between counterfactual and actual series (based on the four-variables VARs)

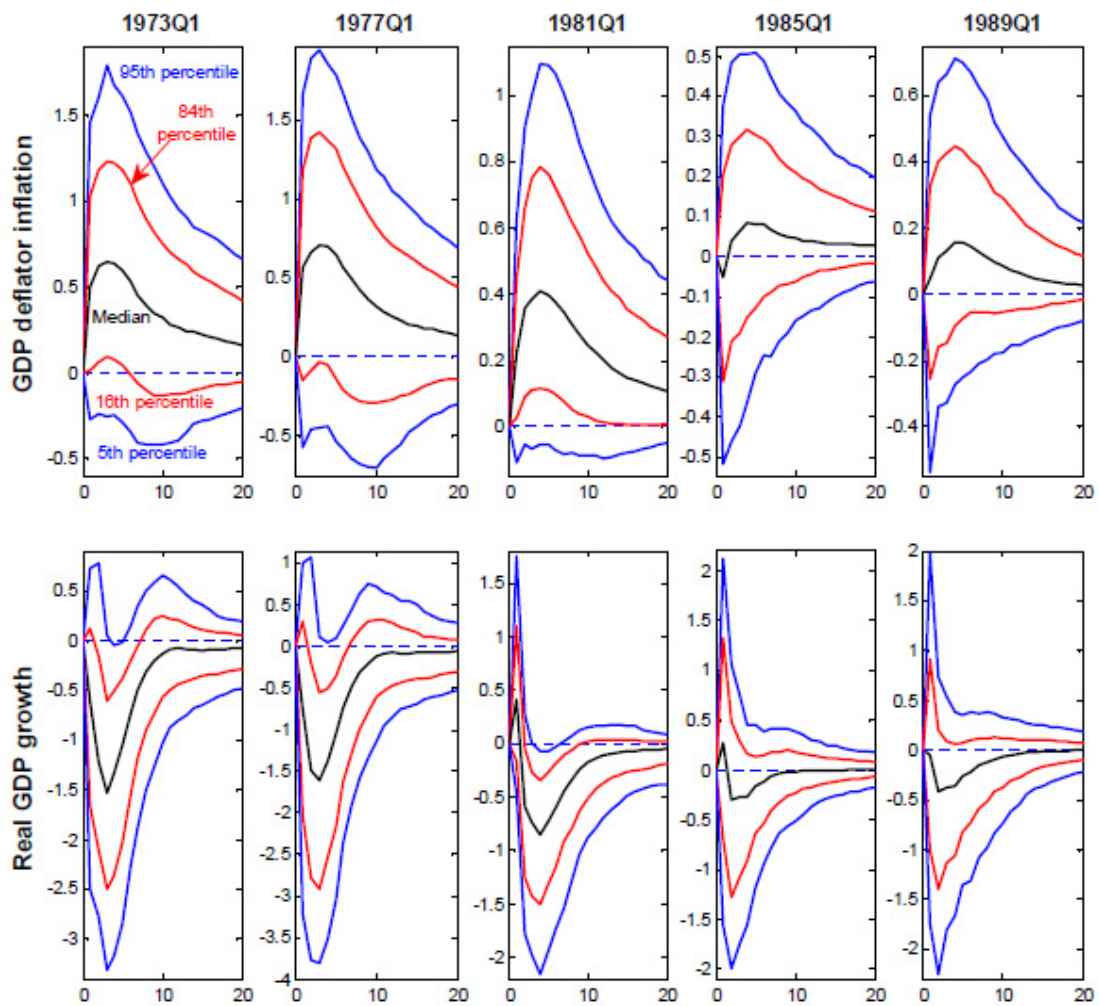


Figure 7 United States: impulse-response functions of inflation and output growth to an identified monetary policy shock based on the identification strategy in the spirit of Sims and Zha, selected quarters (based on the four-variables VARs)

