STOCHASTIC VOLATILITY, FINANCIAL FRICTIONS, AND THE GREAT MODERATION

by

CHARLES RICHARD HIGGINS

A DISSERTATION

Presented to the Department of Economics
and the Graduate School of the University of Oregon
in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy

June 2014

DISSERTATION APPROVAL PAGE

Student: Charles Richard Higgins

Title: Stochastic Volatility, Financial Frictions, and the Great Moderation

This dissertation has been accepted and approved in partial fulfillment of the requirements for the Doctor of Philosophy degree in the Department of Economics by:

Mark Thoma	Chair
Bruce McGough	Core Member
Jeremy Piger	Core Member
Christopher Sinclair	Institutional Representative

and

Kimberly Andrews Espy	Vice President for Research & Innovation/ Dean of the Graduate School

Original approval signatures are on file with the University of Oregon Graduate School.

Degree awarded June 2014

DISSERTATION ABSTRACT

Charles Richard Higgins

Doctor of Philosophy

Department of Economics

June 2014

Title: Stochastic Volatility, Financial Frictions, and the Great Moderation

This dissertation examines changing macroeconomic volatility and some of the empirical difficulties associated with studying volatility. Macroeconomic volatility can potentially have large welfare costs, so understanding why volatility changes over time is important. A natural setting to study changing macroeconomic volatility is the Great Moderation, a period of reduced volatility in the United States. This dissertation studies this time period in two ways. First, it explores the importance of specification when estimating models during this time period. Second, it looks at the role financial frictions, monetary policy, and luck played in causing the Great Moderation. Large, structural models are estimated to study these problems. One of the main findings from the dissertation is that changing financial frictions were an important factor in reducing macroeconomic volatility during the Great Moderation.

CURRICULUM VITAE

NAME OF AUTHOR: Charles Richard Higgins

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:
University of Oregon, Eugene, OR
The Pennsylvania State University, University Park, PA

DEGREES AWARDED:
Doctor of Philosophy, Economics, 2014, University of Oregon
Bachelor of Science, Actuarial Science, 2007, The Pennsylvania State University

AREAS OF SPECIAL INTEREST:
Macroeconomics and Econometrics

ACKNOWLEDGEMENTS

I would like to thank my advisors, Mark Thoma, Jeremy Piger and Bruce McGough, for their guidance and support throughout my graduate study. I would also like to thank the members of the University of Oregon Macro Group for giving me the opportunity to present my research and for providing invaluable feedback. This research was supported by a Major Research Instrumentation grant from the National Science Foundation, Office of Cyber Infrastructure, "MRI-R2: Acquisition of an Applied Computational Instrument for Scientific Synthesis (ACISS)," Grant #: OCI-0960354.

To Brittany, for all the support and encouragement throughout this process.

TABLE OF CONTENTS

Chapter Page

LIST OF FIGURES

Figure Page

Figure Page

LIST OF TABLES

Table Page

CHAPTER I

INTRODUCTION

One of the biggest unsolved problems in macroeconomics is what caused the decline in macroeconomic volatility known as the Great Moderation. This dissertation studies the causes of changing macroeconomic volatility and examines some of the empirical difficulties of doing this. The second chapter examines some of the empirical pitfalls when studying changing macroeconomic volatility, specifically looking at the dangers of misspecification. The third and fourth chapters study the role of changing financial frictions in explaining the Great Moderation.

The second chapter is titled "Jumping or Drifting in the Great Moderation: A Comparison of Parameter Drifting and Regime Switching in DSGE Models." This chapter explores the importance of the specification of DSGE models used to analyze the Great Moderation. Specifically, it studies the importance of correctly specifying Taylor rule monetary policy parameters as discretely changing or drifting over time. Using parameter drifting and stochastic volatility, Fernández-Villaverde, Guerrón-Quintana, and Rubio-Ramírez (2010) show that the Great Moderation appears to be mostly caused by good luck, with less volatile shocks, rather than by changing monetary policy. This chapter analyzes whether there are concerns about using parameter drift in a model where instead there are discrete jumps in monetary policy parameters. In this chapter, I simulate a DSGE model with regime switches (and constant variance shocks) and then estimate the simulated data with a model that has parameter drifting and stochastic volatility. I find little support for the variance of shocks changing over time, but stochastic volatility does greatly improve model fit. This suggests that researchers need to study more than model fit to make conclusions when using models with stochastic volatility.

