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ASSESSING DIFFERENT DRIVERS OF THE GREATMODERATION IN THE U.S.

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Abstract

This paper employs a calibrated new-Keynesian DSGE model to assess the relative importance of two different, potentially important drivers of the Great Moderation in the U.S., namely 'good policy' vs. 'good luck'. The calibrated model is capable to replicate the actual standard deviations of inflation and output. Factual and counterfactual simulations are run in order to gauge the relative importance of the systematic monetary policy vs. the stochastic shocks hitting the economic system in shaping some macroeconomic volatilities. Importantly, under the bad policy scenario sunspots may influence the equilibrium values of the macroeconomic variables of interest, and distortions in the transmission mechanism going from the structural shocks to the variables of interest are allowed for. Our findings support the relevance of both drivers in causing *inflation* volatility. By contrast, *output* volatility can hardly be explained by a monetary policy switch like the one occurred in the U.S. at the end of the '70s.

JEL classification: E30, E52.

Keywords: Great Moderation, indeterminacy, good policy, good luck, counterfactual simulations.

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1 Introduction

One of the most debated topics in modern macroeconomics is undiscussably the 'Great Moderation', i.e. the striking reduction of inflation and output volatilities occurred in the last two decades in several industrialized economies. This fact, common across several countries, is surely a feature of the U.S. economy. Table 1 displays the bootstrapped volatilities of annualized GDP inflation and detrended output in two different samples, i.e. 1960Q1-1979Q3, 1984Q1-1999Q4.[1],[2] Quite evidently, there is some instability regarding these volatilities. For instance, let's take the statistics regarding the subsamples reported in the first row of the Table.[3] Notably, the median value of the volatility of the inflation rate falls from 2.48 to 0.95, while its 90% confidence interval evidently shrinks, and its standard deviation (not shown in the Table) drops from 0.65 to 0.14. As far as detrended output is concerned, the median value of its bootstrapped volatility lowers from 1.69 to 0.92, while also its confidence interval tightens, and its standard deviation moves from 0.5072 down to 0.3435. Table 1 shows that this tendency finds empirical support also when employing the CBO output trend. Overall, these figures suggest that since the beginning of the '80s the U.S. economy has shown a much calmer behavior, a conclusion supported by several recent studies (Kim and Nelson [1999], McConnel and Perez-Quiros [2000], Blanchard and Simon [2001], Stock and Watson [2003], and Kim, Nelson, and Piger [2004] for output; Mumtaz and Surico [2006] for the inflation rate).

[Table 1 about here]

[1] The beginning of the second subsample is suggested by several studies on the Great Moderation (see references cited later). The exclusion of the period 1979Q4-1983Q4 is due to the 'experiment' conducted by the Fed in that period. The choice of cutting the sample in 1999Q4 is justified by the apparent 'disconnect' between inflation and output volatilities that has been observed in the U.S. since the beginning of the current century (Gordon, 2005). However, our results are robust to the extension of the second subsample to 2005Q3, or when starting our investigation in 1982Q4.

[2] These distributions were computed with a semiparametric bootstrap procedure. First, we estimated sub-sample specific AR(3) processes for the series under investigation (first subsample: 1960Q1-1979Q3; second subsample: 1984Q1-1999Q4), specifically $x_t = c^x + \sum_{j=1}^{3} \alpha_j^x x_{t-j} + \varepsilon_t^x$ (with x standing either for inflation or for detrended output). Next, the bootstrapped distributions were computed by simulating 10,000 pseudo-series with the estimated models, keeping fixed the estimated autoregressive parameters. The errors were sampled with replacement from the urns of the estimated residuals. Following Davidson and MacKinnon (2006, eq. 23.11 page 821) the latter were rescaled to make the variance of the sampled errors equal to that of the estimated autoregressive process. AR(2) models for the time-series at hand delivered very similar results.

[3] We mainly concentrate on annualized inflation - 4 times the quarterly inflation computed on the PGDP chain-weighted price index - and detrended real output - HP-filtered real log-GDP (1 decimal). Following Lubik and Schorfheide (2004), we computed the HP filter by considering as initial observation the quarter 1955Q1. As an alternative measure of stochastic trend for the real GDP, we employ the potential output computed by the Congressional Budget Office. In this study we also consider a measure of the short-term interest rate, i.e. the federal funds rate (quarterly averages). The data used in our analysis were downloaded on January 2006 from the Federal Reserve Bank of St. Louis' web-site, i.e. http://research.stlouisfed.org/fred2/.

If this decline in inflation and output volatilities is mainly due to 'good policy' actions (say a better monetary policy management), then the low volatilities scenario we have been observing for about two decades now could be maintained such by keep fighting inflation with the 'right' systematic monetary policy. Evidence of a remarkable policy switch at the end of the '70s is provided - among the others - by Judd and Rudebusch (1998), Clarida, Galí, and Gertler (2000), Lubik and Schorfheide (2004), Boivin and Giannoni (2005), and Cogley and Sargent (2005). By constrast, if the Great Moderation is mostly due to 'good luck' (to be interpreted as more benign macroeconomic shocks), then nothing in principle can prevent the U.S. economy to return to the high volatilities scenario already lived in the '60s and '70s. Supporters of the 'good luck' view include Stock and Watson (2003), Primiceri (2005), Canova and Gambetti (2005), Hansen (2005), Canova, Gambetti, and Pappa (2006), Sims and Zha (2006), Gordon (2005), Arias, Hansen, and Ohanian (2006), and Justiniano and Primiceri (2006).[4]

Most of the above cited studies concentrate on the estimation of VAR-type or backward looking models, as well as on their employment for running factual and counterfactual exercises. These models underscore the role played by inflation expectations in influencing the realizations of the variables of interest, an aspect that is of key-importance when performing counterfactual experiments. Moreover, the VAR-based empirical evidence on Great Moderation is challenged by Benati and Surico (2006), who show that model-misspecification may lead to a severe upward bias in the assessment of the merits of the 'good luck' hypothesis.

Of course, structural models in which agents are rational allow for the study of policy changes. Unfortunately, the few counterfactual experiments conducted with modern DSGE monetary-policy models (e.g. Stock and Watson [2003] and Justiniano and Primiceri [2006], who employ a Smets and Wouters (2003)-type model in their investigations) have neglected the role potentially played by indeterminacy / sunspot shocks in the '60s and '70s in the United States, a role whose statistical significance has been certified by Lubik and Schorfheide (2004).[5],[6] If the move from a 'passive' to an 'active' monetary policy (implying the move from a multiple-equilibria scenario to a unique equilibrium) dramatically reduces the volatility of inflation expectations (and, consequently, of inflation and output), then the omission of the 'passive' monetary policy hypothesis might lead a researcher to underestimate the role that systematic monetary policy has possibly

[4] Bernanke (2004) - among the others - also discusses the role potentially played by changes in the (non-policy) economic structure for the reduction of the observed volatilities. In this paper we line up with most of the literature and concentrate on the 'good policy' vs. 'good luck' drivers. We leave the study of the structural change issue to future research.

[5] For a contribution pointing towards the role of indeterminacy in explaining the dynamics of inflation in reaction to a monetary policy shock in VAR models, see Castelnuovo and Surico (2006). Beyer and Farmer (2005) point out how the support of the indeterminacy hypothesis in the '60s and '70s in the U.S. might be driven by the imposition of untestable restrictions on the structure of the new-Keynesian economic model employed by Lubik and Schorfheide (2004). For a reply, see Lubik and Schorfheide (2006).

[6] A notable exception is provided by Boivin and Giannoni (2005), that allow for indeterminacy in their simulations but miss to gauge the role played by exogenous volatilities' shifts in shaping the macroeconomic scenario.

played as a driver of the Great Moderation.

This paper works with a calibrated standard DSGE new-Keynesian model to perform factual and counterfactual simulations in order to assess the relative importance of 'policy' vs' luck' in explaining the Great Moderation. Importantly, in modeling the monetary policy break, we allow for sunspots and distortions in the monetary transmission mechanism under 'passive' monetary policy, i.e. when the Taylor principle is not met. To our knowledge, this is the first contribution that allows for indeterminacy when running counterfactuals aimed at assessing the relative role of 'good policy' vs. 'good luck' in the United States.