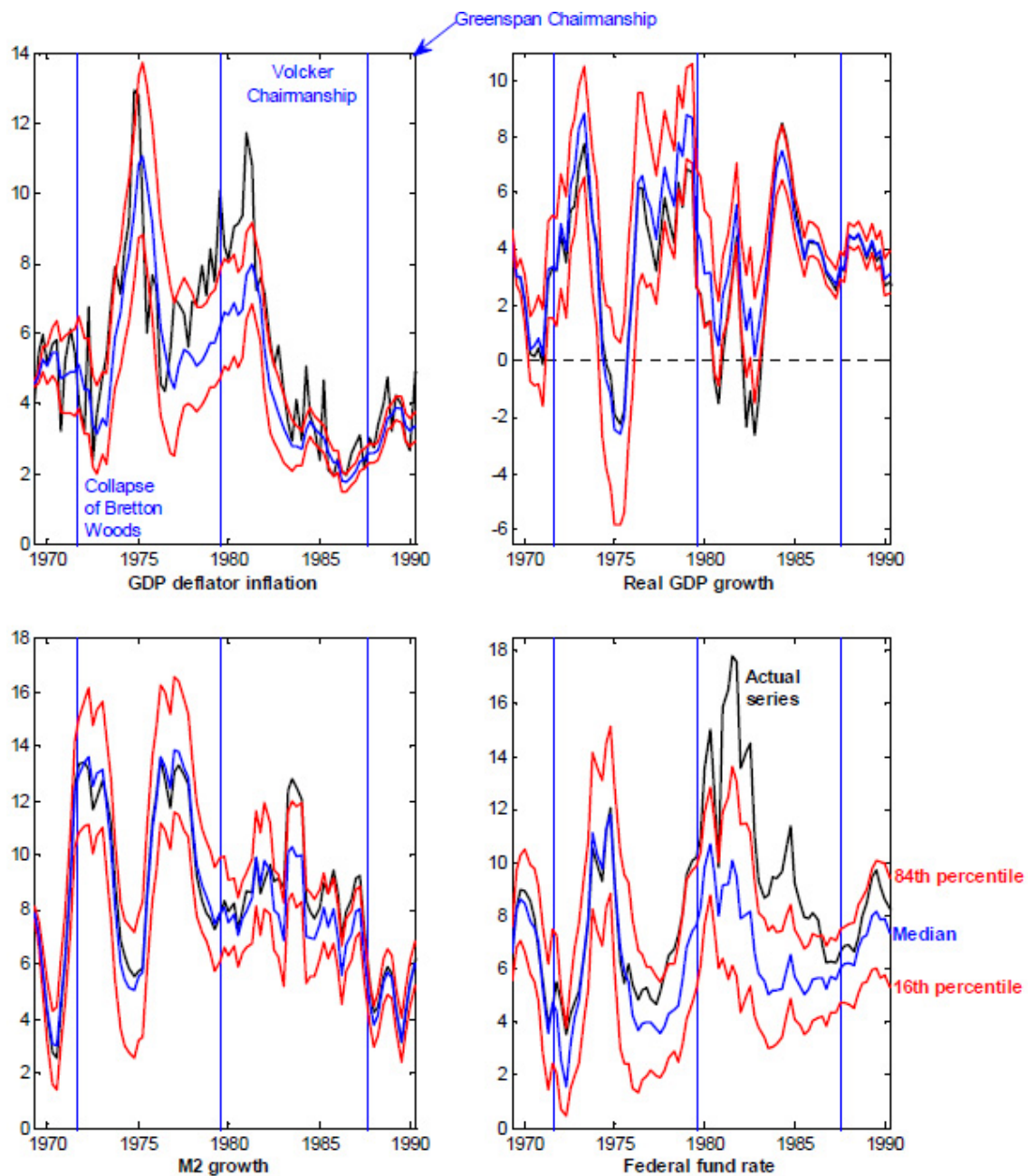


Figure 8 Bringing the *Bundesbank* to the United States: results from counterfactual simulations based on Cholesky (based on the four-variables VARs)