The third chapter is titled "Financial Frictions and Macroeconomic Volatility." In this chapter, a medium scale dynamic stochastic general equilibrium (DSGE) model with financial frictions is augmented with parameter drift and stochastic volatility. This model is estimated using Bayesian techniques and the particle filter to study the causes of the Great Moderation, a period of reduced macroeconomic volatility observed in the U.S. economy from 1984 to 2007. During this time period, I find that financial frictions declined. While the model finds evidence of stochastic volatility and changing monetary policy, the results indicate that the change in financial frictions was the main driver of the Great Moderation.

The fourth chapter is titled ”Changing Macroeconmic Volatility in a New Keynesian Model with Financial Frictions.” In this chapter, a New Keynesian Model with financial frictions is augmented with parameter drift and stochastic volatility. This model is estimated and used to study the causes of the Great Moderation. The model finds evidence of stochastic volatility and a decrease in financial frictions, but does not find support for changes in monetary policy. Based on counterfactual studies, the reduction in financial frictions was an important reason for the reduction in volatility observed during the Great Moderation. It also appears that good luck was a factor in reducing consumption volatility during the Great Moderation.

CHAPTER II

JUMPING OR DRIFTING IN THE GREAT MODERATION: A COMPARISON OF PARAMETER DRIFTING AND REGIME SWITCHING IN DSGE MODELS

Introduction

Understanding the causes of changing macroeconomic volatility is a widely studied and much debated topic, with special emphasis placed on the role monetary policy plays. This paper explores some of the empirical difficulties that occur when studying macroeconomic volatility. Specifically, I analyze whether model misspecification can lead to misinterpreting changes in volatility due to changing monetary policy as being caused by changes in the nature of shocks. To do this, I simulate data from a DSGE model with constant variance shocks and regime switches in the Taylor rule coefficients. I then use the simulated data to estimate two models that have Taylor rules with parameter drifting. One model has stochastic volatility and the other does not. The estimation results are then compared to determine how much of the model misspecification is showing up as changing volatility of shocks.

There has been much debate not only over the causes of volatility changes and the causes of the Great Moderation, but also the empirical techniques used in analyzing the causes. Some research, including Sims and Zha (2006) and McConnell and Perez-Quiros (2000), point to good luck from changes in the structure of shocks as the cause of the Great Moderation. While other research, including Clarida, Galí, and Gertler (1999), argues that good monetary policy should be credited for the moderation. Despite extensive research on the topic, it remains unclear which theory is more valid.[1]

Much of the early research was done using vector autoregressions (VAR). However, Benati and Surico (2009) show that using a VAR in the analysis could lead to incorrect conclusions about the causes of the Great Moderation. They argue that when using a VAR for analysis, changes caused by variations in monetary policy might be incorrectly attributed to variation in the magnitude of structural shocks, even when the variability of the structural shocks did not

[1] Other explanations have been studied, but these are the two main areas of research. For example, some have studied improvements in inventory management cuased by changes in information technology (McConnell and Perez-Quiros, 2000) and others have studied financial innovation (Dynan, Elmendorf, and Sichel, 2006)

change. Due to these findings, recent research uses DSGE models in order to properly identify the causes of the Great Moderation.

Estimating DSGE models to analyze the Great Moderation and changing macroeconomic volatility is not without faults. Due to the size and complexity of some DSGE models, there are limitations to how these models can be estimated. One way to estimate changes in policy and the variance of shocks is to estimate a DSGE model with regime switches in the variance of structural shocks and/or monetary policy rules.[2] However, due to technical limitations, only simple regime switching models can be estimated. Another option is to use models with parameter drifting. This has been done recently in Fernández-Villaverde et al. (2010) where the Taylor rule parameters are allowed to drift and there is stochastic volatility.[3] The models differ in their interpretation of how monetary policy changes over time. If policy changes occur smoothly over time, then a parameter drifting model may be more accurate. However, if policy does in fact change discretely, then regime switching models are more appropriate.[4]

Some studies on the Great Moderation use models with regime switching to analyze changes in policy or changes in the variance of shocks. For example, Sims and Zha (2006) analyze regime switching in a VAR. Liu, Waggoner and Zha (2010) analyze regime switching in a medium-scale DSGE model, but changes in the interest rate rule are in the form of changing inflation targets instead of changes in Taylor rule parameters. While the targets might have changed, changes in the Taylor rule parameters could be more relevant in the good policy versus good luck debate about the Great Moderation. Davig and Doh (2009) estimate a medium-scale DSGE model with markov-switching in the policy coefficient, but their model is log-linearized. However, in order to pick up the effects of policy change on variances in DSGE models, higher-order approximations must be used as shown by Schmitt-Grohe and Uribe (2004). To avoid these critiques I will use a second-order approximation when estimating the DSGE model.

Research also focuses on models with policy parameters and volatility that change smoothly over time. Fernández-Villaverde et al. (2010) use a medium-scale DSGE model with both stochastic volatility and parameter drifting in the Taylor rule. They find overwhelming evidence of

[2] Examples are Bianchi (2009) and Farmer, Waggoner, and Zha (2009).

