Are Policy Counterfactuals Based on Structural VARs Reliable?*

Luca Benati
European Central Bank†

Abstract

Based on standard New Keynesian models I show that policy counterfactuals based on the theoretical structural VAR representations of the models fail to reliably capture the impact of changes in the parameters of the Taylor rule on the (reduced-form) properties of the economy. Based on estimated models for the Great Inflation and the most recent period, I show that, as a practical matter, the problem appears to be non-negligible.

I show analytically that the problem (*i*) is a straightforward implication of the cross-equations restrictions imposed by rational expectations on a model's structural solution; and (*ii*) it is independent of the issue of parameter identification.

These results imply that the outcomes of SVAR-based policy counterfactuals should be regarded with caution, as their informativeness for the specific issue at hand—e.g., understanding the role played by monetary policy in exacerbating the Great Depression, causing the Great Inflation, or fostering the Great Moderation—is, in principle, open to question.

Finally, I argue that SVAR-based policy counterfactuals suffer from a crucial *logical* shortcoming: given that their reliability crucially depends on *unknown* structural characteristics of the underlying data generation process, such reliability cannot simply be assumed, and can instead only be ascertained with a reasonable degree of confidence by estimating structural (DSGE) models.

Keywords: Structural VARs; policy counterfactuals; DSGE models; Taylor rules; monetary policy; Great Depression; Great Inflation; Great Moderation.

---

*I wish to thank Klaus Adam, Roger Farmer, Mike Wickens and especially Fabio Canova for very helpful discussions, and Lutz Kilian and seminar participants at Pompeu Fabra for comments. Part of this material was presented at the EABCN conference 'After the Crisis: A New Agenda for Business Cycle Research?'. The views expressed in this paper are those of the author, and do not necessarily reflect those of the Executive Board of the European Central Bank.

†Address for correspondence is: Luca Benati, Monetary Policy Strategy Division, European Central Bank, Kaiserstrasse 29, D-60311, Frankfurt-am-Main, Germany; email: Luca.Benati@ecb.int.

1 Introduction

Since Sims (1980) introduced the VAR methodology into macroeconomics, monetary policy counterfactuals—in which the interest rate equation of the estimated structural VAR (henceforth, SVAR) for period A is imposed upon the estimated SVAR for period B—have been one of its most prominent applications. SVAR-based policy counterfactuals have been used, for example, by Sims (1998) to explore the role played by monetary policy in the Great Depression, and by Sims and Zha (2006), Primiceri (2005), and Fabio Canova and his co-authors[1] to assess the role played by improved monetary policy in fostering the generalised fall in macroeconomic volatility associated with the Great Moderation.

1.1 How reliable SVAR-based counterfactuals truly are?

In spite of such counterfactuals having been, and being used, to address fundamental economic issues, however, no systematic investigation of their *reliability*—conditional, e.g., on taking a set of (DSGE) macroeconomic models as data generation processes—has ever been performed, so that, within this literature, counterfactuals' reliability has rather routinely been *assumed*.

But how reliable such counterfactuals truly are?

Although, as I pointed out, no systematic investigation of this issue has ever been performed, the only piece of evidence I am aware of on the ability of SVAR-based counterfactuals to correctly capture the impact of changes in the Taylor rule within a DSGE model is *negative*. Benati and Surico (2009) estimate a standard New Keynesian model for the pre- and post-October 1979 United States, imposing in estimation that the *only* source of changes across regimes is the move from passive to active monetary policy. One of the results they obtain 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. Although admittedly limited—being based upon a single model, and a single set of estimates—Benati and Surico's (2009) evidence is nonetheless troubling. For a methodology to be regarded as reliable, indeed, it should be shown to work well under a broad range of plausible circumstances. Given that (i) the model they use is the standard New Keynesian backward- and forward-looking workshorse model, and (ii) the model has been estimated, rather than calibrated, their evidence does not bode well for the reliability of SVAR-based policy counterfactuals[2] ...

[1] See in particular Gambetti, Pappa, and Canova (2006) and Canova and Gambetti (2008).

[2] Another way of putting this—along lines which have become very fashionable following the recent financial crisis—is that Benati and Surico's (2009) results are a sort of black swan. Whereas

1.2 SVAR-based and narrative evidence

It is also worth stressing that, when seen from a traditional narrative/historical perspective, some of the results produced by SVAR-based policy counterfactuals appear as distinctly peculiar. For example,

- whereas the vast majority of the narrative evidence—from Friedman and Schwartz (1963) to the work of Peter Temin and Ben Bernanke—suggest that, in the 1930s, monetary policy mistakes greatly exacerbated the Great Depression,[3] the policy counterfactuals performed by Sims (1998) suggest instead that monetary policy played a minimal, or even no role.[4]

- As documented by Benati and Goodhart (2010) based on an 'off-the-shelf' SVAR, monetary policy counterfactuals suggest that West Germany's Bundesbank—which is (near-)universally regarded, within both academia and central banks, as *the* key reason why West Germany was largely spared the Great Inflation[5]—would *not* have been able to prevent the Great Inflation in either the United States or the United Kingdom. The results produced by this counterfactual are therefore qualitatively the same as those obtained by 'bringing Alan Greenspan back in time'. The key difference is that, whereas in the case of FED officials who have been in charge of U.S. monetary policy over the most recent years

researchers in this literature have routinely assumed that SVAR-based policy counterfactuals work (which is conceptually akin to believing that 'all swans are white') Benati and Surico (2009) produce a single example in which such assumption is not true (which is conceptually akin to spotting a black swan).

[3] On this, see also Orphanides (2004).

[4] In his discussion of Sims (1998), Christiano (1998) suggests one possible reason why Sims obtained such results. As he stressed, post-WWII policymakers never came even close to experiencing the kind of huge macroeconomic shocks associated with the Great Depression (Christiano was writing a decade before the Great Recession of 2008-2009). As a consequence, the structural monetary rule estimated for the Greenspan Chairmanship is not necessarily informative about what Greenspan would have done if he had faced the shocks associated with the Great Depression. (Christiano's argument is obviously predicated on the existence of non-linearities in the response of monetary policy to macroeoconomic shocks, which, however, is not manifestly implausible.)

[5] On this position there is a remarkable extent of convergence between, e.g., a Bundesbanker *par excellence* such as Otmar Issing—see in particular Issing (2005) and Beyer, Gaspar, Gerberding, and Issing (2009)—and Anglo-Saxon academics such as Tim Besley (2008) and Allan Meltzer (2005). In a speech delivered during his tenure as an extermal member of the Bank of England's Monetary Policy Committee, for example, Besley (2008) pointed out that

> '[i]n 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 [...].'

we have no way of knowing how they would have performed had they been in charge of U.S. monetary policy in the 1970s,[6] this is obviously not the case for the 1970s' Bundesbank, as West Germany's central bank was indeed there, and its monetary policy is widely credited for avoiding the Great Inflation.

1.3 What might go wrong with SVAR-based policy counterfactuals?

Taken together, (*i*) the lack of a systematic investigation of the reliability of SVAR-based policy counterfactuals; (*ii*) the fact that the only existing (although, admittedly, very limited) piece of evidence is, quite disturbingly, negative; and (*iii*) the sometimes stark contrast between the results produced by such counterfactuals and the traditional views associated with the narrative approach, naturally suggest (at least, to me) two considerations.

First, they point towards the need of a systematic investigation of the reliability of SVAR-based policy counterfactuals. Second, they suggest that *something* might be not quite right about SVAR-based policy counterfactuals ...

What could this be?

1.3.1 The key issue

The key issue, in my view, can be formulated as a simple question:

'Do changes in the interest rate equation of a SVAR reliably capture the impact of changes in the monetary (e.g., Taylor) rule in the underlying structural model?'

As I previously pointed out, up until now an affirmative aswer to this question has been implicitly assumed by the profession. But what is, in fact, the truth?

1.4 This paper: methodology and key results

Based on estimated standard New Keynesian models, this paper performs a systematic investigation of the reliability of SVAR-based policy counterfactuals, where by 'reliability' I mean 'the ability of such counterfactuals to correctly capture the impact on the (reduced-form) properties of the economy of changes in the monetary rule within the New Keynesian model'.

The paper's main results may be summarised as follows.

- SVAR-based counterfactuals appear, in general, as *unreliable*, exhibiting a clear inability to correctly capture the impact on the economy of changes in the monetary rule within DSGE models. Further, the size of the errors made by

[6] By the same token, we have no way to know whether current U.K. policymakers would have been able to stare U.K. inflation down in the 1970s.

SVAR-based policy counterfactuals—compared to the authentic, DSGE-based counterfactuals—is potentially substantial, thus casting doubts, in principle, on their reliability.

- I show analytically that the problem

  (*i*) is a straightforward implication of the cross-equations restrictions imposed by rational expectations on a model's structural solution;

  (*ii*) it is independent of the issue of parameter identification; and

  (*iii*) it only disappears when the model's solution is vector white noise.

- Unreliability pertains not only individual series' characteristics—such as a series' theoretical standard deviation, or its reduced-form innovations within a VAR context—but also key aspects of the relationships among series, such as their unconditional correlation; the gain and coherence between them; and their lead-lag relationship as captured by either the phase angle or the delay.

- Unreliability appears to be especially severe at the low frequencies, thus impliying that SVAR-based counterfactuals fare especially badly in assessing the role played by monetary policy in causing phenomena such as the Great Inflation and the Great Depression, two episodes characterised by significant low-frequency fluctuations in inflation, and, in the case of the Depression, of output.

- Finally, unreliability depends not only on the extent 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.

1.5 Implications

This paper's results have two main implications.

First, they suggest that the outcomes of SVAR-based policy counterfactuals should be taken with caution, as their informativeness for the issue at hand—e.g., understanding the role played by monetary policy in exacerbating the Great Depression, causing the Great Inflation, or fostering the Great Moderation—is, principle, open to question.

Second—and more subtly—since the extent of reliability of SVAR-based counterfactuals crucially depends on *unknown* structural characteristics of the underlying data generation process, these results imply that reliability cannot simply be assumed, and can rather only be ascertained with a reasonable degree of confidence by estimating structural (DSGE) models. Eschewing estimation of structural macroeconomic models, and performing inference by imposing a minimal set of credible restrictions on the moving-average representation of the data is however the entire point of structural VAR analysis. As this paper shows, unfortunately, one important application of such methodology appears to suffer from a key logical problem, as, in general, its reliability can only be ascertained *via* structural (e.g., DSGE) estimation.

1.6 Related literature

To the very best of my knowledge, only two papers are conceptually related to the present work. The first is the previously mentioned work of Benati and Surico (2009), which, based on an estimated standard New Keynesian model, produces a single example of a data generation process whose characteristics SVAR methods fail to correctly identify. The second one is Adam (2009). Working within a rational inattention framework, he shows that an increased focus on price stability on the part of the policymaker leads to a decrease in the reduced-form innovation variances of the endogenous variables (inflation, the interest rate, and the output gap) within the model-implied theoretical VAR representation, with *no* change, instead, in the VAR coefficient matrix.[7] The implication is that an econometrician armed with VAR methods would be induced to incorrectly interpret the policy-induced fall in the innovation variances for sheer 'luck'—in line with the interpretation of such decreases which has been put forward in several (S)VAR-based contributions on the Great Moderation—thus completely missing the truth. Different from Benati and Surico (2009) and from the present work, however, Adam (2009) does not explore the ability of monetary policy counterfactuals based on the model-implied theoretical SVAR representation to capture the truth.

The paper is organised as follows. The next section briefly discusses the conceptual essence of the problem, stressing the non-equivalence between two alternative notions of policy counterfactuals: the authentic counterfactual (which is performed by switching the Taylor rules within the DSGE model), and the SVAR-based counterfactual (which is instead performed by switching the interest rate rules within the SVAR representation implied by the very same DSGE model). The section then presents a straighforword illustration of the non-equivalence between the two alternative notions of policy counterfactuals based on results from a single stochastic simulation. Section 3 provides several illustrations *via* numerical methods, based on three New Keynesian models with increasing extent of complexity, and conditional on grids of values for the parameters of the Taylor rule. In particular, we explore the unreliability of SVAR-based policy counterfactuals with respect to both individual variables' characteristics (e.g., the series' theoretical standard deviations), and multivariate economic relationships (e.g., the relatonship between inflation and the output gap). Section 4 presents analytical illustrations of the problem at hand, and explores *via* numerical methods the role played by specific model features in generating these results. Section

[7] The intuition for the fall in volatility is that a greater focus on price stability facilitates firms' information processing and better aligns their expectations with the policy objective(s), thus decreasing the amount of noise which monetary policy injects into the system.

5 provides a tentative assessment of the practical relevance of the problem, based on estimated New Keynesian models for the Great Inflation period and the most recent one. Section 6 concludes.

2 The Problem in a Nutshell

The essence of the problem can be succintly described as follows.

2.1 The intuition

Consider a structural macroeconomic model—for the sake of the argument, a standard New Keynesian model—and assume (again, for the sake of the argument) that monetary policy follows the simple Taylor rule with smoothing

$$R_t = \rho R_{t-1} + (1-\rho)[\phi_\pi \pi_t + \phi_y y_t] + \epsilon_{R,t} \tag{1}$$

where R_t, π_t and y_t are the nominal rate, inflation and the output gap; $\epsilon_{R,t}$ is a disturbance to the monetary rule; and ρ, ϕ_π, and ϕ_y are the smoothing coefficient, and the coefficients on inflation and the output gap, respectively.

Consider then two sets of parameters for the Taylor rule:

$$\begin{aligned} \text{Taylor}^1 &\equiv [\rho^1,\, \phi_\pi^1,\, \phi_y^1]' \\ \text{Taylor}^2 &\equiv [\rho^2,\, \phi_\pi^2,\, \phi_y^2]' \end{aligned}$$

with $\text{Taylor}^1 \neq \text{Taylor}^2$. Together with the other structural parameters, equation (1), and the equations describing the behaviour of the private sector, Taylor^1 and Taylor^2 imply two different structures, with two different reduced-form VAR representations, and therefore, as a logical corollary, two different SVAR representations, that is:

$$\begin{aligned} \text{Taylor}^1 &\implies \text{DSGE}^1 \implies \text{VAR}^1 \implies \text{SVAR}^1 \implies \text{MonetaryRule}^1 \\ \text{Taylor}^2 &\implies \text{DSGE}^2 \implies \text{VAR}^2 \implies \text{SVAR}^2 \implies \text{MonetaryRule}^2 \end{aligned}$$

where MonetaryRule^1 and MonetaryRule^2 are the interest rate equations in the two SVAR representations, SVAR^1 and SVAR^2.

2.1.1 Two alternative notions of policy counterfactual

Switching Taylor^1 and Taylor^2 is the *authentic policy counterfactual*, where the adjective 'authentic' simply comes from the fact that such a policy counterfactual is performed

- based on the authentic structure of the economy—the DSGE model—and
- based on the authentic monetary policy rule—the Taylor rule (1).

Switching MonetaryRule[1] and MonetaryRule[2], on the other hand, is the *SVAR-based policy counterfactual*, that is, the one performed by switching the interest rate equations in the theoretical structural VAR representations of the DSGE model generated conditional on the two Taylor rules.

The key issue, then—and the focus of this paper—is that

switching MonetaryRule[1] and MonetaryRule[2] is
not *the same as switching Taylor[1] and Taylor[2]*

in terms of their impact on (properties of) the economy. On the contrary, as this paper will show the difference is sometimes substantial.

2.2 A formal argument

Let the SVAR representation of a DSGE model's solution be

$$A_0^{-1}Y_t = A_0^{-1}B_1 Y_{t-1} + ... + A_0^{-1}B_p Y_{t-p} + \epsilon_t \tag{2}$$

where $Y_t \equiv [R_t,\ X_t']'$ is an $N\times 1$ vector of endogenous variables, with R_t being the nominal interest rate and X_t being an (N-1)$\times$1 vector of variables other than R_t; A_0 being the impact matrix of the structural shocks at zero; B_1, ..., B_p being the AR matrices of the VAR; and $\epsilon_t = A_0^{-1}u_t$—where u_t is the $N\times 1$ vector collecting the VAR's reduced-form shocks—being a vector collecting the VAR's structural shocks. The vector ϵ_t is defined as $\epsilon_t \equiv [\epsilon_{R,t},\ \epsilon'_{\tilde{}R,t}]'$, where $\epsilon_{R,t}$ is the monetary policy shock (that is, the shock to the Taylor rule), and $\epsilon_{\tilde{}R,t}$ is a vector collecting all the structural shocks other than $\epsilon_{R,t}$. Let's define $\tilde{B}_0 \equiv A_0^{-1}$, $\tilde{B}_1 \equiv A_0^{-1}B_1$, ..., $\tilde{B}_p \equiv A_0^{-1}B_p$, and let's partition $\tilde{B}_0$, $\tilde{B}_1$, ..., $\tilde{B}_p$ as

$$\tilde{B}_0(\theta) = \begin{bmatrix} \tilde{B}_0^R(\theta) \\ \tilde{B}_0^{\tilde{}R}(\theta) \end{bmatrix},\ \tilde{B}_1(\theta) = \begin{bmatrix} \tilde{B}_1^R(\theta) \\ \tilde{B}_1^{\tilde{}R}(\theta) \end{bmatrix},\ ...,\ \tilde{B}_p(\theta) = \begin{bmatrix} \tilde{B}_p^R(\theta) \\ \tilde{B}_p^{\tilde{}R}(\theta) \end{bmatrix} \tag{3}$$

where θ is a vector collecting the parameters of the monetary policy rule—that is, within the present context, ρ, ϕ_π, ϕ_y; $\tilde{B}_j^R(\theta)$, j = 1, ..., p, is the first row of $\tilde{B}_j(\theta)$, that is, the one corresponding to the interest rate equation of the SVAR; and $\tilde{B}_j^R(\theta)$ is a (N-1)$\times N$ matrix collecting the other equations of the SVAR representation of a model. In (3) we have made explicit the functional dependence of all of the entries of the matrices $\tilde{B}_1$ on θ: as it is well known, this is a straightforward implication of the cross-equations restrictions imposed by rational expectations on the solution of a general equilibrium model, and it therefore holds without any loss of generality.[8]

Consider now two alternative policy parameters' vectors, θ_1 and θ_2, with $\theta_1 \neq \theta_2$, which imply the following two SVAR representations

$$\tilde{B}_0(\theta_1)Y_t = \tilde{B}_1(\theta_1)Y_{t-1} + ... + \tilde{B}_p(\theta_1)Y_{t-p} + \epsilon_t \tag{4}$$

[8]In section 4 below we will show that these restrictions do not hold only in the extreme case in which the model solution is vector white noise, as in such case θ drops out of $\tilde{B}_j^{\tilde{}R}$ for all j.

$$\tilde{B}_0(\theta_2)Y_t = \tilde{B}_1(\theta_2)Y_{t-1} + ... + \tilde{B}_p(\theta_2)Y_{t-p} + \epsilon_t \quad (5)$$

The policy counterfactual associated with imposing the SVAR's structural monetary rule for regime 2 onto the SVAR for regime 1 produces the following structure:[9]

$$\begin{bmatrix} \tilde{B}_0^R(\theta_2) \\ \tilde{B}_0^{\tilde{R}}(\theta_1) \end{bmatrix} Y_t = \begin{bmatrix} \tilde{B}_1^R(\theta_2) \\ \tilde{B}_1^{\tilde{R}}(\theta_1) \end{bmatrix} Y_{t-1} + ... + \begin{bmatrix} \tilde{B}_p^R(\theta_2) \\ \tilde{B}_p^{\tilde{R}}(\theta_1) \end{bmatrix} Y_{t-p} + \epsilon_t \quad (6)$$

Equation (6) shows that the SVAR-based counterfactual can correctly capture the impact of the authentic, DSGE-based counterfactual only if the policy parameters do not appear in the non-policy equations of the SVAR. As we will see in Section 4 below, this only happens if the model's structural characteristics are such that its solution is vector white noise. In all other cases, the SVAR-based counterfactual fails to correctly capture the impact of the authentic, DSGE-based counterfactual, as the SVAR-based policy switch only affects the SVAR's interest rate equation.

Let's now turn to a simple illustration of the problem at hand based on a single stochastic simulation.

2.3 A straightforward illustration based on a single stochastic simulation

Figure 1 shows results from a single stochastic simulation in which a standard New Keynesian model is fed the same set of structural shocks conditional on two alternative monetary policy rules, a 'good' (that is: comparatively more aggressively counter-inflationary) one, and a 'bad' (that is: comparatively less aggressively counter-inflationary) one.[10] Results for the three variables of interest are reported in blue, for the 'good' policy regime, and in black, for the 'bad' policy regime, respectively. The *authentic* (that is: DSGE-based) policy counterfactual involves switching the two Taylor rules within the DSGE model, and then 'rerunning history' conditional on the same set of structural shocks: *by definition*, the outcome of such a switch implies switching the black and blue lines, so that what was 'bad' becomes 'good', and what was 'good' becomes 'bad'. The *SVAR-based* policy counterfactual from the 'bad' to the 'good' regime, on the other hand, involves imposing the interest rate rule in the SVAR representation of the model conditional on the 'good' policy regime on the SVAR for the 'bad' policy regime, and then 'rerunning history' based on the same shocks. The result from such exercise is shown, for either of the three variables, in red. By definition, if the SVAR-based counterfactual worked fine, the red lines would

[9] The alternative counterfactual is just symmetrical.

[10] Since the issue discussed in this paper is a strictly *conceptual* one, details on the specific characteristics of the model used in this stochastic simulation are, in principle, irrelevant. To be precise, however, the model is the one estimated by Benati (2008) for the post-WWII United States (estimates are reported in his Table XII), which is described by equations (1) and (10)-(11) below. The 'good' monetary policy is the one associated with Benati's (2008) benchmark estimates, whereas the 'bad' one is obtained by setting ρ=ϕ_π=0.

be idenwtical to the blue lines. As the figure shows, however, this is definitely *not* the case: on the contrary, the SVAR-based counterfactual clearly fails to capture the truth as defined by the experiment we designed, with the red lines for inflation and the output gap, in particular, being remarkably close to the *black* lines (that is: to the 'bad' policy regime) rather than to the blue lines, as they should be; as for the interest rate, the red lines are basically 'all over the place', thus highlighting, once again, the unreliability of the SVAR-based counterfactual.