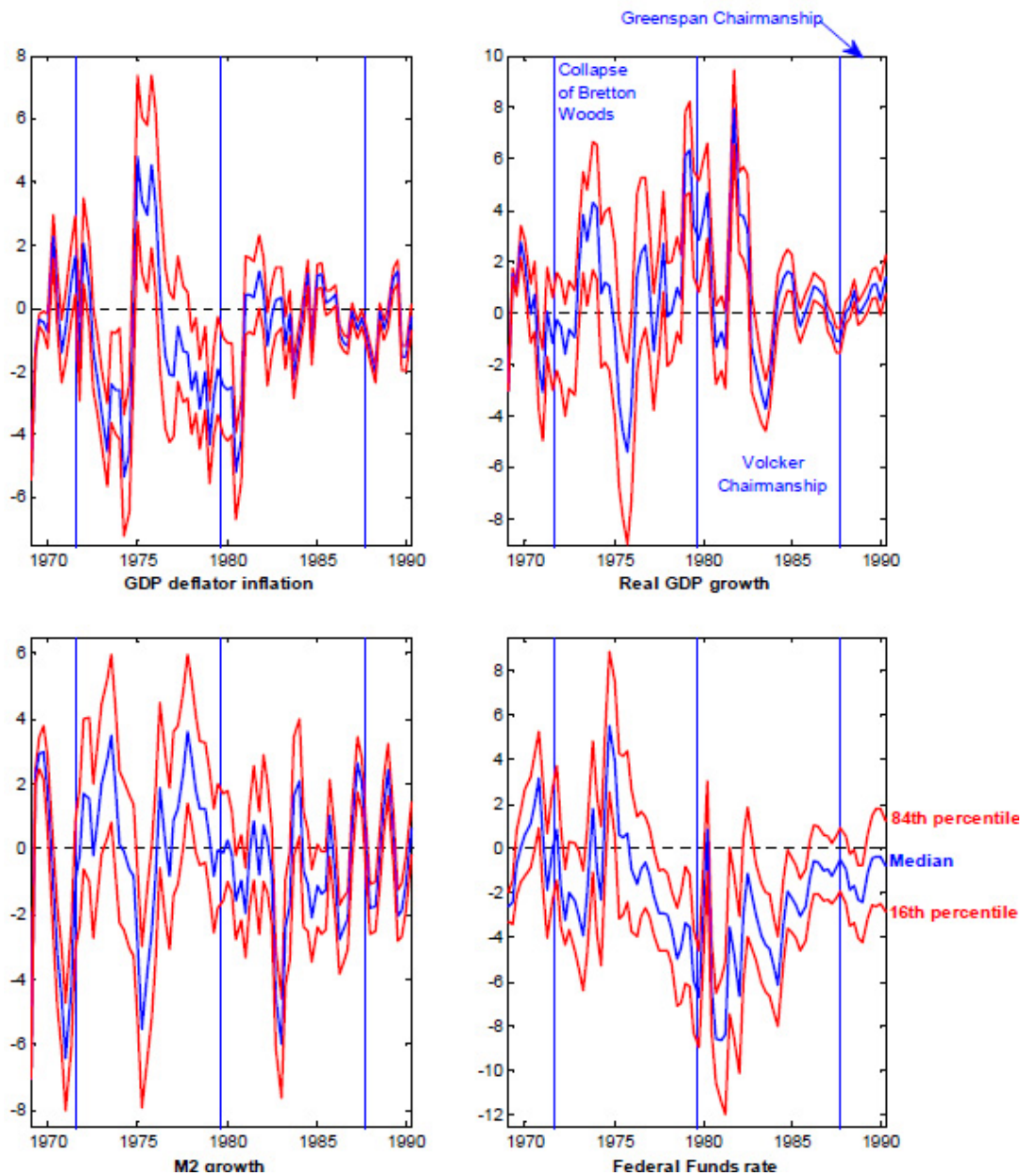


Figure 9 Bringing the *Bundesbank* to the United States: results from counterfactual simulations based on Cholesky: difference between counterfactual and actual series (based on the four-variables VARs)