[3] In models with stochastic volatility, the variance of the structural shocks exogenously drift over time.

[4] Either type of model may better portray the true state of the world since the actual monetary policies used are not known.

parameter drift in the Taylor rule, but find that changes in the variance of the underlying shocks can account for most of the reduction in volatility found during the Great Moderation. While there does appear to be drift in the Taylor rule, there also appear to be regime changes. Based on Figure 9.5 in Fernández-Villaverde et al. (2010), there appear to be regime changes that coincide with changes in leadership of the Federal Reserve. If there are indeed regime switches, there should be a discrete jump in the Taylor rule coefficients. If in the time around the jump in the Taylor rule the model is estimated to have smooth changes, then changes in volatility could very well be attributed to stochastic volatility instead of policy changes (even if the structural shocks actually have constant variances). This might lead to an improper interpretation that changes in volatility are due to good luck when it is actually due to good policy.

Since only small regime switching DSGE models have been estimated, it is important to know how well models with parameter drifting perform if misspecified, which is what I analyze in this paper. This is very important if policy does in fact change discretely, which is reasonable since Federal Reserve leadership changes discretely; therefore it is unclear how well a DSGE model with parameter drifting will pick up the change in policy. To perform this analysis I first simulate data from a New Keynesian model with regime switches in the Taylor coefficients and constant variance shocks. I use a simple model along the lines of Lubik and Schorfheide (2004) and I use their results to calibrate the model. Regime switching in the Taylor coefficients are added to the model. Then, I use the simulated data to estimate a model featuring parameter drift in the monetary policy coefficients and stochastic volatility. I then compare these results with estimates from a model with parameter drift in the Taylor coefficients and constant variance shocks.

While the parameter drifting does a reasonable job of fitting changes in monetary policy, I find evidence of changes in stochastic volatility in the estimated models. Adding stochastic volatility to the model can greatly improve model fit which is concerning, since flat priors are used for the stochastic volatility terms, which should put downward pressure on the marginal likelihood. This should give researchers pause when estimating DSGE models with stochastic volatility and parameter drifting. Great care must be used to ease concerns that there are indeed changes in the variance of innovations, instead of the estimated changes being due to model misspecification. Since this specification is the best that can be feasibly estimated with current technical limitations, more work must be done to check the importance of stochastic volatility beyond looking at marginal likelihoods. One way to study this is to look at the underlying states. Based on the underlying states in this study, there do not appear to be any discernible patterns to the standard deviation of the underlying shocks, and none of the movements appear to be significant. Therefore, it does not appear that the misspecification will hurt efforts to study changes in monetary policy rules. This should give researchers confidence in these models, but the findings of this chapter should be taken into consideration when interpreting the results of similar models.

The rest of the paper is organized as follows. Section 2 presents the model used to generate the data and the two models that are used to estimate the generated data. Section 3 explains how the data was generated and discusses some of the features of the generated data. Section 4 presents the estimation methodology and describes how the likelihood is approximated. Section 5 presents and analyzes the estimation results. Section 6 provides some concluding remarks.

Models

Three models are needed to analyze the misspecification of a regime switching model by estimating a model with parameter drift and stochastic volatility. The first model is one with regime switching that can be used to generate the artificial data. In this model, monetary policy parameters change discretely and the shocks have constant variances. Using the generated data, I estimate a model with a policy rule allowing for drifting parameters and stochastic volatility. For comparison, a model with parameter drift in the monetary policy rule, but without stochastic volatility is estimated as well. All three of these models are based on the simple New Keynesian style model from Lubik and Schorfheide (2004). These models are described in more detail below.

Regime Switching Model

To simulate a case where Federal Reserve policy changes discretely, a model with regime switching is a natural fit. In this model the two parameters that represent the Fed's reaction to inflation and the output fluctuations are allowed to discretely change. All other parameters are held constant. The model is based on a standard, simple New-Keynesian Model that has already been log-linearized. Since a log-linearized model is used as a basis for the model, the only nonlinearities in the model arise from changes in monetary policy.[5] The model is summarized by

$$X_t = E_t X_{t+1} - \tau(R_t - E_t \Pi_{t+1}) + g_t \tag{2.1}$$

$$\Pi_t = \beta E_t \Pi_{t+1} + \kappa(X_t - z_t) \tag{2.2}$$

$$R_t = \rho_R R_{t-1} + (1 - \rho_R)(\psi_{1,t}\Pi_t + \psi_{2,t}(x_t - z_t)) + \sigma_R \varepsilon_{R,t} \tag{2.3}$$

