Post–World War II US macroeconomic history is usually divided into two distinct subperiods. The former period, which extends up to the end of the Volcker disinflation, is characterized by a significant extent of macroeconomic turbulence, with highly volatile inflation and output growth. The latter period, from the end of the Volcker disinflation up to the present day, is marked in contrast by significantly smaller volatilities for both inflation and output growth. These dramatic changes in the reduced-form properties of the US economy over the last several decades characterize a phenomenon known as the “Great Moderation” (see in particular Chang-Jin Kim and Charles Nelson 1999; Margaret McConnell and Gabriel Perez-Quiros 2000).

A vast empirical literature has investigated the source(s) of the Great Moderation in an attempt to disentangle the relative contributions of two main explanations: good policy and good luck. Based on (time-varying or Markov-switching) structural VAR methods, the good luck hypothesis has been advocated by a number of authors, including James H. Stock and Mark W. Watson (2003), Giorgio E. Primiceri (2005), Christopher Sims and Tao Zha (2006), and Luca Gambetti, Evi Pappa, and Fabio Canova (2008).

Based on estimated sticky-price dynamic stochastic general equilibrium (DSGE) models of the US economy, on the other hand, both Thomas Lubik and Frank Schorfheide (2004) and Jean Boivin and Marc Giannoni (2006) have produced evidence suggesting that before October 1979 the US economy may have been in an indeterminate equilibrium, as the Federal Reserve’s monetary policy was insufficiently counter-inflationary. Their findings provide additional support to the good policy explanation originally advocated by Richard Clarida, Jordi Galí, and Mark Gertler (2000), according to which a shift in the systematic component of monetary policy has been the driving force of the greater macroeconomic stability of recent years. Not all analyses based on DSGE models, however, point toward good policy: Alejandro Justiniano and Primiceri (2008), in particular, have identified a reduction in the variance of investment shocks as the key driving force behind the US Great Moderation, with a limited role, instead, for changes in the conduct of monetary policy.1

1 Frank Smets and Rafael Wouters (2007) found that the bulk of the volatility reduction associated with the Great Moderation has been due to a decrease in the variances of the structural shocks, but their results are difficult to interpret, as—different from Justiniano and Primiceri (2008)—they imposed determinacy in estimation. Primiceri (2006) attributed the outburst of macroeconomic volatility associated with the Great Inflation to the underestimation, on the part of policymakers, of both the natural rate of unemployment and the extent of inflation persistence, within a framework in which they recursively learn about the structure of the economy.
This paper tries to reconcile the two sets of conflicting results by asking whether methodologi-
cal differences between the two approaches may account for the different outcomes they tend to
produce. In order to investigate the ability of structural VAR methods to correctly identify the
sources of the Great Moderation, we use as data-generation process a New Keynesian model in
which the only sources of change are the move from passive to active monetary policy, and the
presence of sunspots under indeterminacy. We estimate the model via Bayesian methods, and we
explore the theoretical properties of the estimated structure.

Main Results.—Our main results may be summarized as follows.
First, the shift in the systematic component of monetary policy associated with the move from
indeterminacy to determinacy is sufficient to generate, in population, (i) decreases in the innova-
tion variances for all series, and (ii) decreases in the variances of inflation and the output gap, as
a simple implication of the Robert E. Lucas, Jr. (1976) critique, and without any need of sunspot
shocks. Based on the model including sunspot shocks, the move from indeterminacy to determi-
nacy is associated with decreases in both variances and innovation variances in population, thus
replicating the key features of the Great Moderation.

Second, although a comparison between the structural monetary rules in the theoretical VAR
representations of the model under the two regimes points toward significant changes in mon-
etary policy, counterfactuals fail to capture the role played by policy in fostering changes in the
reduced-form properties of the economy. In particular, substituting the VAR structural monetary
rule corresponding to the determinacy regime into the VAR for the indeterminacy regime causes
a volatility increase—rather than a decrease—for all series.

Third, impulse-response functions to a monetary policy shock exhibit little change across
regimes, although this partly stems from the fact that, in estimation, we impose that the impacts
of the structural shocks on all the variables have the same signs under the two regimes.

Little impact of policy counterfactuals on the reduced-form properties of the economy and
little change in impulse-response functions to a monetary policy shock across regimes are key
pieces of evidence used in the structural VAR-based literature to argue against an important role
of policy in fostering the Great Moderation. Our analysis suggests that key pieces of existing
VAR evidence are difficult to interpret, and they are, in principle, compatible with the notion that
policy may have played a role in fostering the greater macroeconomic stability of recent years.

Explaining the Results.—We identify two key dimensions along which VAR analysis may turn
out to be misleading.
First, changes in the coefficients of the monetary policy rule of the DSGE model exert their
impact on both the coefficients of the VAR representation of the model and the elements of the
VAR covariance matrix of reduced-form innovations. Although this is a direct implication of
the Lucas (1976) critique, this point has generally been overlooked in the structural VAR-based
empirical literature on the Great Moderation, which has routinely interpreted changes in the
volatilities of the reduced-form innovations, accompanied by weak evidence of changes in the
VAR coefficients, as evidence against good policy, and in favor of good luck.

In this paper, we show that, in fact, a change in the systematic component of monetary
policy can have the dominant impact on the elements of the VAR covariance matrix, with a

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2 As we abstract from the role of fiscal policy, the relationship between the monetary policy stance and equilibrium
(in)determinacy in a simple New-Keynesian model is one-to-one, with a passive (active) rule associated with an inde-
terminate (determinate) equilibrium. As shown by Eric Leeper (1991), in more complex settings this is not the case.