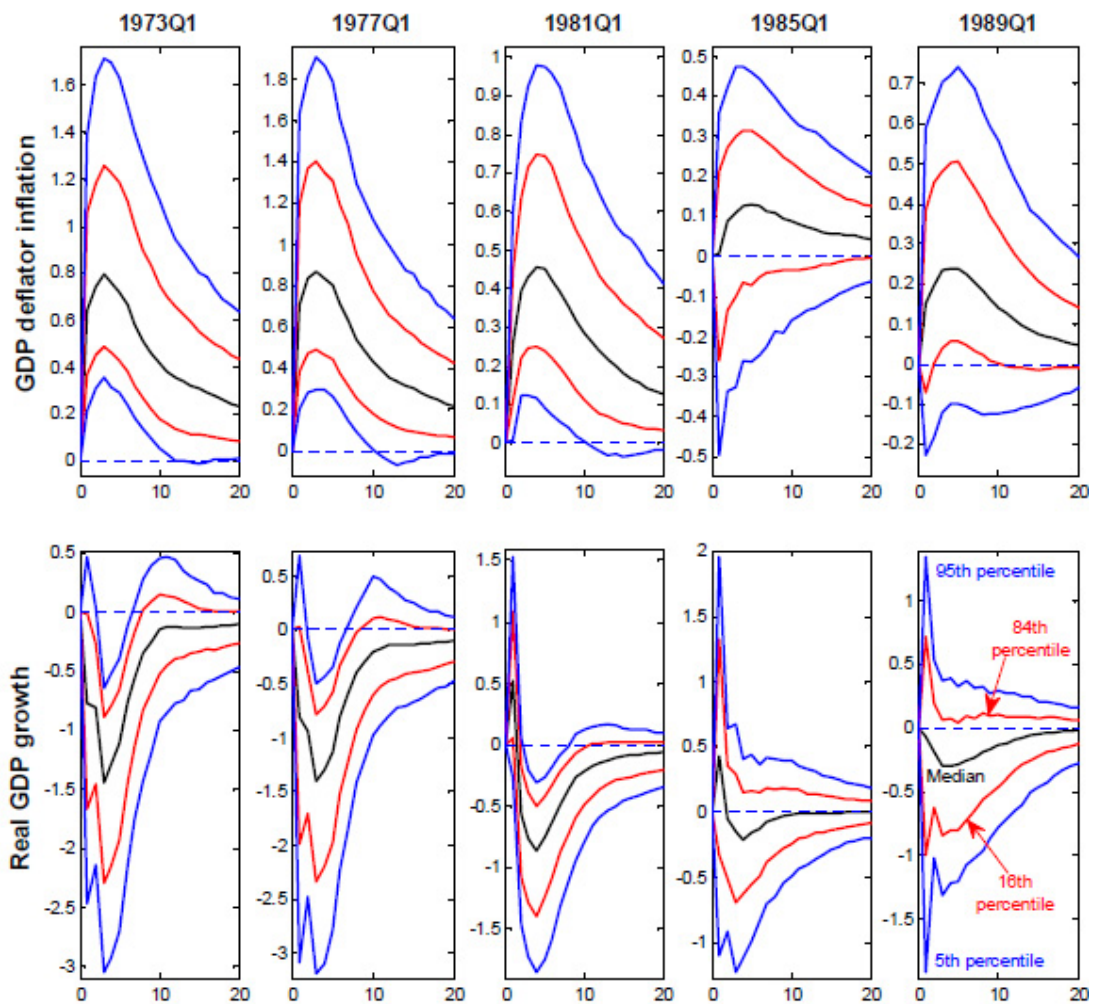


Figure 10 United States: impulse-response functions of inflation and output growth to an identified monetary policy shock based on Cholesky, selected quarters (based on the four-variables VARs)