X, Π and R represent output, inflation and the nominal interest rate respectively.[6] ε_R is an i.i.d. standard normal shock. This model deviates from Lubik and Schorfheide (2004) by how ψ_1, the central bank's response to inflation fluctuations, and ψ_2, the central bank's response to output fluctuations, change over time. These two parameters are defined as

$$\psi_1 = \begin{cases} \alpha_1 & \text{if } s_t = 1 \\ \alpha_2 & \text{if } s_t = 2 \end{cases}$$

$$\psi_2 = \begin{cases} \iota_1 & \text{if } s_t = 1 \\ \iota_2 & \text{if } s_t = 2. \end{cases}$$

The variable s_t represents the state of the economy. When the state of the economy changes, the monetary policy rules discretely change. If the state is unchanged, then the policy rules are also unchanged. The state follows a Markov switching process with the following transition matrix

$$P = \begin{pmatrix} p_{1,1} & p_{1,2} \\ p_{2,1} & p_{2,2} \end{pmatrix}$$

where $p_{i,j} = Prob(s_{t+1} = j | s_t = i)$.

The economy is completed by two univariate AR(1) processes, one for government spending, g, which can be thought of as a demand shock, and a supply shock, z. These processes

[5] Since a first-order approximation is used in the model simulation, this should not change the data simulation.

[6] Lubik and Schorfheide (2004) define these as percentage deviations from the steady state or trend path in the case of output. Therefore, the generated data should be interpreted as percentage deviations from a steady state or trend.

are defined as

$$g_t = \rho_g g_{t-1} + \sigma_g \varepsilon_{g,t} \tag{2.4}$$

$$z_t = \rho_z z_{t-1} + \sigma_z \varepsilon_{z,t}. \tag{2.5}$$

The innovations to these shocks, ε_g and ε_z, are i.i.d. normal mean zero shocks with standard deviations of one. Note that σ_g and σ_z, the standard deviations of the innovations to the shocks, as well as σ_R are all constant.

Model with Parameter Drift and Stochastic Volatility

The data generated from the regime switching model is estimated by a model with stochastic volatility and parameter drift in the monetary policy rule. This model is designed to be similar to the regime switching model while incorporating the parameter drifting and stochastic volatility. The equations for inflation and output are identical to 2.1 and 2.2. Equations 2.3 to 2.5 are modified to incorporate parameter drift and stochastic volatility, and are defined as

$$R_t = \rho_R R_{t-1} + (1-\rho_R)(\psi_{1,t}\Pi_t + \psi_{2,t}(x_t - z_t)) + \sigma_{R,t}\varepsilon_{R,t} \tag{2.6}$$

$$g_t = \rho_g g_{t-1} + \sigma_{g,t}\varepsilon_{g,t} \tag{2.7}$$

$$z_t = \rho_z z_{t-1} + \sigma_{z,t}\varepsilon_{z,t}. \tag{2.8}$$

The logged standard deviations of the shocks follow an AR(1) process defined by

$$\log(\sigma_{R,t}) = \rho_{\sigma_R}\log(\sigma_{R,t-1}) + (1-\rho_{\sigma_R})\log(\sigma_R) + \eta_R u_{R,t} \tag{2.9}$$

$$\log(\sigma_{g,t}) = \rho_{\sigma_g}\log(\sigma_{g,t-1}) + (1-\rho_{\sigma_g})\log(\sigma_g) + \eta_g u_{g,t} \tag{2.10}$$

$$\log(\sigma_{z,t}) = \rho_{\sigma_z}\log(\sigma_{z,t-1}) + (1-\rho_{\sigma_z})\log(\sigma_z) + \eta_z u_{z,t}. \tag{2.11}$$

Instead of discretely changing as in the regime switching model, the coefficients in the monetary policy rule are allowed to drift. The processes for the policy rules are defined by

$$\log(\psi_{1,t}) = \rho_{\psi_1} \log(\psi_{1,t-1}) + (1 - \rho_{\psi_1}) \log(\psi_1) + \eta_{\psi 1} u_{\psi_1,t} \tag{2.12}$$

$$\log(\psi_{2,t}) = \rho_{\psi_2} \log(\psi_{2,t-1}) + (1 - \rho_{\psi_2}) \log(\psi_2) + \eta_{\psi 2} u_{\psi_2,t}. \tag{2.13}$$

All shocks, which are labeled as ε and u, are i.i.d. N(0,1) shocks. All nonlinearities in the model arise from parameter drifting and stochastic volatility. While this may not completely mimic real world applications, it does match the nature of the data generating process of the simulated data.