An obvious objection to these results is that they are based on a single stochastic simulation. The next section, which presents results based on numerical methods, show that the problem is a general one.

3 Illustrations Based on Numerical Methods

In this section we explore the reliability of SVAR-based counterfactuals based on three New Keynesian models, and conditional on grids of values for the two key parameters in the Taylor rule, the smoothing parameter and the long-run coefficient on inflation. We start by exploring the ability of SVAR-based counterfactuals to correctly recover the impact of the authentic counterfactuals on individual series' characteristics (e.g., a series' theoretical standard deviation as implied by the model). We then turn to relationships among variables, such as the one between inflation and the output gap.

Three general findings will emerge from this analysis. *First*, irrespective of the specific model we will use, SVAR-based counterfactuals clearly appear as incapable of correctly capturing the macroeconomic impact of the authentic counterfactual. This holds true for both individual series' characteristics, and the relationship among them. *Second*, problem the problem appears to be especially severe at the low frequencies, and less so at the business-cycle frequencies, thus implying that SVAR-based counterfactuals might fare especially badly in assessing the role played by monetary policy in causing phenomena such as the Great Inflation or the Great Depression, which had both been characterised by prolonged and persistent fluctuations in the series of interest. *Third*, the magnitude of the problem appears, in general, as non-negligible.

3.1 Three models

We consider the following three standard New Keynesian models, characterised by increasing extent of complexity.

The first model is the one estimated by Lubik and Schorfheide (2004), which is described by the following equations:[11]

$$y_t = y_{t+1|t} - \tau(R_t - \pi_{t+1|t}) + g_t \quad (7)$$

[11] In equations (7)-(9) we slightly changed Lubik and Schorfheide's notation in order to put it in line with the notation we use in the rest of the paper.

$$\pi_t = \beta\pi_{t+1|t} + \kappa[y_t - z_t] \tag{8}$$

$$R_t = \rho R_{t-1} + (1-\rho)[\phi_\pi \pi_t + \phi_y (y_t - z_t)] + \epsilon_{R,t} \tag{9}$$

where g_t and z_t are AR(1) shocks, whereas $\epsilon_{R,t}$ is white noise. We calibrate the model based on Lubik and Schorfheide's (2004) mean estimates for the post-1982 period as found in their Table 3.

The second model is the standard forward- and backward-looking model described by

$$y_t = \gamma y_{t+1|t} + (1-\gamma) y_{t-1} - \sigma(R_t - \pi_{t+1|t}) + \epsilon_{y,t} \tag{10}$$

$$\pi_t = \frac{\beta}{1+\alpha\beta}\pi_{t+1|t} + \frac{\alpha}{1+\alpha\beta}\pi_{t-1} + \kappa y_t + \epsilon_{\pi,t} \tag{11}$$

where γ is the forward-looking component in the intertemporal IS curve, α is price setters' extent of indexation to past inflation, and everything else is the same as before. The model is closed with the monetary rule (1), and it is calibrated based on Benati's (2008) modal estimates for the post-WWII United States as reported in his Table XII.

The third model is one proposed by Andrés, López-Salido, and Nelson (2009), which features adjustment costs for real money balances, and is therefore non-block-recursive in money balances. The model and the estimated for the post-WWII United States are described in detail in Appendix A.

3.2 Evidence for individual variables

3.2.1 Macroeconomic volatility

Figures 2-4 show, for either of the three models, results from the following experiment. For either model we compute its theoretical VAR and SVAR representations conditional on the benchmark estimates, which we call VAR^B and SVAR^B respectively. The two representations imply certain benchmark values for the series' theoretical standard deviations, which we collect in a vector labeled as STDs^B. Finally, in line with the notation used in Section 2, we label the benchmark Taylor rule, and the benchmark interest rate equation in SVAR^B as Taylor^B and MonetaryRule^B, respectively. We then consider grids of values for ρ, from 0.4 to 0.95, and for ϕ_π, from 0.25 to 2.5. (On the other hand, we keep the other parameter(s) in the Taylor rule at the value(s) implied by the benchmark estimates we consider.) For each combination of values of ρ and ϕ_π in the grids, we solve the DSGE model,[12] and we compute its theoretical VAR and SVAR representations, which we call VAR^A and

[12] Given the wide ranges of values we consider for ρ and ϕ_π, some of their combinations imply indeterminacy of the model solution. In these cases, we solve the model as in Lubik and Schorfheide (2004), picking the solution that they label as 'continuity'. Further, in order to make the present exercise as transparent as possible, we set the standard deviation of the sunspot shock equal to zero. An important point to stress is that, in this way, we are essentially 'stacking the cards against ourselves', as (*i*) the presence of sunspot shocks under indeterminacy is, in principle, perfectly

SVAR^A respectively—where A stands for 'alternative'—and the associated vector of implied theoretical standard deviations, STDs^A. Again, we label the alternative Taylor rule and the interest rate equation in SVAR^A as Taylor^A and MonetaryRule^A, respectively. By definition, switching Taylor^B and Taylor^A within the DSGE model (that is: performing the authentic counterfactual) inverts the two vectors STDs^B and STDs^A. If the SVAR-based counterfactual worked fine we should be able to obtain *exactly* the same result by switching MonetaryRule^B and MonetaryRule^A. As I will now show, this is not the case. Let SVAR^C—where C stands for 'counterfactual'—the SVAR we obtain by imposing MonetaryRule^B withing SVAR^A (that is, we take away MonetaryRule^A and we replace it with MonetaryRule^B), and let VAR^C be its associated reduced-form VAR. VAR^C implies a vector of theoretical standard deviations for the series of interest, which we label as STDs^C. If the SVAR-based counterfactual worked fine, for each possible combination of alternative values of ρ and ϕ_π in the grids, we would have STDs^C=STDs^B, so that for each individual variable i it would uniformly be STDs$_i^C$/STDs$_i^B$=1. On the other hand, the extent to which the SVAR-based counterfactual fails to replicate the impact of the authentic counterfactual is captured, for each series, by how much such ratio deviates from one.

As Figures 2-4 show, the SVAR-based counterfactual clearly fails to replicate the outcome of the authentic counterfactual: based on either model, and for either of the series, the ratio STDs$_i^C$/STDs$_i^B$ is, in general, different from one—sometimes quite markedly so—and it is very close to one only for combinations of ρ and ϕ_π which are sufficiently close to the benchmark estimates. It is also worth stressing that the magnitude of the error made by the SVAR-based counterfactual is in general non-negligible, and is often quite substantial. Focusing, e.g., on Figure 3, reporting results for the standard three-equation backward- and forward-looking New Keynesian workhorse model, for both inflation and the interest rate the counterfactual standard deviation is, for some combination of alternative vales of ρ and ϕ_π, 50 to 60 per cent higher than it should be. Results for the model of Lubik and Schorfheide (2004), which is purely forward-looking (see Figure 2), are even worse. Given that, in recent years, one of the most prominent application of SVAR-based counterfactuals has been the study of the role played by monetary policy in fostering the generalised fall in macroeconomic volatility associated with the Great Moderation, the results reported in Figures 2-4 are distinctly disturbing. Quite obviously, if a particular methodology produces outcomes characterised by errors of the same order of magnitude of the phenomenon under investigation, the entire point of using such methodology appears as distinctly weak.

legitimate (on the contrary: their *absence* is open to question, and should be regarded as an extreme assumption); and (*ii*) sunspot shocks would inject additional volatility to the economy, and by 'blowing up' the diagonal elements of the covariance matrix of the theoretical reduced-form VAR representation of the model, they would distort the results of the SVAR-based counterfactual. Our choice of excluding sunspot shocks is motivated by out goal of making our results as transparent as possible.

3.2.2 Results based on Fourier analysis

We now turn to results based on Fourier analysis, exploring the theoretical cross-spectral statistics between each individual series as implied by the benchmark VAR, and the same series as implied by the counterfactual VAR. If the SVAR-based counterfactual worked fine, for each individual series i, and for each possible combination of alternative values of ρ and ϕ_π in the grids, the theoretical gain and coherence between the series as implied by SVAR^B and by SVAR^C would be uniformly equal to one, whereas the theoretical phase angle and delay[13] would be uniformly equal to zero.

Figures 5-7, 8-10, and 11-13 show, based on either of three models, respectively, and for each series, the average gain, coherence, and delay[14] between the series as implied by SVAR^B and by SVAR^C. Results are shown for either the low and the business-cycle frequencies, which, following established convention in business-cycle analysis, we identify as those associated with fluctuations with periodicities beyond 8 years, and between six quarters and eight years, respectively. Two main findings emerge from figures 5-13.

First, consistent with the results discussed in the previous sub-section, SVAR-based counterfactuals fare, in general, rather poorly. In particular, whereas the *coherence* is, in general, quite high, and close to one, for most combinations of alternative values of ρ and ϕ_π, the *gain* is often quite off the mark. This implies that whereas the explanatory power of the counterfactual series for the benchmark series (or *vice versa*) is almost uniformly high, what the SVAR-based counterfactual badly misses is the *proportionality* (or scale) between the two series. This is in line with the results of the previous sub-section, where we saw how the SVAR-based counterfactual badly misses the series' volatilities. Finally, as Figures 7, 10, and 13 show, the SVAR-based counterfactual also introduces a phase shift in the series, so that, in general, the counterfactual series is either leading or lagging the benchmark series.

Second, in general the magnitude of the error made by the SVAR-based counterfactual appears to be comparatively larger at the low frequencies, rather than at the business-cycle frequencies (this is especially clear for the gain statistic). This is a key point, because some of the phenomena investigated *via* this type of counterfactual were characterised by prolonged and persistent fluctuations in the series of interest—that is, fluctuations pertaining precisely to the low frequencies. This is the case, for example, of the dramatic output contraction and deflation associated with the Great Depression, and of the prolonged and persistent inflation outburst associated with the Great Inflation.

Let's now turn to (bivariate) macroeconomic relationships. For reasons of space—

[13] For each frequency ω, the delay—which is measured in time units (e.g., quarters)—is defined as the ratio between phase angle and frequency (see Wei (2005)).

[14] I chose to show the delay, rather than the phase angle, because being expressed in quarters, rather than radians, it is easier to interpret. Results for the phase angle are however available upon request.

and also because, as we have seen, the problem explored herein is a general one, and it does not pertain a specific New Keynesian model—in the next Section we only report results based on the standard backward- and forward-looking New Keynesian model described by equatios (1), (10), and (11). Results for the other two models, however, are available upon request.

3.3 Evidence for macroeconomic relationships

3.3.1 Unconditional correlations

Figure 14 shows, for each combination of alternative values of ρ and ϕ_π, the differences between the bivariate unconditional correlations implied by the counterfactual and benchmark VARs. In order to correctly interpret the information contained in the figure, it is important to keep in mind that unconditional correlations are bounded, by construction, between -1 and 1. If the SVAR-based counterfactual worked fine, such differences would uniformly be equal to zero: as the figure shows, however, this is not the case, with the SVAR-based counterfactual failing to capture the truth, and in general by non-negligible extents.

3.3.2 Cross-spectral statistics extracted from the benchmark and the counterfactual VARs

Figures 15-17 show, for each combination of alternative values of ρ and ϕ_π, the differences between the average gain, coherence, and delay asimplied by the counterfactual and benchmark VARs. As in Section 4.2.2, results are shown for both the low and the business-cycle frequencies. The SVAR-based counterfactual appears once again as incapable, in general, of correctly capturing the impact of the authentic counterfactual. In line with the results of sub-section 4.2.2, the magnitude of the errors is comparatively minor for the coherence, and is instead sometimes quite substantial for the gain and the delay.

4 Where Does the Problem Originate From?

Where does the problem originate from? In this section we tackle this issue both analytically and *via* numerical methods, by exploring the impact of individual model features—e.g., the extent of serial correlation of the structural shocks, the extent of interest rate smoothing, etc.—on the reliability of SVAR-based policy counterfactuals.

Consider the following model:

$$R_t = \rho R_{t-1} + (1-\rho)[\phi_\pi \pi_t + \phi_y y_t] + \tilde{\epsilon}_{R,t} \quad (12)$$

$$\pi_t = \beta \pi_{t+1|t} + \kappa y_t + \epsilon_{\pi,t} \quad (13)$$

$$y_t = y_{t+1|t} - \sigma(R_t - \pi_{t+1|t}) + \epsilon_{y,t} \quad (14)$$

with $\epsilon_{R,t}$ $WN(0,\,\sigma_R^2)$, $\epsilon_{\pi,t} = \rho_\pi \epsilon_{\pi,t-1} + \tilde{\epsilon}_{\pi,t}$, and $\epsilon_{y,t} = \rho_y \epsilon_{y,t-1} + \tilde{\epsilon}_{y,t}$. Assuming no reaction to the output gap on the part of the central bank, no interest rate smoothing, and serially uncorrelated shocks—that is, setting ϕ_y=ρ=ρ_π=ρ_y=0—under determinacy model (12)-(14) has the following solution

$$\underbrace{\begin{bmatrix} R_t \\ \pi_t \\ y_t \end{bmatrix}}_{Y_t} = \underbrace{\frac{1}{1+\kappa\sigma\phi_\pi}\begin{bmatrix} 1 & \phi_\pi & \kappa\phi_\pi \\ \text{-}\kappa\sigma & 1 & \kappa \\ \text{-}\sigma & \text{-}\sigma\phi_\pi & 1 \end{bmatrix}}_{A_0} \underbrace{\begin{bmatrix} \tilde{\epsilon}_{R,t} \\ \tilde{\epsilon}_{\pi,t} \\ \tilde{\epsilon}_{y,t} \end{bmatrix}}_{\epsilon_t} \tag{15}$$

with the system exhibiting no dynamics because (*i*) the model is purely forward-looking, and (*ii*) all the shocks are serially uncorrelated. Going from (15) to the structural VAR representation of the model requires inverting the impact matrix A_0. After some tedious algebra, we obtain:

$$\underbrace{\begin{bmatrix} 1 & \text{-}\phi_\pi & 0 \\ 0 & 1 & \text{-}\kappa \\ \sigma & 0 & 1 \end{bmatrix}}_{A_0^{-1}} \underbrace{\begin{bmatrix} R_t \\ \pi_t \\ y_t \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} \tilde{\epsilon}_{R,t} \\ \tilde{\epsilon}_{\pi,t} \\ \tilde{\epsilon}_{y,t} \end{bmatrix}}_{\epsilon_t} \tag{16}$$

Equation (16) exhibits a crucial characteristic: the policy parameter, ϕ_π, does not appear in the equations of the model's SVAR representation other than the interest rate rule. As a consequence, based on our discussion of Section 2.2, we should logically expect the SVAR-based counterfactual to work perfectly. As the first row of Figure 18 shows, under determinacy *this is indeed the case*. Figure 18 shows the ratio between the series' theoretical standard deviations as implied by the SVAR-based policy counterfactual and the benchmark theoretical standard deviations, where the benchmark is defined based on the mean estimates for the post-1982 period reported in Lubik and Schorfheide's (2004) Table 3. In particular, in the first row of Figure 18 all the parameters have been set equal to Lubik and Schorfheide's estimates except for the autocorrelation of the shocks and the interest rate smoothing parameter, which have all been set to zero; in the second row only ρ has been set to zero; and in the third row only the extent of autocorrelation of the shocks has been set to zero.

Several findings emerge from the first row of Figure 18. In particular, with white noise shocks and no interest rate smoothing, the SVAR-based counterfactual works perfectly—as expected—within the determinacy region, where the model's solution is vector white noise. Under indeterminacy,[15] on the other hand, the model's solution is not vector white noise any longer, since—as shown by Lubik and Schorfheide (2003, 2004)—it depends on an additional unobserved and serially correlated state variable,[16] so that the policy parameter does not disappear from the SVAR's equations other

[15] Under indeterminacy we solve the model *via* Lubik and Schorfheide's (2003, 2004) 'continuity' solution.

[16] See e.g. Lubik and Schorfheide (2004, equation 34, page 201).

than the interest rate one. As a consequence, under indeterminacy the SVAR-based counterfactual fails, by a very limited extent.

Let's now relax the extreme assumptions we held so far under a *single* dimension. Specifically, whereas we still assume that ϕ_y=ρ=ρ_π=0, we let the autocorrelation coefficient of the IS curve shock to be non zero, that is $\rho_y \neq 0$. After tedious algebra, it can be shown that, under determinacy, the model's solution for the variables other than R_t—which is what matters for the present purposes—is given by

$$\begin{bmatrix} \pi_t \\ y_t \end{bmatrix} = \frac{1}{(1{+}\kappa\sigma\phi_\pi)} \begin{bmatrix} \text{-}\kappa\sigma & 1 \\ \text{-}\sigma & \text{-}\sigma\phi_\pi \end{bmatrix} \begin{bmatrix} \tilde{\epsilon}_{R,t} \\ \tilde{\epsilon}_{\pi,t} \end{bmatrix} + J(\phi_\pi) \begin{bmatrix} (1\text{-}\lambda_1\rho_y)^{-1}\Gamma_{12}(\phi_\pi) \\ (1\text{-}\lambda_2\rho_y)^{-1}\Gamma_{22}(\phi_\pi) \end{bmatrix} \epsilon_{y,t} \tag{17}$$

where λ_1 and λ_2 are the two roots of the characteristic polynomial of the relevant matrix in the forward-looking rational expectations solution of the model for π_t and y_t, with

$$\lambda_{1,2} = (1 + \kappa\tau\phi_\pi)\frac{(1 + \beta\kappa\phi_\pi) \pm \sqrt{(1 - \beta)^2 + \kappa^{2\tau 2} + \kappa\tau[2(1 + \beta) - 4\beta\phi_\pi]}}{2} \tag{18}$$

the matrix $J(\phi_\pi)$ collects the two eigenvectors associated with λ_1 and λ_2, and is given by

$$J(\phi_\pi) = \begin{bmatrix} \kappa & \kappa \\ \lambda_1(1 + \kappa\sigma\phi_\pi) - \beta - \sigma\tau & \lambda_2(1 + \kappa\sigma\phi_\pi) - \beta - \kappa\sigma \end{bmatrix} \tag{19}$$

and $\Gamma_{12}(\phi_\pi)$ and $\Gamma_{22}(\phi_\pi)$ are equal to

$$\Gamma_{12}(\phi_\pi) = \lambda_2(1 + \kappa\sigma\phi_\pi) - \beta - \kappa\sigma - 1 \tag{20}$$

$$\Gamma_{22}(\phi_\pi) = -\lambda_1(1 + \kappa\sigma\phi_\pi) + \beta + \kappa\sigma + 1 \tag{21}$$

From (17)-(21) we immediately have that

$$\pi_{t+1|t} = \rho_y\pi_t + \rho_y\frac{\kappa\sigma\tilde{\epsilon}_{R,t} - \tilde{\epsilon}_{\pi,t}}{(1{+}\kappa\sigma\phi_\pi)} \tag{22}$$

$$y_{t+1|t} = \rho_y y_t + \rho_y\sigma\frac{\tilde{\epsilon}_{R,t} + \phi_\pi\tilde{\epsilon}_{\pi,t}}{(1{+}\kappa\sigma\phi_\pi)} \tag{23}$$

so that, (*i*) since $\rho_y \neq 0$, $\pi_{t+1|t}$ and $y_{t+1|t}$ on the right-hand side of (13)-(14) will be different from zero, and will therefore not drop out of the SVAR solution of the model; and (*ii*) crucially—as it clearly emerges from (22)-(23)—both $\pi_{t+1|t}$ and $y_{t+1|t}$ depend on the policy parameter, ϕ_π, thus making it enter in the equations for π_t and y_t of the SVAR representation of the model, which is the crucial condition for the outcome of the SVAR-based counterfactual to deviate from the outcome of the DSGE one. Indeed, as the second row of Figure 18 shows, with autocorrelated shocks (these results have been generated by setting both ρ_π and ρ_y to the values estimated by Lubik and Schorfheide (2004)) the SVAR-based counterfactual fails, and it only works, by definition, when the alternative value of ϕ_π is the same as the benchmark. It is also worth stressing how the problem has *nothing* to do with the issue of parameter identification, as none of the structural parameters has disappeared from the model's solution.

Finally, the bottom row of Figure 18 shows results for the case in which ρ has been set to the (non-zero) value estimated by Lubik and Schorfheide (2004), whereas ρ_π and ρ_y have been set to zero. The explanation, once again, has to do with the fact that under *all* circumstances in which the model's solution is not vector white noise, $\pi_{t+1|t}$ and $y_{t+1|t}$ on the right-hand side of (13)-(14) do not drop out, with the result that the cross-equations restrictions implied by rational expectations cause the policy parameter to appear in all the equations of the SVAR form.

The fact that the crucial issue here is the (un)forecastability of π_t and y_t suggests that the problem should appear also in the presence of backward-looking components in the IS and Phillips curves. As Figure 19 shows, this is indeed the case. The results reported in the figure have been generated based on the standard backward- and forward-looking New Keynesian model (1), (10), (11). The model has been calibrated based on Benati's (2008) modal estimates for the post-WWII United States as reported in his Table XII for all parameters except the autoregressive parameters in the shocks' processes, which have been set to zero; and α and γ, for which we consider three sets of values:

(*i*) $[\alpha\ \gamma]'=[0\ 1]'$, which implies that the IS and Phillips curves are purely forward-looking;

(*ii*) $[\alpha\ \gamma]'=[0.5\ 0.5]'$, which implies that they are partly forward- and partly backward-looking;

(*iii*) $[\alpha\ \gamma]'=[0.9\ 0.1]'$, which implies that they are very backward-looking.

For each combination of values of α and γ we perform this paper's standard exercise conditional on grids of values for ρ and ϕ_π as before. For each point in the grid, the benchmark Taylor rule is characterised by a value of ϕ_π equal to Benati's (2008) modal estimate, and by a value of ρ equal to the value taken by ρ *in that point*. So the results reported in Figure 19

(*i*) are based on a set of benchmark values for ρ, and

(*ii*) *uniquely* depend on the difference between the value taken by ϕ_π and its benchmark value.