3 As we discuss is Section IB, the rationale for imposing such constraint is in order to illustrate, by example, the
limited extent of informativeness, for the issue at hand, of a comparison between the impulse-response functions across
regimes.
comparatively milder effect on the VAR coefficients. The implication is that, within our data-generation process, the good policy and good luck explanations are close to observationally equivalent. Furthermore, the good luck interpretation of existing VAR evidence suffers from the logical problem that it implies a simultaneous reduction in the volatilities of conceptually orthogonal primitive shocks. Under the good policy hypothesis, in contrast, we show that the coincidence between historical changes in the monetary policy regime and changes in the VAR innovation variances is not fortuitous, but rather it is the result of changes in the systematic component of monetary policy on the reduced-form VAR representation of the economy.

Second, the implicit presumption behind the policy counterfactuals, which are routinely performed within the structural VAR literature, is that the impact on the properties of the economy from switching the estimated coefficients of the interest rate equations in the structural VAR provides a reasonable approximation to the impact of the authentic policy counterfactual, i.e., the one the researcher would obtain by switching the parameters of the monetary policy rule in the underlying DSGE model. As the present work shows by means of a simple example, however, such a presumption appears difficult to justify.

The paper is organized as follows. Section I describes the standard New Keynesian model and discusses details of both the Bayesian estimation procedure and the specific experiment we design. Section II discusses key theoretical properties of the estimated data-generation process, focusing on the difference between the equivalent minimal state-space representations of the model under the two regimes. In particular, we show that the model possesses a VAR representation under determinacy, and a VARMA one (with a very small MA component) under indeterminacy. In Section III, we assess the extent to which the estimated structure replicates the most salient features of the Great Moderation in population. Section IV shows how neither structural VAR-based policy counterfactuals, nor impulse-response functions to a monetary policy shock, point toward the authentic cause of changes in the data-generation process. Section V concludes.

I. Assessing VAR Studies of the Great Moderation

In order to assess the ability of structural VAR methods to correctly identify the causes of the Great Moderation, we consider the following experiment:

**Suppose that the Great Moderation in the United States has been exclusively due to improved monetary policy, with a passive monetary policy regime in place before October 1979, and an active regime in place thereafter. Would structural VAR techniques be capable of uncovering the authentic causes of the changes in the data-generation process?**

A. The Model

The model we use in what follows is given by

\( R_t = \rho R_{t-1} + (1 - \rho)[\varphi \pi_t + \varphi y_t] + \varepsilon_{R,t}, \)

\( \pi_t = \frac{\beta}{1 + \alpha \beta} \pi_{t+1|t} + \frac{\alpha}{1 + \alpha \beta} \pi_{t-1} + \kappa y_t + \varepsilon_{\pi,t}, \)

\( y_t = \gamma y_{t+1|t} + (1 - \gamma)y_{t-1} - \sigma^{-1}(R_t - \pi_{t+1|t}) + \varepsilon_{y,t}, \)

\(^4\) See, for instance, Primiceri (2005) and Sims and Zha (2006).
where \( R_t, \pi_t, \) and \( y_t \) are the nominal interest rate, inflation, and output gap, respectively; \( \alpha \) and \( \gamma \) are price setters’ extent of indexation to past inflation\(^5\) and the forward-looking component in the intertemporal IS curve, respectively; \( \kappa \) is the slope of the Phillips curve; \( \sigma \) is the elasticity of intertemporal substitution in consumption; \( \rho, \varphi_\pi, \) and \( \varphi_y \) are the smoothing coefficient and the long-run coefficients on inflation and the output gap in the monetary policy rule, respectively; and \( \varepsilon_{x,t}, \varepsilon_{y,t}, \) and \( \varepsilon_{R,t} \) are three structural disturbances following the AR(1) processes \( \varepsilon_{x,t} = \rho \varepsilon_{x,t-1} + \tilde{\varepsilon}_{x,t}, \) for \( x = \pi, y, R, \) with \( \tilde{\varepsilon}_{x,t} \sim N(0, \sigma_x^2). \)

By defining the state vector as \( \xi_t \equiv [R_t, \pi_t, y_t, \pi_{t+1}, y_{t+1}, \varepsilon_{R,t}, \varepsilon_{x,t}, \varepsilon_{y,t}]; \) the vector collecting the structural shocks as \( \varepsilon_t \equiv [\tilde{\varepsilon}_{R,t}, \tilde{\varepsilon}_{\pi,t}, \tilde{\varepsilon}_{y,t}]; \) and the vector of forecast errors as \( \eta_t \equiv [\eta_x^t, \eta_y^t]^{\prime} \)—where \( \eta_x^t \equiv \pi_t - \pi_{t|t-1} \) and \( \eta_y^t \equiv y_t - y_{t|t-1} \)—the model can then be put into the Sims (2002) form \( \Gamma_0 \xi_t = \Gamma_t \xi_{t-1} + \Psi \varepsilon_t + \Pi \eta_t, \) where \( \Gamma_0, \Gamma_t, \Psi \) and \( \Pi \) are matrices conformable to \( \xi_t, \varepsilon_t, \) and \( \eta_t. \) In computing the model’s solution under the two regimes, we follow the procedure outlined in Lubik and Schorfheide (2003, 2004) exactly. In particular, under indeterminacy, we consider the “continuity” solution, which is based on the assumption that impulse-response functions to structural shocks do not jump discontinuously at the boundary between the two regions.

