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Cardiff Economics
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E2010/10

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ISSN 1749-6101
October 2010

US Post-war Monetary Policy: what caused the Great Moderation?*

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October 2010

Updated November 2010

Abstract

Using indirect inference based on a VAR we confront US data from 1972 to 2007 with a standard New Keynesian model in which an optimal timeless policy is substituted for a Taylor rule. We find the model explains the data both for the Great Acceleration and the Great Moderation. The implication is that changing variances of shocks caused the reduction of volatility. Smaller Fed policy errors accounted for the fall in inflation volatility. Smaller supply shocks accounted for the fall in output volatility and smaller demand shocks for lower interest rate volatility. The same model with differing Taylor rules of the standard sorts cannot explain the data of either episode. But the model with timeless optimal policy could have generated data in which Taylor rule regressions could have been found, creating an illusion that monetary policy was following such rules.

Key words: Great Moderation; Shocks; Monetary policy; New Keynesian model; Bootstrap; VAR; Indirect inference; Wald statistic

JEL Classification: E32, E42, E52, E58

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*We are grateful to Michael C. Hatcher, Hao Hong, Vo Phuong Mai Le and David Meenagh, for useful discussions. We also thank Zhongjun Qu and Pierre Perron for sharing their code for test of structural breaks.

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1. Introduction

Since the breakdown of Bretton Woods in 1972 the US economy behaved first rather badly (the 'Great Acceleration') and then from sometime in the early 1980s until around 2007 rather well (the 'Great Moderation'). Economists have attempted to understand why these two episodes differed so much. Some have argued that monetary policy improved; others that the economic environment (the shocks) improved. In this paper we build on a DSGE model we have recently calibrated and tested for the US in the second of these episodes, extend it to the first and test it for that, then use the conclusions of this extended exercise to decompose the changes in US behaviour into policy and environment.

Previous efforts to do this have either focused on time-series descriptions of the data with rather limited theoretical restrictions or have used DSGE models with rather limited testing against the data. The former have tended to point to the environment, the latter to monetary policy, as the causes of the improvement. However in the former it is hard to identify the role of policy with much confidence, even though the facts are well accounted for, while in the latter one cannot be sure the facts are well accounted for. We would argue that one requires a method of evaluation that is well-founded both in theory and in facts.

The method we use here like the first group of authors uses time-series methods to describe the data—a VAR in fact as they do. We combine this with a DSGE model which is tested for consistency with the facts on the basis of its ability to replicate the VAR behaviour found in the data. Thus the DSGE model we use to explain the causality is one that cannot be rejected by the facts as represented by the VAR. In so doing we believe we are using both theory and data in harness. Establishing causality can only be done by theory but in our case that theory is the one that accounts for the facts.

In what follows we first survey the recent literature just summarised (section 2). We then explain our own DSGE theory (section 3), while in section 4 we explain the tests we use to evaluate it against the facts and carry out our decomposition of the causes of the improvement in US behaviour between the two episodes. Section 5 concludes.

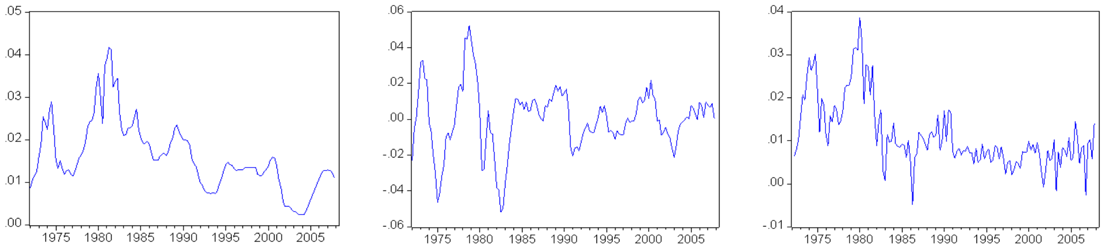
2. The Great Moderation in the US and Its Determinants

The Great Moderation refers to the period during which the volatility of the main economic variables was relatively modest. This began in the US around the early 80s although there is no consensus on the exact date. Figure 2.1 below shows the time paths of three main US macro variables from 1972 to 2007: the nominal Fed interest rate, the output gap[1] and CPI inflation. It shows that the massive fluctuations of the 70s ceased after the early 80s, indicating the economy's transition from the Great Acceleration to the Great Moderation.

Figure 2.1: Time Paths of Main Macro Variables of the US Economy

(Quarterly Data, 1972-2007)

Nominal Quarterly Fed Rate | Output Gap | Quarterly CPI Inflation



Data source: the Federal Reserve Bank of St. Louis (http://research.stlouisfed.org/fred2/, accessed November 2009). Fed rate and inflation unfiltered; the output gap is the log deviation of real GDP from its HP trend.

While a number of factors might have helped to explain the US Moderation, good shocks and good policy have been the two focused on. In particular, based on structural VAR analysis, Stock and Watson (2002) claimed that over 70% of the reduction in GDP volatility was due to luck in the form of lower shocks to productivity, commodity prices and forecast errors. Primiceri (2005) focused on the rate of inflation and unemployment, arguing that the stagflation in the 70s was better explained by non-policy shocks than by the Fed's less active role in stabilization; a

[1] Note the output gap here is defined as the percentage deviation of real GDP from its HP trend. We plot this series instead of the actual output usually discussed in the context of Great Moderation as this is what our baseline model will predict. Yet the actual data show the correlation coefficient between these two series is as high as 0.98.

similar conclusion was drawn by Gambetti, Pappa and Canova (2008). Sims and Zha (2006) found in the same vein that an empirical model with variation only in the variance of the structural disturbance fitted the data best and that alteration in the monetary regime—even if assumed to occur—would not much influence the observed inflation dynamics.

The logic underlying the structural VAR approach is that, when actual data are modelled with a structural VAR, their dynamics will be determined both by the VAR coefficient matrix reflecting the propagation mechanism (including the structure of the economy and the policy regime in place), and by the variance-covariance matrix of prediction errors which takes into account the impact caused by exogenous disturbances. Hence, by analysing the variation of these two matrices across different subsamples, it is possible to work out whether it is the change in the propagation mechanism or in the error variability that has caused the change in the data variability. It is the second that these studies have identified as the dominant cause. Hence almost all these structural VAR analyses have suggested good shocks as the main cause of the Moderation with the change of policy regime in a negligible role.

Nevertheless, since this structural VAR approach relies on supposed model restrictions to decompose the variations in the VAR between its coefficient matrix and the variance-covariance matrix of its prediction errors, there is a pervasive identification problem. As Benati and Surico (2009) have argued, the problem that 'lies at the very heart' of this approach is the difficulty in connecting the structure of a DSGE model to the structure of a VAR.

Thus many authors have taken the alternative approach of basing their analysis directly on a DSGE model. The DSGE approach to the Great Moderation focuses on how changes in the propagation mechanism of the model, and especially in the policy regime, would affect the dynamics of the economy. Typically the model is the three-equation New Keynesian framework, consisting of the 'IS' curve derived from the representative agent's optimization problem, the Phillips curve (PP) derived from the firm's optimal price-setting behaviour, and a Taylor rule approximating the Fed's monetary policy. Based on counterfactual experiments, this approach generally suggests that the US economy's improved stability was largely due to stronger monetary policy responses to inflation rather than due to better shocks (Clarida, Gali and Gertler (2000), Lubik and Schorfheide (2004), Boivin and Giannoni (2006) and Benati and Surico (2009) are examples). The contrast was made between the ‘passive’ monetary policy of the 1970s, with low Taylor rule responses, and the ‘active’ policy of the later period in which the conditions for a unique stable equilibrium (the Taylor Principle in this context) are met, these normally being that the inflation response in the Taylor rule be greater than unity.

Thus Clarida, Gali and Gertler (2000) claimed that the passive interest rate response adopted by the Fed in 1970s led the US economy into a region of indeterminacy, within which ‘sunspot fluctuations’ (appearing as the Great Acceleration) would arise as a result of self-fulfilling behaviour. Hence the Great Moderation in the 80s was essentially due to the Fed’s switchover from this passive regime to an active one in which the Taylor Principle was observed, so moving the economy into the region of determinacy.[2]

However, while such a NK-Taylor rule approach to the Great Moderation is supported by qualitative analysis of this sort, the explanation is invalidated if the models being used are strongly rejected by the data. Yet in an earlier paper (Minford and Ou, 2010) we found that these models fitted post-1982 US history rather poorly. The problem lay in the representation of monetary policy by a Taylor rule; when this was replaced by the assumption of an optimising policy, the model was not rejected.