The reason for doing this is to explore the impact of ϕ_π on the reliablity of the SVAR-based counterfactual *conditional* on several alternative benchmark values of ρ. As the figure shows,

- if the IS and Phillips curves are purely forward-looking, the problem is clearly apparent under indeterminacy, whereas under determinacy it only appears for comparatively high values of ρ (this is especially apparent for the output gap). Consistent with the previous analysis based on the (modified) model of Lubik and Schorfheide (2004), if ρ=0, under determinacy the counterfactual works perfectly.

- If the IS and Phillips curves are not purely forward-looking, however, the problem is clearly always there, as $\pi_{t+1|t}$ and $y_{t+1|t}$ are not equal to zero, thus causing the policy parameter to appear in the equations for π_t and y_t in the SVAR representation of the model.

A crucial point to stress here is that, *in practice*, the extent of forward-lookingness of the IS and Phillips curves is *unknown*, and, in particular, the extent of forward-lookingness of the Phillips curves is still subject to intense debate (see e.g. Benati (2008)). This automatically implies that reliability of the SVAR-based counterfactual cannot simply be assumed, and can rather only be ascertained with a reasonable degree of confidence by estimating a DSGE model.

5 How Relevant Is the Problem in Practice?

What is the practical relevance of the problem discussed in the present work? Specifically, what is the likely size of the error incurred by a researcher when performing a SVAR-based policy counterfactual, where such error is defined as the difference between the outcome of the SVAR-based counterfactual, and the outcome of the authentic counterfactual which the researcher would have performed had (s)he known the true (e.g., DSGE) model of the economy? Providing a precise answer to this question is obviously impossible, as this would require knowledge of the true data generation process. A necessarily limited and tentative answer can however be provided (*i*) for a specific counterfactual—e.g., 'bringing Alan Greenspan back in the 1970s'—and (*ii*) conditional on a specific estimated DSGE model. In this section we therefore estimate both the standard backward- and forward-looking New Keynesian model described by equations (1), (10), and (11),[17] and the Model of Andres *et al.* (2009), for the United States and the United Kingdom. For either country, the models are estimated for both a Great Inflation sample, and the most recent regime/period.[18] Bayesian estimation *via* Random-Walk Metropolis is performed as in An and Schorfheide (2007), with the single exception of the method we use to calibrate the covariance matrix's scale factor, for which we follow the methodology described in Appendix D.3 of Benati (2008).[19] Finally, in estimation we allow for one-dimensional indeterminacy, solving the model under indeterminacy *via* Lubik

[17] For the sake of simplicity, we assume that the three structural shocks—$\epsilon_{R,t}$, $\epsilon_{\pi,t}$, and $\epsilon_{y,t}$—are white noise.

[18] Specifically, for the Great Inflation sample we consider the period 1965:1:1979:4. As for the most recent regime/period, for the U.S. we consider the period following the end of the Volcker stabilisation (which, following Clarida, Gali, and Gertler (2000), we date in the fourth quarter of 1982), whereas for the U.K. we consider the inflation-targeting regime. Data are from FRED for the U.S., and from the Office for National Statistics for the U.K..

[19] We also follow Benati (2008) in maximising the log-posterior *via* the simulated annealing algorithm proposed by Corana, Marchesi, Martini, and Ridella (1987).

and Schorfheide's (2004) 'continuity' solution.[20] We run a burn-in sample of 200,000 draws which we then discard. After that, we run a sample of 100,000 draws, keeping every draw out of 100 in order to decrease the draws' autocorrelation, thus ending up with a sample of 1,000 draws for the ergodic distribution.

Table 2 reports, for each of the model's structural parameters, its domain and the chosen density, together with two key objects characterising it, the mode and the standard deviation, whereas Table 3 reports, for either country, the mode and the 90%-coverage percentiles of the posterior distribution generated *via* Random-Walk Metropolis. The prior probability of determinacy as implied by the densities' modes and standard deviations as reported in Table 2 is equal to 0.937. On the other hand, the fractions of draws from the ergodic distribution impliying determinacy for the United States and the United Kingdom are equal to 0.325 and 0.094, respectively, for the Great Inflation period, and to 1.000 and 0.754, respectively, for the most recent one. Empirical evidence therefore clearly suggests that, for both countries, the most recent period has been characterised by determinacy, whereas for the Great Inflation years—in line with Clarida, Gali, and Gertler (2000) and Lubik and Schorfheide (2004)—evidence suggests a significantly greater probability of indeterminacy.[21]

Based on the median estimates reported in Table 3 we then 're-run history' exactly as we did, based on a single stochastic simulation, in Section 2.2 (the only difference with section 2.2 is that there we performed the counterfactuals based on simulated data, whereas here do it based real data). Specifically, based on both the DSGE models conditional on the median estimates, and their implied theoretical SVAR(MA) representations,[22] we switch monetary rules across periods, by imposing the most recent period's rule in the Great Inflation period, and, *vice versa*, by imposing the Great Inflation rule into the most recent period

The results are reported in Figures 20-27. Specifically, Figures 20, 22, 24, and 26 report, for either country, and for either period—the Great Inflation in the top row, and the most recent period in the bottom row—the true series for the interest rate, inflation, the output gap, and real money balances (in black), together with the series produced by the DSGE-based and the SVAR-based counterfactuals (in blue and red, respectively). Figures 21, 23, 25, and 27, on the other hand, show, for either period, and for each variable, the difference between the results produced by the SVAR-based and the DSGE-based counterfactual—that is, the error made by the SVAR-based counterfactual. Overall, the results clearly suggest that the problem is, potentially, non-negligible, and in several cases it is especially serious. This is

[20] Lubik and Schorfheide (2003) and Lubik and Schorfheide (2004) contain extensive discussions of why this solution is preferable to the alternative 'orthogonality' one.

[21] In line with Kiley (2007) and Ascari (2004), Benati and Goodhart (2010) show that taking into account of the fact that trend inflation is typically non-zero makes a dramatic difference for the probability of determinacy associated with the Great Inflation episode, which for all the countries they consider—with the exception of Canada—shrinks towards zero.

[22] I say SVAR(MA) because the DSGE model has a VAR representation under determinacy, and VARMA one under indeterminacy.

the case, for example, of the United Kingdom when imposing the SVAR's estimated interest rate rule for the Great Inflation period onto the the SVAR for the more recent years. Once again, a crucial issue to be stressed is that, since the reliability of the SVAR-based counterfactual crucially depends on unknown structural characteristics of the underlying data generation process, without estimating a structural model, there is simply *no way* to know—or even to conjecture—how reliable the SVAR-based counterfactual can be for a specific application.

Finally, a further, important issue is the following. All of the counterfactuals shown in Figures 20-27 have been based on models in which, as we pointed out, we allowed, in principle, for one-dimensional indeterminacy. What we did not allow, on the other hand, is for sunspot shocks under indeterminacy. The reason for this is straighforward: if we had allowed for sunspots under indeterminacy, we would have ran into an identification problem. With *three* reduced-form residuals from the VAR, and *four* structural shocks, there would have been no way to identify the structural shocks. In order to give SVARs a fair chance of succeding, we therefore ruled out sunspots from the outset. From a conceptual point of view, however, it is very difficult to justify ruling out sunspots under indeterminacy, as this is essentially a 'corner solution', and it is therefore much more reasonable to assume that, under that regime, sunpots play *some* role—that is, their standard deviation is non-zero. If that's the case, however, this is going to create two fundamental problems to SVAR analysis. *First*, as we just mentioned, an identification problem, in the sense that it is impossible for the researcher to correctly identify all of the four shocks based on the three VAR's reduced-form residuals. This implies that the identified structural shocks under indeterminacy will be unavoidably 'contaminated' by the sunspots. *Second*, it will (further) distort the results of the SVAR-based counterfactual compared with those of the authentic, DSGE-based one. To fix ideas, supposed that, for the post-WWII U.S., we identify, in line with Clarida *et al.* (2000), indeterminacy for the Great Inflation period, and determinacy for the later period. This automatically implies that, when imposing the Taylor rule for the later period into the DSGE for the first period, one of the implications of such counterfactual will be to 'kill off' the sunspots, thus automatically decreasing, *ceteris paribus*, macroeconomic volatility across the board. When performing instead the SVAR-based counterfactual, on the other hand, this—by the very logic of the exercise—will not happen, with the result that such counterfactual will necessarily understate the stabilising impact of the change in monetary policy.

6 Conclusions

Based on standard New Keynesian models I have shown that policy counterfactuals based on the theoretical structural VAR representations of the models fail to reliably capture the impact of changes in the parameters of the Taylor rule on the (reduced-form) properties of the economy. Based on estimated models for the Great Inflation and the most recent period, I have shown that, as a practical matter, the problem appears to be non-negligible. I have shown analytically that the problem (*i*) is a straightforward implication of the cross-equations restrictions imposed by rational expectations on a model's structural solution; and (*ii*) it is independent of the issue of parameter identification. These results imply that the outcomes of SVAR-based policy counterfactuals should be regarded with caution, as their informativeness for the specific issue at hand—e.g., understanding the role played by monetary policy in exacerbating the Great Depression, causing the Great Inflation, or fostering the Great Moderation—is, in principle, open to question. Finally, I have argued that SVAR-based policy counterfactuals suffer from a crucial logical shortcoming: given that their reliability crucially depends on unknown structural characteristics of the underlying data generation process, reliability cannot simply be assumed, and can instead only be ascertained with a reasonable degree of confidence by estimating structural (DSGE) models.

References

Adam, K. (2009): "Monetary Policy and Aggregate Volatility," *Journal of Monetary Economics*, forthcoming.

An, S., and F. Schorfheide (2007): "Bayesian Analysis of DSGE Models," *Econometric Reviews*, 26(2-4), 113–172.

Andrés, J., J. D. López-Salido, and E. Nelson (2009): "Money and the Natural Rate of Interest: Structural Estimates for the United States and the Euro Area," *Journal of Economic Dynamics and Control*, 33(3), 758–76.

Ascari, G. (2004): "Staggered Prices and Trend Inflation: Some Nuisances," *Review of Economic Dynamics*, 7, 642–667.

Benati, L. (2008): "Investigating Inflation Persistence Across Monetary Regimes," *Quarterly Journal of Economics*, 123(3), 1005–1060.

Benati, L., and C. Goodhart (2010): "Monetary Policy Regimes and Economic Performance: The Historical Record, 1979-2008," *forthcoming in B. Friedman, B., and Woodford, M. (eds.), Handbook of Monetary Economics, Volume 1D, North Holland.*

Benati, L., and P. Surico (2009): "VAR Analysis and the Great Moderation," *American Economic Review*, 99(4), 1636–Ű52.

Besley, T. (2008): "Speech Given at the Canada-UK Chamber of Commerce, London, 22 April 2008," .

Beyer, A., V. Gaspar, C. Gerberding, and O. Issing (2009): "Opting Out of the Great Inflation: German Monetary Policy after the Break Down of Bretton Woods," *in Michael D. Bordo and Athanasios Orphanides, editors, The Great Inflation, Forthcoming from University of Chicago Press.*

Canova, F., and L. Gambetti (2008): "Structural Changes in the US Economy: Is There a Role for Monetary Policy?," *Journal of Economic Dynamics and Control*, forthcoming.

Christiano, L. J. (1998): "Discussion of Sims' paper," *in Jeffrey C. Fuhrer and Scott Schuh, editors, 'Beyond Shocks: What Causes Business Cycles'*, Federal Reserve Bank of Boston Conference Volume(42), 161–70.

Clarida, R., J. Gali, and M. Gertler (2000): "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, CXV(1), 147–180.

Corana, A., M. Marchesi, C. Martini, and S. Ridella (1987): "Minimizing Multimodal Functions of Continuous Variables with the Simulated Annealing Algorithm," *ACM Transactions on Mathematical Software*, 13, 262–80.

Friedman, M., and A. Schwartz (1963): *A Monetary History of the United States, 1867-1960*. Princeton University Press.

Gambetti, L., E. Pappa, and F. Canova (2006): "The Structural Dynamics of U.S. Output and Inflation: What Explains the Changes?," *Journal of Money, Credit, and Banking*, 40(2-3), 369–388.

Issing, O. (2005): "Why Did the Great Inflation Not Happen in Germany?," *Federal Reserve Bank of St. Louis Review, March/April 2005,*, 87(2, Part 2), 329–35.

Kiley, M. T. (2007): "Is Moderately-To-High Inflation Ineherently Unstable?," *International Journal of Cental Banking*, 3(2), 173–201.

Lubik, T., and F. Schorfheide (2003): "Computing Sunspot Equilibria in Linear Rational Expectations Models," *Journal of Economic Dynamics and Control*, 28(2), 273–285.

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

Meltzer, A. H. (2005): "Origins of the Great Inflation," *Federal Reserve Bank of St. Louis Review, March/April 2005,*, 87(2, Part 2), 145–75.

Orphanides, A. (2004): "Monetary Policy in Deflation: The Liquidity Trap in History and Practice," *North American Journal of Economics and Finance*, 15, 101–124.

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

Sims, C. (1980): "Macroeconomics and reality," *Econometrica*.

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

Sims, C. A. (1998): "The Role of Interest Rate Policy in the Generation and Propagation of Business Cycles: What Has Changed Since the 1930s?," *in Jeffrey C. Fuhrer and Scott Schuh, editors, 'Beyond Shocks: What Causes Business Cycles'*, Federal Reserve Bank of Boston Conference Volume(42), 121–60.

Wei, W. (2005): *Time Series Analysis: Univariate and Multivariate Methods*. Addison Wesley.

A The Model of Andrés, López-Salido, and Nelson (2009)

The model proposed by Andrés, López-Salido, and Nelson (2009) is of interest because, different from the vast majority of models in the literature, it is not block-recursive in money balances. The model is described by the following equations[23]

$$R_t = \rho R_{t-1} + (1-\rho)[\phi_\pi \pi_t + \phi_y y_t + \phi_\mu \mu_t] + \epsilon_{R,t} \tag{A.1}$$

$$\pi_t - \kappa\pi_{t-1} = \beta(\pi_{t+1|t} - \kappa\pi_t) + \lambda mc_t \tag{A.2}$$

$$(\phi_1+\phi_2)y_t = \phi_1 y_{t-1} + (\beta\phi_1+\phi_2)y_{t+1|t} - R_t + \pi_{t+1|t} - \beta\phi_1 y_{t+2|t} + \tag{A.3}$$

$$+\frac{\psi_2}{\psi_1(1\text{-}\beta h)}[m_t\text{-}(1+\beta h)m_{t+1|t}+\beta h m_{t+2|t}\text{-}(1\text{-}\beta h\rho_e)(1\text{-}\rho_e)e_t]+\frac{(1\text{-}\beta h\rho_a)(1\text{-}\rho_a)a_t}{(1\text{-}\beta h)}$$

$$mc_t = (\chi+\phi_2)y_t - \phi_1 y_{t-1} - \beta\phi_1 y_{t+1|t} - (1-\chi)z_t - \frac{\beta h(1-\rho_a)a_t}{(1-\beta h)} + \tag{A.4}$$

$$+\frac{\psi_2}{\psi_1(1-\beta h)}[\beta h m_{t+1|t} - m_t + (1-\beta h\rho_e)e_t]$$

$$m_t[1+\delta_0(1+\beta)]=\gamma_1 y_t\text{-}\gamma_2 R_t+y_{t-1}[\gamma_2(r\text{-}1)(h\phi_2\text{-}\phi_1)\text{-}h\gamma_1]\text{-}y_{t+1|t}[\gamma_2(r\text{-}1)\beta\phi_1]+ \tag{A.5}$$

$$+\delta_0 m_{t-1}+m_{t+1|t}\left[\frac{\psi_2(r\text{-}1)\beta h\gamma_2}{\psi_1(1\text{-}\beta h)}+\delta_0\beta\right]\text{-}a_t\frac{\gamma_2(r\text{-}1)\beta h(1\text{-}\rho_a)}{(1\text{-}\beta h)}+$$

$$+\left[1\text{-}(r\text{-}1)\gamma_2\left(1+\frac{\psi_2\beta h\rho_e}{\psi_1(1\text{-}\beta h)}\right)\right]e_t$$

where mc_t is the log-deviation of the marginal cost from the steady-state, e_t, a_t, z_t, and $\epsilon_{R,t}$ are structural disturbances, and $\varkappa \equiv(\varphi+\alpha)/(1\text{-}\alpha)$, $\lambda \equiv \xi(1\text{-}\theta)(1\text{-}\beta\theta)$, $\xi \equiv \theta^{-1}(1\text{-}\alpha)/[1+\alpha(\epsilon\text{-}1)]$, $\phi_1 \equiv h(\psi_1^{-1}\text{-}1)/(1\text{-}\beta h)$, $\phi_2 \equiv[\psi_1^{-1}+(\psi_1^{-1}\text{-}1)\beta h^2\text{-}\beta h]/(1\text{-}\beta h)$. κ and λ in (A.2) are the extent of indexation to past inflation and the slope of the Phillips curve, respectively; h is the habit-formation parameter in the utility function; γ_1 and γ_2 are the elasticities of the demand for real balances with respect to output and the interest rate, respectively; θ is the Calvo parameter; (1-α) is the elasticity of output with respect to hours in the Cobb-Douglas production function; and ψ_1 and ψ_2 are parameters defined in Section 2.4 of Andrés, López-Salido, and Nelson (2009), as the ratios of derivatives evaluated at the steady-state.

We estimate the model based on Bayesian methods for the United States for the full post-WWII period, based on exactly the same methodology we used in Benati (2008). Table 1 reports both the Bayesian priors, and the mode and the lower and upper 90%-coverage percentiles of the posterior distribution produced by the Random-Walk Metropolis algorithm.

[23] I am using exactly the same notation as Andrés, López-Salido, and Nelson (2009).

Table 1 Bayesian estimates for the post-WWII United States for the model of Andrés, López-Salido, and Nelson (2009)

Parameter	Domain	Density	Prior distribution Mode	St. dev.	Posterior distribution: mode and 90%-coverage percentiles
σ_a^2	$\mathbb{R}^+$	Inverse Gamma	1	2	3.40 [1.39; 7.96]
σ_e^2	$\mathbb{R}^+$	Inverse Gamma	1	2	3.08 [1.86; 5.06]
σ_z^2	$\mathbb{R}^+$	Inverse Gamma	1	2	0.86 [0.70; 2.36]
σ_R^2	$\mathbb{R}^+$	Inverse Gamma	1	2	0.77 [0.67; 0.92]
φ	$\mathbb{R}^+$	Gamma	1	0.1	1.02 [0.87; 1.21]
h	[0; 1]	Beta	0.7	0.2	0.98 [0.95; 0.99]
θ	(0; 1]	Beta	2/3	0.025	0.68 [0.65; 0.72]
κ	[0; 1]	Uniform	–	0.29	0.01 [0.00; 0.01]
ρ	[0; 1)	Beta	0.8	0.1	0.82 [0.78; 0.83]
ϕ_π	$\mathbb{R}^+$	Gamma	1.5	0.25	0.97 [0.82; 1.17]
ϕ_y	$\mathbb{R}^+$	Gamma	0.5	0.15	1.03 [0.84; 1.45]
ϕ_μ	$\mathbb{R}^+$	Gamma	0.5	0.25	0.24 [0.11; 0.39]
δ_0	[0; 20]	Uniform	–	5.77	2.88 [2.06; 4.48]
γ_1	$\mathbb{R}^+$	Gamma	1	0.05	1.00 [0.92; 1.08]
γ_2	$\mathbb{R}^+$	Gamma	0.1	0.01	0.11 [0.09; 0.12]
ψ_1	$\mathbb{R}^+$	Gamma	0.5	0.5	0.33 [0.28; 0.54]
ψ_2	$\mathbb{R}^+$	Gamma	0.1	0.1	0.06 [0.02; 0.17]
ϵ-1	$\mathbb{R}^+$	Gamma	10	1	10.40 [8.77; 12.06]
ρ_a	[0; 1)	Beta	0.5	0.5	0.35 [0.27; 0.58]
ρ_e	[0; 1)	Beta	0.5	0.5	0.79 [0.70; 0.87]
ρ_z	[0; 1)	Beta	0.5	0.5	0.96 [0.93; 0.98]

Table 2 Bayesian priors for the backward- and forward-looking New Keynesian model of section 5

Parameter	Domain	Density	Mode	St. dev.
σ_R^2	$\mathbb{R}^+$	Inverse Gamma	1	2
σ_π^2	$\mathbb{R}^+$	Inverse Gamma	1	2
σ_y^2	$\mathbb{R}^+$	Inverse Gamma	1	2
κ	$\mathbb{R}^+$	Gamma	0.05	0.01
σ	$\mathbb{R}^+$	Gamma	2	2
α	[0; 1]	Uniform	–	0.29
γ	(0; 1]	Uniform	–	0.29
ρ	[0; 1)	Beta	0.5	0.25
ϕ_π	$\mathbb{R}^+$	Gamma	1.5	0.50
ϕ_y	$\mathbb{R}^+$	Gamma	0.5	0.25

Table 3 Bayesian estimates for the backward- and forward-looking New Keynesian model of section 5: medians and 90%-coverage percentiles of the posterior distributions

	United States		United Kingdom	
	Great Inflation	Post-Volcker stabilisation	Great Inflation	Inflation targeting
σ_R^2	0.84 [0.65; 1.15]	0.49 [0.39; 0.62]	1.37 [1.01; 1.86]	0.30 [0.23; 0.41]
σ_π^2	1.02 [0.74; 1.48]	0.54 [0.39; 0.76]	18.20 [12.80; 33.38]	2.45 [1.85; 3.35]
σ_y^2	0.74 [0.49; 1.09]	0.48 [0.38; 0.61]	1.62 [1.07; 2.38]	0.25 [0.20; 0.34]
κ	0.04 [0.03; 0.06]	0.03 [0.02; 0.04]	0.04 [0.03; 0.05]	0.04 [0.03; 0.06]
σ	4.31 [2.85; 6.87]	12.55 [9.42; 17.08]	10.55 [7.27; 15.71]	7.08 [4.99; 10.51]
α	0.74 [0.64; 0.83]	0.48 [0.27; 0.71]	0.55 [0.31; 0.68]	0.05 [0.01; 0.17]
γ	0.13 [0.01; 0.29]	0.04 [0.00; 0.12]	0.09 [0.01; 0.26]	0.02 [0.00; 0.07]
ρ	0.64 [0.56; 0.72]	0.86 [0.83; 0.90]	0.86 [0.77; 0.93]	0.90 [0.84; 0.94]
ϕ_π	0.91 [0.78; 1.09]	2.31 [1.63; 3.18]	0.62 [0.39; 0.99]	0.98 [0.54; 1.71]
ϕ_y	1.16 [0.92; 1.42]	1.14 [0.62; 1.69]	1.41 [1.01; 1.86]	1.13 [0.71; 1.69]