\[ \begin{align*}
\text{B. The Experiment Design} \\
\text{Our goal is to assess the performance of structural VARs conditional on a DGP in which neither luck (i.e., changes in the volatilities of the structural shocks), nor structural change (in the present case, changes in the nonpolicy parameters, \( \alpha, \gamma, \kappa, \sigma, \) and all of the \( \rho_x \)’s), play any role whatsoever.} \\
\text{We therefore estimate (1)–(3):} \\
\text{• Imposing indeterminacy for the pre–October 1979 period and determinacy for the period following the end of the Volcker stabilization, by allowing for different values of \( \rho, \varphi_\pi, \) and \( \varphi_y \) across periods;} \\
\text{• Imposing that the signs of the impacts at zero of the three structural shocks are the same across regimes for all variables.\(^6\)} \text{This constraint serves to illustrate, by example, the limited extent of informativeness, for the issue at hand, of a comparison between the impulse-response functions across regimes (see also the discussion in Canova 2007).} \\
\text{• Imposing that \( \alpha, \gamma, \kappa, \sigma, \) the \( \rho_x \)’s, and the \( \sigma_x^2 \)’s—with \( x = \pi, y, R \)—are identical across regimes. This is obtained by jointly estimating the two models for the pre–October 1979 and the post-Volcker stabilization periods;} \\
\text{• Allowing for sunspot shocks under indeterminacy.} \\
\text{By showing that this DGP can replicate the key features of the Great Moderation, our results will show that existing VAR evidence is difficult to interpret, and is in principle compatible with the good policy explanation of the Great Moderation.} \\
\end{align*} \]

\[ \begin{align*}
\text{\( ^5 \text{See for instance Smets and Wouters (2003) and Lawrence J. Christiano, Martin Eichenbaum, and Charles Evans (2005). The specific formulation we use herein is that of Smets and Wouters.} \)} \\
\text{\( ^6 \text{Technically, when the parameters’ vector corresponding to the determinacy regime is sufficiently far away from the boundary between determinacy and indeterminacy, the Lubik and Schorfheide (2003, 2004) “continuity” solution does not guarantee that the signs of the impacts of the structural shocks at zero are the same across regimes. By construction, indeed, such solution minimizes the difference between the impacts of the shocks at zero for the two parameters vectors \( \theta_{\text{IND}} \) and \( \theta \) (the former belonging to the indeterminacy region, the latter being an auxiliary parameters vector just inside the determinacy region). Although this guarantees that the signs on impact are the same for \( \theta_{\text{IND}} \) and \( \theta \), this does not necessarily imply that this will also be the case for any parameter vector \( \theta_{\text{DET}} \) that belongs to the determinacy region.} \)}
\end{align*} \]
C. Bayesian Estimation

We estimate (1)–(3) via Bayesian methods. Following, e.g., Lubik and Schorfheide (2004) and Sungbae An and Schorfheide (2007), all structural parameters are assumed, for the sake of simplicity, to be a priori independent from one another. The third column of Table 1 reports the parameters’ prior densities, whereas the fourth and the fifth columns report two key objects characterizing them, the mode and the standard deviation. In the Appendix, we discuss both the simulated annealing algorithm we use to maximize the log posterior, and the Random Walk Metropolis algorithm we use to generate draws from the posterior distribution of the model’s structural parameters.

The last two columns of Table 1 report the medians and the 90 percent coverage percentiles of the distributions of the model’s structural parameters, whereas Figures 1 and 2 show—for the pre–October 1979 period, and for the one following the end of the Volcker stabilization, respectively—the sample autocorrelations, together with the medians and the 90 percent-coverage percentiles of the distributions of the elements of the autocorrelation matrix based on 2,000 stochastic simulations of the estimated model.7 As the figures make clear, the fit of the estimated model—in terms of its ability to replicate the autocorrelation structure seen in the data—is, overall, quite satisfactory, considering that we are working with a very stylized, three-equation macroeconomic model. The main shortcomings pertain, for the pre–October 1979 period, to

\[\sigma_{R2}^{R+}\] Inverse Gamma 0.25 0.25 0.492 [0.413; 0.592]
\[\sigma_{R+}^2\] Inverse Gamma 0.50 0.50 0.391 [0.272; 0.562]
\[\sigma_{R+}^2\] Inverse Gamma 0.10 0.25 0.055 [0.039; 0.078]
\[\sigma_{\kappa}^2\] Inverse Gamma 0.25 0.25 0.193 [0.108; 0.406]
\[\kappa\] Gamma 0.05 0.01 0.044 [0.035; 0.056]
\[\sigma\] Gamma 2.00 1.00 8.062 [6.352; 10.434]
\[\alpha\] Beta 0.75 0.20 0.059 [0.030; 0.099]
\[\gamma\] Beta 0.25 0.20 0.744 [0.688; 0.822]
\[\rho\] Beta 0.75 0.20 0.744 [0.688; 0.822]
\[\varphi_{\pi}\] Gamma 1.00 0.50 0.821 [0.701; 0.893]
\[\varphi_y\] Gamma 0.15 0.25 0.527 [0.383; 0.672]
\[\rho_{\pi}\] Beta 0.25 0.20 0.404 [0.289; 0.518]
\[\rho_y\] Beta 0.25 0.20 0.418 [0.302; 0.521]
\[\rho_y\] Beta 0.25 0.20 0.796 [0.738; 0.843]