Our results suggest that systematic monetary policy is likely to have played an important role in stabilizing inflation in the '80s and '90s. However, it turns out that output stability is hardly linked to an improvement in the monetary policy management. Moreover, the relative importance of the role played by more benign macroeconomic shocks in influencing both inflation and the business cycle is likely to be higher than the one played by the monetary policy switch occurred at the end of the '70s.

The paper is structured as follows. Section 2 describes the model employed as DGP for our factual and counterfactual exercises, and describes our calibration strategy. Section 3 explains the alternative scenarios we concentrate on, and presents our results, whose robustness is discussed in Section 4. Section 5 concludes, and References follow.

2 Macroeconomic framework

As pointed out in the Introduction, in performing our simulations we employ the standard new-Keynesian framework surveyed by Clarida et al (1999). A key-element for the choice of this model is the fact that it is the only new-Keynesian monetary policy model estimated by allowing for indeterminacy (see the work by Lubik and Schorfheide [2004]). The model reads as follows:[7]

$$\pi_t = \beta E_t \pi_{t+1} + \kappa(x_t - z_t) \tag{1}$$

$$x_t = E_t x_{t+1} - \tau(R_t - E_t \pi_{t+1}) + g_t \tag{2}$$

$$R_t = (1-\rho)[\rho_\pi \pi_t + \rho_x(x_t - z_t)] + \rho R_{t-1} + \varepsilon_t^{MP} \tag{3}$$

$$z_t = \rho_z z_{t-1} + \varepsilon_t^z, g_t = \rho_g g_{t-1} + \varepsilon_t^g \tag{4}$$

where x stands for real output, π represents inflation, R is the short term nominal interest rate, z captures exogenous shifts of the marginal costs of production, g is a

[7]The variables of the model are expressed in percentage deviation with respect to their steady state values, or in the case of output from a trend path.

demand disturbance,[8] and ε^{MP} is a monetary policy shock. The random variables z and g follow AR(1) processes whose roots are - respectively - ρ_z and ρ_g. The shocks $\varepsilon^z, \varepsilon^g$, and ε^{MP} are white noise stochastic elements whose variance is, respectively, $\sigma^2_{\varepsilon^z}, \sigma^2_{\varepsilon^g}$, and $\sigma^2_{\varepsilon^{MP}}$.

Eq. (1) is the Euler equation maximizing the profit of the representative, monopolistically competitive firm whose discount factor is identified by the parameter β. Prices are sticky due to a Calvo-type rigidity that allows only a fraction of firms to reoptimize their prices or to quadratic adjustment costs. The slope coefficient κ relates output and the marginal costs to the inflation rate.

Eq. (2) is a log-linearized IS curve stemming from the household's intertemporal problem in which consumption and bond holdings are the control variables. Contemporaneous output is caused both by expectations on future realizations of the business cycle and by the ex-ante real interest rate, the impact of the latter being regulated by the intertemporal elasticity of substitution τ.

Eq. (3) is an interest rate rule according to which the central bank adjusts the policy rate in response to fluctuations in inflation and output. We interpret the random variable ε^{MP}_t as the monetary policy shock.

It is well known that this linear rational expectations model can be associated to a unique solution as long as the Taylor principle is satisfied, i.e. the condition $\rho_\pi > 1 - \frac{(1-\beta)}{\kappa}\rho_x$ is met (Clarida et al, 2000; Woodford, 2003). If this condition does not hold, monetary authorities are unable to uniquely pin down private sector's expectations. Following Lubik and Schorfheide (2003,2004), under indeterminacy we allow both for i) a zero-mean i.i.d. sunspot shock ζ_t - whose variance is σ^2_ζ - to influence the equilibrium values of the variables of interest, and for ii) a distortion in the transmission mechanism going from the vector of structural shocks to the endogenous variables under consideration.[9] Notice that, given its simplicity, this model is likely to give systematic monetary policy a more important role than the one that other frameworks - say Smets and Wouters (2003)'s - acknowledge it.

Model calibration

We employ the new-Keynesian model (1)-(4) to run simulations in order to compute the volatilities of inflation and output. To do so, we need to calibrate the model. We divide the vector θ of the parameters of the model in three groups: policy parameters

[8]Since the underlying model has no investment, output is proportional to consumption up to an exogenous process that can be interpreted as time-varying government spending or, more broadly, as preference change.

[9]Technically, such a distortion is implemented by considering a vector $\widetilde{M}$ affecting the transmission from the structural shocks ε_t to the endogenous forecast errors $\eta_t = [(x_t - E_{t-1}x_t), (\pi_t - E_{t-1}\pi_t)]'$. Lubik and Schorfheide (2003,2004) propose to compute the vector $\widetilde{M}$ so to minimize the distance between the *on-impact* reactions of the endogenous variables s_t to the shocks ε_t under indeterminacy and those computed at the frontier dividing the parameter space into determinacy and indeterminacy. We adopt this identification strategy, labeled as 'continuity', as also done by Castelnuovo and Surico (2006) and Benati and Surico (2006). A Technical Appendix containing further details is available upon request.

$\theta_{pol} = \{\rho_\pi, \rho_x, \rho\}$, volatilities $\theta_{vol} = \{\sigma_{\varepsilon^z}, \sigma_{\varepsilon^g}, \sigma_{\varepsilon^{MP}}, \sigma_\zeta\}$, and non-policy, 'structural' parameters $\theta_{npol} = \{\tau, \kappa, \rho_z, \rho_g\}$. For calibrating the Taylor rules, we employ the point estimates by Clarida, Galí, and Gertler (2000, Table 2 p. 157). These estimates are fairly in line with those provided by other authors on the U.S. monetary policy conduct (see e.g. Judd and Rudebusch [1998], Lubik and Schorfheide [2004]). As far as the macroeconomic shocks are concerned, in our benchmark calibration we employ Lubik and Schorfheide (2004)'s estimated volatilities. Interestingly, the magnitudes of the supply shocks are very similar to those one may obtain by estimating a VAR-type model a la Rudebusch and Svensson (1999), while those of the demand shocks seem to be slightly underestimated.[10] For calibrating the remaining 'non-policy' parameters, we follow Canova (1994) and employ some (independent) 'prior' distributions for each of the parameters of such vector. A recent study by Fuhrer and Rudebusch (2004) points towards a relatively small value of the intertemporal elasticity of substitution τ for the U.S. economy (spanning from 0.002 to 0.081 when the HP detrended real log-GDP is considered), slightly smaller than the one provided by Rudebusch (2002). Following Lubik and Schorfheide (2004), we choose (for τ^{-1}) a gamma distribution having mean 19.94 (corresponding to $\overline{\tau} = 0.05$) and a fairly large standard, deviation, i.e. 14.07, in order to allow for flat tails and a fairly wide range of drawn values in the calibration exercise. To take into account the large uncertainty surrounding the value of the slope coefficient κ (which, according to Lubik and Schorfheide [2004]'s posterior means, may span from .27 up to 1.12), we consider a gamma distribution having mean 0.75 and standard deviation 0.31. Finally, we sample the values of the autoregressive parameters ρ_z and ρ_g by imposing - respectively- a beta prior with mean 0.95 and standard deviation 0.05 and a beta prior with mean 0.50 and standard deviation 0.09.[11] Fixed the priors, we implement the following algorithm:

1. we sample a tuple $j : \{\tau^j, \kappa^j, \rho_z^j, \rho_g^j\}$ from the given distributions;

2. given the remaining parameters of the model (calibrated as discussed above) and the tuple j coming from step 1, we simulate 500 times the new-Keynesian model (1)-(4), and compute the medians of the simulated distributions of the endogenous variables of interest;[12]

3. given the medians computed at step 2, we compute the following measure of

[10] In particular, we OLS estimated the supply curve $\pi_t = \sum_{i=1}^{4} \alpha_i \pi_{t-i} + \alpha_x x_{t-1} + \varepsilon_t^\pi$ and the demand curve $x_t = \sum_{i=1}^{2} \beta_i x_{t-i} - \beta_r(\bar{i}_{t-1} - \overline{\pi}_{t-1}) + \varepsilon_t^x$ (where the upper-barred variables identify backward-looking MA(4) processes) for the two subsamples 1960Q1-1979Q3, 1984Q1-1999Q4, and obtained: $\widehat{\sigma_{\varepsilon^\pi}} = 1.18$, $\widehat{\sigma_{\varepsilon^x}} = 0.89$ (first sample); $\widehat{\sigma_{\varepsilon^\pi}} = 0.71$, $\widehat{\sigma_{\varepsilon^x}} = 0.43$ (second sample). We concentrate on these point-estimates in our Robustness check.