Model with Parameter Drift and Constant Variance Shocks

In order to consider the importance of stochastic volatility when the model is estimated using parameter drifting in the policy coefficients, I must also estimate a model with parameter drift and constant variance shocks. This model is a nested version of the model in subsection 2.2, which simplifies down to the following processes:

$$X_t = E_t X_{t+1} - \tau(R_t - E_t \Pi_{t+1}) + g_t \tag{2.14}$$

$$\Pi_t = \beta E_t \Pi_{t+1} + \kappa(X_t - z_t) \tag{2.15}$$

$$R_t = \rho_R R_{t-1} + (1 - \rho_R)(\psi_{1,t} \Pi_t + \psi_{2,t}(x_t - z_t)) + \sigma_R \varepsilon_{R,t} \tag{2.16}$$

$$g_t = \rho_g g_{t-1} + \sigma_g \varepsilon_{g,t} \tag{2.17}$$

$$z_t = \rho_z z_{t-1} + \sigma_z \varepsilon_{z,t}. \tag{2.18}$$

Where the shocks are distributed i.i.d. N(0,1). The monetary policy parameters, ψ_1 and ψ_2, follow the same process as in equations 2.12 and 2.13.

Data

The data used in this analysis is artificial data generated from the models described above. The models are calibrated using the results from Lubik and Schorfheide (2004). Data is generated from two different specifications of the regime switching model as well as a specification of the model with parameter drift and stochastic volatility. Data is also generated from a model with parameter drift and constant variance shocks, which is the same model as the one used for the estimation. For each model, 12 sets of data are generated for 193 periods after an initial data generation of 10,000 periods is discarded for each set. The data mimics a quarterly sample of data from 1959:Q1 to 2007:Q1, which is a standard set of data to use when analyzing the great moderation.[7] From the generated data, it is assumed that only R, Π and X are observed, which is a reasonable assumption based on real data that is actually available for estimation.

Regime Switching Models

There are two types of regime switching models used to generate data, one model is forced to have one regime change while the other allows for multiple regime changes. Both models use the calibration found in Table 1. In the data with only one change, hereafter referred to as the baseline data, $p_{1,1}$ and $p_{2,2}$ are both set to 0.99. In the alternative regime switching data, $p_{1,1}$ and $p_{2,2}$ are both set to 0.9 and regimes are allowed to freely change at those probabilities. For the baseline data, there is a regime change in the 101st period, which would correspond to 1984:Q1, roughly the start of the Great Moderation, from the state 1 to 2. This corresponds to the Federal Reserve running a policy where $\psi_1 = 0.89$ and $\psi_2 = 0.15$ prior to 1984.[8] Then, in 1984 the Fed switches to a more active policy where $\psi_1 = 2.19$ and $\psi_2 = 0.3$ in all later periods, which is in line with the results from Lubik and Schorfheide (2004). In the alternative regime switching data, there are an average of 17.25 regime changes in each data set.

TABLE 1. Calibration Values for Regime Switching Model

	Value		Value
τ	0.5	ρ_R	0.65
β	0.99	ρ_g	0.81
κ	0.66	ρ_z	0.76
α_1	0.89	σ_R	0.2
α_2	2.19	σ_g	0.2
ι_1	0.15	σ_z	0.8
ι_2	0.3		

[7]This is the time period used in Fernández-Villaverde et al. (2010) which is closest to the type of model I'm studying.

[8]While a coefficient of 0.89 usually implies the possibility of sunspot equilibria, this is not necessarily the case for a model with regime switching. As long as there is the chance that policy will switch to a more active policy in the future, the model may not suffer from indeterminacy.

To generate the data from the regime switching models, the model must first be approximated. A first-order approximation is done using the techniques developed in Foerster, Rubio-Ramírez, Waggoner, and Zha (2011).[9] Each calibration described above has a unique, non-explosive solution around the steady-state. To determine this, mean square stability (MSS), which determines whether a solution is stable or not, is used. Since in both cases, only one solution satisfies the MSS criterion, the model has a unique, stable first-order approximation as explained in Foerster et al. (2011).

The generated baseline data shows decreasing volatility of inflation following the switch from passive to active monetary policy. Across the 12 simulated data sets,the average standard deviation of inflation decreases from 1.43% down to 0.6% which is a 58% drop. The average standard deviation of output decreased by 1.3% from 1.01% to 1%. The changes in standard deviations are in line with the changes experienced during the Great Moderation.[10] The standard deviation of inflation from 1959:Q1-1983:Q4 decreases by 52% from 0.95% to 0.47% for the data from 1984:Q1-2007:Q1. During the same time period, the standard deviation of output increased by 7%, increasing from 0.28% to 0.30%. While the simulated data does not perfectly match the actual data; overall, the volatility of the simulated data is comparable to the actual data and mimics the changes observed during the Great Moderation.