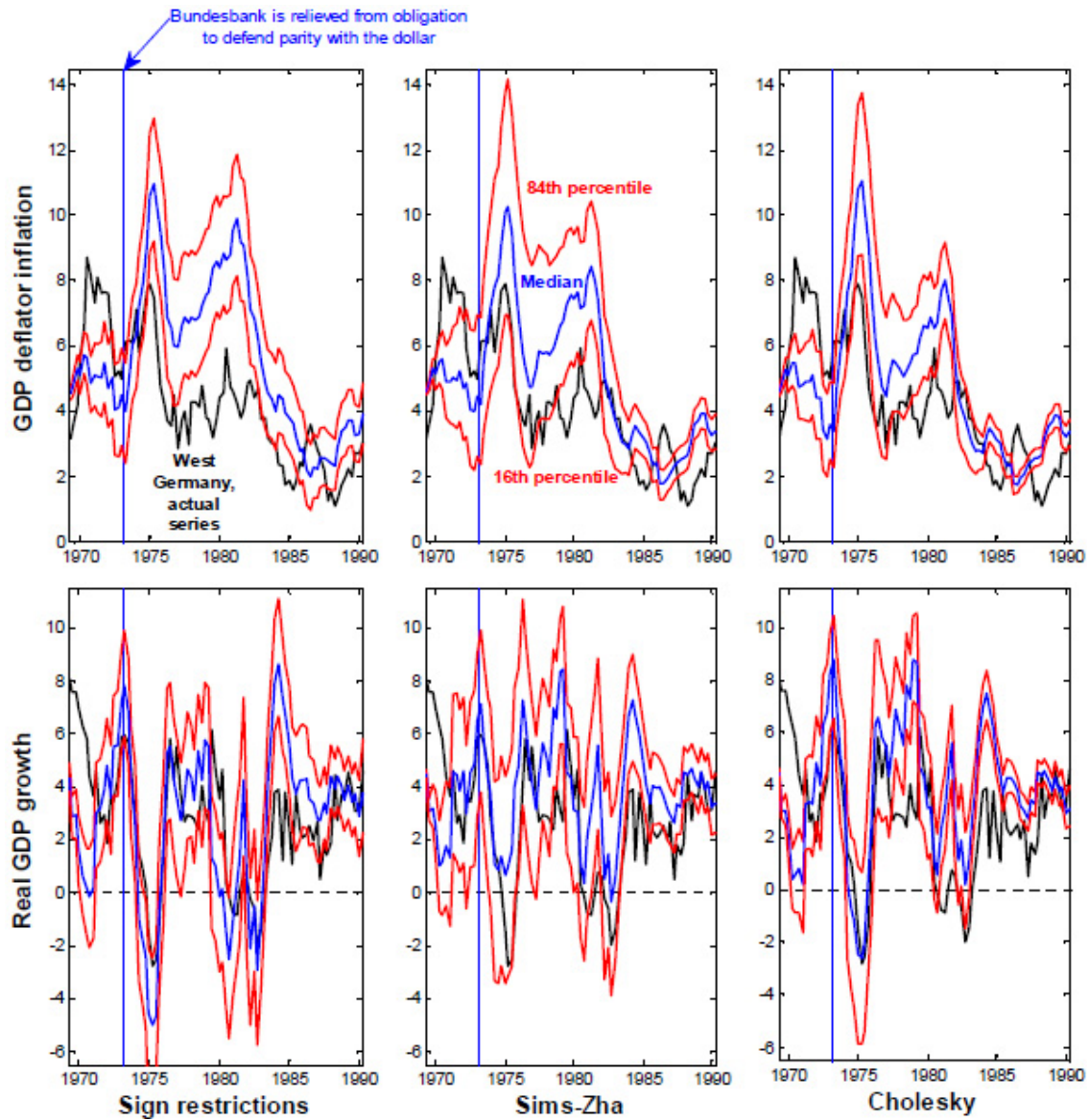


Figure 11 Inflation and output growth: comparing the results from the counterfactual simulations for the United States with the actual series for West Germany (based on the four-variables VARs)