[11] The means of the beta distributions were selected on the basis of a preliminary grid-search we performed by considering the following discrete domains (step-length: 0.05): $\tau\epsilon[0 - 0.35], \kappa\epsilon[0.55 - 1.0], \rho_z\epsilon[0.4 - 0.95], \rho_g\epsilon[0.4 - 0.95]$.

[12] For all the model simulations we consider, we produce 1,000 pseudo-subsamples of a lenght comparable to the historical one, i.e. 78 observations for the first subsample, and 65 for the second one. The model simulations are stochastically initialized, and the first 100 pseudo-observations are discarded.

distance:

$$D^j(\xi^{nkm,j}(\theta_j), \xi^{act}, V) = \left[\left(\xi^{nkm,j}(\theta_j) - \xi^{act}\right)' V^{-1} \left(\xi^{nkm,j}(\theta_j) - \xi^{act}\right)\right] \quad (5)$$

where $\xi^{nkm,j} = \begin{bmatrix} \sigma_\pi^{nkm,j} & \sigma_y^{nkm,j} \end{bmatrix}'$ and $\xi^{act} = \begin{bmatrix} \sigma_\pi^{act} & \sigma_y^{act} \end{bmatrix}'$ are $(2x1)$ vectors containing the medians of the distributions of the standard deviations of time-series of interest, 'nkm' and 'act' stand respectively for 'new-Keynesian' (simulated) and 'actual' (bootstrapped), and V is a $(2x2)$ diagonal matrix whose non-zero elements are represented by the standard deviations of the bootstrapped distributions of the actual time-series in the sample under analysis;

4. we store the so computed distance D^j and the tuple j, and go back to step 1.

We repeat steps 1-4 1,000 times. At the end of the loop, we pin down the tuple j^* that minimizes the distance (5) in the subsample at hand. In order to have a calibration robust to sample uncertainty, we consider the best (in terms of minimum distance) 5% tuples and compute a weighted average of their elements, the weights being the inverse of the distance (5) for all the considered j_s. Notice that our measure of distance is sample-specific, i.e. we perform the minimum-distance search for each of the two subsamples.

The results of our calibration are displayed in Table 2.[13] It turns out that to match the volatilities of inflation and output one must impose a low degree of intertemporal elasticity of substitution τ, very much in line with the above mentioned literature. The slope coefficient κ is higher than the one suggested by the posterior means by Lubik and Schorfheide (2004), and it is interestingly outside the 90%-interval of our prior, so suggesting that the data (and not the prior) is actually driving the result. The autoregressive coefficient of the demand shock is very similar to the posterior mean (first subsample) provided by Lubik and Schorfheide (2004), while the one of the shocks to marginal costs is lower. Given the similarity of the two sets of subsample 'estimates' we obtained, we constraint the vector $\left\{\tau, \kappa, \rho_z, \rho_g\right\}$ to assume the same values in both the subsamples of our interest.[14] We summarize our calibration choices for the whole vector of parameters identifying the structure of the model (1)-(4) in Table 3.[15]

[Tables 2 and 3 about here]

[13] The same exercise perfomed with the vector $\xi^{x,j} = \begin{bmatrix} \sigma_\pi^{x,j} & \sigma_y^{x,j} & \sigma_i^{x,j} \end{bmatrix}'$, with $x \in \{nkm, act\}$, delivered very similar results, i.e. τ=0.0488, κ=1.3335, ρ_g=0.9479, ρ_z=0.4988 for the first subsample, and τ=0.0328, κ=1.0563, ρ_g=0.9500, ρ_z=0.5374 for the second one.

[14] We employ the battery of the point-estimates obtained for the second subsample. The alternative choice implies very similar results.

[15] Notice that in terms of number of structural shocks there is an asymmetry between the first and the second subsample due to the presence of the sunspot shock in the former but not in the latter. Nevertheless, our results are robust to the 'elimination' of the sunspot shock from the picture.

3 'Good policy' or 'good luck'? Counterfactual simulations

Once calibrated, the model is ready for performing factual and counterfactual simulations. In particular, we first want to understand if this framework is able to deliver 'factual' simulated volatilities which are in line with the 'actual' bootstrapped ones. For 'factual' we mean the volatilities computed with the model calibrated as described in the previous Section.

Table 4 reports the results of our factual simulations. The new-Keynesian model at hand seems to offer a fairly good fit of the facts; in particular, all the medians of the simulated volatilities fall inside the bootstrapped interval defined by the [5th; 95th] percentiles. We take this calibration and the implied factual simulations as our benchmark against which to confront the outcome of our conterfactual simulations.

We simulate four different counterfactual scenarios: i) 'Good Policy', implemented by 'planting' the Volcker-Greenspan monetary policy conduct in the '60s and '70s; ii) 'Good Luck', featured by the presence of the more benign shocks of the '80s and '90s also in the two earlier decades; iii) 'Bad Policy', characterized by a 'passive' monetary policy in both the simulated subsamples; and iv) 'Bad Luck', a scenario in which the economy is hit by highly volatile shocks all time long. What we expect is a better economic outcome - i.e. lower medians and tighter intervals - under the 'Good' scenarios, and a worse one - i.e. higher medians and volatilities - under the 'Bad' ones. But are these changes quantitatively important?

Figure 1 displays the benchmark vs. counterfactual distributions of inflation and output. All the distributions are tilted in the expected directions, but the magnitudes of the shifts are different from each other. In particular, planting a good monetary policy in the '60s and '70s does exert a remarkable impact on the distribution of inflation in terms of median and standard deviation (both significantly lower); by contrast, the distribution of output is basically unaffected by such a regime shift.[16] This result finds its confirmation in the somewhat 'symmetric' scenario, when the bad policy is imposed in the second subsample. In fact, according to our simulations under a passive monetary policy we would have observed a worse outcome in terms of inflation volatility in the second subsample (though the impact of the 'bad policy' on the volatility of inflation seems to be lower than the one of the 'good policy' in absolute terms), but not so much in terms of output volatility. This is confirmed by the figures collected in Table 3, that show how and how much the distributions vary when different systematic monetary policies are implemented.

Differently, the role of (either good or bad) luck seems to be relevant for *both* volatilities. In fact, according to our simulations milder shocks in the '60s and '70s would have implied a much calmer behavior of the U.S. economy, both in terms of inflation and

[16] Notice that, according to the Kolmogorov-Smirnov 2-sided test, all the 'counterfactual' distributions plotted in Figure 1 are statistically different (at the 10% significance level) with respect to the 'factual' ones. However, in this paper we are concerned with the economic relevance of the 'policy' vs 'luck' drivers.

in terms of output. 'Simmetrically', big macroeconomic shocks in the last two decades would have triggered a large macroeconomic instability also under good monetary policy.

Table 5 offers a synthetic summary of our results. First, systematic monetary policy does influence the volatility of inflation. Such volatility would have been about 32% smaller (or 30% bigger) if monetary policy had been tighter (or less aggressive). These figures support the role played by the Fed in the '80s and '90s in stabilizing the volatility of the inflation rate, as also found by Cogley and Sargent (2005) and Mumtaz and Surico (2006). Hence, indeterminacy triggered by a 'passive' monetary policy is likely to have played an important role in forming the macroeconomic scenario of the pre-Volcker era, as previously pointed out by Clarida, Galí, and Gertler (2000) and Lubik and Schorfheide (2004). Nevertheless, monetary policy has hard time in explaining the lower output volatility of the '80s and '90s. Indeed, the historically relevant policy switch does not trigger much of a reaction in the business cycle. This finding supports the results coming from Stock and Watson (2003)'s counterfactual simulations. Third, the role played by good luck seems to be relatively more important than the one of good policy in both subsamples. In this sense, our results corroborate those by Canova and Gambetti (2005), Canova, Gambetti, and Pappa (2006), Primiceri (2005), Sims and Zha (2006), Arias, Hansen, and Ohanian (2006), and Justiniano and Primiceri (2006).

[**Table 4, Figure 1, Table 5 about here**]

4 Robustness check

We perform a robustness check along three dimensions: The magnitude of the supply shocks, that of the intertemporal elasticity of substitution τ in the IS curve, and that of the slope parameter κ in the Phillips curve.