Parameter Drift Model and Constant Parameter Model

The parameter drift model with constant variance shocks described above is used to generate 12 sets of data. Another variation of this model, where the parameters are all held constant (ψ_1 and ψ_2 are both constant), is used to generate another 12 sets of data. Both specifications use calibrations similar to those found in Table 1. For the model with parameter drift, the coefficients on the terms controlling the drift process are set to $\rho_{\psi_1} = 0.95$, $\psi_1 = 1.5$, $\eta_{\psi 1} = 0.2$, $\rho_{\psi_2} = 0.95$, $\psi_2 = 0.2$, and $\eta_{\psi 1} = 0.2$. Both models are approximated using a second-order perturbation. The data is generated using the pruned state-space specification described in Andraesen, Fernández-Villaverde, and Rubio-Ramírez (2013).

[9]Unlike with a standard approximation, Foerster et al. (2011) show that models with regime switching do not face certainty equivalence with first-order approximations.

[10]As in Lubik and Schorfheide (2004), I use percent deviations of log Real GDP from its HP filtered trend for my measure of output. Inflation is defined as the percentage change of CPI from the year before. The raw data is retrieved from the FRED database and their codes are GDPC3 and CPIAUCSL.

Estimation Methodology

The models described in sections 2.2 and 2.2 are estimated using a Metropolis-Hastings Algorithm. There are two main problems that arise when estimating the model with stochastic volatility. First, there is not a simple closed form solution to these models so the solution must be approximated. Second, the model and its approximation are non-linear, so calculating the likelihood function, which is needed to get the posterior distribution, is not analytically possible. To overcome the first problem, I use a second-order approximation using perturbation methods.[11]. A second-order or higher approximation is needed to capture changes in the variance of shocks over time in the approximation, so a first-order approximation is not sufficient. The second-order approximation is an inherently non-linear approximation so the likelihood function cannot be directly calculated nor approximated with the Kalman Filter. Therefore, I use a particle filter along the lines of Fernández-Villaverde and Rubio-Ramírez (2007) to approximate the likelihood. This is then combined with a prior distribution to run a Metropolis-Hastings algorithm to estimate the posterior distribution. In the following paragraphs I will first briefly describe the estimation procedure and then explain how the likelihood is approximated.

Both models that are estimated can be generically rewritten in state space format as $Y_t = g(S_t)$ and $S_{t+1} = f(S_t, W_{t+1})$ with an Nx1 vector of coefficients θ. The posterior distribution of the coefficients can be estimated using a Metropolis-Hastings algorithm. First, a starting value $\theta^{[0]}$ is selected to initialize the algorithm. Next, a second-order approximation is done using perturbation methods, yielding $Y_t \approx G(S_t)$ and $S_{t+1} \approx F(S_t, W_{t+1})$. The likelihood function is then evaluated using a particle filter, which is described in more detail below. Then, a new θ is proposed based on random walk given by $\theta^* = \theta^{[0]} + \eta$. The increment random variable, η, is picked to be a multivariate normal distribution with mean 0_N and a variance that is selected to achieve an appropriate acceptance rate.[12] With the new proposal, θ^*, the model and likelihood are approximated. The likelihood is then combined with the prior, $p(\theta^*)$, in order to calculate the acceptance probability, $\alpha(\theta^{[0]}, \theta^*) = \min\left[\frac{p(\theta=\theta^*|Y)}{p(\theta=\theta^[g]|Y)}, 1\right]$. $\theta^{[1]}$ is set to θ^* with probability α and is

[11] Aruoba, Fernández-Villaverde, and Rubio-Ramírez (2006) show that perturbation methods are extremely fast and very accurate. For more information on the methodology, see Schmitt-Grohé and Uribe (2004) and Klein and Gomme (2011)

[12] Other distributions could be used, but the multivariate normal distribution was chosen for ease of computation.

set to $\theta^{[0]}$ with probability $1 - \alpha$. The algorithm then proceeds like this for 10,000 draws after a burn-in of 5,000 draws.[13]

Due to the nonlinearities of the approximation to the model, a particle filter is used to approximate the likelihood for each draw of θ. To set up the particle filter, I define a vector of observed variables $\tilde{O}_t$ for each time period, $t = 1, ..., T$, in the case of this model the observed data is defined as X_t, Π_t and R_t from from the generated data The observables are realizations of a measurement equation, $O_t = j\left(S_t, V_t|\theta\right)$, which includes a term for measurement error,V_t.[14] The underlying innovations, W_t are partitioned into two vectors, $W_{1,t}$ and $W_{2,t}$, such that $\dim\left(W_{2,t}\right) + \dim\left(V_t\right) \geq \dim\left(O_t\right)$, which is necessary for running the particle filter.