\textbf{Table 1—Bayesian Estimates of the Structural Parameters}

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Domain</th>
<th>Density</th>
<th>Mode</th>
<th>Standard deviation</th>
<th>Before October 1979</th>
<th>After the Volcker stabilization</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\sigma_{R2}^{R+})</td>
<td>(\mathbb{R}^+)</td>
<td>Inverse Gamma</td>
<td>0.25</td>
<td>0.25</td>
<td>0.492 [0.413; 0.592]</td>
<td></td>
</tr>
<tr>
<td>(\sigma_{R+}^2)</td>
<td>(\mathbb{R}^+)</td>
<td>Inverse Gamma</td>
<td>0.50</td>
<td>0.50</td>
<td>0.391 [0.272; 0.562]</td>
<td></td>
</tr>
<tr>
<td>(\sigma_{R+}^2)</td>
<td>(\mathbb{R}^+)</td>
<td>Inverse Gamma</td>
<td>0.10</td>
<td>0.25</td>
<td>0.055 [0.039; 0.078]</td>
<td></td>
</tr>
<tr>
<td>(\sigma_{\kappa}^2)</td>
<td>(\mathbb{R}^+)</td>
<td>Inverse Gamma</td>
<td>0.25</td>
<td>0.25</td>
<td>0.193 [0.108; 0.406]</td>
<td></td>
</tr>
<tr>
<td>(\kappa)</td>
<td></td>
<td>Gamma</td>
<td>0.05</td>
<td>0.01</td>
<td>0.044 [0.035; 0.056]</td>
<td></td>
</tr>
<tr>
<td>(\sigma)</td>
<td>(\mathbb{R}^+)</td>
<td>Gamma</td>
<td>2.00</td>
<td>1.00</td>
<td>8.062 [6.352; 10.434]</td>
<td></td>
</tr>
<tr>
<td>(\alpha)</td>
<td>[0, 1]</td>
<td>Beta</td>
<td>0.75</td>
<td>0.20</td>
<td>0.059 [0.030; 0.099]</td>
<td></td>
</tr>
<tr>
<td>(\gamma)</td>
<td>[0, 1]</td>
<td>Beta</td>
<td>0.25</td>
<td>0.20</td>
<td>0.744 [0.688; 0.822]</td>
<td></td>
</tr>
<tr>
<td>(\rho)</td>
<td>[0, 1]</td>
<td>Beta</td>
<td>0.75</td>
<td>0.20</td>
<td>0.744 [0.688; 0.822]</td>
<td></td>
</tr>
<tr>
<td>(\varphi_{\pi})</td>
<td>(\mathbb{R}^+)</td>
<td>Gamma</td>
<td>1.00</td>
<td>0.50</td>
<td>0.821 [0.701; 0.893]</td>
<td>1.749 [1.107; 2.568]</td>
</tr>
<tr>
<td>(\varphi_y)</td>
<td>(\mathbb{R}^+)</td>
<td>Gamma</td>
<td>0.15</td>
<td>0.25</td>
<td>0.527 [0.383; 0.672]</td>
<td>1.146 [0.744; 1.610]</td>
</tr>
<tr>
<td>(\rho_{\pi})</td>
<td>[0, 1]</td>
<td>Beta</td>
<td>0.25</td>
<td>0.20</td>
<td>0.404 [0.289; 0.518]</td>
<td></td>
</tr>
<tr>
<td>(\rho_{\pi})</td>
<td>[0, 1]</td>
<td>Beta</td>
<td>0.25</td>
<td>0.20</td>
<td>0.418 [0.302; 0.521]</td>
<td></td>
</tr>
<tr>
<td>(\rho_y)</td>
<td>[0, 1]</td>
<td>Beta</td>
<td>0.25</td>
<td>0.20</td>
<td>0.796 [0.738; 0.843]</td>
<td></td>
</tr>
</tbody>
</table>

Fraction of accepted draws 0.246

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7 Specifically, for either of the two subperiods we generate 2,000 stochastic simulations from the estimated model of length equal to the actual sample length (\(T = 100\) for the pre–October 1979 period, and \(T = 98\) for the period following the end of the Volcker stabilization), and for each of them we compute the autocorrelation matrix exactly as we did based on the actual data. In order to reduce as much as possible dependence from the initial conditions, we run a 100-period “presimulation,” which we then discard (an alternative would have been to draw from the unconditional distributions of the state variables).
the autocorrelation of the nominal rate, and to the cross correlation of inflation with the nominal rate, at lags greater than two years. For the period following the end of the Volcker stabilization, they pertain to the cross correlation of the nominal rate with the output gap at lags greater than two years, and to the autocorrelation of inflation at lags between three and eight quarters. Figure 3 shows the actual standard deviations of the nominal interest rate, inflation, and the output gap before October 1979 and after the Volcker stabilization, together with the distributions of the model-implied standard deviations (based, once again, on 2,000 stochastic simulations of length $T = 100$ and $T = 98$ for the two periods). Under this dimension, the performance of the model is less satisfactory: although it can replicate the main qualitative features of the Great Moderation, with volatility declines for all series, it is less precise in replicating the precise numerical values seen in the data. An important point to stress, however, is that the present exercise focuses on conceptual issues in the interpretation of the results produced by the structural VAR literature on the Great Moderation, and, therefore, the ability of the model to replicate all features of the data from a qualitative and quantitative point of view should be downplayed.
II. Theoretical Properties of the Estimated Data-Generation Process

In this section we explore the theoretical properties of the estimated data-generation process under the two regimes by analyzing the structural VAR(MA) representations of the model, the structural innovations’ theoretical impact matrices and impulse-response functions, the VAR(MA)’s reduced-form innovation variances, and the series’ theoretical variances under determinacy and indeterminacy.