Magnitude of the Supply Shocks

So far the analysis has mainly relied upon Lubik and Schorfheide (2004)'s estimates of the volatilities of inflation, output, and the structural shocks. As a check, we estimate an alternative model - i.e. the Rudebusch and Svensson (1999) model - and concentrate on the estimated standard deviations of the errors. We find $\widehat{\sigma_{\varepsilon^\pi}} = 1.18$, $\widehat{\sigma_{\varepsilon^x}} = 0.89$ for the first sample, and $\widehat{\sigma_{\varepsilon^\pi}} = 0.71$, $\widehat{\sigma_{\varepsilon^x}} = 0.43$ for the second one.[17] The remarkable drop in the supply shock - estimated by Lubik and Schorfheide (2004) - seems to be confirmed, but the relative magnitude of the demand shock with respect to the supply shock is much higher. By conditioning on these new values of the volatilities of the demand and supply shocks, and keeping the vector of policy parameters θ_{pol} and the volatility of the monetary policy shock $\sigma_{\varepsilon^{MP}}$ and that of the sunspot shocks σ_ζ unchanged, we recalibrate the vector $\left\{\tau, \kappa, \rho_z, \rho_g\right\}$ in order to match the medians of the actual volatilities.

[17] Newey-West correction for the VCV matrix (3 lags). A check with the CBO potential output (as to substitute the HP measure for the output trend) delivered very similar estimates. The whole set of estimates of the Rudebusch and Svensson (1999)'s model is available upon request.

The results of our calibration, reported in Table 6, point towards 'estimates' that are fairly similar to those previously obtained, with a slightly higher intertemporal elasticity of sustitution and a slighly lower slope of the Phillips curve. As previously done, we employ the same set of calibrated parameter values for both the subsamples: Our new calibration is available in Table 7.[18]

[Tables 6 and 7 about here]

The factual simulations confirm that the model is able to fit the data with a fair precision (see Table 8). We then run new counterfactual simulations. As far as the conclusions about the role of systematic monetary policy vs. structural shocks is concerned, also these simulations lead us to remark the relevance of systematic monetary policy on inflation volatility, and that of the different magnitude of the supply and demand shocks on both the volatilities under investigation. Figure 2 and Tables 8 and 9 give support to this statement.

[Table 8, Figure 2, Table 9 about here]

Higher Intertemporal Elasticity of Substitution τ

Our benchmark calibration delivers a value of τ of about 0.06, fairly in line with recent estimates of the IS curve for the U.S. by Fuhrer and Rudebusch (2004). However, alternative, higher estimates may be found in the literature. To assess the robusness of our findings, we perform our simulations by raising its value up to 0.09, as in Rudebusch (2002). All the other parameters are calibrated as in Table 3.

Factual simulations reveal that this parameterization delivers (median) volatilities that lay within the (or close to the) 90% bootstrapped confidence intervals. As far as our qualitative results are concerned, Tables 10 and 11, as well as Figure 3, testify that this parameter perturbation does not affect our qualitative conclusions.

[Table 10, Figure 3, Table 11 about here]

Lower Slope of the Phillips curve κ

Given the importance of the parameter κ in the Phillips curve, we perturb it in order to perform a further robustness check. We assign to κ a new value, i.e. 0.58, a value in line with the posterior mean obtained by Lubik and Schorfheide (2004). We notice that the factual simulations deliver median values for inflation that are much smaller than the actual ones. However, when running our simulations with such a small value for the parameter κ (the other parameter estimates are as those reported in Table 3), our qualitative results turn out to be confirmed (see Tables 12 and 13 and Figure 4).

[Table 12, Figure 4, Table 13 about here]

[18] As before, we employ the battery of the point-estimates obtained for the second subsample. The alternative choice implies very similar results.

5 Conclusions

In this paper we calibrated a new-Keynesian model to perform factual and counterfactual simulations relative to the U.S. macroeconomic behavior in order to understand the relative merits of the 'Good (Monetary) Policy' vs. 'Good Luck' hypotheses for explaining the Great Moderation. Importantly, in performing our simulations under the 'bad' policy scenario, we allowed for sunspot shocks and distortions in the transmission mechanism from the structural shocks to the endogenous variables to affect the equilibrium values of the variables of interest.

Our results show that both an aggressive policy against inflation fluctuations and benign macroeconomic shocks are likely to have played a big role in shaping the path of inflation and output. In particular, systematic monetary policy moves turn out to have been important in stabilizing the inflation rate, but have not been as effective in stabilizing the business cycle. By contrast, less volatile macroeconomic shocks are quite important for explaining the behavior of both variables.

All in all, while supporting the role of systematic monetary policy in influencing inflation fluctuations, this paper supports the importance of the relative role played by structural shocks in the determination of the U.S. macroeconomic volatilities. This finding corroborates some recent contributions by Stock and Watson (2003), Arias, Hansen, and Ohanian (2006), and Justiniano and Primiceri (2006), who argue that variations regarding - respectively - pure supply shocks, total factor productivity, and investment-specific technological shocks might be the causes of the reduced volatility of the business cycle. Regarding the fluctuations of the inflation rate, our results seem to offer some support to Mankiw (2006, p. 184) who recently wrote: "I wonder whether we exaggerate the role of policy decisions and understate the role of luck. One reason is that the bad inflation performance of the 1970s and the good inflation performance of the 1990s were not limited to the United States. If there was policy failure in the 1970s and success in the 1990s, the blame and credit go to the world community of central bankers, not to the single person leading the Federal Reserve. I suspect, however, that the difference cannot be fully explained by policy at all. [...] The favorable supply-side developments of the 1990s were not caused by monetary policy, but they did make the job of policymakers a lot easier. Luck plays a large role in how history judges central bankers."

However, it must be recognized that a more cautious measurement of such 'exogenous' shocks is warranted. In fact, what we label as 'exogenous' might be (at least in part) the product of economic policies. Citing Krueger (2003, p. 64), "The [shock] that leaps to mind immediately is the oil price increase in 1973-74, which I think of as having come at the end of a commodity price boom - itself a result of the dollar inflation and, for that matter, labor union strikes and things like this, which I think were partly because of uncertainty about relative prices. If so, treating those as macroeconomic shocks that are quite exogenous may understate quite significantly the role of improved monetary policy".

To take Krueger's consideration up, one should work with more sophisticated models able to take into account exchange rate fluctuations, imperfections in the labor market, price heterogeneity, and so on, features that are just lacking in the simplified view of the world that the simple 3 equation new-Keynesian monetary policy model offers us. We plan to pursue further research along this avenue in the future.

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	1960Q1-1979Q3		*1984Q1-1999Q4*	
Output trend	σ_π	σ_x	σ_π	σ_x
HP	*2.48* *[1.68; 3.84]*	*1.69* *[1.24; 2.25]*	*0.95* *[0.77; 1.23]*	*0.92* *[0.65; 1.33]*
CBO	2.48 [1.68; 3.84]	2.33 [1.62; 3.28]	0.95 [0.77; 1.23]	1.40 [.95; 2.20]

Table 1: INFLATION AND OUTPUT, BOOTSTRAPPED VOLATILITES. The Table displays the 50th [5h; 95th] percentiles of simulated distributions computed with a semiparametric bootstrap procedure. First, we estimated sub-sample specific AR(3) processes for the series under investigation. Next, the bootsrapped distributions were computed by simulating 10,000 pseudo-series with the estimated AR models, keeping fixed the estimated autoregressive parameters. The errors were sampled with replacement from the urns of the estimated residuals. Following Davidson and MacKinnon (2006, eq. 23.11 page 821) the latter were rescaled to make the variance of the sampled errors equal to the autogressive processes's estimated one. Initial conditions for the AR processes: Hystorical values. ARCH-Lagrange Multiplier test (3 lags) supported the assumption of homoschedasticity of the estimated errors. First observation for the HP trend computation: 1955Q1; last observation: 2005Q3. CBO: Output trend computed by the Congressional Budget Office.