Table 4 Bayesian estimates for the model of Andres, Lopez-Salido, and Nelson: medians and 90%-coverage percentiles of the posterior distributions

	United States		United Kingdom	
Parameter	Great Inflation	Post-Volcker stabilisation	Great Inflation	Inflation targeting
σ_a	1.18 [0.94; 2.13]	1.15 [0.98; 2.23]	2.39 [1.34; 3.49]	1.25 [0.88; 1.58]
σ_e	2.04 [1.54; 2.91]	1.18 [0.97; 1.45]	4.65 [4.01; 5.11]	3.30 [2.28; 3.78]
σ_z	1.39 [1.05; 2.55]	0.95 [0.85; 1.75]	6.95 [6.65; 7.55]	6.76 [6.40; 7.25]
σ_R	0.93 [0.80; 1.11]	0.62 [0.56; 0.71]	1.30 [1.12; 1.59]	0.56 [0.48; 0.64]
φ	1.01 [0.87; 1.20]	1.06 [0.88; 1.21]	1.07 [0.91; 1.25]	1.13 [0.96; 1.31]
h	0.98 [0.92; 1.00]	0.99 [0.97; 1.00]	0.99 [0.98; 1.00]	0.99 [0.96; 1.00]
θ	0.64 [0.61; 0.69]	0.66 [0.62; 0.70]	0.60 [0.56; 0.63]	0.58 [0.55; 0.61]
κ	0.02 [0.00; 0.03]	0.00 [0.00; 0.01]	0.03 [0.00; 0.11]	0.00 [0.00; 0.00]
ρ	0.77 [0.70; 0.84]	0.86 [0.82; 0.88]	0.90 [0.86; 0.93]	0.90 [0.86; 0.93]
ϕ_π	1.20 [0.91; 1.44]	1.38 [1.07; 1.66]	0.88 [0.70; 1.12]	1.42 [1.08; 1.84]
ϕ_y	0.93 [0.60; 1.20]	0.89 [0.67; 1.31]	0.90 [0.62; 1.25]	0.54 [0.34; 0.79]
ϕ_μ	0.32 [0.16; 0.60]	0.25 [0.14; 0.55]	0.24 [0.11; 0.44]	0.55 [0.26; 1.02]
δ_0	3.82 [2.57; 8.64]	1.49 [0.85; 2.35]	2.20 [1.42; 3.31]	2.02 [0.83; 3.45]
γ_1	1.02 [0.93; 1.09]	1.00 [0.93; 1.09]	1.00 [0.92; 1.09]	1.00 [0.93; 1.08]
γ_2	0.11 [0.09; 0.12]	0.10 [0.09; 0.12]	0.10 [0.08; 0.12]	0.10 [0.09; 0.12]
ψ_1	0.60 [0.45; 0.77]	0.27 [0.24; 0.52]	0.44 [0.33; 0.60]	0.20 [0.15; 0.27]
ψ_2	0.08 [0.03; 0.21]	0.19 [0.14; 0.43]	0.04 [0.01; 0.09]	0.02 [0.01; 0.05]
ϵ-1	10.18 [8.07; 11.32]	9.20 [8.33; 11.33]	8.60 [7.30;10.26]	8.51 [7.37;10.06]
ρ_a	0.56 [0.31; 0.73]	0.55 [0.39; 0.76]	0.21 [0.10; 0.35]	0.37 [0.23; 0.51]
ρ_e	0.88 [0.80; 0.98]	0.72 [0.64; 0.85]	0.72 [0.64; 0.79]	0.56 [0.47; 0.67]
ρ_z	0.98 [0.91; 1.00]	0.96 [0.91; 0.99]	0.88 [0.84; 0.91]	0.34 [0.24; 0.47]

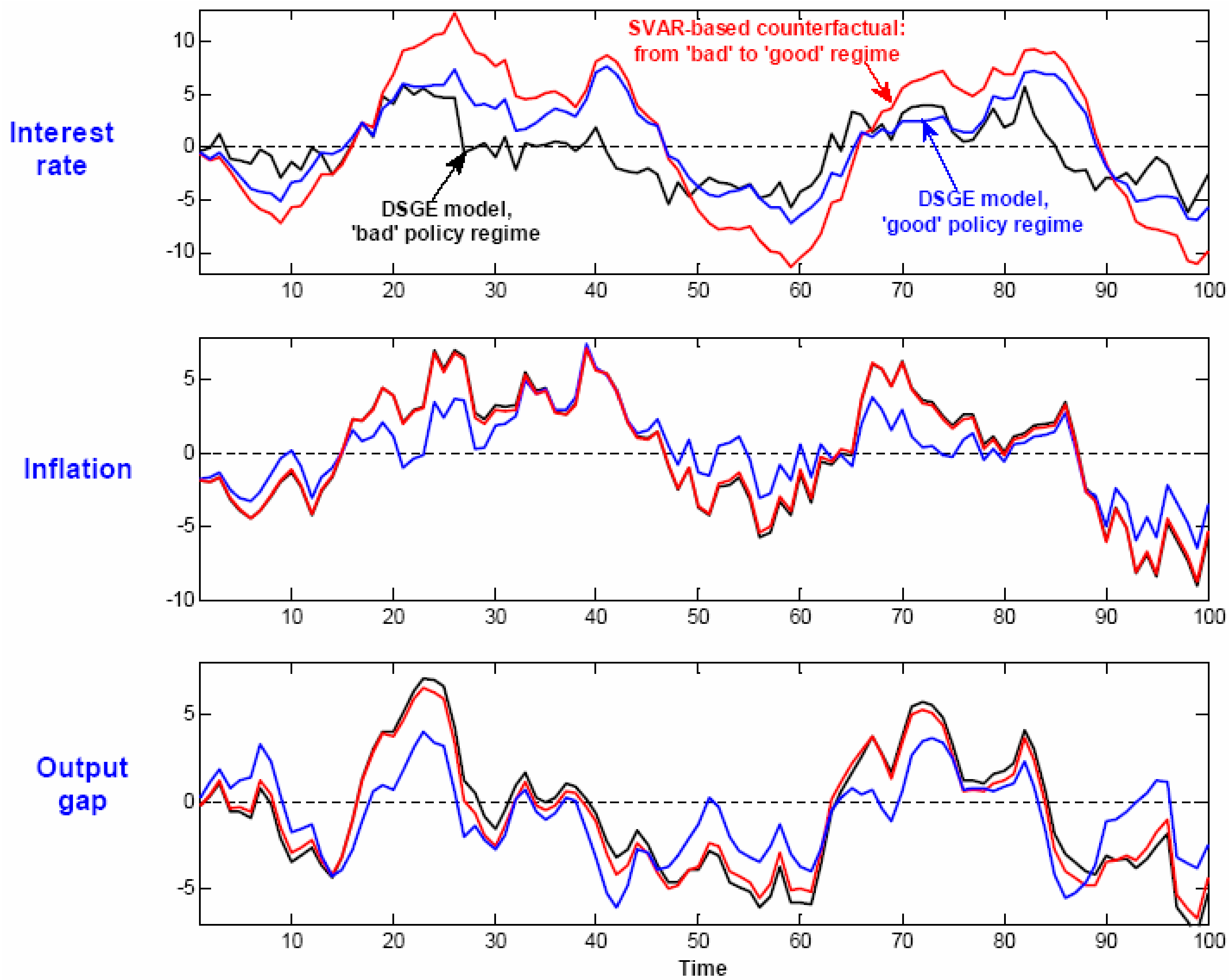

Figure 1 A simple illustration based on a single stochastic simulation: results for the 'bad' and the 'good' policy regimes, and from the SVAR-based policy counterfactual from 'bad' to 'good'

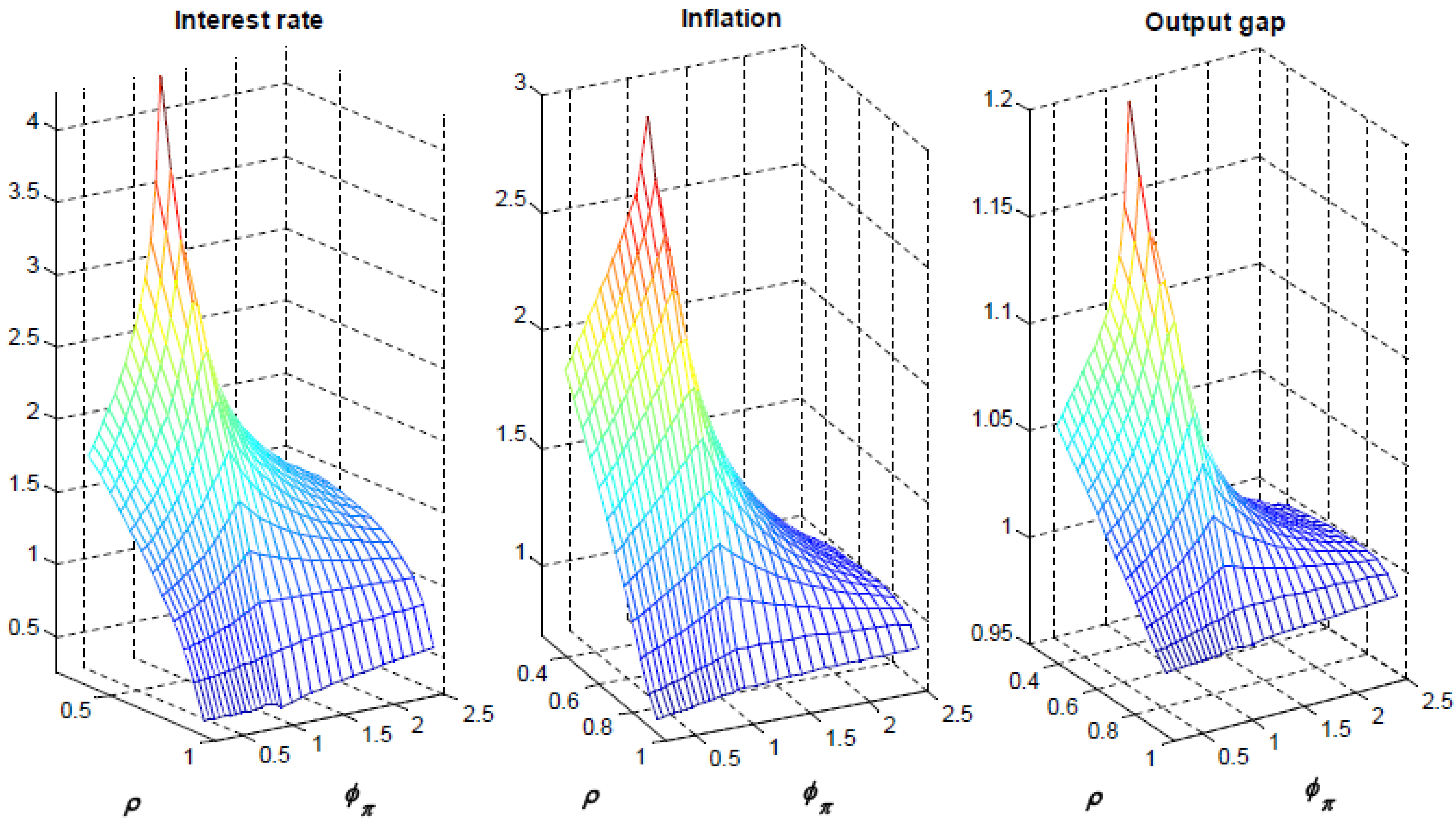

Figure 2 Ratios between the series' theoretical standard deviations from the SVAR-based policy counterfactual and the series' benchmark standard deviations (based on the model of Lubik and Schorfheide, 2004)

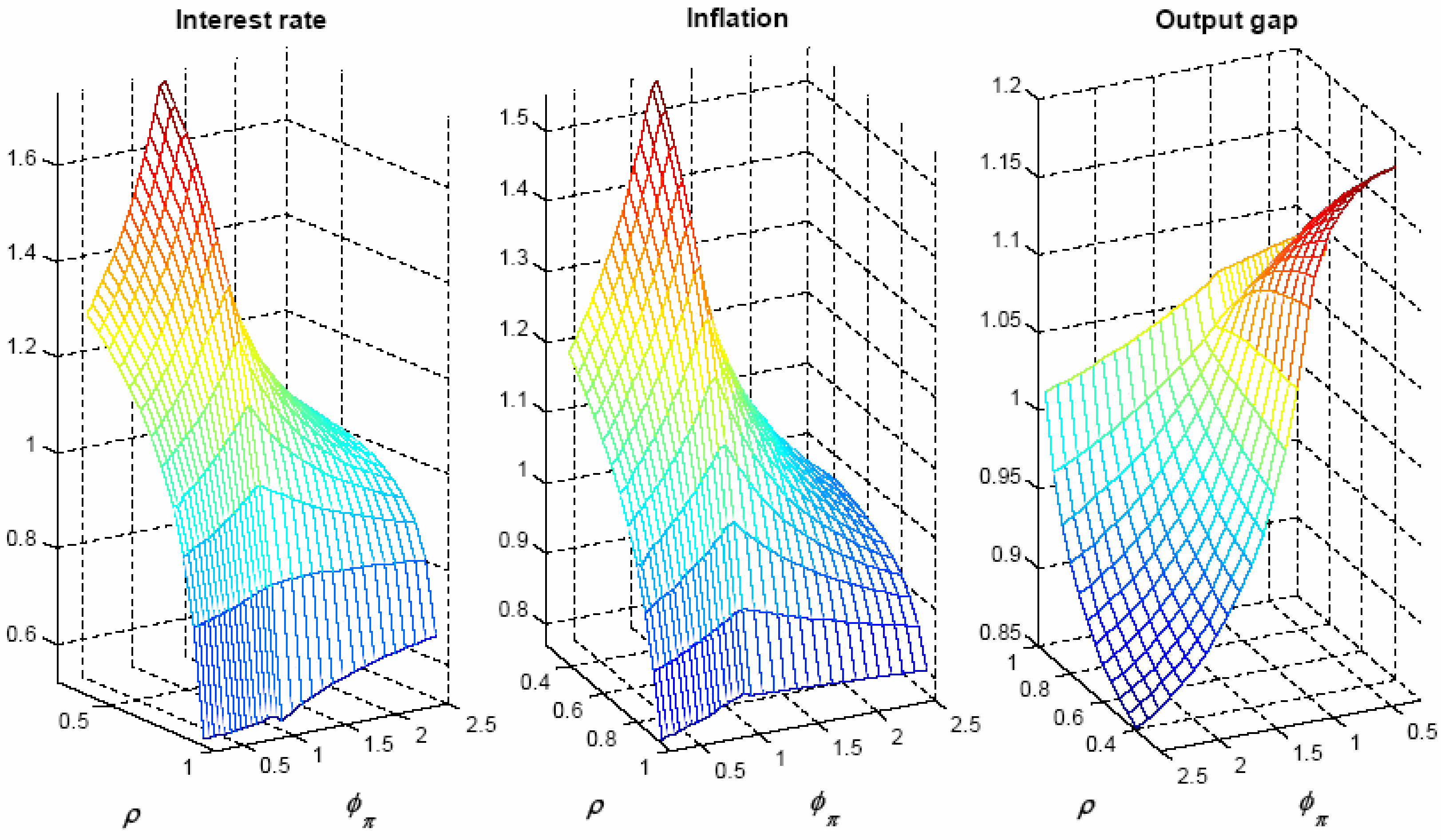

Figure 3 Ratios between the series' theoretical standard deviations from the SVAR-based policy counterfactual and the series' benchmark standard deviations (based on the model of Benati, 2008)

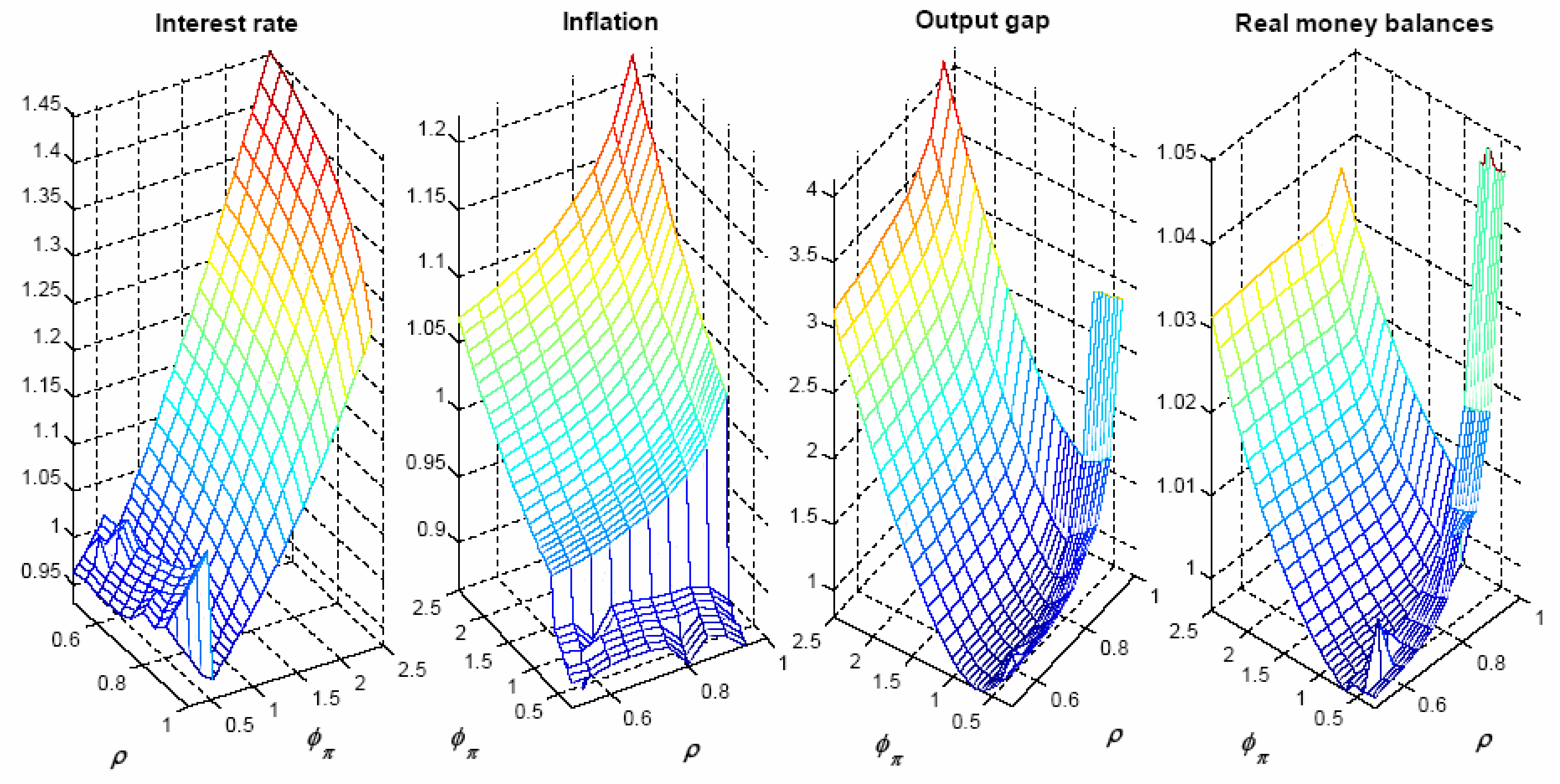

Figure 4 Ratios between the series' theoretical standard deviations from the SVAR-based policy counterfactual and the series' benchmark standard deviations (based on the model of Andres *et al.*, 2008)

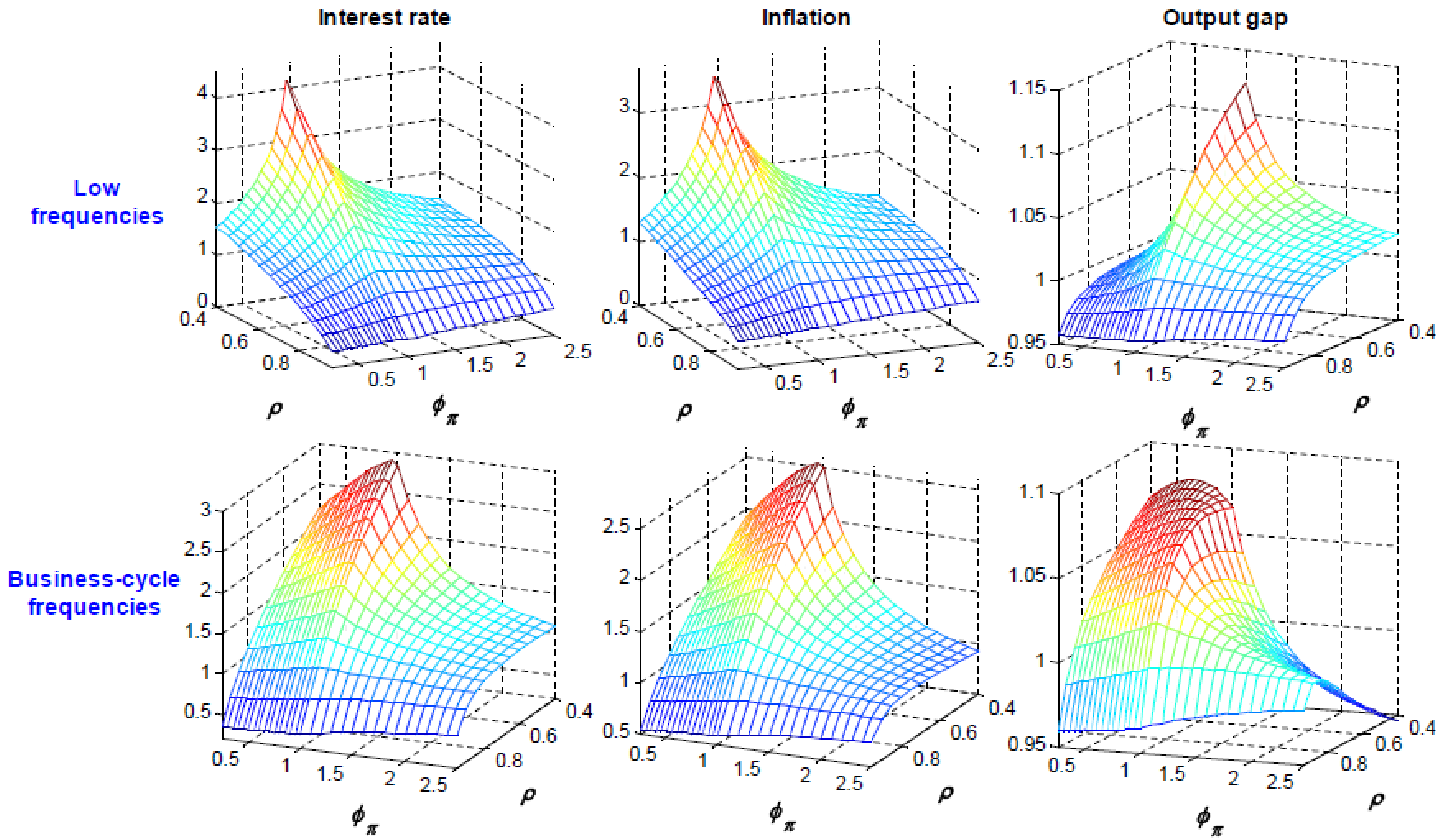

Figure 5 Average gain between the series as implied by the benchmark VAR and the same series as implied by VAR produced by the SVAR-based policy counterfactual (based on the model of Lubik and Schorfheide, 2004)