The particle filter uses a sequential Monte Carlo filter to approximate the likelihood, $p\left(\tilde{O}|\theta\right)$. To start, a large number of particles, P, and a large number of initialization periods, K, must be selected. For this analysis 10,000 particles were used. The particle filter follows the following steps:

1. Initialize the filter by setting all of the values of S equal to their steady state values. Use the approximated solution of the model to generate several periods, K, of data P times by drawing from the distribution of W. Store the K$^{\text{th}}$ period of generated data of S and K$^{\text{th}}$ period draws of W_1 for each of the the P particles and label these as $\{s^i_{0|0}, W^i_{0|0}\}^P_{i=1}$.
2. Set t=1.
3. Sample P values of $s^i_{t-1|t-1}$ and $s^i_{1,t-1|t-1}$ from $\{S^i_{t-1|t-1}, W^i_{1,t-1|t-1}\}^P_{i=1}$.
4. Generate P draws from the distribution of $W_{1,t}$ and $W_{2,t-1}$ and label these $\{w_{1,t}, w_{2,t-1}\}$.
5. Calculate P values of $\{s^i_t, w^i_{1,t}\}^P_{i=1}$ using the information from steps 3 and 4.
6. Calculate $\{w^i_{2,t}, v^i_t\}^P_{i=1}$ by comparing $G(s^i_t)$ to $\tilde{O}_t$.
7. Calculate the weights
$$q^i_t = \frac{p\left(w^i_{2,t}, v^i_t\right)}{\Sigma^P_{i=1} p\left(w^i_{2,t}, v^i_t\right)}.$$
8. Sample with replacement P values of $\{s^i_t, w^i_{1,t}\}$ using the weights given by q^i_1. Call these samples $\{S^i_{t|t}, W^i_{1,t|t}\}^P_{i=1}$.

[13] This is done with a starting value of θ that is picked from a grid search to find the maximum of the posterior pdf as has been done in other papers. For example, see Fernández-Villaverde et al. (2010).

[14] The inclusion of measurement error is not always necessary. In this chapter the model with stochastic volatility is estimated with and without measurement error.

9. If $t < T$, set $t \rightsquigarrow t+1$ and go to step 3. Otherwise, stop.

From this filtering process, the marginal likelihood can be approximated as

$$p(\tilde{O}|\theta) \approx \Pi_{t=1}^{T} \frac{1}{P} \Sigma_{i=1}^{N} p\left(w_{1,t}^{i}, v_{t}^{i}\right).$$

This marginal likelihood is then combined with the prior in order to run the Metropolis-Hastings algorithm.[15]

Estimation Results

In this section I will present the estimation results. First, I will discuss the priors and my reason for selecting the priors I chose. Second, I will present and analyze the parameter estimates by describing the posterior distributions. Third, I will present the data for the underlying states. Finally, I will compare the two models and see which model is preferred by the data.

Priors

The prior distributions for parameters were selected to mimic priors that have been used in previous research and to limit the parameters to areas of determinacy. In order to mimic standard research practices, I chose a uniform distribution for most parameters as can be seen below in Table 2. The priors for the model without stochastic volatility are the same as the model with stochastic volatility excluding the parameters the two models do not share. The parameters that are U(0,1) are constrained at 1 in order for there to be a steady state which is needed in order to use the perturbation approximation. The parameters set as U(0,3) are set to a disperse range that is large enough to hold any plausible values. The prior distribution of the variance of the measurement errors, σ_{γ_X}, σ_{γ_Π} and σ_{γ_R}, is a little less straight forward. Since measurement errors are difficult to identify, I placed a relatively tight prior distribution on these parameters. Overall, these priors play a rather small role in the estimation of the posterior distribution since most of the priors are flat. When comparing models, the use of flat priors does affect the analysis. The flat priors impose a penalty on the model with stochastic volatility. This makes it less likely that

[15] As recommended in Fernández-Villaverde and Rubio-Ramírez (2007), the random shocks differ by period but are the same in each respective period across draws in order to cut down on excess noise from random draws. This is not necessary, but it greatly increases the efficiency of the procedure.

the data prefers the model with stochastic volatility since it has more parameters and all the additional parameters have flat priors. However, the role the flat priors play is not too large since the priors are the same for all the parameters shared between the models.