A. The Equivalent Minimal State-Space Representations of the Model under the Two Regimes

Conditional on the median estimates reported in Table 1, the theoretical state-space representations of the model under the two regimes can easily be computed. By applying MATLAB’s routine ss.m to the two state-space forms, we then obtain the two equivalent minimal state-space representations—henceforth, EMSSR—of the model (the specific numerical values taken by the
two EMSSR are not reported here but are available upon request). A comparison between the two EMSSR highlights a fundamental difference between the two regimes. Whereas under determinacy the EMSSR has six states, under indeterminacy it has seven. (The fact that under indeterminacy the economy possesses one additional state compared with the determinacy regime was first pointed out by Lubik and Schorfheide (2004, 201)). An important point to stress is that the presence of an additional state variable under indeterminacy has nothing to do with the presence of a sunspot shock. Indeed, first, it can be easily shown that this feature of the DGP remains unchanged even if we set the variance of the sunspot shock to zero. Second, and more fundamentally, given that the sunspot shock is pure white noise, on strictly logical/mathematical grounds it cannot belong to the state vector, so that the additional state under indeterminacy ought to be something else—specifically, we conjecture that it is a linear combination of \( \pi_{t+1|t} \) and \( y_{t+1|t} \).

**B. The VARMA Representations**

Such finding has the following important implication. Since, once the EMSSR has been appropriately rotated,\(^8\) three of its states are equal to the three structural disturbances \((\varepsilon_{R,t}, \varepsilon_{\pi,t}, \varepsilon_{y,t})\), this automatically implies that under determinacy, with six states in the EMSSR, the model possesses a VAR representation in \( R_t, \pi_t \), and \( y_t \). Indeed, by applying a MATLAB code for computing the finite-order VAR representation of a state-space form (kindly supplied by Juan Rubio-Ramirez) to the EMSSR of the model under determinacy, we obtain the VAR(2) representation.

---

\(^8\) In general, state-space forms are unique up to a rotation.
\[
Y_t = \begin{bmatrix}
1.21 & 0.01 & 0.14 \\
-0.03 & 0.47 & 0.07 \\
-0.11 & -0.05 & 1.02
\end{bmatrix} Y_{t-1} + \begin{bmatrix}
-0.32 & -0.01 & -0.05 \\
0.02 & -0.02 & -0.02 \\
0.08 & 0.00 & -0.23
\end{bmatrix} Y_{t-2} + v_t,
\]

\eqref{4}

with \( \text{Var}(v_t) = \begin{bmatrix}
0.44 & 0.26 & -0.17 \\
0.26 & 1.18 & 0.04 \\
-0.17 & 0.04 & 1.02
\end{bmatrix} \)

and with the covariance matrix of the observables equal to

\eqref{5}

\[
\text{Var}(Y_t) = \begin{bmatrix}
2.95 & 0.45 & -0.27 \\
0.45 & 1.51 & 0.21 \\
-0.27 & 0.21 & 3.55
\end{bmatrix},
\]

thus implying that the theoretical standard deviations of \( R_t, \pi_t, \) and \( y_t \) under determinacy are equal to 1.72, 1.23, and 1.88, respectively.\(^9\)

Under indeterminacy, on the other hand, the very same logic implies that, with one additional state variable in the EMSSR, the model does not possess a pure VAR representation in \( R_t, \pi_t, \) and \( y_t, \) but rather a VARMA one, with a small moving-average component. The VAR matrices at lags 1 and 2 in the theoretical VAR(\( \infty \)) implied by the VARMA representation of the model under indeterminacy—i.e., the ones corresponding to those reported in \eqref{4}—are given by

\eqref{6}

\[
B_1^{\text{IND}} = \begin{bmatrix}
1.02 & 0.07 & 0.18 \\
0.05 & 0.62 & 0.11 \\
0.01 & -0.03 & 1.06
\end{bmatrix} \quad \text{and} \quad B_2^{\text{IND}} = \begin{bmatrix}
-0.24 & 0.01 & -0.07 \\
-0.01 & 0.03 & -0.06 \\
0.03 & 0.01 & -0.25
\end{bmatrix},
\]

whereas a simple illustration of the speed of decay toward zero of the coefficients of the matrices \( B_p^{\text{IND}} \) for \( p > 2 \)—and therefore, of the extent to which the VAR(\( \infty \)) departs from a VAR(2)—is provided by the evolution of the maximum among the absolute values of the elements of the \( B_p^{\text{IND}} \)'s. At lag 3, such maximum is equal to 0.0513, whereas at lags 10 and 20 it decreases to 0.014 and 2.2E–3, respectively, and at lags 50, 75, and 100 it further declines to 8.6E–6, 8.4E–8, and 1.6E–9, respectively.\(^{10}\) Finally, the covariance matrix of reduced-form innovations of the VARMA representation of the model is given by

\(^9\) The difference between the theoretical standard deviations and the (modes of) the distributions shown in Figure 3 is uniquely due to the fact that, in performing stochastic simulations, we used sample lengths equal to the actual sample lengths for the periods before October 1979 and after the Volcker stabilization, respectively (see footnote 5). In other words, it is a small sample issue. (Indeed, performing stochastic simulations with sample lengths equal to 10,000, we correctly capture the true theoretical values.)