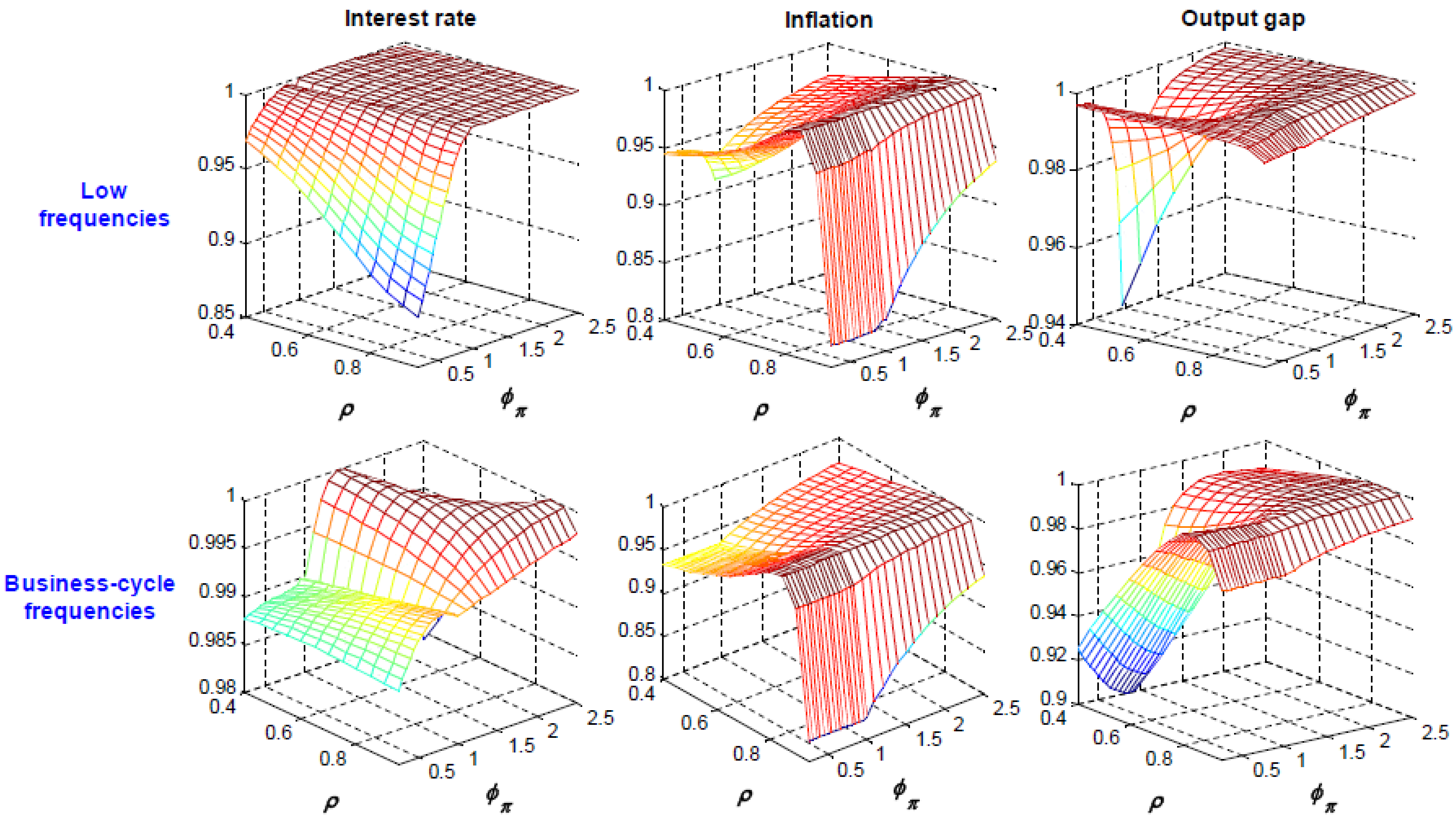

Figure 6 Average coherence between the series as implied by the benchmark VAR and the same series as implied by VAR produced by the SVAR-based policy counterfactual (based on the model of Lubik and Schorfheide, 2004)

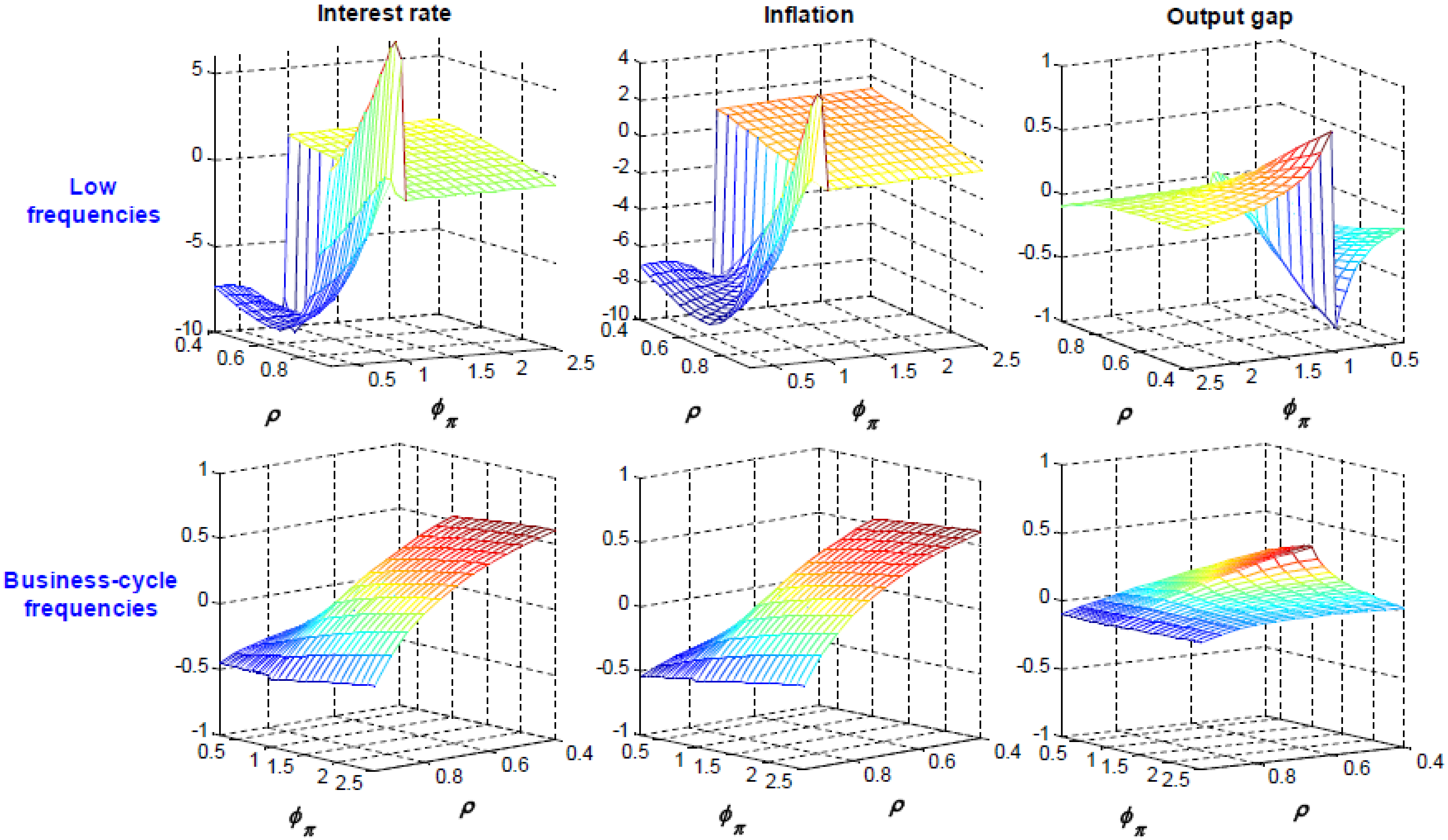

Figure 7 Average delay (in quarters) between the series as implied by the benchmark VAR and the same series as implied by VAR produced by the SVAR-based policy counterfactual (based on the model of Lubik and Schorfheide, 2004)

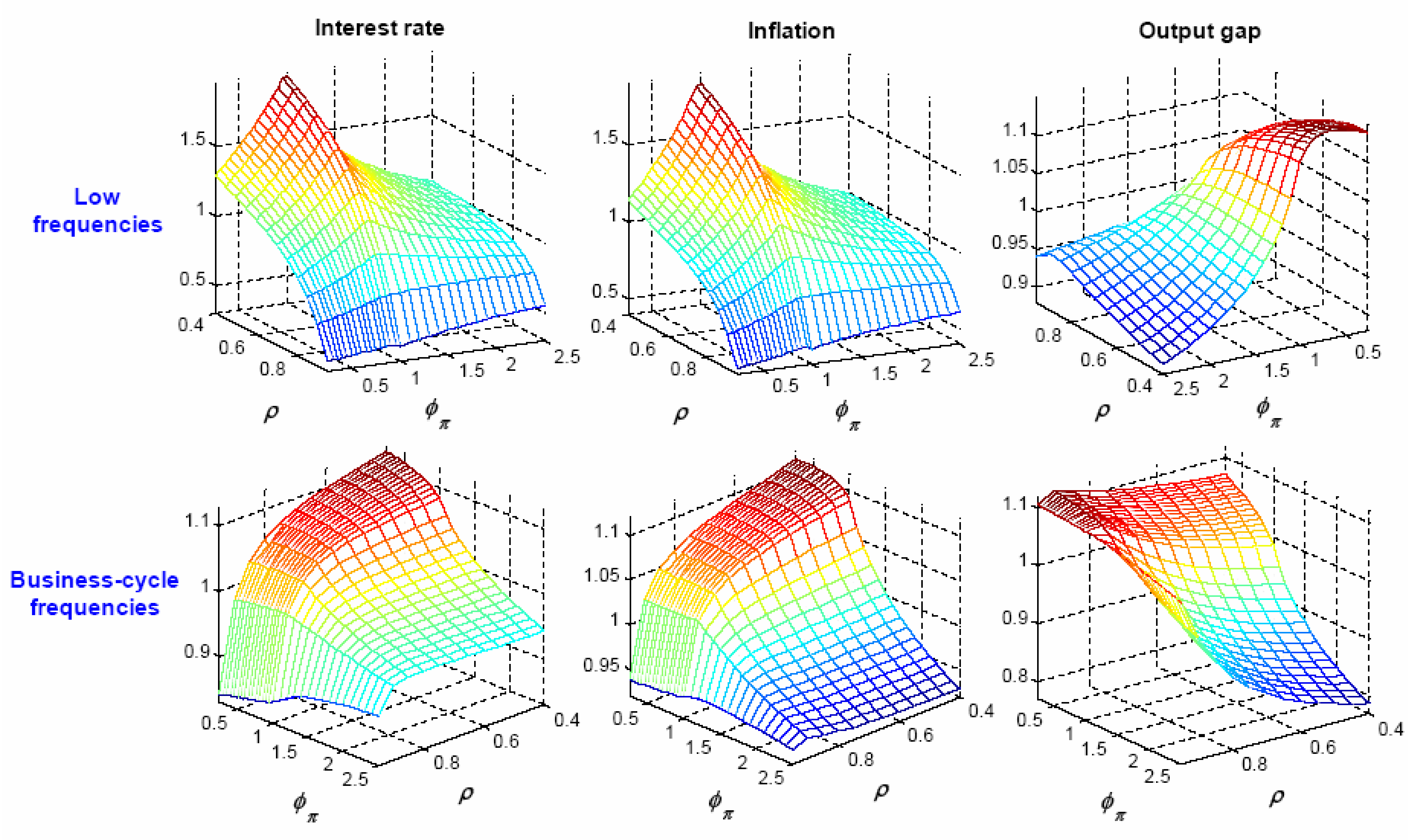

Figure 8 Average gain between the series as implied by the benchmark VAR and the same series as implied by VAR produced by the SVAR-based policy counterfactual (based on the model of Benati, 2008)

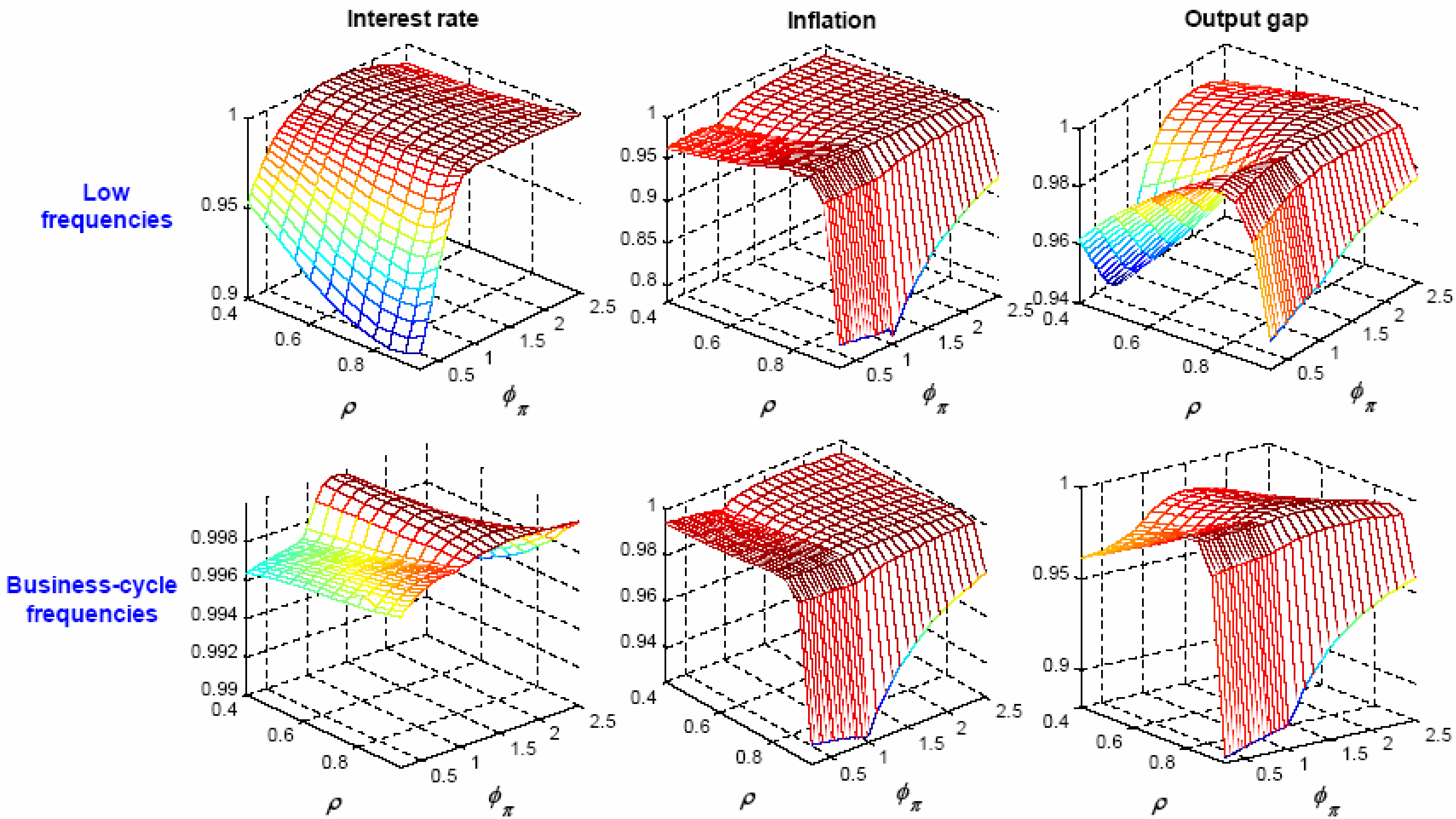

Figure 9 Average coherence between the series as implied by the benchmark VAR and the same series as implied by VAR produced by the SVAR-based policy counterfactual (based on the model of Benati, 2008)

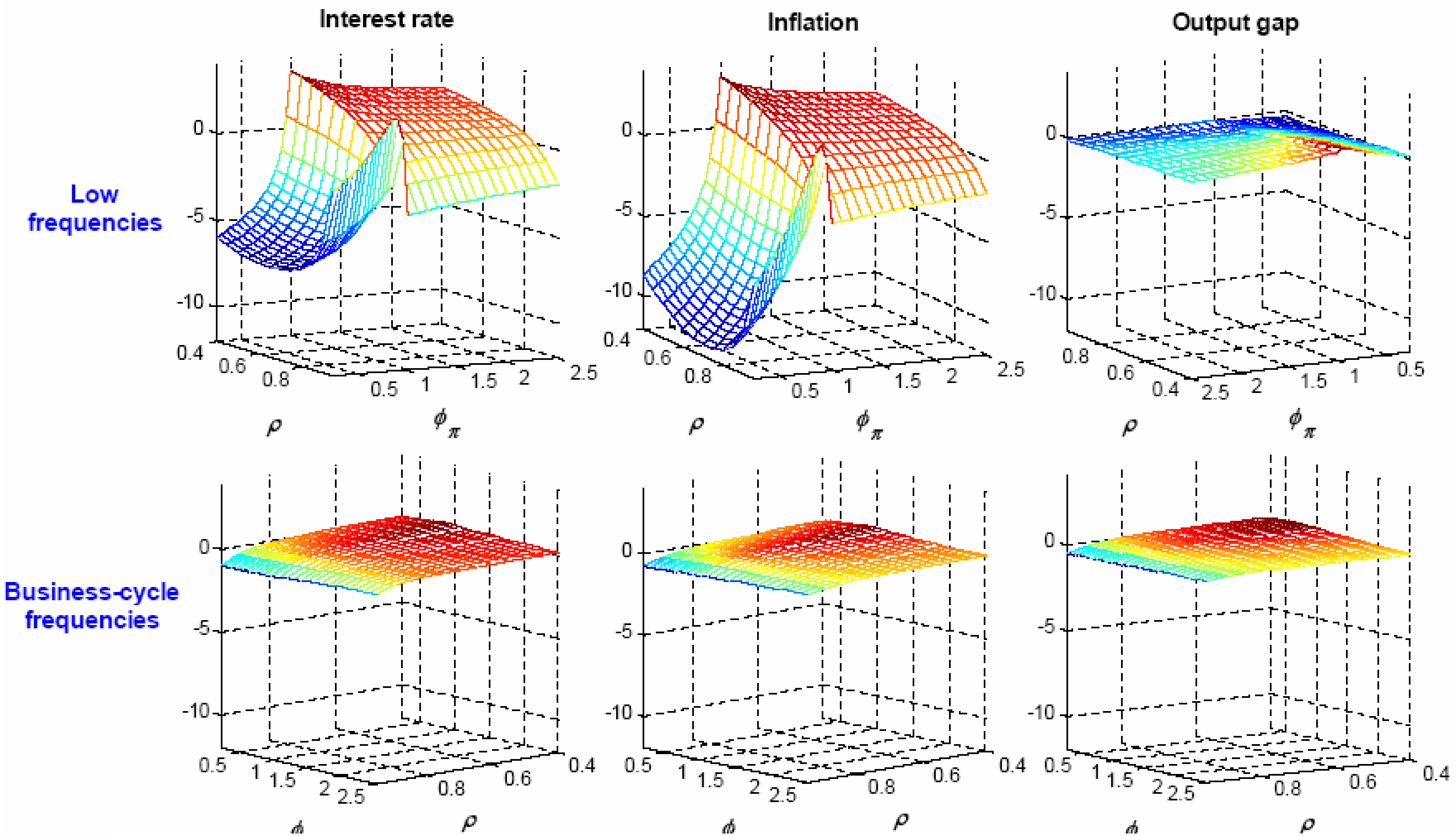

Figure 10 Average delay (in quarters) between the series as implied by the benchmark VAR and the same series as implied by VAR produced by the SVAR-based policy counterfactual (based on the model of Benati, 2008)