In these tests we used the ability of the DSGE model to replicate the description of the facts provided by a VAR. Thus we were combining the two elements in this literature of episode comparison: the VAR description and the DSGE causal framework. What we found in effect for the post-1982 period was that the DSGE model accounting for the facts as described by a VAR was one in which monetary policy was modelled by the optimal timeless rule. We therefore proceed here to investigate if the same or some other model could account as well for the facts of the earlier period. With such an account we could then compare the two episodes and their causes. We go on to explain the steps involved in the rest of this paper.

[2] With full-model estimation, Lubik and Schorfheide (2004) found that the US economy was in a region of indeterminacy before 1980 but was in one of determinacy afterwards.

3. A Simple New Keynesian Model of the US Economy

Having tested three popular hypothetical alternatives, we found in our earlier paper that the only NK model not strongly rejected by the post-1982 US data was the one where the Fed's policy was to pursue the optimal tiles rule[3]. This model is:

$$x_t = E_t x_{t+1} - (\frac{1}{\sigma})(\tilde{i}_t - E_t \pi_{t+1}) + v_t \qquad [3.1]$$

$$\pi_t = \beta E_t \pi_{t+1} + \gamma x_t + \kappa u_t^w \qquad [3.2]$$

$$\pi_t = -\frac{\alpha}{\gamma}(x_t - x_{t-1}) + \xi_t \qquad [3.3]$$

where $v_t = \rho_v v_{t-1} + \varepsilon_t^v$, $u_t^w = \rho_{u^w} u_{t-1}^w + \varepsilon_t^{u^w}$, $\xi_t = \rho_\xi \xi_{t-1} + \varepsilon_t^\xi$, and variables have their usual meanings[4].

This is a fully micro-founded NK model, with equation [3.1] denoting the 'IS' curve derived from the representative agent's optimization problem and output market-clearing, equation [3.2] representing the Phillips curve implied by firms' optimal price-setting behaviour under Calvo (1983) contracts, and equation [3.3]—the targeting rule—being the optimality condition to be ensured when the monetary authority commits to minimize a quadratic social welfare loss function in timeless perspective [5]. Stochastic shocks embedded in the system are the 'demand disturbance' v_t, the wage-setting 'supply disturbance' u_t^w and a 'trembling-hand policy disturbance' ξ_t; they are each assumed to follow an AR(1) process.

Compared to the usual three-equation NK framework with a Taylor rule, in this the Fed's policy is to adjust the nominal interest rate so that the economic relationship described in [3.3] (with ξ_t=0) is caused to occur. This rule is implicit, in the sense

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[3] The other two models rejected assumed the original Taylor rule and its interest rate-smoothed version as the Fed's policy, respectively.

[4] That is, $\tilde{i}_t \equiv$ percentage deviation of interest rate from its steady-state level, $x_t \equiv$ output gap and, $\pi_t \equiv$ inflation.

[5] Note that γ and κ are functions of other structural parameters and some steady-state relationships, and α is the relative weight the Fed puts on loss from output variations against inflation variations (See table 4.1 for calibrations in the next section for details). Full derivations of the model are available in the Supporting Annex to Minford and Ou (2010) on the Cardiff Business School working paper webpage at: http://www.cf.ac.uk/carbs/faculty/minfordp/E2009_19Annex.pdf.

that the Fed effectively is solving the model for the interest rate, output gap and inflation that satisfy the three equations; it then chooses to set that solution interest rate which in turn pins down the other solution values for inflation and output gap.

4. Confronting the Model with Facts

4.1. Testing the Baseline Model of US using Indirect Inference

Methodology

We use the method of indirect inference to evaluate the baseline model's validity in explaining the US history. The general idea of this method is that, when a theoretical model is tested against the actual data, an auxiliary model that is completely independent of the theoretical one is employed to produce descriptors of the data against which the performance of the theory can be evaluated indirectly. Such descriptors can be either the estimated parameters of the auxiliary model or functions of these. While these are treated as the 'reality', the theoretical model being evaluated is simulated to find its implied values for them.

Indirect inference has been widely used in the estimation of structural models (e.g., Smith (1993), Gregory and Smith (1991, 1993), Gourieroux et al. (1993), Gourieroux and Monfort (1996) and Canova (2005)). Here we make a different use of indirect inference as our aim is to evaluate an already estimated or calibrated structural model[6]. The common element is the use of an auxiliary time series model. In estimation the parameters of the structural model are chosen so that when this model is simulated it generates estimates of the auxiliary model similar to those obtained from the actual data. The optimal choices of parameters for the structural model are those which minimise the distance between a given function of the two sets of estimated coefficients of the auxiliary model. Common choices of this function are the actual coefficients, the scores or the impulse response functions. In model evaluation the parameters of the structural model are taken as given. The aim is to compare the

[6] Recent applications of this technique include Minford, Theodoridis and Meenagh (2009), Meenagh, Minford and Wickens (2009), Le, et al. (2009, 2010) and Minford and Ou (2010).

performance of the auxiliary model estimated on simulated data derived from the given estimates of a structural model—which is taken as the true model of the economy, the null hypothesis—with the performance of the auxiliary model when estimated from the actual data. If the structural model is correct then its predictions about the impulse responses, moments and time series properties of the data should statistically match those based on the actual data: the comparison is based on the distribution of those properties under the null hypothesis of the structural model. In our comparisons here we use as the relevant properties the VAR parameters themselves (since the impulse response functions that are our primary interest are weighted averages of these, which therefore serve as a parsimonious representation of them); and also the variances of the data to ensure that the model is sized correctly. We call these the 'chosen features' of the data description.

The detailed testing procedure therefore involves first constructing the errors derived from the previously estimated structural model and the actual data. These errors are then bootstrapped and used to generate for each bootstrap new data based on the structural model. An auxiliary time series model (a VAR in our case) is then fitted to each set of data and the sampling distribution of the chosen features is obtained from these estimates. Finally a Wald statistic is computed that determines whether the chosen features estimated on the actual data lie in some confidence interval implied by this sampling distribution[7].

We take, as in Minford and Ou (2010), a VAR(1) as the appropriate auxiliary model for the macro variables, namely the nominal interest rate, the output gap and inflation. Our chosen features of the data are then summarised by nine autoregressive coefficients and three variances of the involved variables. The Wald statistic is

[7] While more details of this 'three-step' testing procedure can be found in Minford, Theodoridis and Meenagh (2009), Meenagh, Minford and Wickens (2009), Le, et al. (2009, 2010), it is worth emphasizing that the simulated sampling distribution of the relevant parameters of the auxiliary model is generated based on bootstrapping the innovations implied by the data and the theoretical model. Such a bootstrapped distribution is generally more accurate for small samples than the asymptotic distribution and is shown to be consistent by Le et al. (2010) given that the Wald statistic is 'asymptotically pivotal'; it also has quite good accuracy in small sample Montecarlo experiments according to Le et al. (2010). In particular, in this paper we draw the bootstraps as time vectors, so that any contemporaneous correlation between the innovations is preserved.

computed from these[8]. In other words, we are concerned with the model's capacity to capture the observed dynamics and variability of the economy as summed up by the VAR and the data variances. The Wald statistic is given by:

$$(\Phi - \overline{\Phi})' \Sigma_{(\Phi\Phi)}{}^{-1} (\Phi - \overline{\Phi}) \qquad [4.1]$$

where Φ is the vector of chosen features in the data, with $\overline{\Phi}$ and $\Sigma_{(\Phi\Phi)}$ representing respectively the means and variance-covariance matrix of these estimates calculated across the simulations. The whole test procedure can be illustrated diagrammatically in figure 4.1 as follows:

Figure 4.1: The Principle of Testing using Indirect Inference

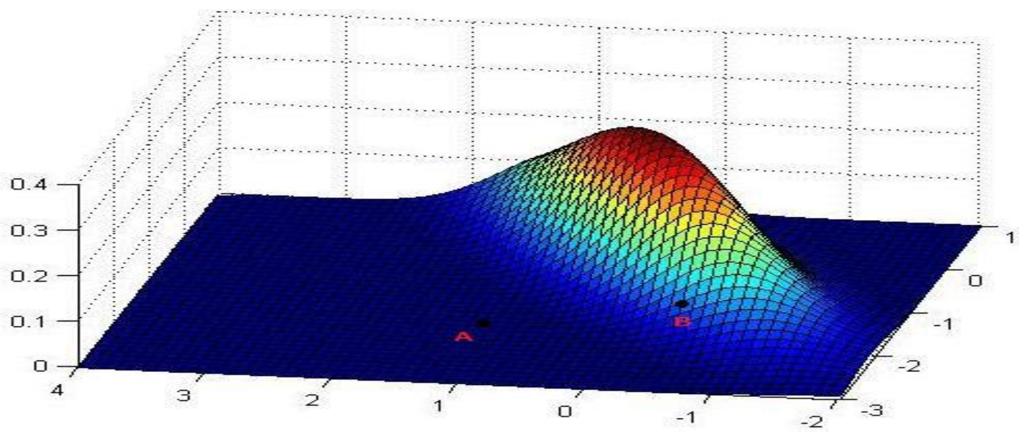
Panel A:

Model(s) to be tested
↓ (Bootstrap simulations)

Actual data	Simulated data
↓	↓
VAR representation	VAR representation
↓	↓
The VAR inference (the 'reality')	Distribution(s) of the VAR inference

The VAR inference (the 'reality') *vs.* Distribution(s) of the VAR inference → Wald statistic

Panel B:



While the first panel in figure 4.1 summarises the main steps of the methodology just described, the mountain-shaped diagram replicated from Meenagh, Minford and

[8] Note that the VAR impulse response functions, the co-variances, as well as the auto/cross correlations of the left-hand-side variables will all be implicitly examined when the VAR coefficient matrix is considered, since the former are functions of the latter.

Wickens (2009) in panel B gives an example of how 'reality' is compared to the model's predictions using the Wald test when two parameters (reflecting the chosen features of data) are considered: let either of the spots in panel B indicate the real-data-based estimates of the chosen features and the mountain represents their corresponding joint distribution generated from model simulations; when the real-data-based estimates are given at point A, the theoretical model in hand will fail to provide a sensible explanation for the real world, since what the model predicts is too far away from what reality suggests; this is in contrast to the case when the real-data-based estimates are given at point B, which, according to the diagram, means the reality is captured by the joint distribution of the chosen features implied by the model. The reported Wald statistic formally evaluates these distances.

Data and Calibration

We test the model against the US experience since the breakdown of the Bretton Woods system using quarterly data published by the Federal Reserve Bank of St. Louis from 1972Q1 to 2007Q4[9]. This covers both the Great Acceleration and the Great Moderation episodes of the US history.

The time series involved for the given baseline model include $\tilde{i}_t$, measured as the deviation of the current Fed rate from its steady-state value, the output gap x_t, approximated by the percentage deviation of real GDP from its HP trend, and the quarterly rate of inflation π_t, defined as the log difference between the current CPI and the CPI captured in the last quarter[10].

We should find a break in the VAR process reflecting the start of the Great Moderation. Accordingly we split the time series into two subsamples and estimate the VAR representation before and after the break; the baseline model is then evaluated against the VAR of each subsample separately. We set the break at 1982Q3.

[9] Data base of Federal Bank of St. Louis: http://research.stlouisfed.org/fred2/ (accessed November 2009).

[10] Notice that the annual Fed rates obtained from the FRED® are purposely adjusted into quarterly rates such that the frequencies of all time series are kept consistently on quarterly basis. We also assume zero-inflation steady state so that the steady-state value of nominal interest rate i is given by: $i = 1/\beta - 1$.

This makes the Moderation episode consistent with the data sample used in Minford and Ou (2010) and is also supported by the Qu and Perron (2007) test which suggests a break at 1984Q3, with 95% confidence interval between 1980Q1 and 1984Q4 (See table A.1 in appendix for the Qu-Perron test results).

For simplicity, the data we use are demeaned so that a VAR(1) representation of them contains no constants but only nine autoregressive parameters in the coefficient matrix; a linear trend is also taken out of the interest rate series for the post-break sample to ensure stationarity (see figure A.1 and table A.2 in appendix for plots of all the time series and the relevant unit root test results).

The model is calibrated by choosing the parameters commonly accepted for the US economy in the literature. Their values are listed in table 4.1 as follows:

Table 4.1: Calibration of Parameters

Parameters	Definitions		Calibrated values	
β	time discount factor		0.99	
σ	inverse of elasticity of intertemporal consumption		2	
η	inverse of elasticity of labour		3	
ω	Calvo contract price non-adjusting probability		0.53	
G/Y	steady-state government expenditure to output ratio[11]		0.23	
Y/C	steady-state output to consumption ratio		1/0.77	(implied)
κ	$\kappa = \frac{(1-\omega)(1-\omega\beta)}{\omega}$		0.42	(implied)
γ	$\gamma = \kappa(\eta + \sigma\frac{Y}{C})$		2.36	(implied)
θ	price elasticity of demand		6	
$\alpha/\gamma \equiv \theta^{-1}$	parameter driving the optimal timeless policy[12]		1/6	(implied)
ρ_v	autoregressive coefficient of demand disturbance	(pre-break)	0.88	(sample estimate)
ρ_{u^w}	autoregressive coefficient of supply disturbance	(pre-break)	0.91	(sample estimate)
ρ_ξ	autoregressive coefficient of policy disturbance	(pre-break)	0.59	(sample estimate)
ρ_v	autoregressive coefficient of demand disturbance	(post-break)	0.93	(sample estimate)
ρ_{u^w}	autoregressive coefficient of supply disturbance	(post-break)	0.80	(sample estimate)
ρ_ξ	autoregressive coefficient of policy disturbance	(post-break)	0.38	(sample estimate)

[11] We assumed Y=C+G and used the steady-state G/Y ratio to calculate the steady-state Y/C ratio.
[12] Nistico (2007) showed that the relative weight the central bank puts on output volatility in a micro-founded quadratic social welfare loss function is equal to the ratio of the slope of the New Keynesian Phillips curve to the price elasticity of demand, i.e., $\alpha = \gamma/\theta$.

As table 4.1 shows, the quarterly time discount rate is calibrated as 0.99, implying an approximately 1% quarterly (or equivalently 4% annual) rate of interest in steady state. σ and η are set to as high as 2 and 3 respectively as in Carlstrom and Fuerst (2008), who emphasized the values' consistency with the inelasticity evident in US data for both intertemporal consumption and labour supply. The Calvo price stickiness of 0.53 and the price elasticity of demand of 6 are both taken from Kuester, Muller and Stolting (2009): these values imply a contract length of more than three quarters[13] and a constant mark-up of price to nominal marginal cost of 1.2. The implied steady-state output-consumption ratio of 1/0.77 is calculated based on the steady-state ratio of government expenditure to output of 0.23 calibrated in Foley and Taylor (2004). The last six lines in table 4.1 also report the autoregressive coefficients of the structural disturbances implied by the model, which are all sample estimates from the data in our subsamples[14]. Notice that in both the Great Acceleration and Great Moderation the demand and supply shocks are found to be highly persistent, in contrast to the policy shocks.

Results

The model's performance in each subsample is evaluated in this section. In particular, since we have chosen the dynamics and size of the actual data for the model to fit, in evaluation this involves examining both the autoregressive coefficients of the VAR(1) representation and the variances of the L.H.S. variables of it[15]. We do this using the Wald test by checking on two kinds of Wald statistic; that is, a 'directed' Wald that accounts only for a particular aspect of the chosen features, and a 'full' Wald where all the chosen features of the data are jointly considered.

[13] To be accurate, $2\omega^{-1} - 1 \approx 3.26$.
[14] These estimates are all significant at the 5% significance level.
[15] Note that the VAR(1) representation is assumed to take the form:

$$\begin{bmatrix} \tilde{i}_t \\ x_t \\ \pi_t \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} \tilde{i}_{t-1} \\ x_{t-1} \\ \pi_{t-1} \end{bmatrix} + \Sigma_t$$

Model performance in the Great Moderation:

We first replicate with the data we use here the results in our earlier paper (Minford and Ou, 2010) in which we focused on the model's performance over the post-1982 data period, the Great Moderation subsample here. Table 4.2 shows the results[16].