\(^{10}\) The values taken by the coefficients of the theoretical VAR(\( \infty \)) implied by the VARMA representation of the model under indeterminacy are available upon request.
Var \( (v_t) = \begin{bmatrix} 0.64 & 0.56 & 0.10 \\ 0.56 & 1.63 & 0.30 \\ 0.10 & 0.30 & 1.19 \end{bmatrix}, \)

whereas the covariance matrix of the observables is equal to

\[
\text{Var}(Y_t) = \begin{bmatrix} 19.43 & 18.09 & 6.81 \\ 18.09 & 19.19 & 6.16 \\ 6.81 & 6.16 & 6.14 \end{bmatrix},
\]

thus implying that the theoretical standard deviations of \( R_t, \pi_t, \) and \( y_t \) under indeterminacy are equal to 4.41, 4.38, and 2.48, respectively.

III. Replicating the Great Moderation

A. Volatility Decreases in Population

A comparison between the diagonal elements of the covariance matrices in (7) and (4) shows that the move from indeterminacy to determinacy is associated with decreases in the theoretical innovation variances for all series.\(^\text{11}\) As we discuss in Section IIIB, this is the case even if we set the variance of sunspot shocks to zero. Whereas earlier contributions have interpreted decreases in reduced-form innovation variances as \textit{prima facie} evidence in favor of good luck, and against good policy, our results show that this kind of evidence is difficult to interpret. Further, as we previously mentioned, the move from indeterminacy to determinacy causes a fall in the theoretical standard deviations of all the three variables, thus replicating a second key stylized fact associated with the Great Moderation. Under this respect, as we discuss in Section IIIB, sunspots play a role only for the interest rate.

The shift in the parameters of the Taylor rule considered herein is of course an oversimplification for the actual change in monetary policy that occurred following October 1979. In particular, two key features of the Volcker disinflation are not captured—by definition—within the present framework. First, as stressed (for instance) by Christopher Erceg and Andrew T. Levin (2003) and Marvin Goodfriend and Robert G. King (2005), imperfect credibility has most likely caused learning about the Fed’s inflation objective to be a significant part of the overall story. The rational expectations assumptions adopted within the present context, on the other hand, rules out this mechanism by assumption. Second, for a significant portion of the Volcker disinflation episode, the Fed targeted nonborrowed reserves, and thus, for that period, a simple Taylor rule like (1) can hardly be regarded as a fully satisfactory description of the Fed’s actual monetary policy conduct. It should be noted that a change in the conduct of monetary policy over and above a change in the interest rate rule would be labelled as a “shock” in a VAR. Volcker’s experiment of targeting nonborrowed reserves, for instance, typically shows up in a VAR as a big negative money shock, whereas the monetary expansion before that manifests itself as a period of positive shocks. This is another important dimension along which caution is urged in the interpretation of results from VARs.

\(^{11}\) See also Lubik and Paolo Surico (forthcoming).
B. The Role of Sunspot Shocks

What role do sunspot shocks play in allowing the shift from indeterminacy to determinacy to replicate the main qualitative features of the Great Moderation? Overall, quite a limited one. First, setting the standard deviation of sunspot shocks to zero, and keeping all other parameters at the median estimates reported in Table 1, the covariance matrix of reduced-form innovations of the VARMA representation of the model under indeterminacy becomes equal to

\[
\text{Var}(v_t) = \begin{bmatrix}
0.58 & 0.43 & 0.07 \\
0.43 & 1.28 & 0.21 \\
0.07 & 0.21 & 1.16
\end{bmatrix},
\]

thus clearly showing that, even without sunspot shocks, the estimated policy shift generates, in population, a decline in the reduced-form innovation variances for all series. Second, the theoretical standard deviations of \(R_t, \pi_t, \) and \(y_t\) under indeterminacy now become equal to 1.65, 1.32, and 2.11, thus implying that, by itself, the policy shift causes a decrease in the standard deviations of both inflation and the output gap, and a slight increase in the standard deviation of the nominal rate.

IV. Can Structural VAR Methods Uncover the Data-Generation Process?

A. Changes in the Structural Monetary Rule

As we pointed out in Section IIB, the model possesses a VAR(2) representation under determinacy, and a VARMA one with a very small moving-average component under indeterminacy. We start by approximating the VAR(\(\infty\)) implied by the VARMA representation under indeterminacy with a VAR(100), and we augment the VAR(2) under determinacy with 98 further AR matrices equal to 0,3 \times 3. Based on the structural shocks’ theoretical impact matrices for the two regimes, we then put the two theoretical VARs into the corresponding structural VAR forms,

\[
\begin{align*}
A_{0,\text{IND}}^{-1} Y_t &= \tilde{B}_{1}^{\text{IND}} Y_{t-1} \ldots + \tilde{B}_{100}^{\text{IND}} Y_{t-100} + \varepsilon_t, \\
A_{0,\text{DET}}^{-1} Y_t &= \tilde{B}_{1}^{\text{DET}} Y_{t-1} \ldots + \tilde{B}_{100}^{\text{DET}} Y_{t-100} + \varepsilon_t,
\end{align*}
\]

where \(\tilde{B}_j^x = A_{0,x}^{-1} B_j^x\), with \(x = \text{IND}, \text{DET}\) (with IND for “indeterminacy” and DET “determinacy”), \(A_{0,x}\) being the impact matrix of the three structural shocks (\(\tilde{\varepsilon}_{R_t}, \tilde{\varepsilon}_{\pi_t}, \tilde{\varepsilon}_{y_t}\)) at zero, and \(j = 0, 1, ..., 100\). A crucial point to stress is that, since we are working here with the impact matrices of the three structural shocks, we are implicitly setting the variance of the sunspot shock to zero—to put it differently, the version of the model we are working in both this subsection and the next is the one without sunspots.