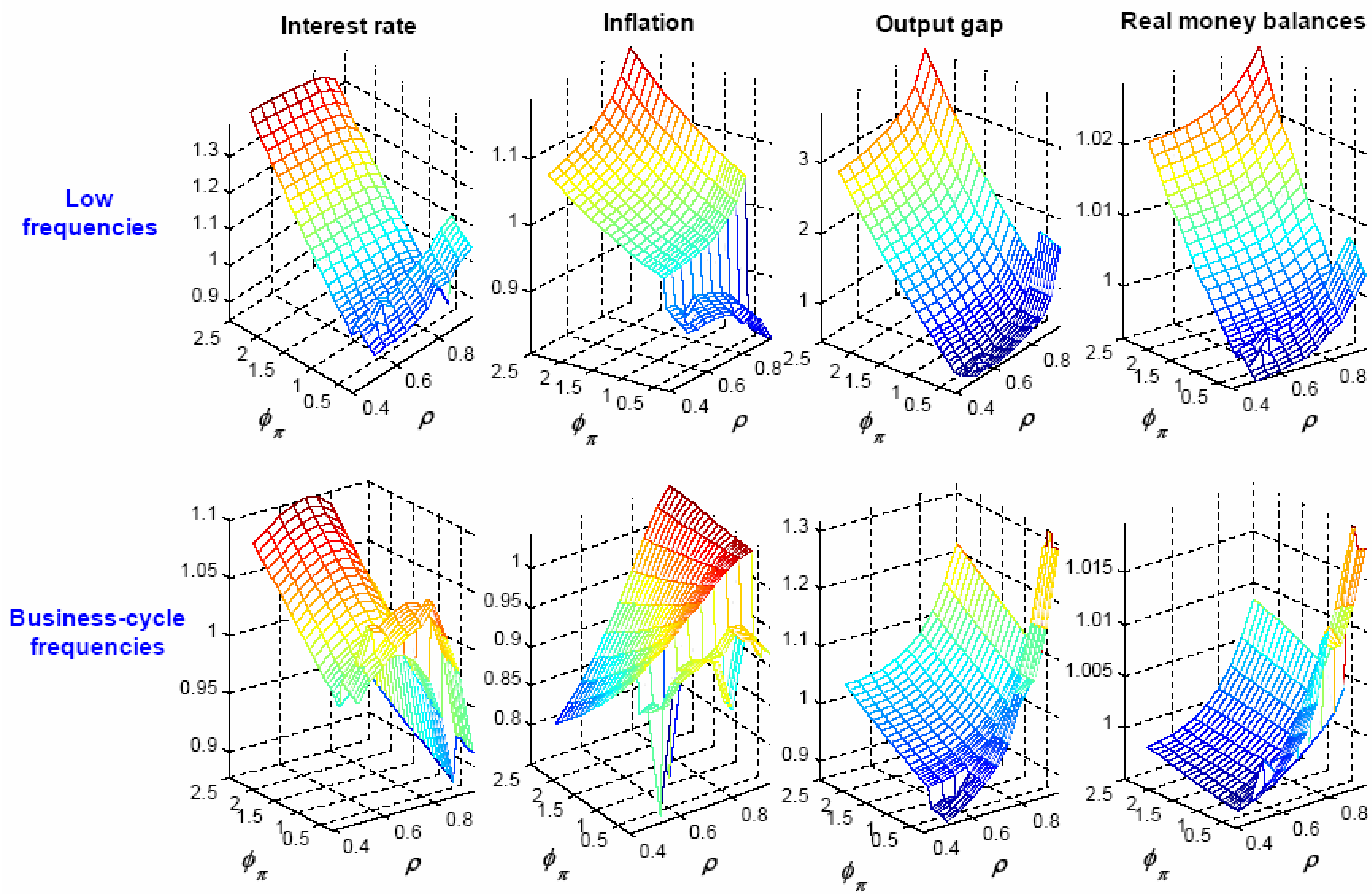

Figure 11 Average gain between the series as implied by the benchmark VAR and the same series as implied by VAR produced by the SVAR-based policy counterfactual (based on the model of Andres *et al.*, 2008)

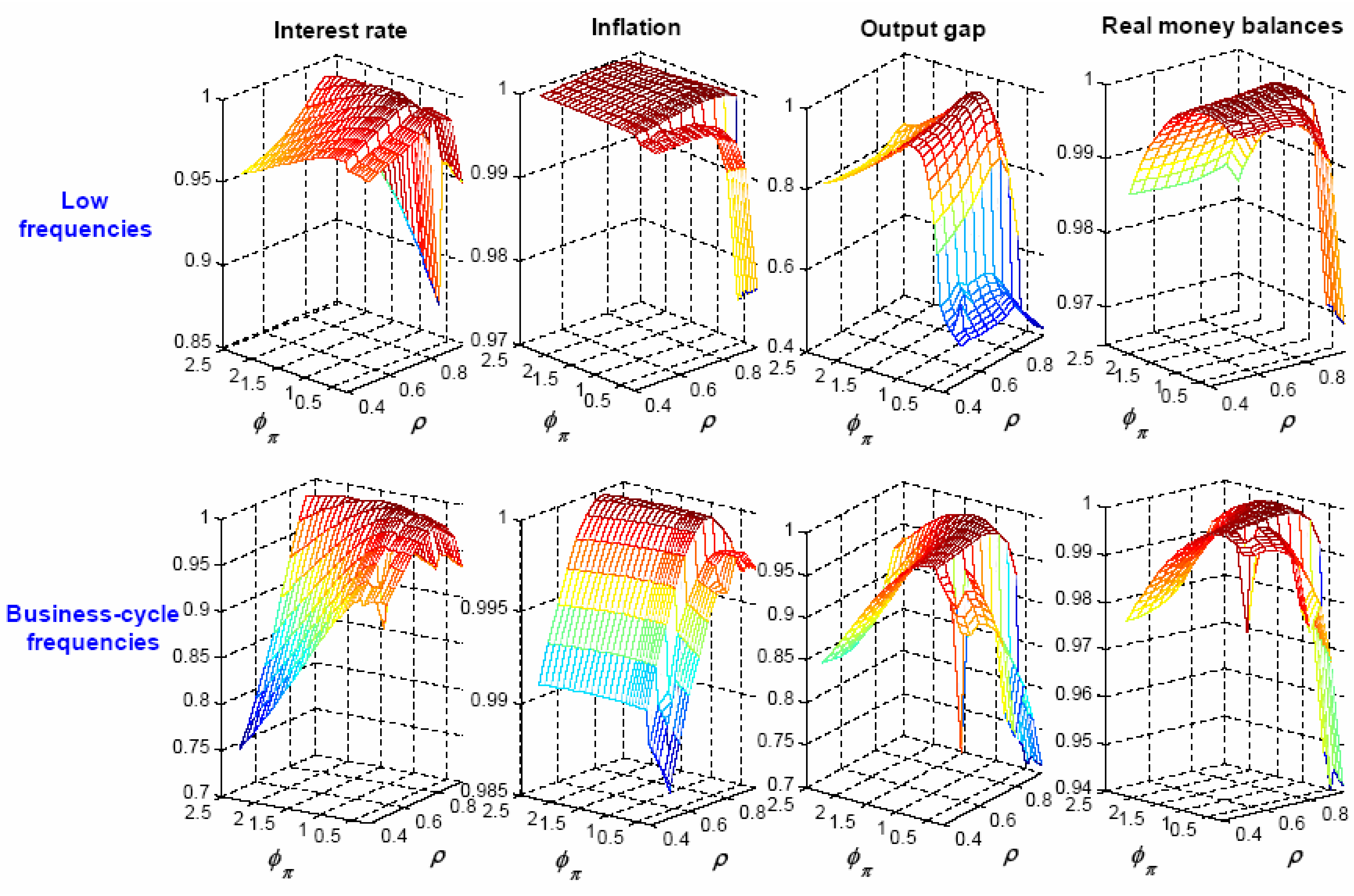

Figure 12 Average coherence between the series as implied by the benchmark VAR and the same series as implied by VAR produced by the SVAR-based policy counterfactual (based on the model of Andres *et al.*, 2008)

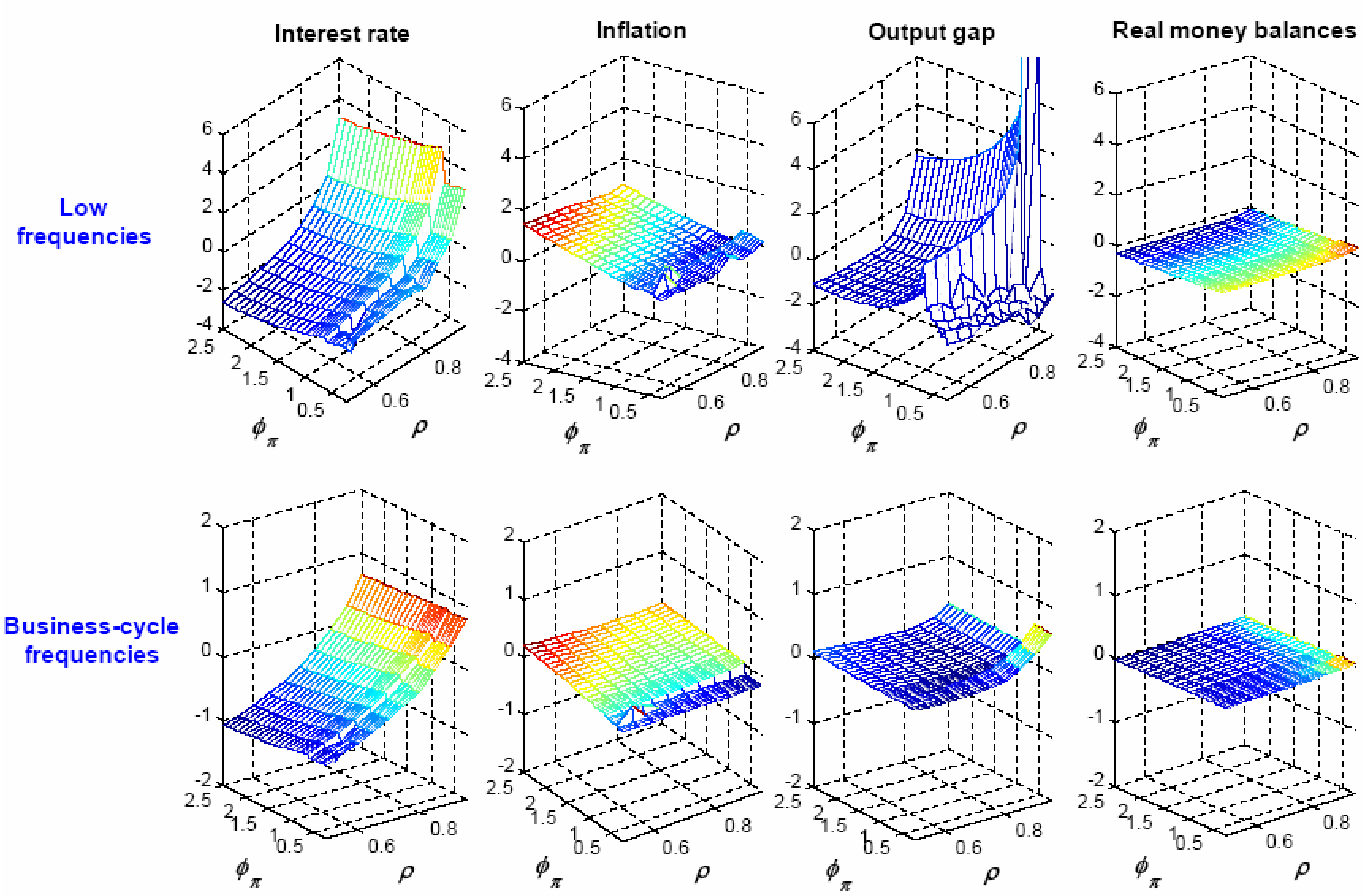

Figure 13 Average delay (in quarters) between the series as implied by the benchmark VAR and the same series as implied by VAR produced by the SVAR-based policy counterfactual (based on the model of Andres *et al.*, 2008)

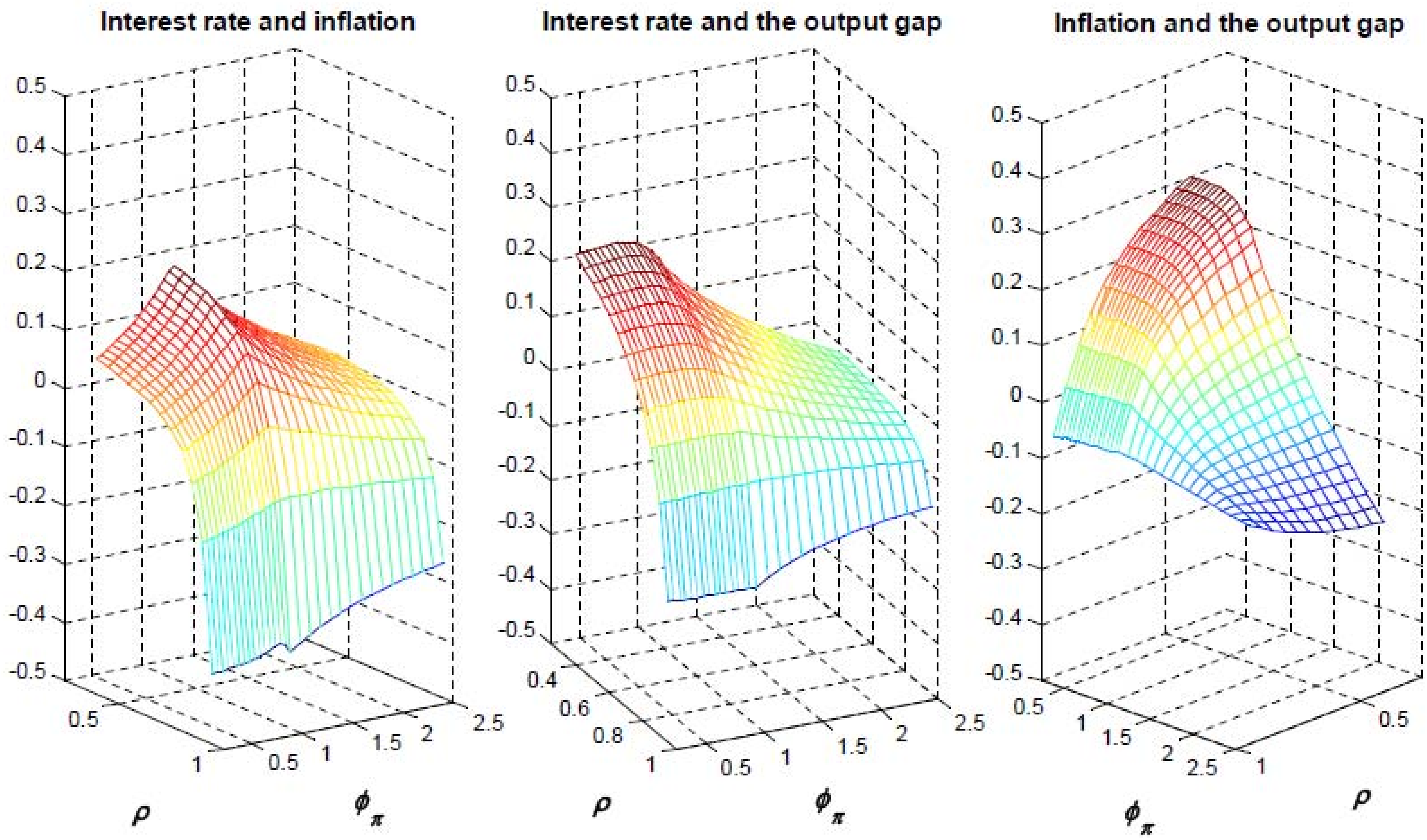

Figure 14 Exploring the distortions induced in macroeconomic relationships: difference between counterfactual and benchmark unconditional correlations (based on the model of Benati, 2008)

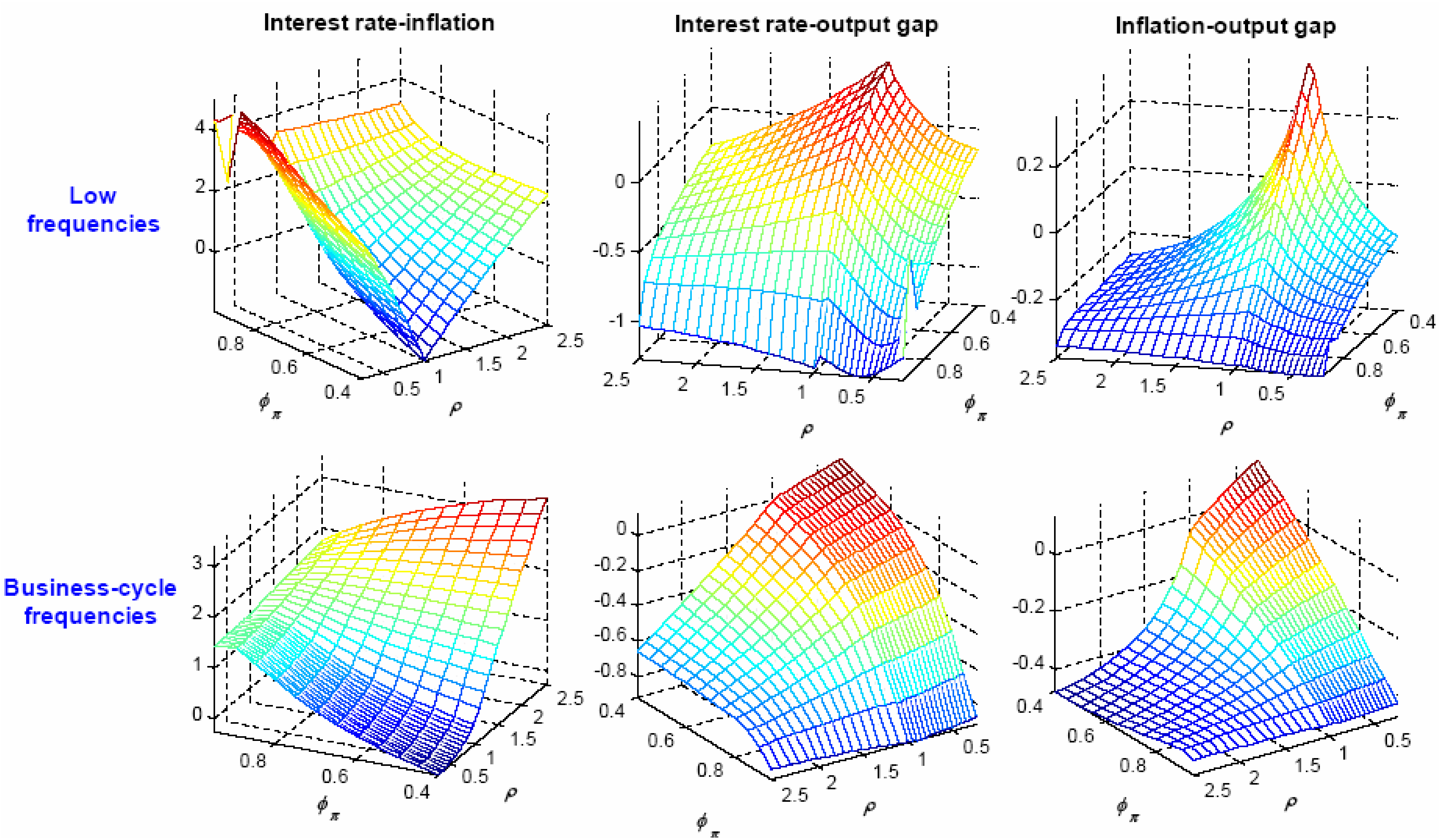

Figure 15 Exploring the distortions induced in macroeconomic relationships: difference between the counterfactual and benchmark gain (based on the model of Benati, 2008)

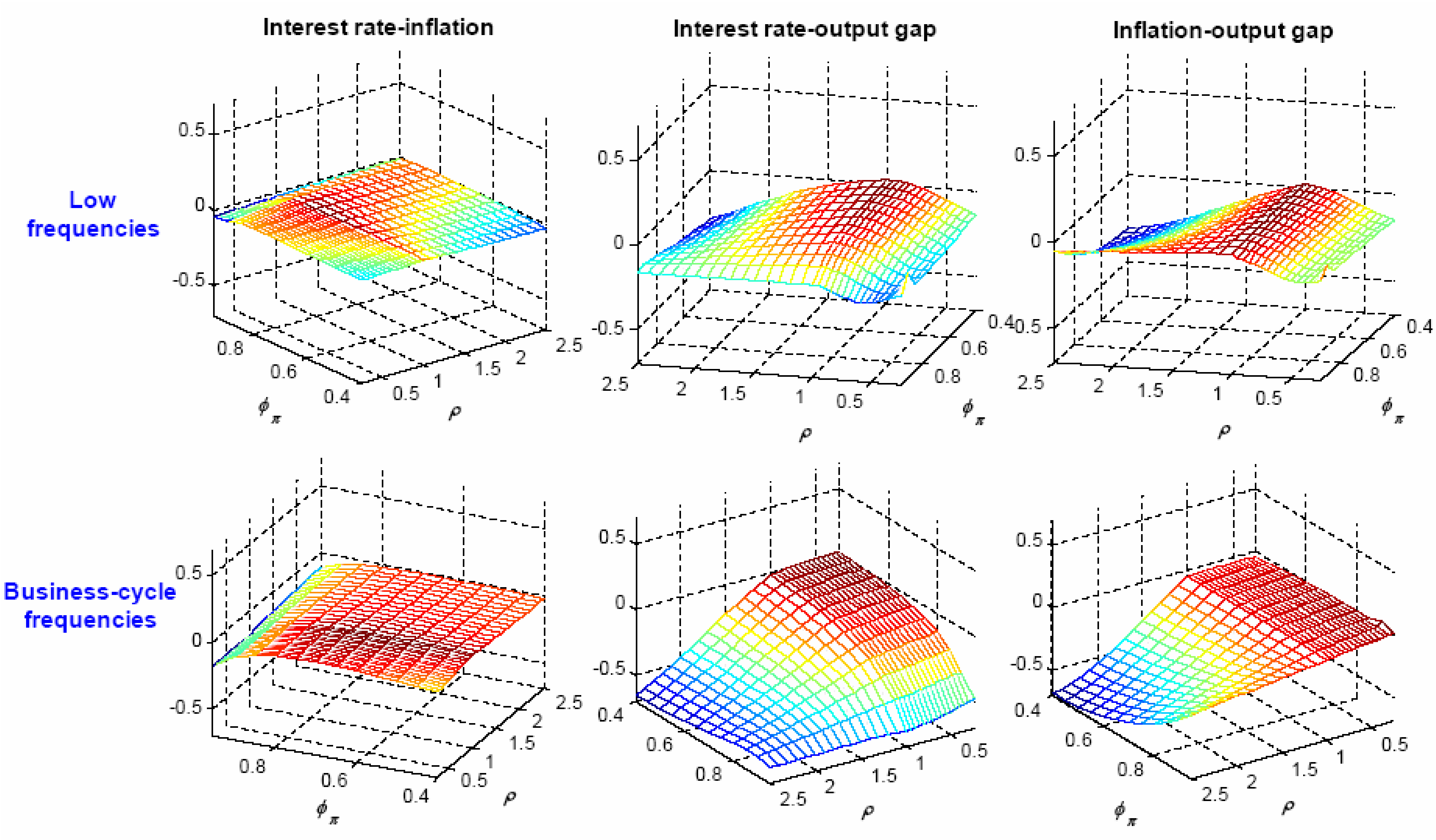

Figure 16 Exploring the distortions induced in macroeconomic relationships: difference between the counterfactual and benchmark coherence (based on the model of Benati, 2008)