Table 4.2: Evaluating the Model with the Optimal Timeless Rule in the Great Moderation

Panel A: Individual VAR Coefficients—Directed Wald Statistic

VAR(1) Coefficients	95% lower bound	95% upper bound	Values estimated with real data	In/Out
β_{11}	0.7408	0.9689	0.8950	In
β_{12}	-0.0316	0.0329	0.0395	**Out**
β_{13}	-0.0709	0.0896	0.0315	In
β_{21}	-0.2618	0.8132	-4.28e-05	In
β_{22}	0.4102	0.7617	0.8243	**Out**
β_{23}	-0.3954	0.3056	-0.0657	In
β_{31}	-0.3197	0.2122	0.0105	In
β_{32}	0.0050	0.1735	0.0979	In
β_{33}	0.1090	0.5052	0.2353	In
Directed Wald statistic (for dynamics)			86.4%	

Panel B: Volatilities of the Endogenous Variables—Directed Wald Statistic

Volatilities of the endogenous variables	95% lower bound	95% upper bound	Values calculated with real data	In/Out
$\mathrm{var}(\tilde{i})$	0.0042	0.0264	0.0156	In
$\mathrm{var}(x)$	0.0686	0.1627	0.1620	In
$\mathrm{var}(\pi)$	0.0095	0.0204	0.0149	In
Directed Wald statistic (for volatilities)			89.6%	

Note: Estimates reported in panel B (table 4.2) are magnified by 1000 times as their original values.

[16] The results shown here are numerically different from those in Minford and Ou (2010) due to data revision by FRED®; in particular, the time series of real GDP, and therefore the output gap, have been significantly revised for the 1980s.

Panel C: The Full Wald Statistic

The concerned model properties	Full Wald statistic
Dynamics + Volatilities	77.1%

As panel A in table 4.2 shows, while two out of the nine VAR(1) coefficients (i.e., the interest rate's response to the lagged output gap and the output gap's response to its own lagged value) estimated with the actual data are found to lie beyond the 95% upper bounds implied by the model, the test returns a directed Wald statistic of 86.4%. This means at 95% (or even at 90%) confidence level the real-data-based estimates are easily explained by their joint distribution generated from model simulations; it indicates the model has in general captured the dynamic features of the data pretty precisely.

As far as the size (or variability) of the data is concerned, panel B shows that the observed variances of the endogenous variables not only all lie individually within their respective 95% bounds, but are also jointly explained by the model at 95% confidence (indeed, also marginally at 90%), with the directed Wald statistic at 89.6%; our model is therefore also correctly sized compared to the actual data.

To evaluate how the model behaves in fitting the facts in an overall sense, we now consider the full Wald where the VAR(1) coefficients and the variances of the data are simultaneously taken into account. This is reported in panel C as 77.1%. Such a low Wald statistic indicates that what we observe in reality is fairly close to what the model on average predicts; thus even at 90% confidence level the data do not reject the model jointly on both dynamics and size. Hence, we conclude our model cannot be rejected as the data-generating process for the US economy in the episode of the Great Moderation.

This is not the case, however, when a standard Taylor rule is substituted for the optimal timeless rule assumed above. Table 4.3 replicates this result from our earlier paper on the latest data. It can be seen that when [3.3] is replaced with the original

Taylor rule or its interest rate-smoothed version with commonly accepted calibrations, the data in the same subsample strongly reject the model at 99%[17].

Table 4.3: Wald Statistics for Typical Taylor Rule Models in the Great Moderation

	Taylor rule model versions	
Chosen features	with original Taylor rule	with interest rate-smoothed Taylor rule
Directed Wald (dynamics only)	100%	99.8%
Directed Wald (volatilities only)	99.2%	99%
Full Wald (dynamics + volatilities)	100%	99.7%

Model performance in the Great Acceleration:

We now proceed to evaluate how the model with the optimal timeless rule behaves before 1982, i.e., in the Great Acceleration subsample. Table 4.4 shows the results.

Table 4.4: Evaluating the Model with the optimal timeless Rule in the Great Acceleration

Panel A: Individual VAR Coefficients—Directed Wald Statistic

VAR(1) Coefficients	95% lower bound	95% upper bound	Values estimated with real data	In/Out
β_{11}	0.4146	1.0629	0.9519	In
β_{12}	-0.2505	0.1274	0.0592	In
β_{13}	-0.8794	0.5251	-0.1089	In
β_{21}	-0.3401	0.3581	-0.5006	**Out**
β_{22}	0.6090	0.9994	0.9474	In
β_{23}	-0.8439	0.7108	-0.4702	In
β_{31}	-0.1360	0.1962	0.1398	In
β_{32}	-0.0551	0.1566	0.0865	In
β_{33}	-0.0147	0.7576	0.5490	In
Directed Wald statistic (for dynamics)			98.2%	

[17] This is the exercise conducted in Minford and Ou (2010). Note we have assumed the interest rate-smoothed Taylor rule takes the form $\tilde{i}_t = (1-\rho)[\gamma_\pi \pi_t + \gamma_x x_t] + \rho \tilde{i}_{t-1} + \xi_t$, with $\xi_t = \rho_\xi \xi_{t-1} + \varepsilon_t^\xi$; we also set $\rho = 0.76$, $\gamma_\pi = 1.44$ and $\gamma_x = 0.14$. The rule contains no constant as demeaned data are used.

Panel B: Volatilities of the Endogenous Variables—Directed Wald Statistic

Volatilities of the endogenous variables	95% lower bound	95% upper bound	Values calculated with real data	In/Out
$\mathrm{var}(\tilde{i})$	0.0905	0.6543	0.0841	**Out**
$\mathrm{var}(x)$	0.1559	1.4	0.7420	In
$\mathrm{var}(\pi)$	0.0262	0.0722	0.0586	In
Directed Wald statistic (for volatilities)			89.6%	

Note: Estimates reported in panel B (table 4.4) are magnified by 1000 times as their original values.

Panel C: Full Wald Statistic

The concerned model properties	Full Wald statistic
Dynamics + Volatilities	97.3%

The first panel in table 4.4 shows the VAR(1) coefficients estimated with the actual data are well captured by their respective 95% bounds implied by the model, apart from β_{21} which lies below its lower limit—thus at 95% confidence level the model overpredicts this partial response of the output gap to the lagged interest rate. The directed Wald statistic at 98.2% shows that these estimates, though individually almost all within their 95% bounds, are jointly rejected at 95% but not at 99%.

Turning to the model's performance in fitting the data size, panel B suggests that except for the variance of the interest rate, which is slightly overpredicted by the model, the variances lie well within the model-implied 95% bounds. The directed Wald statistic at 89.6% lies within 90% confidence bounds.

Overall, when we combine all features of the data, the full Wald statistic in panel C is 97.3% and so fails to be rejected at confidence levels between 95 and 99%. So while the model fits the facts less well than in the case of the Moderation subsample, it still fits those of the turbulent Acceleration episode reasonably well.

Unfortunately we are unable to test the DSGE model with the generally proposed pre-1982 Taylor rules because the solution is indeterminate, the model not satisfying the Taylor Principle. Such models have a sunspot solution and therefore any outcome is possible and also consistent formally with the theory. The assertion of those supporting such models is that the solutions, being sunspots, accounted for the volatility of inflation. Unfortunately there is no way of testing such an assertion. Since a sunspot can be anything, any solution for inflation that occurred implies such a sunspot—equally of course it might not be due to a sunspot, rather it could be due to some other unspecified model. There is no way of telling. To put the matter technically in terms of indirect inference testing using the bootstrap, we can solve the model for the sunspots that must have occurred to generate the outcomes; however, the sunspots that occurred cannot be meaningfully bootstrapped because by definition the sunspot variance is infinite. Values drawn from an infinite-variance distribution cannot give a valid estimate of the distribution, as they will represent it with a finite-variance distribution. To draw representative random values we would have to impose an infinite variance; by implication all possible outcomes would be embraced by the simulations of the model and hence the model cannot be falsified. Thus the pre-1982 Taylor rule DSGE model proposed is not a testable theory of this period.

However, it is open to us to test the model with a pre-1982 Taylor rule that gives a determinate solution; we do this by making the Taylor rule as unresponsive to inflation as is consistent with determinacy, implying a long-run inflation response of just above unity. Such a rule shows considerably more monetary 'weakness' than the rule typically used for the post-1982 period, when the long-run response of interest rates to inflation was 1.5 in the rule without smoothing and as high as 6 in the rule with smoothing which is the one that fits the data least badly.

We implement this weak Taylor rule across a spectrum of combinations of smoothing coefficient and short-run response to inflation, with in all cases the long-run coefficient equalling 1.001. The Wald statistics are shown in Table 4.5.