By means of simple manipulations of the monetary rules in the two structural VARs—i.e., the first equations in (10) and (11)—it is possible to compute both the sum of the coefficients on the lagged interest rate and the long-run coefficients on inflation and the output gap, which are

\[12\text{ As we pointed out in Section IIIB, at lag 100 the maximum among the absolute values of the elements of the AR matrix of the VAR(\(\infty\)) is of an order of magnitude of } 10^{\text{10}}, \text{ which implies that all lags beyond the hundredth can safely be ignored.} \]
conceptually linked to $\rho$, $\phi_{\pi}$, and $\phi_{y}$, respectively, in (1). Whereas under indeterminacy they are equal to 0.76, 0.85, and 0.43, respectively, under determinacy they increase to 0.90, 1.75, and 1.15, respectively. In population, structural VAR methods therefore point toward changes in monetary policy across regimes, with an increase in both the extent of interest rate smoothing and the long-run responses of the interest rate to inflation and the output gap. It should be noted, however, that our population evidence is not in contrast with the inference drawn from structural VARs on actual data. Primiceri (2005, 821), for example, finds that the "systematic responses of the interest rate to inflation and unemployment exhibit a trend toward a more aggressive behavior, despite remarkable oscillations." Sims and Zha (2006, 55), while favoring a specification that only exhibits changes in the VAR covariance matrix, report that "[t]he best fitting model among those that do allow coefficients to change is one that constrains the changes to occur only in the monetary policy equation [...]". Like Cogley and Sargent (in press) and Primiceri (in press), we find that the point estimates of the changes are not trivial, even though the data leave their magnitudes uncertain." It is worth emphasizing that in the analyses of both Primiceri (2005) and Sims and Zha (2006), the conclusion that monetary policy played little role in fostering macroeconomic stability is based primarily on policy counterfactuals. As the next subsection shows, however, although structural VAR methods are able to identify changes in the monetary rule, policy counterfactuals would suggest, even in population, that such changes are not at the root of the changes in the reduced-form properties of the economy. This is very much in line with the results upon which Primiceri (2005) and Sims and Zha (2006) base their conclusions.

**B. Theoretical Structural Policy Counterfactuals**

After switching the monetary rules in (10) and (11), we convert the counterfactual structural VARs into corresponding counterfactual reduced-form VARs, from which theoretical counterfactual standard deviations for the three series can trivially be computed. As we pointed out in Section III, under determinacy the true theoretical standard deviations are equal to 1.72, 1.23, and 1.88, respectively. Quite strikingly, the theoretical counterfactual standard deviations we obtain by imposing the structural monetary rule corresponding to the indeterminacy regime onto the structural VAR for the determinacy regime (i.e., the counterfactual in which we "bring Arthur Burns into the post-Volcker stabilization era," so to speak) are equal to 1.21, 1.22, and 1.92, thus implying a volatility decrease for two series out of three, rather than an increase. Results from the alternative counterfactual in which we impose the structural monetary rule corresponding to the determinacy regime onto the structural VAR for the indeterminacy regime (i.e., we "bring Paul Volcker or Alan Greenspan back in time") are equally striking. Whereas, under indeterminacy, the true standard deviations of the three series are equal to 1.65, 1.32, and 2.11, respectively, the counterfactual standard deviations we obtain via the policy switch are equal to 16.84, 9.47, and 2.12, respectively, thus implying a volatility increase for all series, rather than a decrease, thus highlighting, once again, the failure of structural VAR-based policy counterfactuals to capture the truth.

These findings suggest that results from counterfactual simulations such as those of Primiceri (2005) and Sims and Zha (2006) are, in principle, difficult to interpret. One possibility, indeed, is that their policy counterfactuals correctly captured the authentic policy changes that took place in the underlying structural model of the economy. If this were the case, their results would provide evidence against good policy, and in favor of good luck. Another plausible interpretation, however, is that their VAR-based policy counterfactuals failed to capture the authentic policy switch, in which case such results would provide, in principle, no useful information on the issue at hand. A key point to stress is that, when performing counterfactual simulations in structural VARs, the implicit presumption is that switching the VAR estimated structural policy rules provides a reasonable
approximation to the *authentic* policy switch, i.e., the one between the Taylor rules in the underlying DSGE model. As our results show, however, such presumption is, in general, unwarranted.\footnote{The reliability of structural-VAR based policy counterfactuals is extensively analyzed by Luca Benati (2008b). Taking a standard New Keynesian model as DGP, he explores the conditions under which SVAR-based policy counterfactuals may provide a reasonably good approximation to the “authentic” policy switch, i.e., the one between the Taylor rules in the New Keynesian model.}

### C. Impulse-Response Functions

Let’s now turn to impulse-response functions (henceforth, IRFs). Little change over time in estimated IRFs to an identified monetary policy shock has been traditionally regarded as evidence in favor of good luck, and against good policy. As we will now show, however, such evidence is, once again, difficult to interpret.