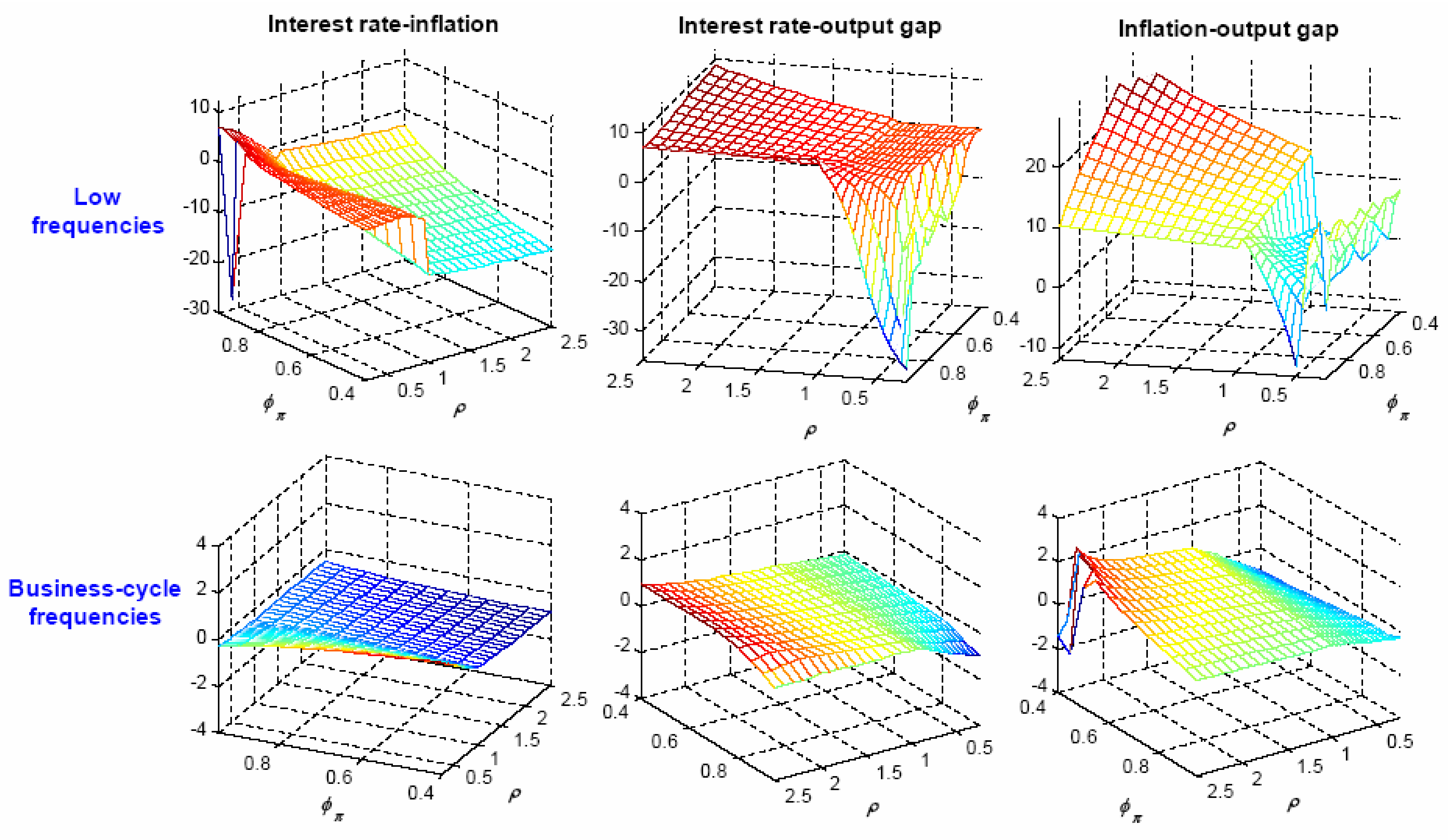

Figure 17 Exploring the distortions induced in macroeconomic relationships: difference between the counterfactual and benchmark delay (based on the model of Benati, 2008)

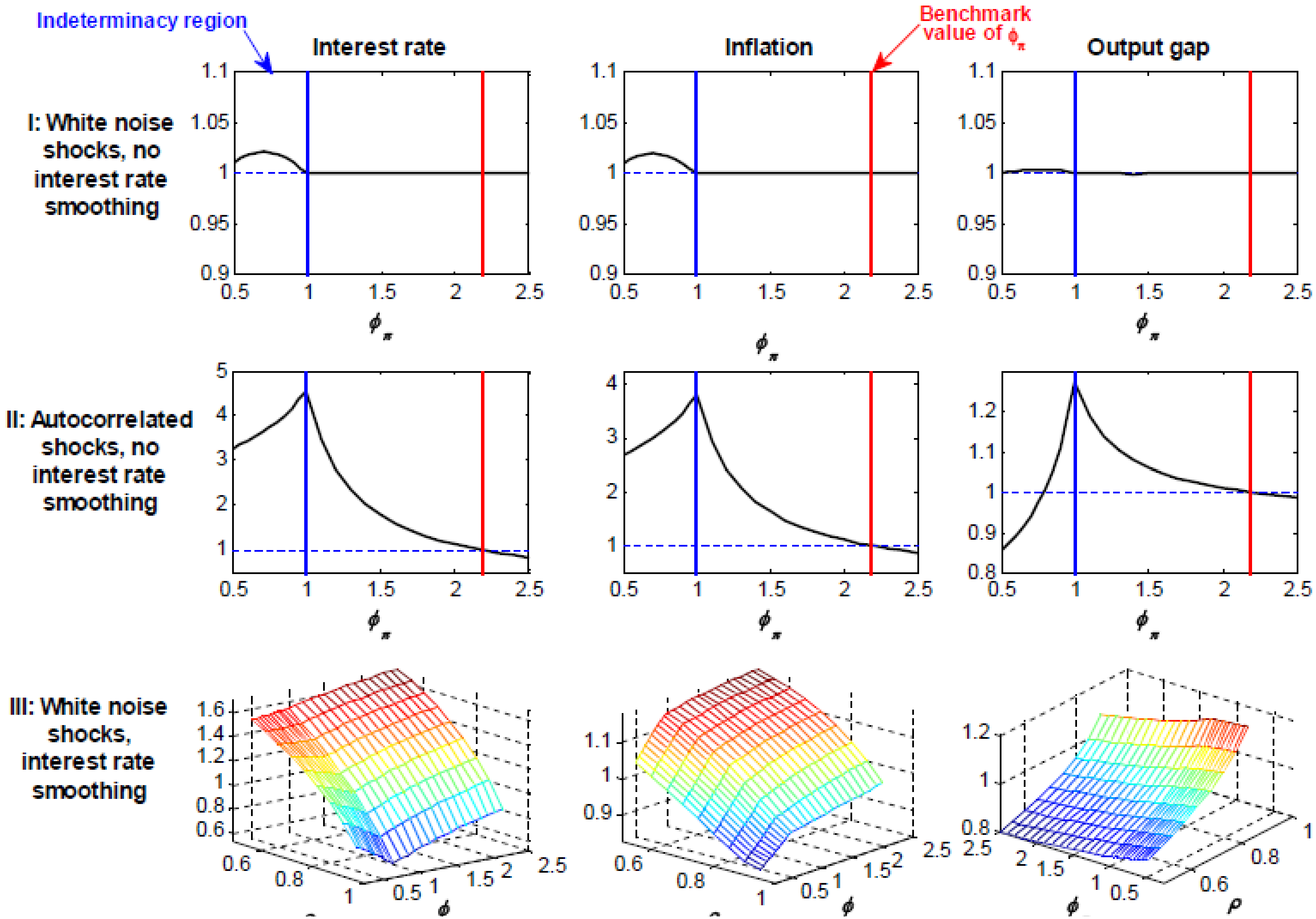

Figure 18 Exploring the role played by the serial correlation of the shocks and by interest rate smoothing (based on the model of Lubik and Schorfheide, 2004)

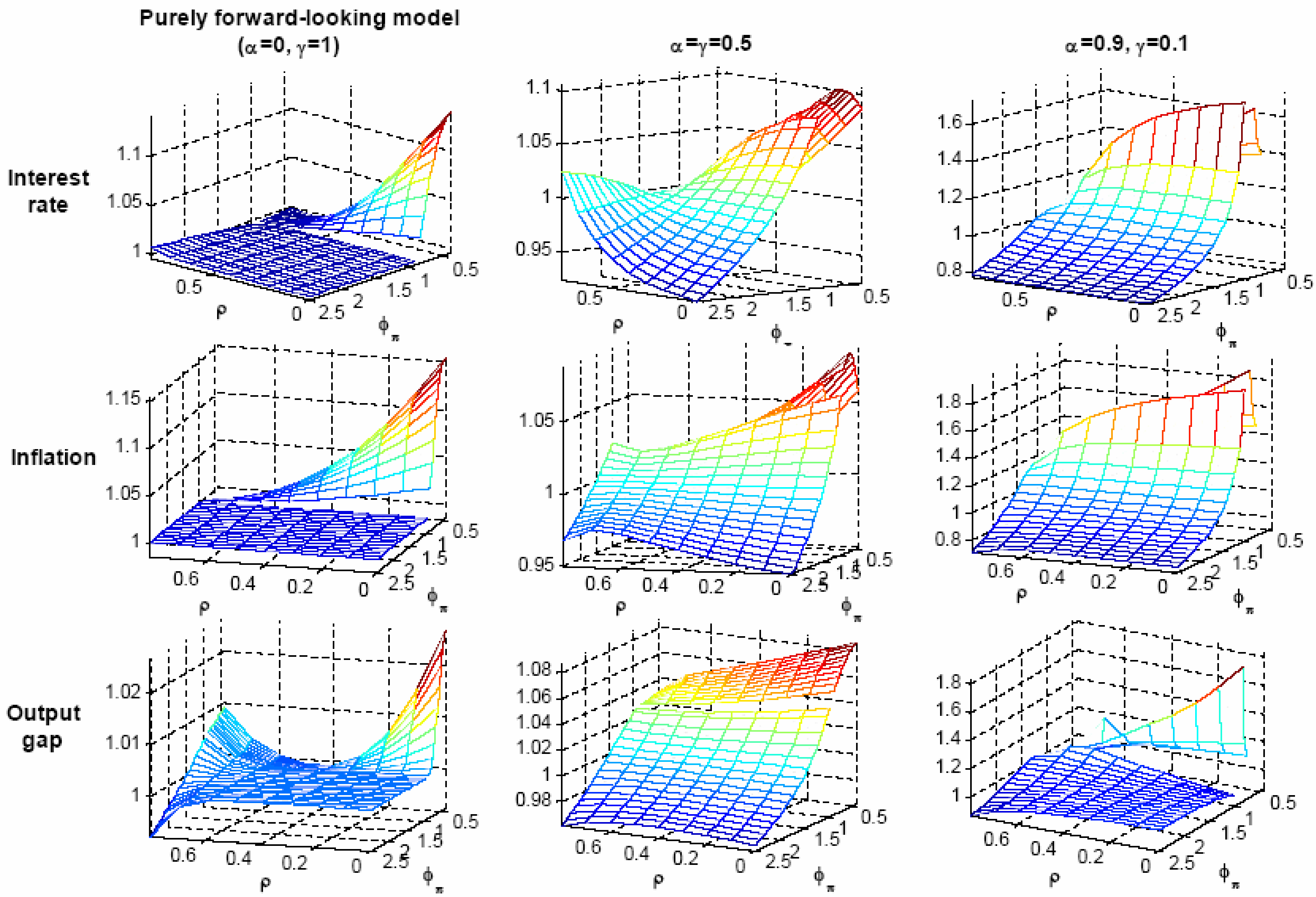

Figure 19 Exploring the role played by the model's extent of forward-lookingness (based on the standard New Keynesian backward- and forward-looking model with white noise shocks)

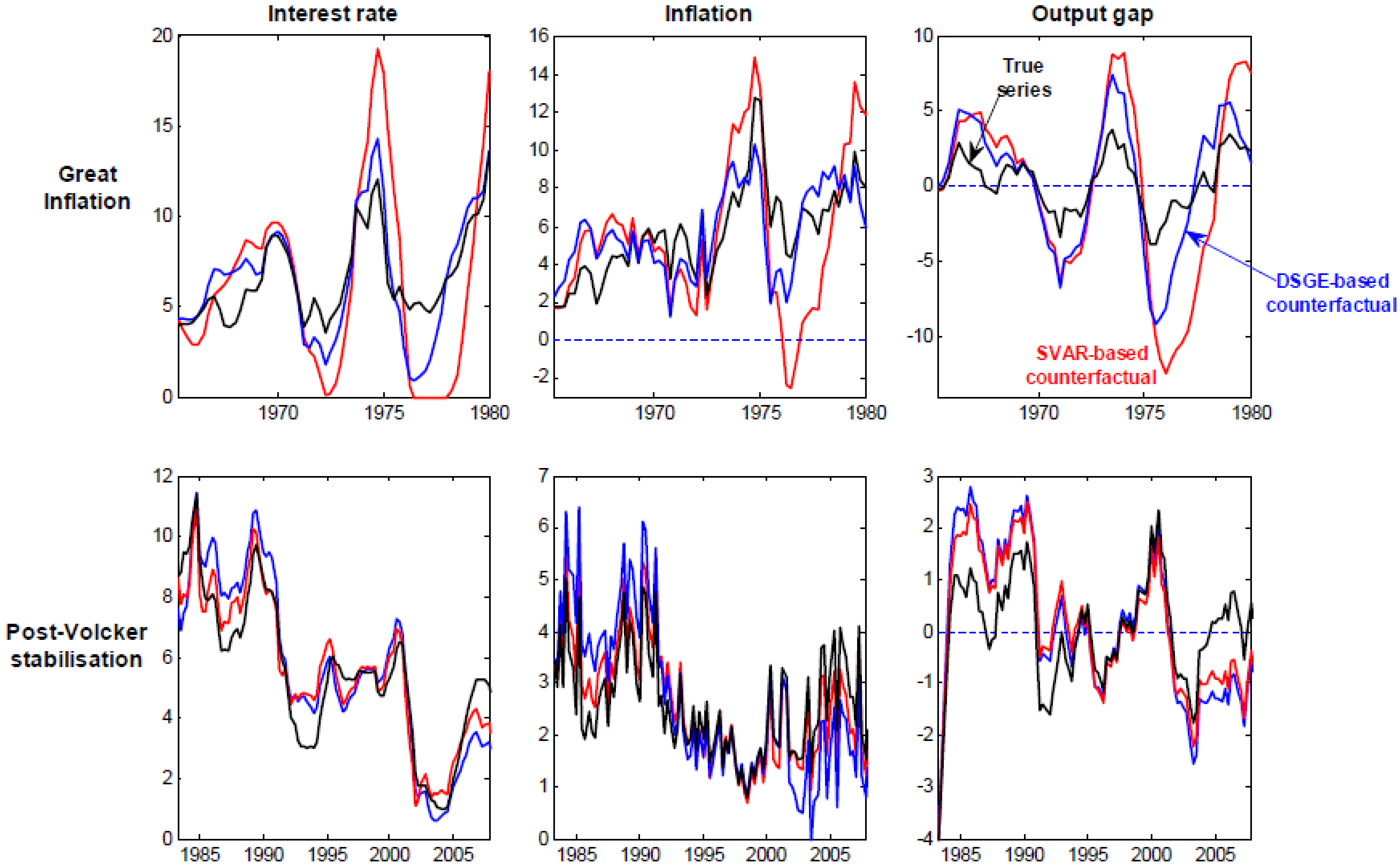

Figure 20 Rerunning U.S. post-WWII macroeconomic history conditional on taking estimated DSGE models as the truth: true series, and DSGE-based and SVAR-based counterfactual series (based on the standard New Keynesian backward- and forward-looking model)

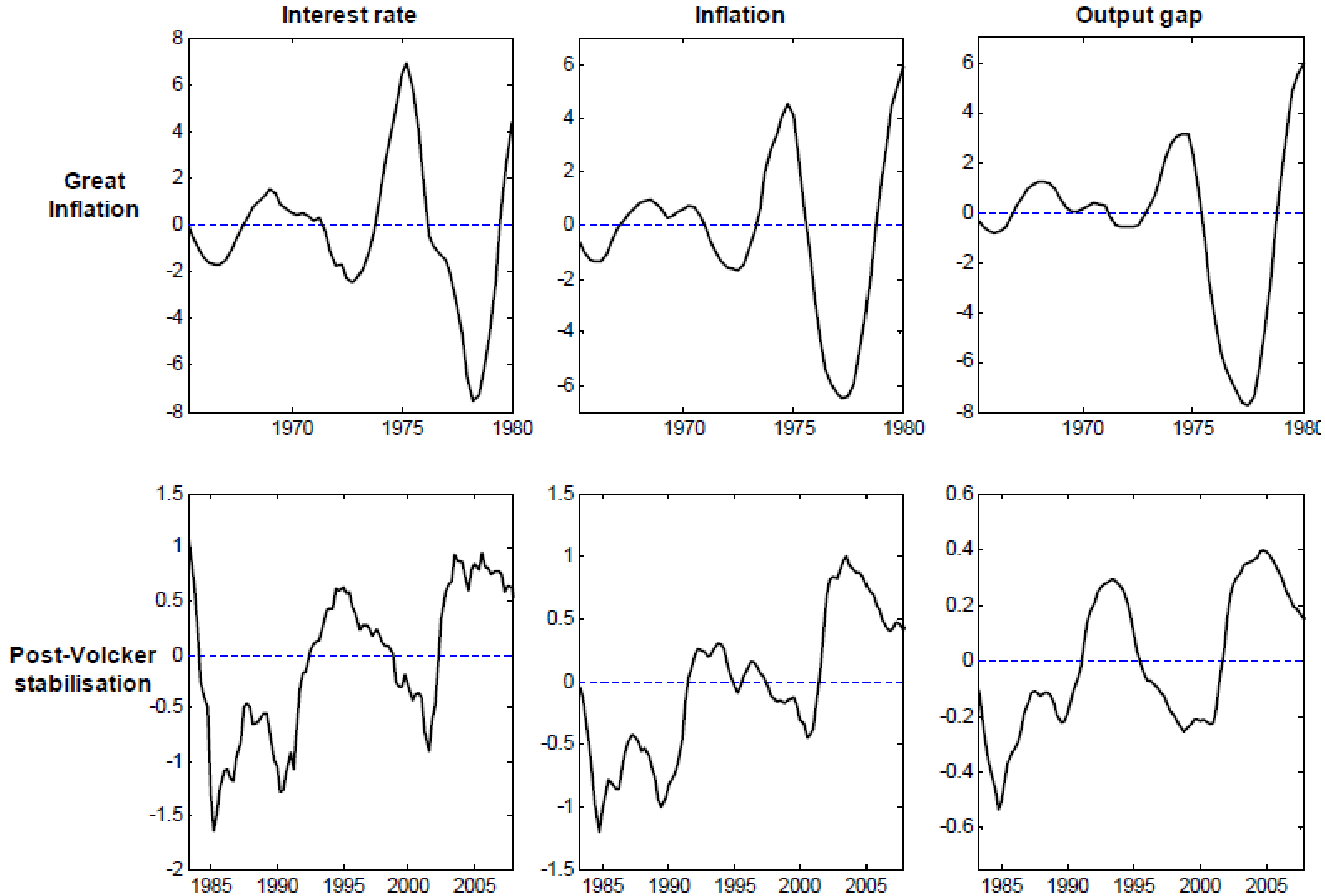

Figure 21 Rerunning U.S. post-WWII macroeconomic history conditional on taking estimated DSGE models as the truth: difference between SVAR-based and DSGE-based counterfactual series (based on the standard New Keynesian backward- and forward-looking model)