	'Prior' distributions				*Calibrated values*	
Parameters	Type	Mean	Std	90%-interval	1st subsample	2nd subsample
τ^{-1}	Gamma	19.94	14.07	[3.56; 47.02]	0.0551 (τ)	0.0594 (τ)
κ	Gamma	0.75	0.31	[0.33; 1.31]	1.3581	1.3641
ρ_g	Beta	0.95	0.05	[0.85; 0.99]	0.9438	0.9407
ρ_z	Beta	0.50	0.09	[0.35; 0.65]	0.4655	0.4603

Table 2: CALIBRATED PARAMETER VALUES. Calibration of the non-policy parameters performed by minimizing a distance function that takes into account the gaps between the model consistent vs. actual standard deviations (medians) of the variables in the model. The moments are weighted via the variance of the standard deviations of the actual data. The 'point estimates' of the non-policy parameters are a weighted average of the elements of the best 5 percent tuples. 1st subsample: 1960Q1-1979Q3, 2nd subsample: 1984Q1-1999Q4.

Parameters	*1st subsample*	*2nd subsample*
ρ_π	0.83	2.15
ρ_x	0.27	0.93
ρ	0.68	0.79
σ_{ε^z}	1.13	0.64
σ_{ε^g}	0.27	0.18
$\sigma_{\varepsilon^{MP}}$	0.23	0.18
σ_ζ	0.20	–
τ	0.0594	
κ	1.3641	
ρ_g	0.9407	
ρ_z	0.4603	

Table 3: CALIBRATION OF THE DGP NEW-KEYNESIAN MODEL. Parameter values borrowed from the literature (see main text) / calibrated via a minimim distance estimation. 1st subsample: 1960Q1-1979Q3, 2nd subsample: 1984Q1-1999Q4.

	'60Q1-'79Q3		*'84Q1-'99Q4*	
	σ_π	σ_x	σ_π	σ_x
Actual (bootstr.)	2.48 [1.68; 3.84]	1.69 [1.24; 2.25]	0.95 [0.77; 1.23]	0.92 [0.65; 1.33]
Factual (simulat.)	*1.92 [1.66; 2.24]*	*2.15 [1.84; 2.52]*	*0.79 [0.67; 0.93]*	*1.14 [0.95; 1.36]*
'Good Policy' (simulat.)	1.40 [1.21; 1.62]	2.02 [1.72; 2.36]	Factual	Factual
'Good Luck' (simulat.)	1.14 [0.97; 1.34]	1.23 [1.05; 1.45]	Factual	Factual
'Bad Policy' (simulat.)	Factual	Factual	1.06 [0.89; 1.25]	1.21 [1.00; 1.45]
'Bad Luck' (simulat.)	Factual	Factual	1.40 [1.19; 1.63]	2.03 [1.70; 2.38]

Table 4: VOLATILITIES COMPUTED WITH FACTUAL AND COUNTERFACTUAL SIMULATIONS, BENCHMARK CALIBRATION. The Table displays the 50th [5th; 95th] percentiles of the simulated distributions based on 10,000 repetitions. 1st subsample: 1960Q1-1979Q3; 2nd subsample: 1984Q1-1999Q4.

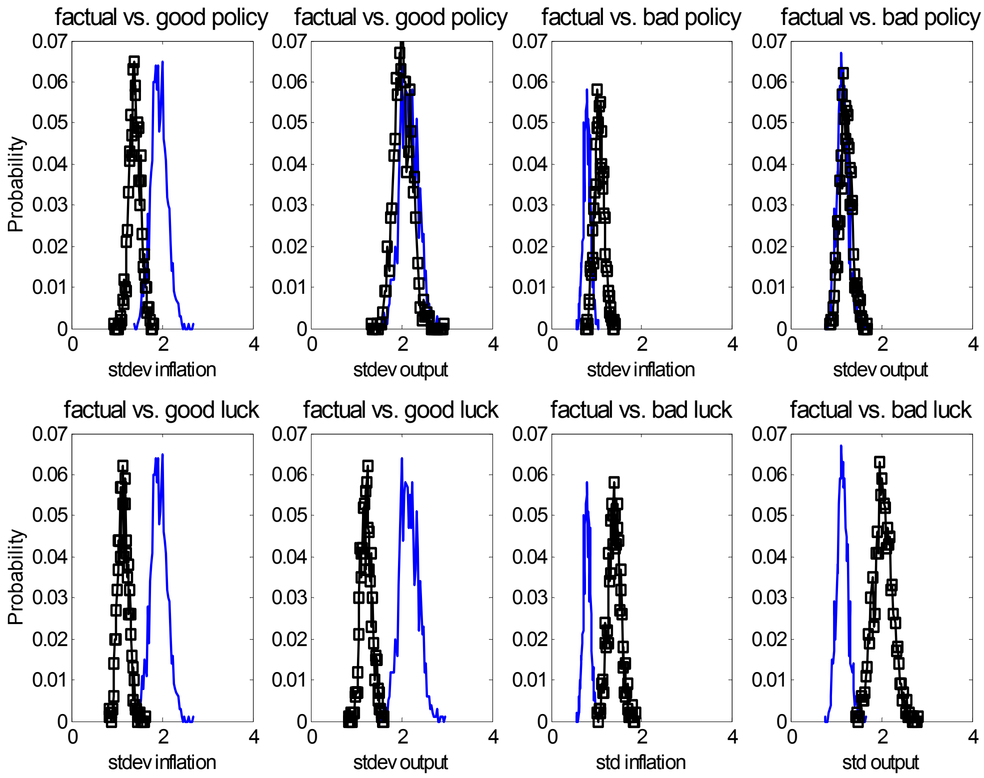

Figure 1: FACTUAL VS. COUNTERFACTUAL SIMULATIONS. Solid line: Factual distributions; 'Squared' line: Counterfactual distributions. Calibration of the model: Benchmark (see the explanation in the text). Number of repetitions: 10,000.

	'60Q1-'79Q3		*'84Q1-'99Q4*	
	σ_π, % var	σ_x, % var	σ_π, % var	σ_x, % var
'Good Policy' (simulat.)	-31.70%	-6.48%	-	-
'Good Luck' (simulat.)	-52.02%	-56.37%	-	-
'Bad Policy' (simulat.)	-	-	29.53%	6.14%
'Bad Luck' (simulat.)	-	-	57.23%	57.51%

Table 5: STANDARD DEVIATION, PERCENTAGE VARIATION. The percentage variations were computed on the medians of the simulated volatilities with respect to the benchmark factual scenario based on 10,000 repetitions. 1st subsample: 1960Q1-1979Q3; 2nd subsample: 1984Q1-1999Q4.

Parameters	*'Prior' distributions*				*Calibrated values*	
	Type	Mean	Std	90%-interval	1st subsample	2nd subsample
τ^{-1}	Gamma	19.94	14.07	[3.56; 47.02]	0.0627 (τ)	0.0771 (τ)
κ	Gamma	0.75	0.31	[0.33; 1.31]	1.2946	1.2841
ρ_g	Beta	0.95	0.05	[0.85; 0.99]	0.9435	0.9436
ρ_z	Beta	0.50	0.09	[0.35; 0.65]	0.4486	0.4516

Table 6: CALIBRATED PARAMETER VALUES, RUDEBUSCH AND SVENSSON (1999)'S DEMAND AND SUPPLY SHOCKS. Calibration of the 'non-policy' parameters performed by minimizing a distance function that takes into account the gaps between the model consistent vs. actual standard deviations (medians) of the variables in the model. The moments are weighted via the variance of the standard deviations of the actual data. The 'point estimates' of the non-policy parameters are a weighted average of the elements of the best 5 percent tuples. 1st subsample: 1960Q1-1979Q3, 2nd subsample: 1984Q1-1999Q4.

Parameters	*1st subsample*	*2nd subsample*
ρ_π	0.83	2.15
ρ_x	0.27	0.93
ρ	0.68	0.79
σ_{ε^z}	1.13	0.64
σ_{ε^g}	0.27	0.18
$\sigma_{\varepsilon^{MP}}$	0.23	0.18
σ_ζ	0.20	–
τ	0.0771	
κ	1.2841	
ρ_g	0.9436	
ρ_z	0.4516	

Table 7: CALIBRATION OF THE DGP NEW-KEYNESIAN MODEL, RUDEBUSCH AND SVENSSON (1999)'S DEMAND AND SUPPLY SHOCKS. Rest of the calibration: See the main text. 1st subsample: 1960Q1-1979Q3, 2nd subsample: 1984Q1-1999Q4.