Table 4.5: Wald Statistics for 'Weak' Taylor Rule Models in the Great Acceleration
(with 'weak' rule defined as having a long-run interest rate response to inflation equalling 1.001)

Taylor rule: $\tilde{i}_t = \rho \tilde{i}_{t-1} + \gamma_\pi \pi_t + \xi_t$		Wald statistics for chosen features *(Normalized t-values in parenthesis[18])*		
Rule parameters	Dynamics of error process estimated from data	Directed Wald for dynamics	Directed Wald for volatilities	Full Wald for dynamics & volatilities
$\rho = 0, \gamma_\pi = 1.001$	$\xi_t \sim AR(1)$	100% *(39.81)*	78.9% *(0.22)*	100% *(40.24)*
$\rho = 0.3, \gamma_\pi = 0.7007$	$\xi_t \sim AR(1)$	100% *(30.26)*	92% *(1.08)*	100% *(28.01)*
$\rho = 0.5, \gamma_\pi = 0.5005$	$\xi_t \sim AR(1)$	100% *(22.69)*	95.9% *(1.77)*	100% *(21.98)*
$\rho = 0.7, \gamma_\pi = 0.3003$	$\xi_t \sim iid$	100% *(19.26)*	98.2% *(2.73)*	100% *(18.24)*
$\rho = 0.9, \gamma_\pi = 0.1001$	$\xi_t \sim iid$	100% *(9.09)*	99% *(3.56)*	100% *(9.03)*

What we see here is that with a low smoothing coefficient the model encompasses the variance of the data well, in other words picking up the Great Acceleration. However, when it does so, the data dynamics reject the model very strongly. If one increases the smoothing coefficient, the model is rejected less strongly by the data dynamics and also overall but it is then increasingly at odds with the data variances. In all cases the model is rejected strongly overall by the data, though least badly with the highest smoothing coefficient. Thus the testable model that gets nearest to the position that the shift in behaviour was due to the shift in Taylor rule coefficients is rejected most conclusively.

Ireland's alternative Taylor rule representation of Fed policy:

[18] T-value normalization of the Wald statistics is calculated based on Wilson and Hilferty (1931)'s method of transforming a chi-squared distribution into a standard normal distribution. The formula we use takes the form: $Z = \{[(2M^{squ})^{1/2} - (2n)^{1/2}]/[(2M^{squ^{95th}})^{1/2} - (2n)^{1/2}]\} \times 1.645$, where M^{squ} is the square of the Mahalanobis distance calculated from equation [4.1] with actual data, $M^{squ^{95th}}$ is its corresponding 95% critical value on the simulated (chi-squared) distribution, n is the degrees of freedom of the variate, and Z is the normalized test statistic; it can be derived by employing a square root and assuming n tends to infinity when the Wilson and Hilferty (1931)'s transformation is performed.

A recent paper by Ireland (2007), unlike the other New Keynesian authors we have cited above, estimates a model in which there is a non-standard Taylor rule that is held constant across both post-war episodes. His policy rule always satisfies the Taylor Principle because unusually it is the change in interest rates that is set in response to inflation and the output gap so that the long-run response to inflation is infinite. He distinguishes the policy actions of the Fed between the two subperiods not by changes in the rule's coefficients but by a time-varying inflation target which he treats under the assumptions of 'opportunism' largely as a function of the shocks to the economy. Ireland's model like ours here implies that the cause of the Great Moderation is the fall in shock variances. However the difference is that it attributes the policy variance change partly to the change in the variance of the inflation target, whereas ours attributes it entirely to the change in the variance of the policy ('trembling hand') error.

A full test of Ireland's model by our methods cannot be carried out here because his model restricts the target-related part of the error in his Taylor rule to be a function of the other errors in his model according to his opportunistic theory of policy target choice**;** as our model here is different from his in a variety of ways, we cannot test his restrictions on our model. However, we can test his model in unrestricted form, where we let his particular Taylor rule error be freely determined by the data. Table 4.6 shows the results of this exercise.

Table 4.6: Wald Statistics for the Baseline Model with Ireland-type Policy

Wald statistics for chosen features	Ireland's rule in unrestricted form: $\tilde{i}_t = \tilde{i}_{t-1} + \gamma_\pi \pi_t + \gamma_g (g_t - g) + \xi_t$ & equivalent transformation[19]: $\tilde{i}_t = \tilde{i}_{t-1} + \gamma_\pi \pi_t + \gamma_g (x_t - x_{t-1}) + \xi_t$	
	pre-1982 sample	post-1982 sample
Directed Wald for dynamics	98.9%	79.0%

[19] Ireland (2007)'s original rule takes the form: $\tilde{i}_t = \tilde{i}_{t-1} + \gamma_\pi \pi_t + \gamma_g (g_t - g) - \gamma_\pi \pi_t^* - \Delta\pi_t^* + \Omega_t$, where π_t^* is the inflation target, g_t is the output growth rate and g is its steady-state level. In our exercise here we test its unrestricted form, where $\tilde{i}_t = \tilde{i}_{t-1} + \gamma_\pi \pi_t + \gamma_g (g_t - g) + \xi_t$ and $\xi_t = -\gamma_\pi \pi_t^* - \Delta\pi_t^* + \Omega_t$. In particular, we rewrite the unrestricted rule as $\tilde{i}_t = \tilde{i}_{t-1} + \gamma_\pi \pi_t + \gamma_g (x_t - x_{t-1}) + \xi_t$ so that it can be evaluated within our baseline framework; such an equivalent transformation is derived by writing: $g_t - g = \ln y_t - \ln y_{t-1} - (\ln y_t^{hptr} - \ln y_{t-1}^{hptr}) = \ln y_t - \ln y_t^{hptr} - (\ln y_{t-1} - \ln y_{t-1}^{hptr}) = x_t - x_{t-1}$.

Directed Wald for volatilities	78.8%	89.4%
Full Wald for dynamics & volatilities	98.1%	71.1%

Note: 1. Ireland (2007)'s ML estimates suggest $\gamma_\pi = 0.91, \gamma_g = 0.23$.

2. All equation errors follow an AR(1) process according to the data and model.

It turns out that Ireland's model is hardly distinguishable from our optimal timeless rule model. His Taylor rule changes interest rates until the optimal timeless rule is satisfied, in effect forcing it on the economy. Alternatively we can write his rule as a rule for inflation determination (i.e. with inflation on the left hand side), which reveals that it is identical to the timeless rule's setting of inflation apart from the term in the change in interest rates and some slight difference in the coefficient on output gap change[20]. Since the Ireland rule is so similar to the timeless optimal rule, it is not surprising that the Wald statistics for it are hardly different: 71.1% in the Great Moderation (against 77.1% for the optimal timeless rule model) and 98.1% in the Great Acceleration (against 97.3%).

Ireland's Taylor rule can in principle be distinguished from the optimal timeless rule via his restriction on the rule's error. As noted earlier we cannot apply this restriction within our model so that Ireland's Taylor rule in its unrestricted form here only differs materially from the optimal timeless rule in the interpretation of the error. But from a welfare viewpoint it makes little difference whether the cause of the policy error is excessive target variation or excessively variable mistakes in policy setting; the former can be seen as a type of policy mistake. Thus both versions of the rule imply that what changed in it between the two subperiods was the policy error.

It might be argued that the success of Ireland's rule reveals that a type of Taylor rule does after all explain the data. This would be true. But in the context of the debate over the cause of the Great Moderation it is to be firmly distinguished from what we call the 'standard Taylor rule' under which policy shifts in the rule are regarded as the

[20] Note the Ireland rule $\tilde{i}_t = \tilde{i}_{t-1} + \gamma_\pi \pi_t + \gamma_g (x_t - x_{t-1}) + \xi_t$ can be rewritten as $\pi_t = \frac{1}{\gamma_\pi}(\tilde{i}_t - \tilde{i}_{t-1}) - \frac{\gamma_g}{\gamma_\pi}(x_t - x_{t-1}) - \frac{1}{\gamma_\pi}\xi_t$ that mimics the optimal timeless rule [3.3]; its coefficient on output gap change, according to Ireland's estimation, is 0.25, close to that of 0.17 in the latter.

cause. In Ireland's rule there are no such shifts and as we have seen the behaviour under it is essentially identical to that from the optimal timeless rule. This finding and its corollaries are the key contributions of this paper, however one chooses to describe the rule.