Figure 4 plots the theoretical IRFs of the model to the three structural shocks under the two regimes. As the figure shows, in most cases the difference between the IRFs under determinacy and indeterminacy is far from dramatic—in a few cases it is essentially trivial—thus pointing toward intrinsic difficulties in distinguishing between the two regimes based on an analysis of the IRFs, even excluding sunspot shocks. (An important point to stress, however, is that—as discussed in Section IB—such similarity partly results from our imposition, in estimation, of identical signs across regimes for the impacts of the structural shocks on the endogenous variables.) When, on top of this, you consider that (i) in practice, IRFs to structural shocks are not known, and rather ought to be estimated, and (ii) under indeterminacy, the presence of sunspot shocks injects additional noise into the system, it can reasonably be expected that, in most cases, the null of no variation in the IRFs across regimes will be difficult to reject. Figure 5 provides evidence by showing, for the two regimes, the medians and the 90 percent coverage percentiles of the distributions of the estimated IRFs to a 100-basis-point monetary policy shock, based on 1,000 stochastic simulations. Specifically, for each of the 1,000 simulations:

- We generate artificial data under the two regimes from the estimated DGP,\footnote{Specifically, for either regime we generate artificial samples of length equal to the actual sample length, i.e., \( T = 100 \) for the pre-October 1979 period, and \( T = 98 \) for the period following the end of the Volcker stabilization.} and we estimate reduced-form VARs, choosing the lag order based on the AIC.

- Based on the VARs estimated covariance matrices, we estimate the impact matrices of the structural shocks for the two regimes by imposing the true theoretical sign restrictions\footnote{The reason for using sign restrictions is that any other identification scheme (e.g., Cholesky) would be false in population—in the sense of being inconsistent with the true data generation process—so that its results could not be meaningfully interpreted in any way. This is conceptually in line with Canova and Joaquim Pires Pina (2005).} via the procedure introduced by Juan Rubio-Ramirez, Daniel Waggoner, and Zha (2005). We impose the sign restrictions for a total of four periods (on impact, and for three subsequent periods). We integrate out rotation uncertainty by computing, for each of the 1,000 stochastic simulations, 200 impact matrices satisfying the sign restrictions, and then taking the average among them.

- Based on the estimated VARs and the estimated structural impact matrices, we compute the IRFs to a 100-basis-point shock to the interest rate.

As the figure shows, first, in general it is not possible to reject, at the 90 percent level, the null hypothesis of no change in the IRFs across regimes; and second, both for inflation, and especially
for the output gap, the distributions of the estimated IRFs appear to be quite remarkably similar. These results forcefully bring home the point that, although little change in estimated IRFs to a monetary policy shock have routinely been interpreted as evidence in favor of good luck and against good policy, evidence like that produced by Primiceri (2005, figs. 2 and 3) and Gambetti, Pappa, and Canova (2008, fig. 3) is—in principle—difficult to interpret, and is not incompatible with the notion that monetary policy may have played an important role in fostering the greater macroeconomic stability of recent years.

D. An Identification Problem under Indeterminacy

The presence of sunspot shocks under indeterminacy creates a fundamental identification problem under that regime. Given that, with $N$ VAR residuals, it is mathematically impossible to recover the $N + 1$ original shocks under that regime, this automatically implies that most structural VAR analyses of the pre–October 1979 period may suffer from a potential identification problem, which casts doubts on their conclusions. The problem is unfortunately intractable within the structural VAR framework because, as it can be easily shown, the sunspot shock affects, on impact, all the variables in the system, so that it cannot be disentangled from other shocks via (say) zero restrictions on impact. On the other hand, sunspot shocks, by definition, do not have a long-run impact on anything, so that even long-run zero restrictions are not an option.
Most analyses of the US Great Moderation have been based on structural VAR methods, and have consistently pointed toward good luck as the main explanation for the greater macroeconomic stability of recent years. Based on an estimated New-Keynesian model in which the only sources of change are the move from passive to active monetary policy, and the presence of sunspots under indeterminacy, we show that VAR users may misinterpret good policy for good luck. In particular, the estimated DGP exhibits decreases in population in both variances and innovation variances for all series. Policy counterfactuals based on the theoretical structural VAR representations of the model under the two regimes fail to capture the truth, whereas impulse-response functions to a monetary policy shock exhibit little change across regimes. Since these results are in line with those found in the structural VAR-based literature on the Great Moderation, our analysis suggests that existing VAR evidence is compatible with the “good policy” explanation of the Great Moderation.

APPENDIX

We numerically maximize the log posterior—defined as $\ln L(\theta | Y) + \ln P(\theta)$, where $\theta$ is the vector collecting the model's structural parameters, $L(\theta | Y)$ is the likelihood of $\theta$ conditional on
the data, and \( P(\theta) \) is the prior—via simulated annealing. We implement the simulated annealing algorithm of Angelo Corana et al. (1987) as described in Appendix D.1 of Benati (2008a). We then generate draws from the posterior distribution of the model's structural parameters via the Random Walk Metropolis (RWM) algorithm as described in, e.g., An and Schorfheide (2007). In implementing the RWM algorithm we follow An and Schorfheide (2006, Section 4.1) exactly, with the single exception of the method we use to calibrate the covariance matrix's scale factor—the parameter \( c \) below—for which we follow the methodology described in Appendix D.3 of Benati (2008a). We run a burn-in sample of 200,000 draws, which we then discard. After that, we run a sample of 200,000 draws, keeping every draw out of 100 in order to decrease the draws' autocorrelation, thus ending up with a sample of 2,000 draws.

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