	'60Q1-'79Q3		*'84Q1-'99Q4*	
	σ_π	σ_x	σ_π	σ_x
Actual (bootstr.)	2.48 [1.68; 3.84]	1.69 [1.24; 2.25]	0.95 [0.77; 1.23]	0.92 [.065; 1.33]
Factual (simulat.)	*1.73* *[1.46; 1.97]*	*2.20* *[1.85; 2.54]*	*0.74* *[0.64; 0.86]*	*1.22* *[1.04; 1.45]*
'Good Policy' (simulat.)	1.22 [1.05; 1.42]	2.04 [1.74; 2.39]	Factual	Factual
'Good Luck' (simulat.)	1.09 [0.92; 1.28]	1.32 [1.11; 1.55]	Factual	Factual
'Bad Policy' (simulat.)	Factual	Factual	1.01 [0.85; 1.18]	1.31 [1.09; 1.55]
'Bad Luck' (simulat.)	Factual	Factual	1.22 [1.03; 1.43]	2.03 [1.70; 2.44]

Table 8: VOLATILITIES COMPUTED WITH FACTUAL AND COUNTERFACTUAL SIMULATIONS, DEMAND AND SUPPLY SHOCKS A LA RUDEBUSCH AND SVENSSON (1999). The Table displays the 50th [5th; 95th] percentiles of the simulated distributions based on 10,000 repetitions. 1st subsample: 1960Q1-1979Q3; 2nd subsample: 1984Q1-1999Q4.

	'60Q1-'79Q3		*'84Q1-'99Q4*	
	σ_π, % var	σ_x, % var	σ_π, % var	σ_x, % var
'Good Policy' (simulat.)	-34.32%	-7.28%	-	-
'Good Luck' (simulat.)	-45.76%	-51.21%	-	-
'Bad Policy' (simulat.)	-	-	30.97%	7.27%
'Bad Luck' (simulat.)	-	-	50.33%	50.96%

Table 9: VOLATILITIES COMPUTED WITH FACTUAL AND COUNTERFACTUAL SIMULATIONS. SHOCKS A LA RUDEBUSCH AND SVENSSON (1999). The percentage variations were computed on the medians of the simulated volatilities with respect to the benchmark factual scenario based on 10,000 repetitions. 1st subsample: 1960Q1-1979Q3; 2nd subsample: 1984Q1-1999Q4.

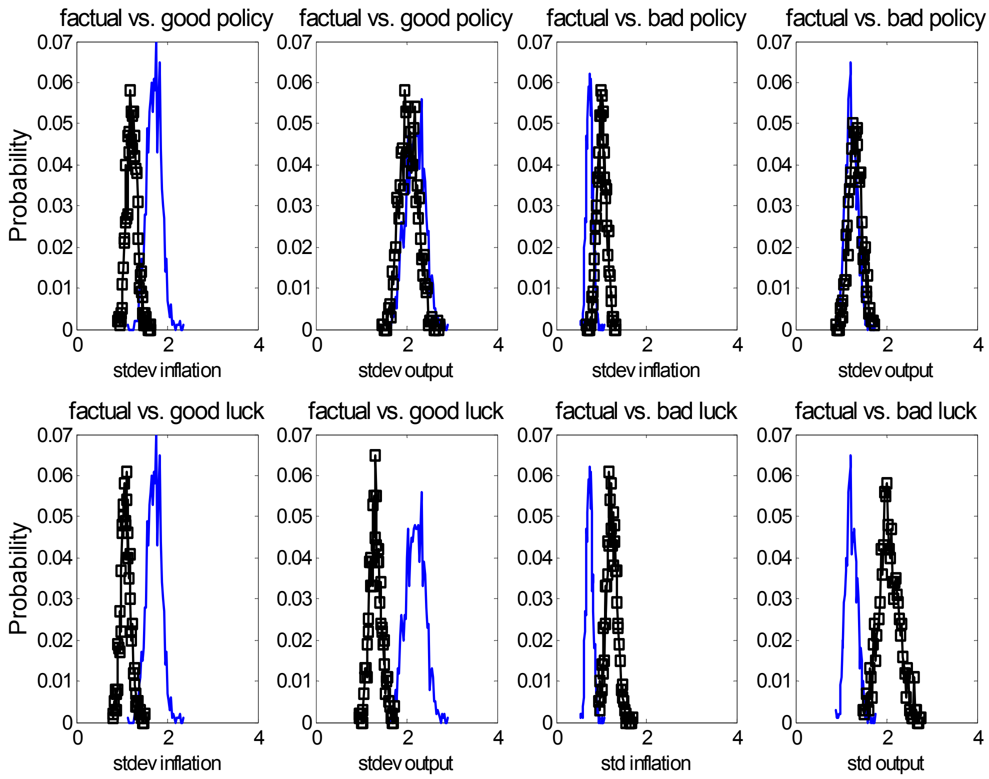

Figure 2: FACTUAL VS. COUNTERFACTUAL SIMULATIONS, SHOCKS A LA RUDEBUSCH AND SVENSSON (1999). Calibration of the model driven by the shocks estimated with the Rudebusch and Svensson (1999)'s model. Solid line: Factual distributions; 'Squared' line: Counterfactual distributions. Number of repetitions: 10,000.

	'60Q1-'79Q3		*'84Q1-'99Q4*	
	σ_π	σ_x	σ_π	σ_x
Actual (bootstr.)	2.48 [1.66; 3.83]	1.68 [1.24; 2.24]	0.97 [0.78; 1.29]	1.23 [1.08; 1.43]
Factual (simulat.)	*1.74* [*1.48*; *2.02*]	*2.11* [*1.79*; *2.46*]	*0.70* [*0.59*; *0.81*]	*1.10* [*0.93*; *1.30*]
'Good Policy' (simulat.)	1.21 [1.05; 1.38]	1.95 [1.67; 2.27]	Factual	Factual
'Good Luck' (simulat.)	1.04 [0.89; 1.23]	1.21 [1.02; 1.40]	Factual	Factual
'Bad Policy' (simulat.)	Factual	Factual	0.96 [0.81; 1.13]	1.19 [0.99; 1.41]
'Bad Luck' (simulat.)	Factual	Factual	1.22 [1.03; 1.43]	1.96 [1.64; 2.31]

Table 10: VOLATILITIES COMPUTED WITH FACTUAL AND COUNTERFACTUAL SIMULATIONS, HIGH IES. The Table displays the 50th [2.5th; 97.5th] percentiles of the simulated distributions based on 10,000 repetitions. 1st subsample: 1960Q1-1979Q3; 2nd subsample: 1984Q1-1999Q4.

	'60Q1-'79Q3		*'84Q1-'99Q4*	
	σ_π, % var	σ_x, % var	σ_π, % var	σ_x, % var
'Good Policy' (simulat.)	-36.07%	-7.89%	-	-
'Good Luck' (simulat.)	-51.27%	-55.89%	-	-
'Bad Policy' (simulat.)	-	-	32.32%	7.19%
'Bad Luck' (simulat.)	-	-	55.62%	57.29%

Table 11: VOLATILITIES COMPUTED WITH FACTUAL AND COUNTERFACTUAL SIMULATIONS, HIGH IES. The percentage variations were computed on the medians of the simulated volatilities with respect to the benchmark factual scenario based on 10,000 repetitions. 1st subsample: 1960Q1-1979Q3; 2nd subsample: 1984Q1-1999Q4.