Concluding remarks on the comparison of the optimal timeless rule and the Taylor rule:

While by contrast our chosen DSGE model with the optimal timeless rule has more trouble explaining the pre-1982 period than the post-1982, it is therefore not rejected at reasonable levels of confidence. So we suggest that it is worth investigating what it implies as a causal explanation of the shift in behaviour between the periods. If this model is the true data-generating mechanism of US history since the early 70s, it does of course imply that there was no structural shift in the parameters between the two periods since it is the same model that we have used to fit both periods. Accordingly it also implies that the changes were due to the errors. We now go on to investigate in more detail how the errors changed according to the DSGE model.

4.2. Evaluating the Impacts of Shocks—a Variance Decomposition Analysis

Table 4.7 outlines the size of structural errors for both episodes according to our baseline model and the actual data.

Table 4.7: The Shrinking Size of Shocks

Standard deviation of	Pre-1982	Post-1982
Demand shock	0.0358	0.0143
	(0.0043)	*(0.0010)*
Supply shock	0.7867	0.1595
	(0.0708)	*(0.0319)*
Policy shock	0.0132	0.0053
	(0.0054)	*(0.0033)*

Note: 1. Values in parenthesis are sample estimates of standard deviation of innovation.
2. Standard deviation of shocks is calculated using formula sd(err.)=sd(innov.)/(1-rho) where rho is the AR(1) coefficient: shocks in both episodes are all shown to follow an AR(1) process. The values of rhos are given in calibration table 4.1.

As the figures show, the standard deviations of the shocks generally fall sharply after the break in 1982. The standard deviation of the demand and policy shock each fell by 60%, while that of the supply shock fell by a massive 80%; of this 80% drop just under half was due to the fall in the persistence of the shock.

We can evaluate the impact of these shocks on the economy by decomposing the variance of the variables involved.

Table 4.8: Variance Decomposition for the Model with the optimal timeless rule

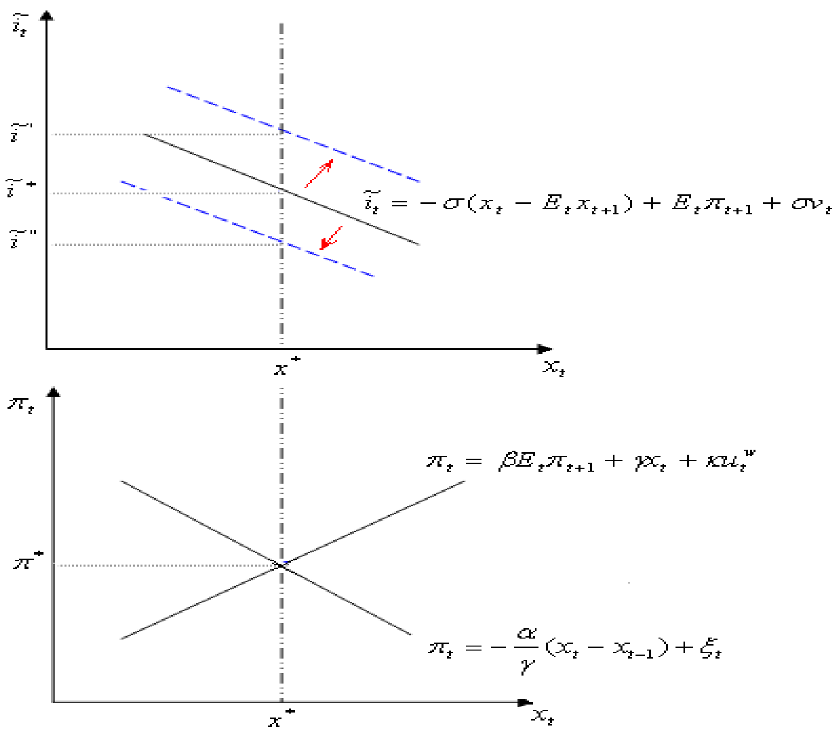
Variables / Shocks	$\tilde{i}_t$ (pre-break)	x_t (pre-break)	π_t (pre-break)	$\tilde{i}_t$ (post-break)	x_t (post-break)	π_t (post-break)
Demand shock	91.3%	0%	0%	75.4%	0%	0%
Supply shock	5.9%	99.9%	8.4%	24%	99.1%	6.6%
Policy shock	2.8%	0.1%	91.6%	0.5%	0.9%	93.4%
Total contribution	100%	100%	100%	100%	100%	100%

Table 4.8 shows that the model is operating in a recursive manner. The output gap is dominated by the Phillips curve ('supply') shocks, while inflation is dominated by monetary policy shocks. With output gap and inflation set entirely independently of demand shocks, interest rates move to offset these as well as reacting to output and inflation.

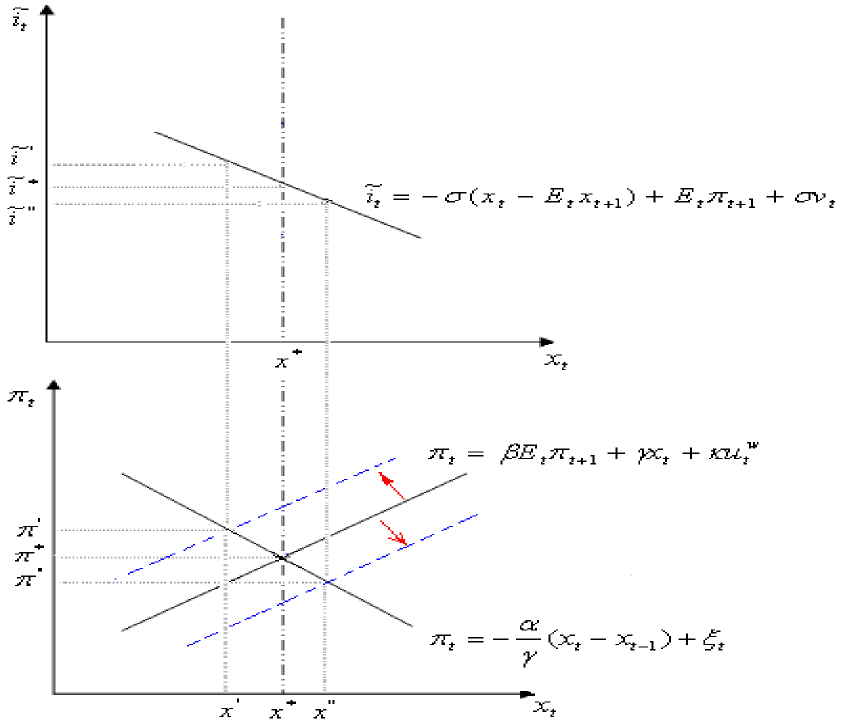
To understand this recursiveness, recall that pursuing the optimal timeless policy [3.3] requires keeping inflation equal to a fixed fraction of the first difference of the output gap. In effect, such a policy constitutes a simultaneous pair with the Phillips curve in the model that pins down the equilibrium output gap and inflation; in the optimal timeless rule inflation responds to the first difference in the output gap, while in the Phillips curve something close to the first difference of future inflation is negatively related to the level of the output gap. Given that both inflation and the output gap are highly autoregressive both because of the errors and the model dynamics, these first differences will be rather small; hence in the Phillips curve the level of the output gap will largely be set by the equation (supply) error, while in the inflation rule the level of inflation will largely be set by that equation's (trembling hand) policy error. If we now turn to the IS curve, with inflation and the output gap already set, the equilibrium interest rate is then recursively set in its turn by the IS curve alone. In other words, under the optimal policy any innovation to the demand side will be fully neutralized by the adjustment of the real interest rate, leaving the output gap and inflation unaffected. The real interest rate also responds to the expected change in output gap but this is small because of output gap autocorrelation. The nominal interest rate also responds to expected future inflation; but this is dominated by the policy error which dies away quickly and so moves little also. Hence the dominance of the demand shock on nominal interest rates; the supply shock intrudes more on interest rates in the Great Moderation period because it is less persistent and so the expected change in the output gap is larger, affecting the real interest rate more. This structure is illustrated in figure 4.2; derivations are shown in appendix B.