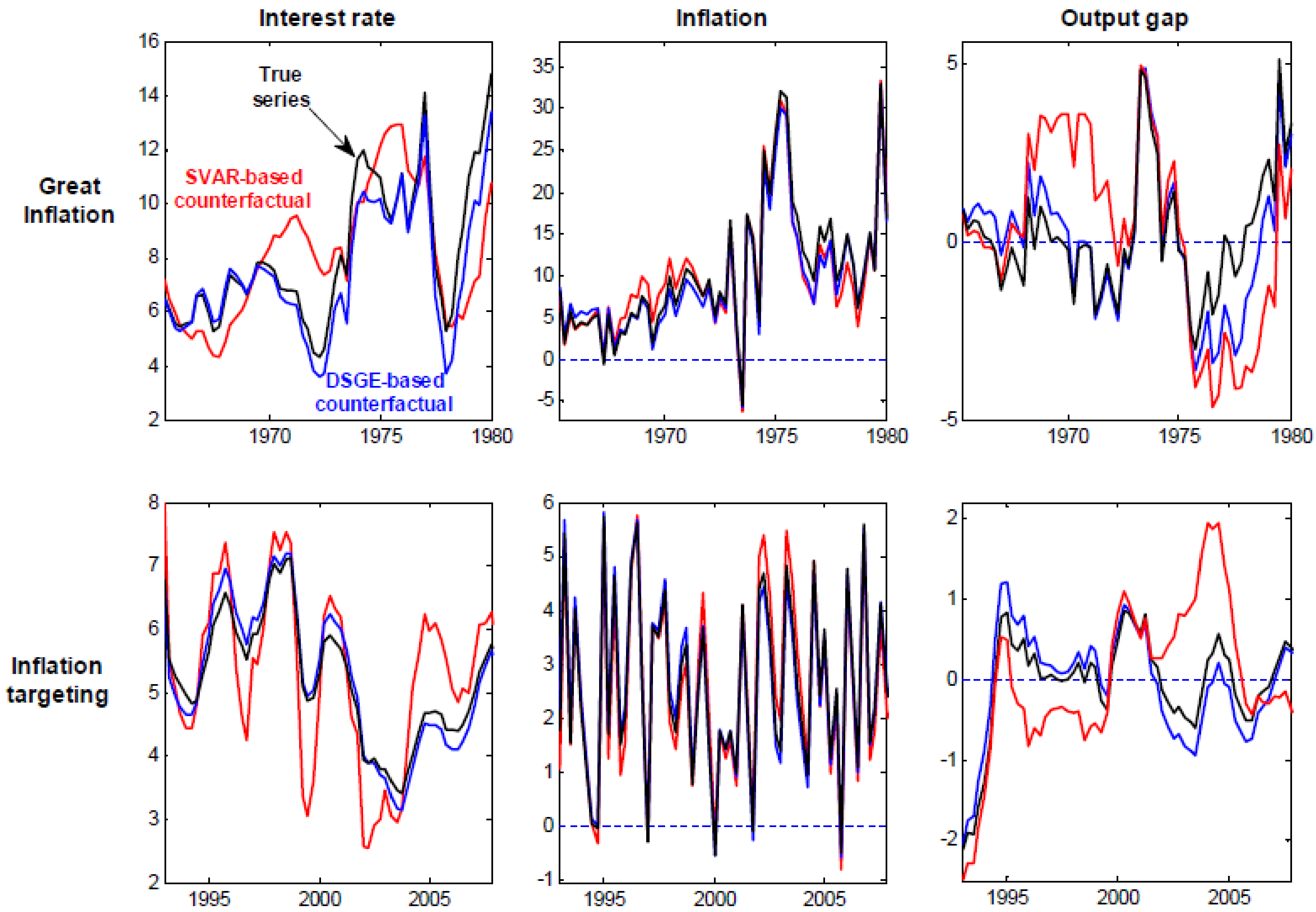

Figure 22 Rerunning U.K. post-WWII macroeconomic history conditional on taking estimated DSGE models as the truth: true series, and DSGE-based and SVAR-based counterfactual series (based on the standard New Keynesian backward- and forward-looking model)

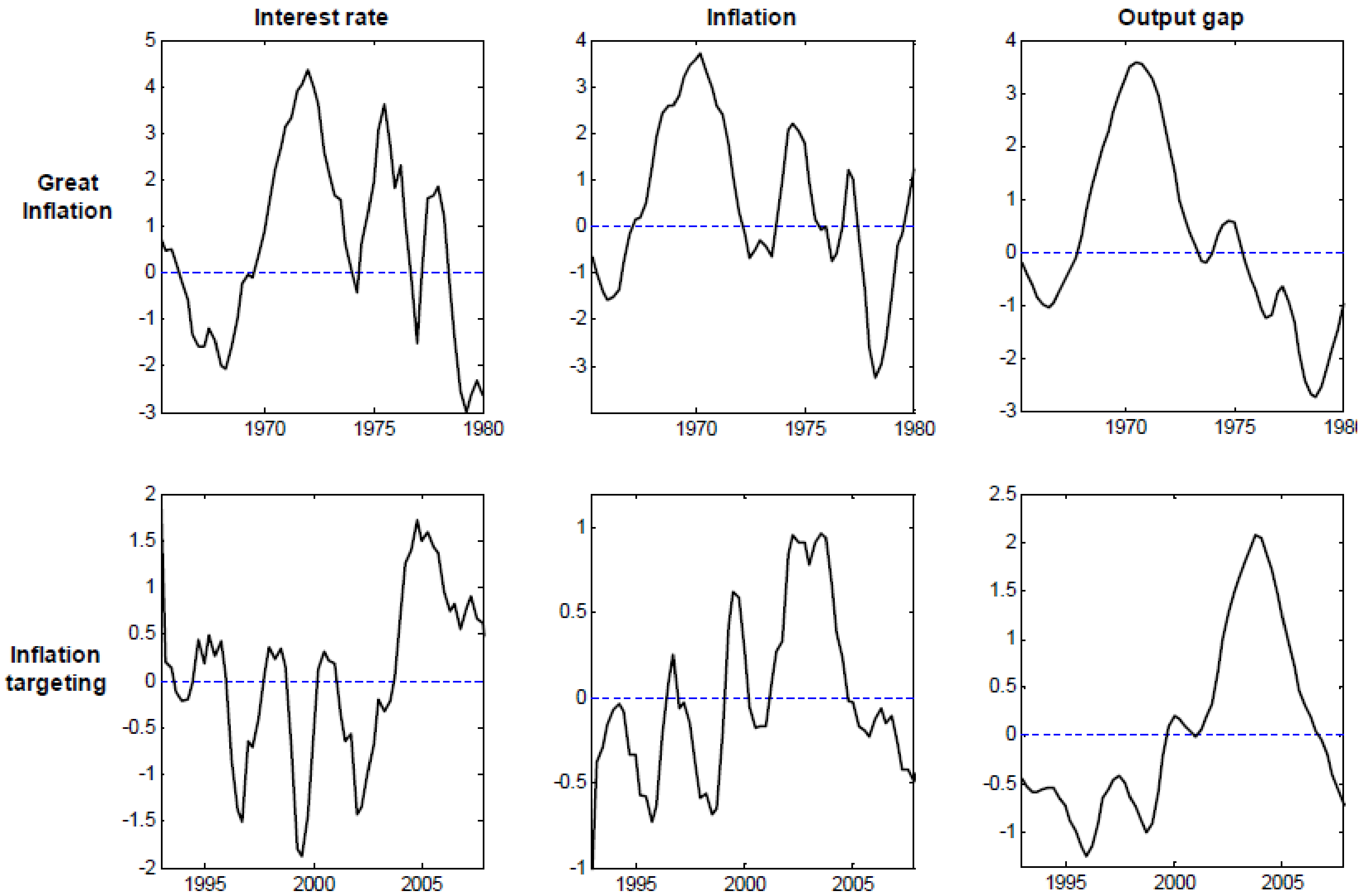

Figure 23 Rerunning U.K. post-WWII macroeconomic history conditional on taking estimated DSGE models as the truth: difference between SVAR-based and DSGE-based counterfactual series (based on the standard New Keynesian backward- and forward-looking model)

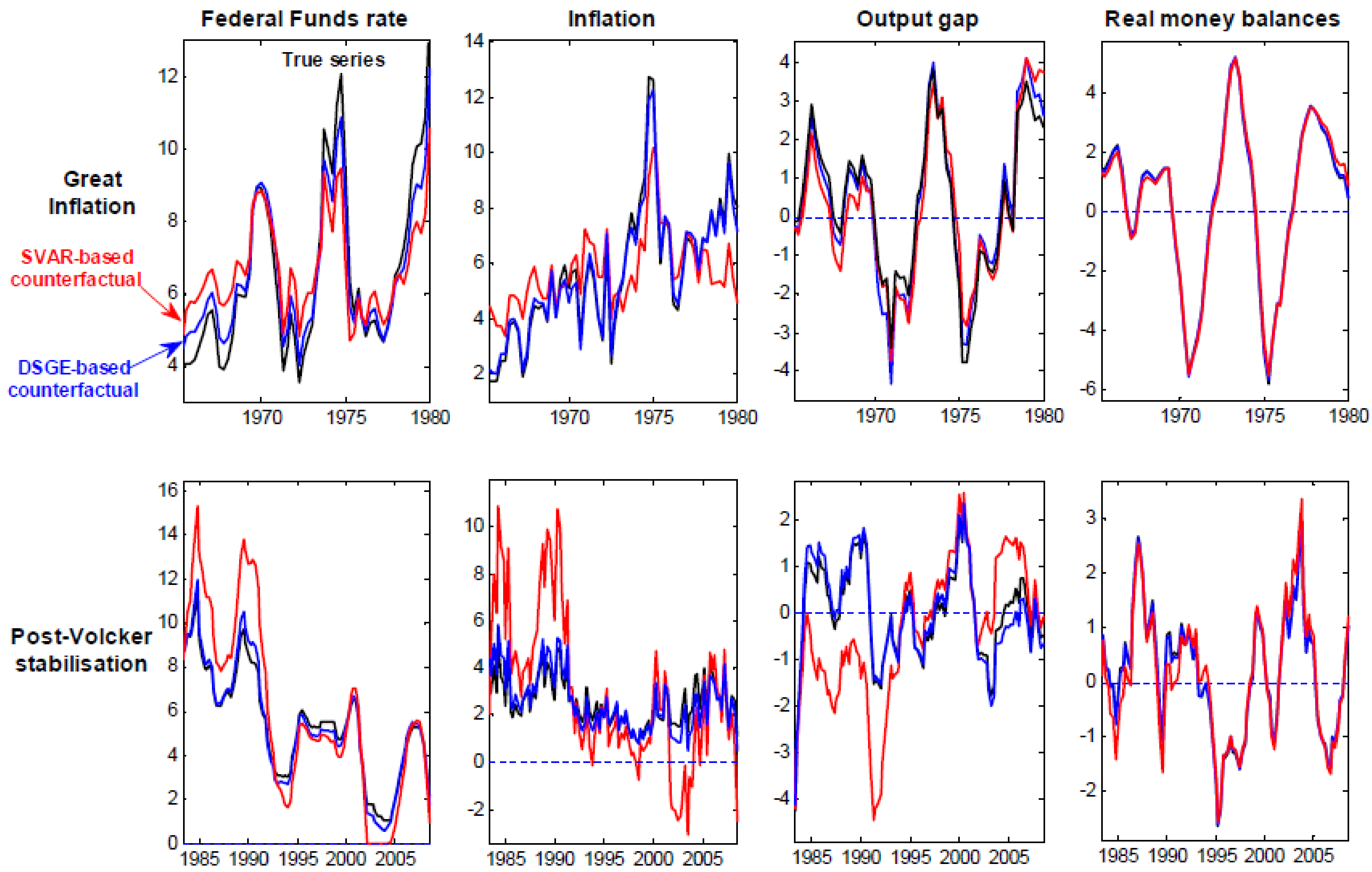

Figure 24 Rerunning U.S. post-WWII macroeconomic history conditional on taking estimated DSGE models as the truth: true series, and DSGE-based and SVAR-based counterfactual series (based on the model of Andres *et al.*, 2009)

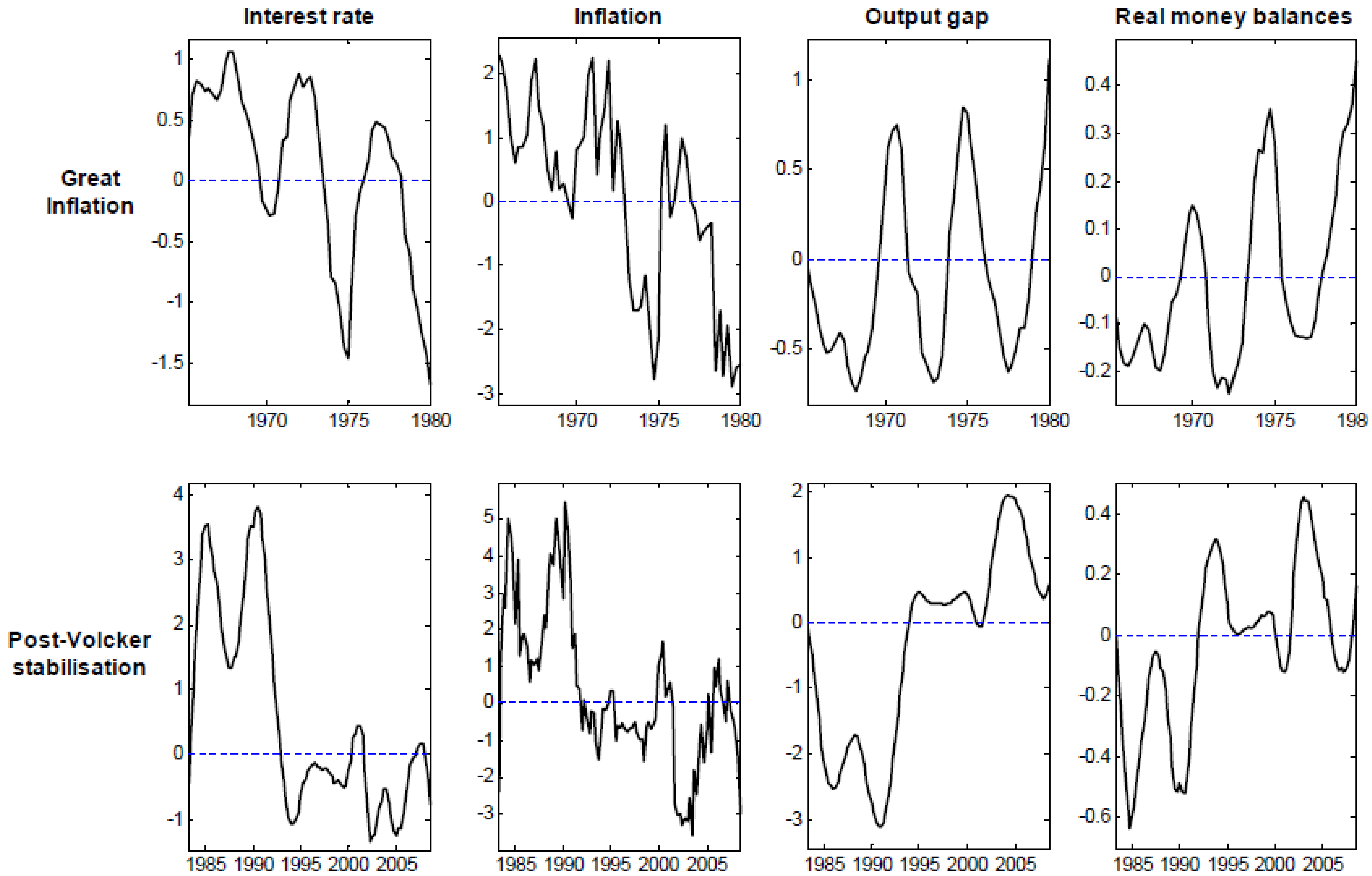

Figure 25 Rerunning U.S. post-WWII macroeconomic history conditional on taking estimated DSGE models as the truth: difference between SVAR-based and DSGE-based counterfactual series (based on the model of Andres *et al.*, 2009)

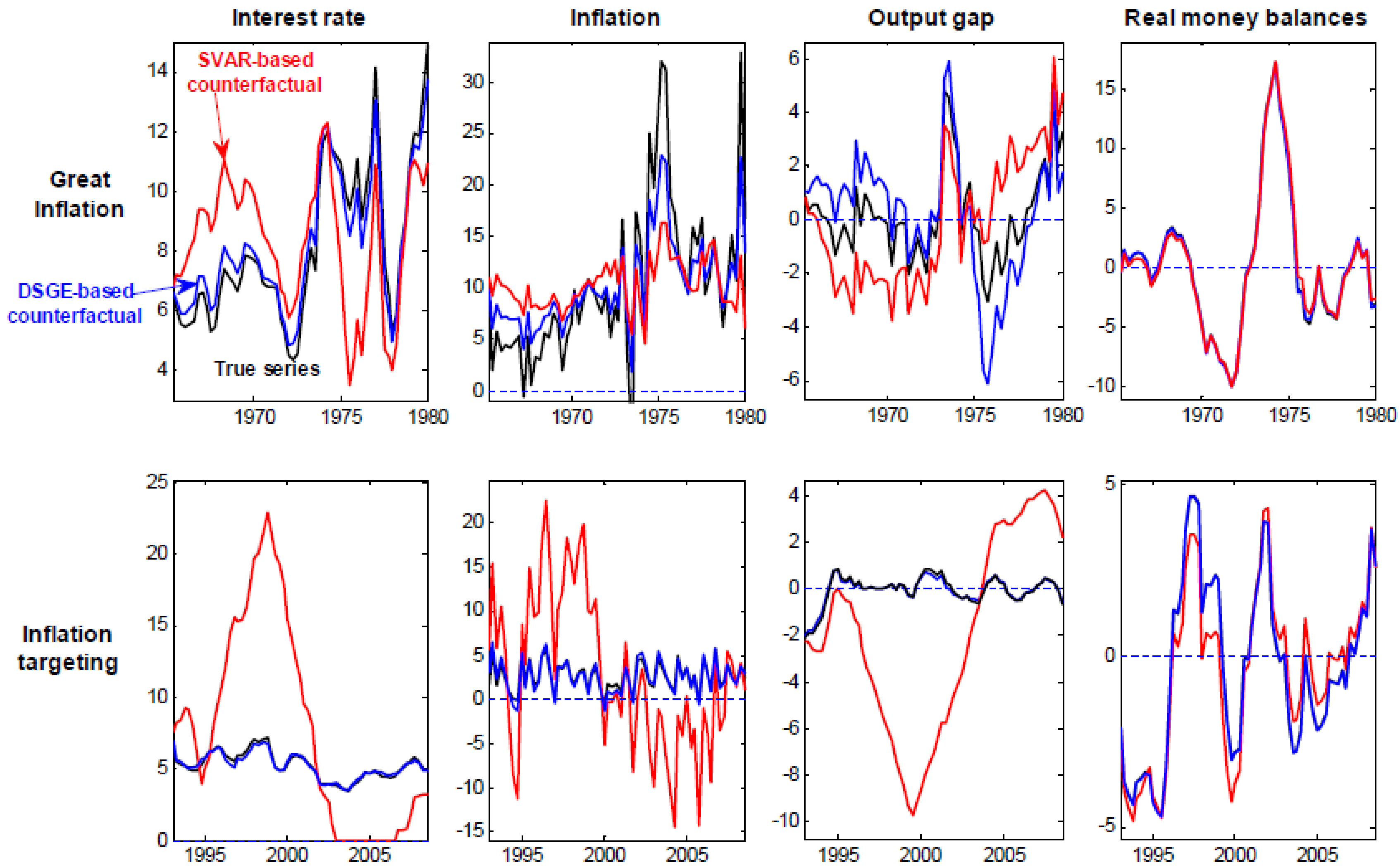

Figure 26 Rerunning U.K. post-WWII macroeconomic history conditional on taking estimated DSGE models as the truth: true series, and DSGE-based and SVAR-based counterfactual series (based on the model of Andres *et al.*, 2009)

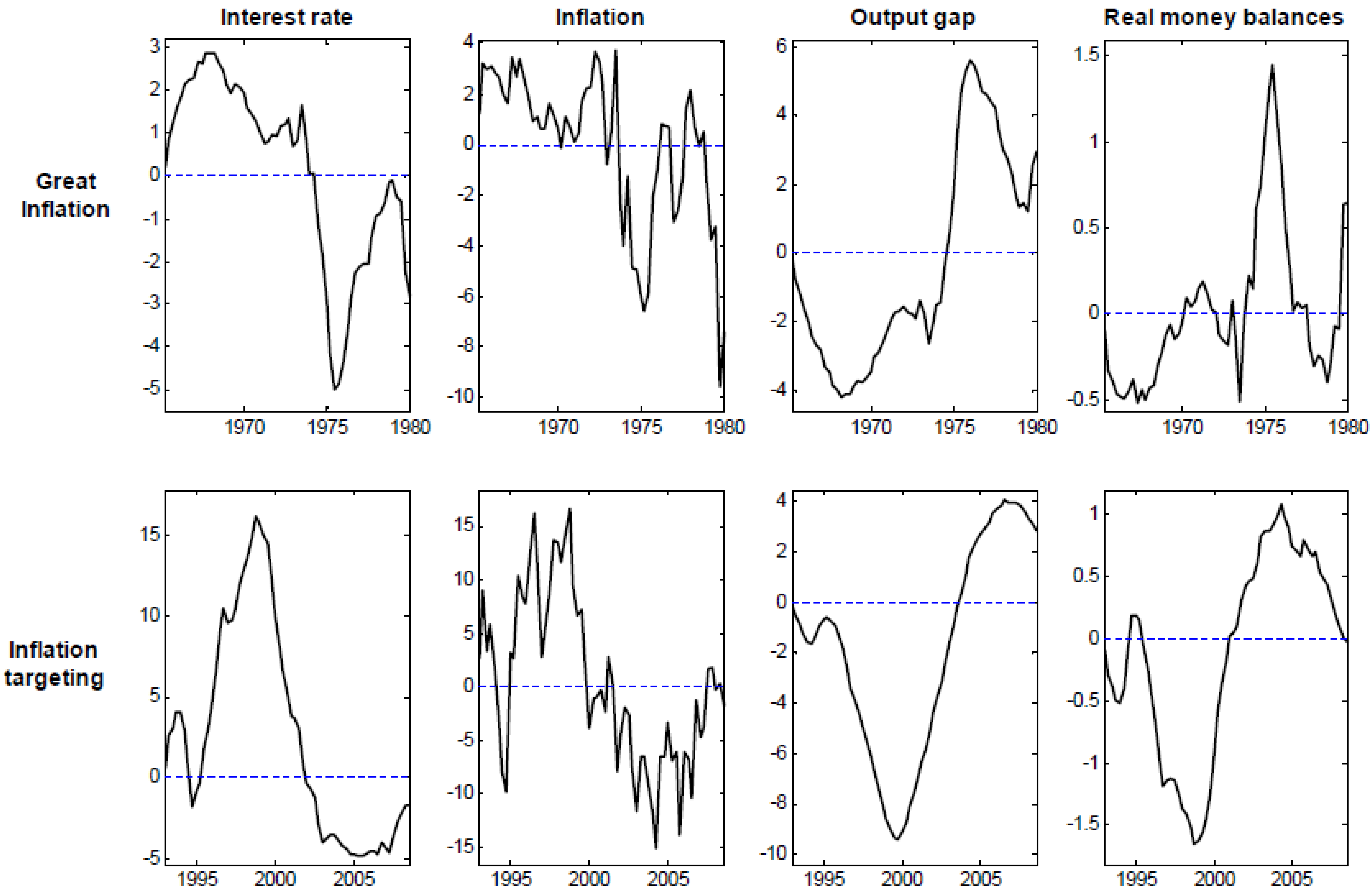

Figure 27 Rerunning U.K. post-WWII macroeconomic history conditional on taking estimated DSGE models as the truth: difference between SVAR-based and DSGE-based counterfactual series (based on the model of Andres *et al.*, 2009)