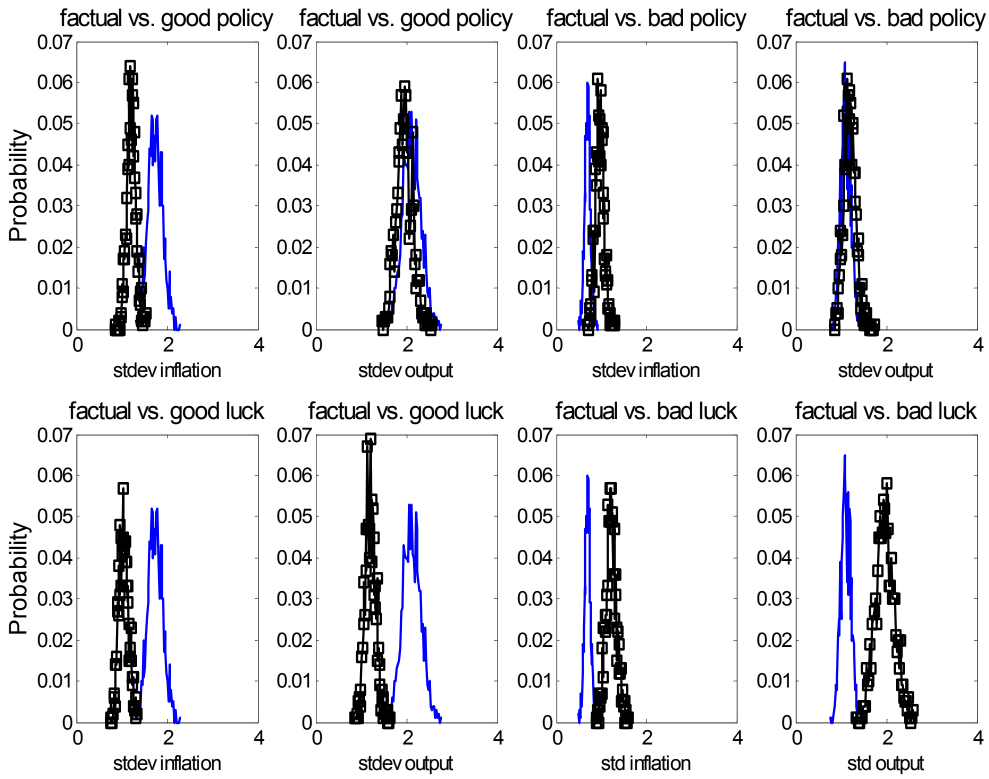

Figure 3: FACTUAL VS. COUNTERFACTUAL SIMULATIONS, HIGH IES τ. High intertemporal elasticity of substitution, benchmark calibration for the rest of the model. Solid line: Factual distributions; 'Squared' line: Counterfactual distributions. Number of repetitions: 10,000.

	'60Q1-'79Q3		*'84Q1-'99Q4*	
	σ_π	σ_x	σ_π	σ_x
Actual (bootstr.)	2.48 [1.66; 3.83]	1.68 [1.24; 2.24]	0.97 [0.78; 1.29]	1.23 [1.08; 1.43]
Factual (simulat.)	*1.02 [0.85; 1.24]*	*2.23 [1.86; 2.61]*	*0.40 [0.34; 0.48]*	*1.19 [0.99; 1.43]*
'Good Policy' (simulat.)	0.71 [0.61; 0.81]	2.10 [1.80; 2.47]	Factual	Factual
'Good Luck' (simulat.)	0.69 [0.54; 0.95]	1.26 [1.05; 1.48]	Factual	Factual
'Bad Policy' (simulat.)	Factual	Factual	0.52 [0.43; 0.61]	1.25 [1.04; 1.48]
'Bad Luck' (simulat.)	Factual	Factual	0.71 [0.59; 0.82]	2.10 [1.75; 2.49]

Table 12: VOLATILITIES COMPUTED WITH FACTUAL AND COUNTERFACTUAL SIMULATIONS, LOW SLOPE k. The Table displays the 50th [5th; 95th] percentiles of the simulated distributions based on 10,000 repetitions. 1st subsample: 1960Q1-1979Q3; 2nd subsample: 1984Q1-1999Q4.

	'60Q1-'79Q3		*'82Q4-'98Q4*	
	σ_π, % var	σ_x, % var	σ_π, % var	σ_x, % var
'Good Policy' (simulat.)	-36.82%	-5.93%	-	-
'Good Luck' (simulat.)	-39.29%	-57.31%	-	-
'Bad Policy' (simulat.)	-	-	25.40%	4.64%
'Bad Luck' (simulat.)	-	-	55.99%	56.71%

Table 13: VOLATILITIES COMPUTED WITH FACTUAL AND COUNTERFACTUAL SIMULATIONS, LOW SLOPE k. The percentage variations were computed on the medians of the simulated volatilities with respect to the benchmark factual scenario based on 10,000 repetitions. 1st subsample: 1960Q1-1979Q3; 2nd subsample: 1984Q1-1999Q4.

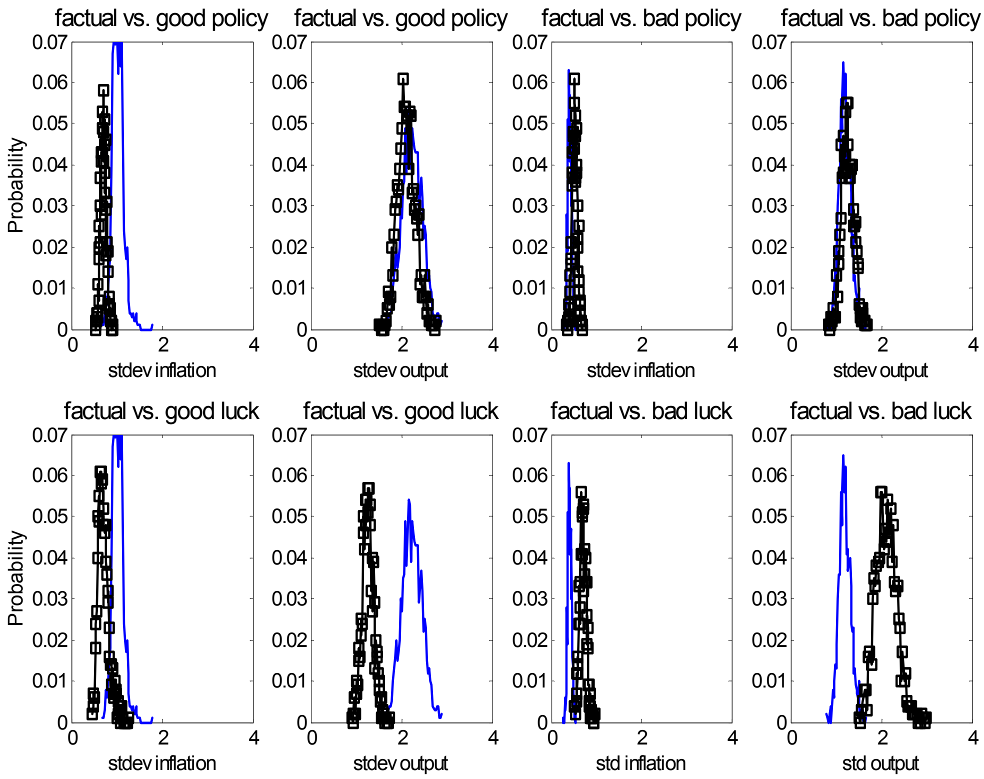

Figure 4: FACTUAL VS. COUNTERFACTUAL SIMULATIONS, LOW SLOPE κ. Low slope coefficient in the Phillips curve, benchmark calibration for the rest of the model. Solid line: Factual distributions; 'Squared' line: Counterfactual distributions. Number of repetitions: 10,000.

Technical Appendix: Solution of the LRE Model

Let's consider a linear rational expectations model as the following one:

$$\pi_t = \beta[\phi_\pi E_t \pi_{t+1} + (1-\phi_\pi)\pi_{t-1}] + \kappa(x_t - z_t)$$

$$x_t = \phi_x E_t x_{t+1} + (1-\phi_x)x_{t-1} - \tau(R_t - E_t \pi_{t+1}) + g_t$$

$$R_t = (1-\rho)[\rho_\pi \pi_t + \rho_x(x_t - z_t)] + \rho R_{t-1} + \varepsilon_t^{MP}$$

$$z_t = \rho_z z_{t-1} + \varepsilon_t^z, g_t = \rho_g g_{t-1} + \varepsilon_t^g$$

This model can be cast in the following canonical form:

$$\Gamma_0(\theta)s_t = \Gamma_1(\theta)s_{t-1} + \Psi(\theta)\varepsilon_t + \Pi(\theta)\eta_t \tag{A1}$$

where the vector $s_t = [x_t, \pi_t, R_t, E_t x_{t+1}, E_t \pi_{t+1}, g_t, z_t]'$ collects the n variables of the system, $\varepsilon_t = [\varepsilon_t^{MP}, \varepsilon_t^{\pi}, \varepsilon_t^{x}]$ is the vector of l fundamental shocks, $\eta_t = [(x_t - E_{t-1}x_t), (\pi_t - E_{t-1}\pi_t)]'$ collects the k rational expectations forecast errors, and θ is the vector of the parameters of the model outlined in the previous section. The matrices of the canonical form are presented below:

$$\Gamma_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & (1-\rho)\rho_x \\ 0 & 0 & \tau & -\phi_x & -\tau & 0 & 1 \\ 0 & 0 & 0 & 0 & -\beta\phi_\pi & 0 & \kappa \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\Gamma_1 = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & \rho & (1-\rho)\rho_x & (1-\rho)\rho_\pi & 0 & 0 \\ (1-\phi_x) & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & \beta(1-\phi_\pi) & 0 & \kappa & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \rho_g & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \rho_z \end{bmatrix}$$

$$\Psi = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \Pi = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ (1-\rho)\rho_x & (1-\rho)\rho_\pi \\ -1 & 0 \\ \kappa & -1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

In the exercises proposed in the paper, we set $\phi_x = \phi_\pi = 1$.