Figure 4.2: Workings of the Baseline Model in Face of Shocks

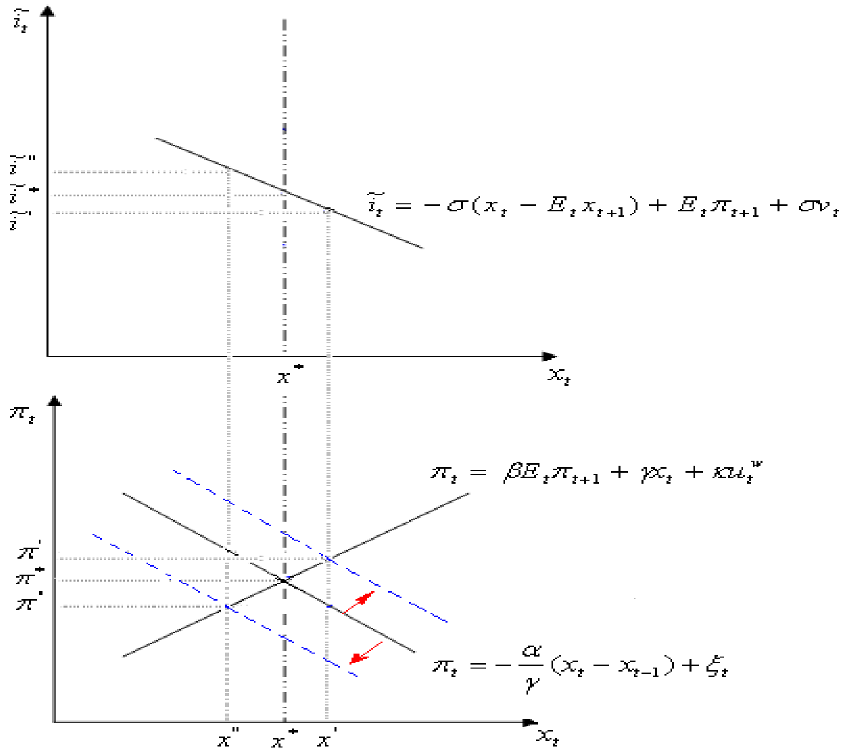
Panel A: When Demand Shocks Occur



Panel B: When Supply Shocks Occur



Panel C: When Policy Shocks Occur



To summarise, while a decline in the variances of all shocks brought about the switch from the Great Acceleration to the Great Moderation, our variance decomposition here shows that the relative impact of these shocks on the economy has been fairly similar over time, apart from an increase in the role of the supply shock in interest rates.

4.3. The 'Good Policy' Explanation of the Great Moderation: a Taylor Rule Illusion?

So far, it has been clear that our model with the optimal timeless rule can explain the Great Moderation, not by any change in the policy regime but rather purely through the changing variances of the shocks. How then can it be that economists have observed different Taylor rules across the two regimes and concluded from these that policy regime changes were at work? Our suggestion is that such apparent rules were statistically observable because produced by the behaviour of the economy in conjunction with the true (constant) monetary policy rule.

The typical 'good policy' explanation of the Moderation relies on evidence from an estimated Taylor rule that is presumed to describe the true behaviour of the Fed, and interprets the corresponding change of the rule parameters estimated with different subsamples as shifts in monetary policy. However, a Taylor-type relation between the data may well be representing something else implied by the true model where there is no structural Taylor rule at all—the identification problem as discussed in Minford, Perugini and Srinivasan (2001, 2002) and Cochrane (2007). Such changing Taylor rule estimates could be an illusion arising from alterations in statistical relationships within the data driven by the true, unchanged policy.

We can test for this within our model using the method of indirect inference. We can evaluate the model's capacity to generate the Taylor-type relations that we might observe in the data[21]. Table 4.9 below shows several variants of the Taylor rule that the data may display before and after the break based on OLS and the extent to which these can be explained by our model:

To compare the regression results we find in the data with those commonly found in the US Taylor rule literature we must emphasise that for the post-82 subsample a linear trend is taken out of the interest rate series to ensure stationarity. When estimated on the stationary data we have used here, the Taylor rules obtained generally fail to satisfy the Taylor Principle, in much the same way as those pre-1982. Thus econometrically the standard estimates of the long-run Taylor rule response to inflation post-1982 are biased upwards. There is little statistical difference in the data of the two periods for estimated Taylor rule long-run responses to inflation. Table 4.9 shows that this is exactly what our model of Fed behaviour implies.

Table 4.9: 'Taylor Rules' Shown by Real Data (with OLS)
and Explanatory Power of the Targeting rule model

Panel A: 'Taylor rules' in the Great Acceleration

Taylor rule estimated	γ_π	γ_x	ρ	Adjusted R^2	Wald statistic
$\tilde{i}_t = \gamma_\pi \pi_t + \gamma_x x_t + \rho \tilde{i}_{t-1} + \xi_t$	0.09	0.06	0.90	0.84	97.2%
$\tilde{i}_t = \gamma_\pi \pi_t + \gamma_x x_t + \xi_t$ $\xi_t = \rho_\xi \xi_{t-1} + \varepsilon_t$	0.30	0.07	0.92	0.85	96.7%
$\tilde{i}_t = \gamma_\pi \pi_{t-1} + \gamma_x x_{t-1} + \xi_t$	0.60	-0.01	N/A	0.24	36.1%
$\tilde{i}_t = \rho \tilde{i}_{t-1} + \gamma_\pi \pi_{t-1} + \gamma_x x_{t-1} + \xi_t$	-0.11	0.06	0.82	0.83	65.6%

[21] In terms of the methodology, this involves treating, in each case, the 'Taylor rule' specified as the auxiliary model and its corresponding rule parameters estimated with real data as the 'reality'.

Panel B: 'Taylor rules' in the Great Moderation

Taylor rule estimated	γ_π	γ_x	ρ	Adjusted R^2	Wald statistic
$\tilde{i}_t = \gamma_\pi \pi_t + \gamma_x x_t + \rho \tilde{i}_{t-1} + \xi_t$	0.08	0.05	0.89	0.92	21.7%
$\tilde{i}_t = \gamma_\pi \pi_t + \gamma_x x_t + \xi_t$ $\xi_t = \rho_\xi \xi_{t-1} + \varepsilon_t$	0.07	0.06	0.93	0.90	47.4%
$\tilde{i}_t = \gamma_\pi \pi_{t-1} + \gamma_x x_{t-1} + \xi_t$	0.26	0.13	N/A	0.24	10.9%
$\tilde{i}_t = \rho \tilde{i}_{t-1} + \gamma_\pi \pi_{t-1} + \gamma_x x_{t-1} + \xi_t$	0.03	0.04	0.89	0.91	85%

In both subsamples (panel A and panel B, respectively) the four hypothetical Taylor rules estimated with the actual data are all explained by the targeting rule model, as indicated by the Wald statistics, at varying confidence levels. In other words, in both episodes if our DSGE model is the true data-generating mechanism we would find such relationships in the data exactly as the data says we do.

Our conclusion from this last exercise is first that econometrically Taylor rules changed little between the two episodes once non-stationarity is allowed for; second, that the Taylor rules found in the data could have been generated by the completely different monetary rule, the timeless optimum, that we found fits the data in general.

5. Conclusion

In this paper we have attempted a fresh investigation of the reason for the shift to the US Great Moderation from its predecessor period, the Great Acceleration. The conventional DSGE approach to these episodes starts with a New Keynesian model including a standard Taylor rule where the level of interest rates responds to inflation; the output gap may also enter, and so may the lagged interest rate as a smoothing mechanism. It goes on to claim that the shift was the result of improved policy in the form of higher Taylor rule responses to inflation. We challenge this view, as we find that the Fed's policy is better understood as following an identical optimal timeless rule in both episodes. From this it follows that the Great Moderation was due to much reduced volatility of shocks.

Our findings are based on the method of indirect inference in which we compare the simulated behaviour from the DSGE model with a VAR estimated on the actual data. The standard New Keynesian model with this optimal timeless rule instead of the Taylor rule explains the dynamics and volatility of US economy both before and after 1982. It also explains the existence of Taylor rule regressions found in the data, and how the illusion of a regime switch could arise statistically.

Turning to the policy interpretation of our work, we argue that in that it followed the optimal timeless rule the Fed did a good job during the Great Acceleration of dealing with the sizeable demand and supply shocks which occurred after 1972. These shocks had much lower variances after 1982—a key cause of the Great Moderation. However the fall in the variance of the monetary policy shock between the two episodes also suggests that the Fed's performance improved substantially. So in our account the Great Moderation in output and interest rates was due to luck but the Great Moderation in inflation was due to better monetary management.

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Appendix:

A. Tables and Figures

Table A.1: Qu-Perron Test for Structural Break

Estimated break date	95% confidence interval lower	upper	supLR test statistic for a fixed number of breaks	5% critical value
1984Q3	1980Q1	1984Q4	164.84	31.85

Note: 1. Time series model: VAR(1) (without constant).
2. H_0: there is no structural break; H_1: there is one structural break.
3. Observation sample (adjusted): 1972Q2—2007Q4.

Table A.2: Unit Root Tests for Stationarity

Panel A: The Acceleration Subsample

Time series	5% critical value	10% critical value	ADF test statistics	p-values*
$\tilde{i}_t$	-1.95	-1.61	-1.71	0.0818
x_t	-1.95	-1.61	-1.67	0.0901
π_t	-1.95	-1.61	-2.86	0.0053

Note: 1. $\tilde{i}_t$ ≡deviation of quarterly Fed rate from its steady-state value; x_t ≡log difference of quarterly real GDP from its HP trend; π_t ≡quarterly CPI inflation.
2. '*' denotes the Mackinnon (1996) one-sided p-values.
3. H_0: the time series has a unit root.
4. Observation sample (adjusted): 1972Q3—1982Q3.

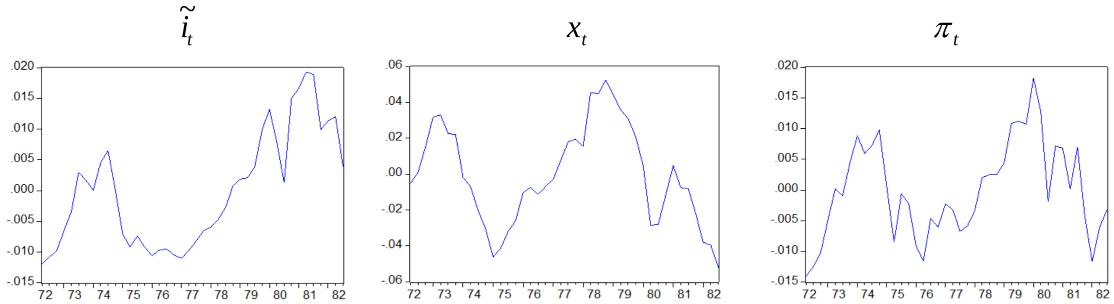
Panel B: The Moderation Subsample

Time series	5% critical value	10% critical value	ADF test statistics	p-values*
$\tilde{i}_t$	-1.94	-1.61	-2.91	0.0040
x_t	-1.94	-1.61	-4.42	0.0000
π_t	-1.94	-1.61	-3.34	0.0010

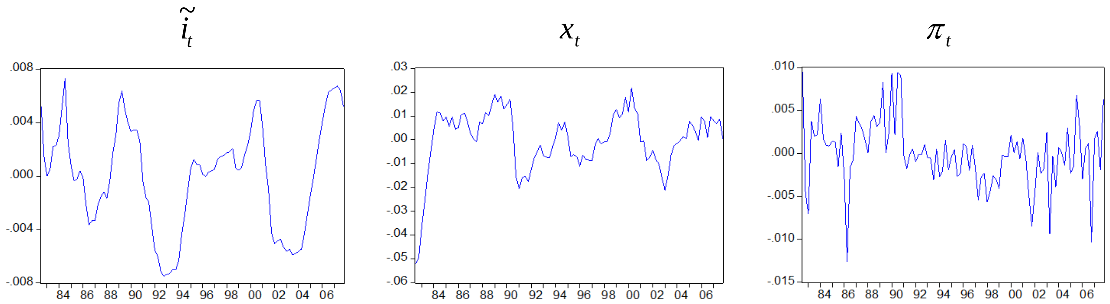
Note: 1. $\tilde{i}_t$ ≡deviation of quarterly Fed rate from its steady-state value; x_t ≡log difference of quarterly real GDP from its HP trend; π_t ≡quarterly CPI inflation.
2. '*' denotes the Mackinnon (1996) one-sided p-values.
3. H_0: the time series has a unit root.
4. Observation sample (adjusted): 1982Q4—2007Q4.

Figure A.1: Time Paths of the Involved Variables
(Demeaned, Detrended Data)

Panel A: The Acceleration Subsample (1997Q2-1982Q3)



Panel B: The Moderation Subsample (1982Q3-2007Q4)



Note: $\tilde{i}_t$ $\equiv$ deviation of quarterly Fed rate from its steady-state value; x_t $\equiv$ log difference of quarterly real GDP from its HP trend; π_t $\equiv$ quarterly CPI inflation.

B. Analytical Derivation of responses to shocks

a. Impulse response of inflation to shocks:

Given rational expectations and equations:

$$\pi_t = \beta E_t \pi_{t+1} + \gamma x_t + \kappa u_t^w \qquad [3.2]$$

$$\pi_t = -\frac{\alpha}{\gamma}(x_t - x_{t-1}) + \xi_t \qquad [3.3]$$

Rewrite [3.2] as:

$$x_t = \frac{(1-\beta B^{-1})\pi_t - \kappa u_t^w}{\gamma} \qquad ①$$

Also, write [3.3] as:

$$x_t = \frac{(\pi_t - \xi_t)\gamma}{(L-1)\alpha} \qquad ②$$

Equate ① to ② such that:

$$\frac{(1-\beta B^{-1})\pi_t - \kappa u_t^w}{\gamma} = \frac{(\pi_t - \xi_t)\gamma}{(L-1)\alpha} \qquad ③$$

Solve for π_t from ③ to obtain:

$$\pi_t = \frac{\gamma^2\alpha^{-1}\xi_t + \kappa u_t^w - \kappa u_{t-1}^w}{(1-L)[1-\beta B^{-1} + \gamma^2\alpha^{-1}(1-L)^{-1}]} \qquad ④$$

Now note that the supply error has a high autocorrelation so that the terms in it nearly cancel, while also the coefficient on it (kappa) is small, leaving the policy error as the dominant factor in inflation.

b. Impulse response of output gap to shocks:

Given rational expectations and equations:

$$\pi_t = \beta E_t \pi_{t+1} + \gamma x_t + \kappa u_t^w \qquad [3.2]$$

$$\pi_t = -\frac{\alpha}{\gamma}(x_t - x_{t-1}) + \xi_t \qquad [3.3]$$

Rewrite [3.2] as:

$$\pi_t = \frac{\gamma x_t + \kappa u_t^w}{1-\beta B^{-1}} \qquad ①'$$

Put ①' into [3.3] to obtain:

$$x_t = \frac{(1-\beta B^{-1})\xi_t - \kappa u_t^w}{\gamma + (1-\beta B^{-1})\frac{\alpha}{\gamma}(1-L)} \qquad ②'$$

Since $\xi_t = \rho_\xi \xi_{t-1} + \varepsilon_t^\xi$, the term in the policy error is small and as the standard deviation of the supply error is also massively larger than that of the policy error, this supply error then dominates the output gap.

c. Impulse response of interest rate to shocks:

Given 'IS' curve:

$$x_t = E_t x_{t+1} - (\frac{1}{\sigma})(\tilde{i}_t - E_t \pi_{t+1}) + v_t \qquad [3.1]$$

Rewrite [3.1] as:

$$\tilde{i}_t = \sigma(E_t x_{t+1} - x_t) + E_t \pi_{t+1} + \sigma v_t \qquad ①''$$

Now lead the targeting rule [3.3] for one period and take expectation at t to get:

$$E_t \pi_{t+1} = -\frac{\alpha}{\gamma}(E_t x_{t+1} - x_t) + E_t \xi_{t+1} \qquad ②''$$

Substitute ②'' into ①'' to obtain:

$$\tilde{i}_t = (\sigma - \frac{\alpha}{\gamma})(E_t x_{t+1} - x_t) + E_t \xi_{t+1} + \sigma v_t \qquad ③''$$

Since $\xi_t = \rho_\xi \xi_{t-1} + \varepsilon_t^\xi$ and therefore $E_t \xi_{t+1} = \rho_\xi \xi_t$, the above equals:

$$\tilde{i}_t = (\sigma - \frac{\alpha}{\gamma})(E_t x_{t+1} - x_t) + \rho_\xi \xi_t + \sigma v_t \qquad ④''$$

Note the expected change in output gap dominated by the supply error is small due to high autocorrelation, the standard deviation of demand error is some three times that of the policy error and σ is large, this demand error then dominates the interest rate.