In order to transform the canonical form and solve the model, we follow Sims (2001) and exploit the generalized complex Schur decomposition (QZ) of the matrices Γ_0 and Γ_1. This corresponds to computing the matrices Q, Z, Λ and Δ such that $QQ' = ZZ' = I_n$, Λ and Δ are upper triangular, $\Gamma_0 = Q'\Lambda Z$ and $\Gamma_1 = Q'\Delta Z$. Defining $w_t = Z's_t$ and pre-multiplying (A1) by Q, we obtain:

$$\begin{bmatrix} \Lambda_{11} & \Lambda_{12} \\ 0 & \Lambda_{22} \end{bmatrix} \begin{bmatrix} w_{1,t} \\ w_{2,t} \end{bmatrix} = \begin{bmatrix} \Delta_{11} & \Delta_{12} \\ 0 & \Delta_{22} \end{bmatrix} \begin{bmatrix} w_{1,t-1} \\ w_{2,t-1} \end{bmatrix} + \begin{bmatrix} Q_{1.} \\ Q_{2.} \end{bmatrix} (\Psi\varepsilon_t + \Pi\eta_t) \tag{A2}$$

where, without loss of generality, the vector of generalized eigenvalues λ, which is the vector of the ratios between the diagonal elements of Δ and Λ, has been partitioned such that the lower block collects all the explosive eigenvalues. The matrices Δ, Λ and Q have been partitioned accordingly, and therefore $Q_{j.}$ collects the blocks of rows that correspond to the stable ($j = 1$) and unstable ($j = 2$) eigenvalues respectively.

The explosive block of (A2) can be rewritten as:[1]

$$w_{2,t} = \Lambda_{22}^{-1}\Delta_{22}w_{2,t-1} + \Lambda_{22}^{-1}Q_{2.}(\Psi\varepsilon_t + \Pi\eta_t) \tag{A3}$$

Given the set of m equations (A3), a non-explosive solution of the linear rational expectations model (A1) for s_t requires $w_{2,t} = 0 \ \forall t \geq 0$. This can be obtained by setting $w_{2,0} = 0$ and choosing for every vector ε_t the endogenous forecast error η_t that satisfies the following condition

$$Q_{2.}(\Psi\varepsilon_t + \Pi\eta_t) = 0 \tag{A4}$$

A general stable solution for the endogenous forecast error can be computed through a singular value decomposition of $\underbrace{Q_{2.}\Pi}_{mxk} = \underbrace{U}_{mxm}\underbrace{D}_{mxk}\underbrace{V'}_{kxk} = \underbrace{U_{.1}}_{mxr}\underbrace{D_{11}}_{rxr}\underbrace{V'_{.1}}_{rxk}$, where D_{11} is a diagonal matrix and D and U are orthonormal matrices. Using this decomposition,

[1] It is possible to have some zero-elements on the main diagonal of Λ_{22}. In this case, the latter matrix is not invertible. The 'solving-forward' solution proposed by Sims (2001) and extended by Lubik and Schorfheide (2003) overcomes this problem. A Technical Appendix with a more detailed discussion of the solution strategy is available from the authors upon request.

Lubik and Schorfheide (2003) show that in equilibrium the vector of endogenous forecast errors reads as follows:

$$\eta_t = (-V'_{.1}D_{11}^{-1}U_{.1}Q_{2.}\Psi + V_{.2}\widetilde{M})\varepsilon_t + V_{.2}\zeta_t \tag{A5}$$

where $\widetilde{M}$ is the $(k-r)xl$ matrix governing the influence of the sunspot shock on the model dynamics.

Assuming that Γ_0^{-1} exists, the solution (A5) can be combined with (A1) to yield the following law of motion for the state vector:

$$s_t = \Gamma_1^* s_{t-1} + \left[\Psi^* - \Pi^* V_{.1}D_{11}^{-1}U'_{.1}Q_{2.}\Psi + \Pi^* V_{.2}\widetilde{M}\right]\varepsilon_t + \Pi^* V_{.2}\zeta_t \tag{A6}$$

where a generic $X^* = \Gamma_0^{-1}X$.

In general, we can be confronted with three cases. If the number of endogenous forecast errors k is equal to the number of nonzero singular values r, the system is determined and the stability condition (A4) uniquely determines η_t. In such a case, $V_{.2} = 0$, then the last two addends of (A6) drop out. This implies that the dynamics of s_t is purely a function of the structural parameters θ.

If the number of endogenous forecast errors k exceeds the number of nonzero singular values r, the system is indeterminate and sunspot fluctuations can arise. Lubik and Schorfheide (2003) show that this can influence the solution along two dimensions. First, sunspot fluctuations ζ_t can affect the equilibrium dynamics. Second, the transmission of fundamental shocks ε_t is no longer uniquely identified as the elements of $\widetilde{M}$ are not pinned down by the structure of the linear rational expectations model.

Alternatively, the number of endogenous forecast errors k can be smaller than the number of nonzero singular values r, and then the system has no solutions. These three conditions generalize the procedure in Blanchard and Kahn (1980) of counting the number of unstable roots and predetermined variables.[2]

In order to compute $\widetilde{M}$ and then the solutions of the model under indeterminacy, it is necessary to impose some additional restrictions on the endogenous forecast errors. Following Lubik and Schorfheide (2004), we choose $\widetilde{M}$ such that the impulse responses $\frac{\partial s_t}{\partial \varepsilon'_t}$ associated with the system (A6) are continuous at the boundary between the determinacy and the indeterminacy region. This solution is labelled 'continuity'. In particular, let Θ^I and Θ^D be the sets of all possible vectors of parameters $\theta's$ in the indeterminacy and determinacy region respectively. For every vector $\theta \in \Theta^I$ we identify

[2] The solution method proposed by Sims (2001) has the advantage that it does not require the separation of predetermined variables from 'jump' variables. Rather, it recognizes that in equilibrium models expectational residuals are attached to equations and that the structure of the coefficient matrices in the canonical form implicitly selects the linear combination of variables that needs to be predetermined for a solution to exist.

a corresponding vector $\tilde{\theta} \in \Theta^D$ that lies on the boundary of the two regions and choose $\widetilde{M}$ such that the response of s_t to ε_t conditional on θ mimics the response conditional on $\tilde{\theta}$. This corresponds to requiring that the condition

$$\frac{\partial s_t}{\partial \varepsilon_t'}(\theta) = B_1(\theta) + B_2(\theta) = \Psi^* - \Pi^* V_{.1} D_{11}^{-1} U_{.1}' Q_{2.} \Psi + \Pi^* V_{.2} \widetilde{M} \tag{A7}$$

be as close as possible to the condition

$$\frac{\partial s_t}{\partial \varepsilon_t'}(\widetilde{\theta}) = B_1(\widetilde{\theta}) \tag{A8}$$

Applying a least-square criterion, we can then compute

$$\widetilde{M} = \left[B_2'(\theta) B_2(\theta)\right]^{-1} B_2'(\theta) \left[B_1(\widetilde{\theta}) - B_1(\theta)\right] \tag{A9}$$

and use (A9) to calculate the solution of the model in (A5) and (A6).

The new vector $\tilde{\theta}$ is obtained from θ by replacing ρ_π with the condition that marks the boundary between the determinacy and indeterminacy region. Woodford (2003) shows that this condition corresponds to the following interest rate reaction to inflation

$$\widetilde{\rho_\pi} = 1 - \frac{(1-\beta)}{\kappa} \rho_x \tag{A10}$$

As an alternative to the 'continuity' solution, we also compute the solution of the model under indeterminacy by imposing $\widetilde{M} = 0_{(k-r)xl}$, i.e. the effects of the sunspot shocks are orthogonal to the effects of the structural shocks. This solution is dubbed 'orthogonality'.

Contributions cited in this Technical Appendix

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