TABLE 2. Priors

Parameter	Prior	Parameter	Prior
τ	U(0,1)	σ_g	U(0,4)
κ	U(0,1)	σ_z	U(0,4)
ρ_R	U(0,1)	η_R	U(0,4)
ρ_g	U(0,1)	η_g	U(0,4)
ρ_z	U(0,1)	η_z	U(0,4)
ρ_{ψ_1}	U(0,1)	ψ_1	U(1,4)
ρ_{ψ_2}	U(0,1)	ψ_2	U(0,2)
ρ_{σ_R}	U(0,1)	σ_{γ_X}	Gamma$(1,\frac{1}{200})$
ρ_{σ_g}	U(0,1)	σ_{γ_Π}	Gamma$(1,\frac{1}{200})$
ρ_{σ_z}	U(0,1)	σ_{γ_R}	Gamma$(1,\frac{1}{200})$
σ_R	U(0,4)		

Parameter Estimates

The full posterior estimates can be found in Tables A.3 to A.10 in Appendix A for all of the estimates for the stochastic volatility models without measurement error. Each of the estimations show strong persistence of the monetary policy parameters, as shown in Tables 3 to 6 which average across all data sets for each data type. Not surprisingly, the persistence is larger in the baseline specification of the regime switching model than in the other specifications. One thing that is surprising is the posterior mean persistence of the monetary policy parameters in the estimation of the drifting parameter data is much lower, $\rho_{\psi_1} = 0.78$ and $\rho_{\psi_1} = 0.52$, than the true values of the underlying data, where ρ_{ψ_1} and ρ_{ψ_2} both equal 0.95. For the data that was generated from the constant parameter data, the standard deviation of the shocks to ψ_1 are much smaller than in any other specification, which is a sign that the model may be accurately identifying the movements in the parameter. However, the standard deviation of the shocks to ψ_2 are similar throughout all models, so that may not be well identified.

In the baseline case, Table 3 shows that there is a relatively high level of persistence in the monetary policy rule on inflation as the mean of ρ_{ψ_1} is 0.83. This is not surprising since the probability of switching policy parameters is only 1% each period and the actual parameters only

TABLE 3. Posterior Mean for Baseline Regime Switching Data

ψ_1	ρ_{ψ_1}	η_{ψ_1}
1.89	0.83	0.54
ψ_2	ρ_{ψ_2}	η_{ψ_2}
0.22	0.54	0.27

TABLE 4. Posterior Mean for Alternative Regime Switching Data

ψ_1	ρ_{ψ_1}	η_{ψ_1}
1.46	0.58	0.34
ψ_2	ρ_{ψ_2}	η_{ψ_2}
0.22	0.59	0.20

change once. The steady states for the parameters are given by ψ_1 and ψ_2 which have means of 1.89 and 0.22 are similar to the true mean policy parameters for all periods which are 1.52 and 0.22. In the alternative specification, there is much less persistence in the inflation term, as the mean of ρ_{ψ_1} is 0.53, which is not surprising since there are several changes in the policy terms. In both specifications, there is estimated to be a relatively large degree of volatility as the standard deviations of the innovations to the policy parameter drifts are estimated to be well above 0. This is not surprising, as large standard deviations will allow the model to better pick up changes in policy parameters.

TABLE 5. Posterior Mean for Drifting Parameter Data

ψ_1	ρ_{ψ_1}	η_{ψ_1}
1.61	0.78	0.32
ψ_2	ρ_{ψ_2}	η_{ψ_2}
0.27	0.52	0.27

The coefficient estimates for the parameters driving the stochastic volatility processes show quite large variances, which can be seen in Tables 7 to 10. There is also a large degree of persistence across all estimations. This is surprising since the underlying data has constant variance shocks. Even for the data generated from the model with constant policy parameters, the stochastic volatility shocks have large variances and a high degree of persistence. Table 9 shows

TABLE 6. Posterior Mean for Constant Parameter Data

ψ_1	ρ_{ψ_1}	η_{ψ_1}
1.48	0.52	0.12
ψ_2	ρ_{ψ_2}	η_{ψ_2}
0.23	0.48	0.24

that even when the monetary policy parameters are correctly specified, the data still shows a high level of persistence and variability in the stochastic volatility terms.

TABLE 7. Posterior Mean for Baseline Regime Switching Data

σ_R	ρ_R	η_{σ_R}
0.34	0.69	0.98
σ_g	ρ_g	η_{σ_g}
0.26	0.73	0.63
σ_z	ρ_z	η_{σ_z}
0.82	0.79	0.43

TABLE 8. Posterior Mean for Alternative Regime Switching Data

σ_R	ρ_R	η_{σ_R}
0.31	0.66	0.1.13
σ_g	ρ_g	η_{σ_g}
0.25	0.75	0.66
σ_z	ρ_z	η_{σ_z}
0.73	0.81	0.41

Underlying States

Getting an understanding of just how much the standard deviation of shocks and policy parameters change over time is of major importance in studies like this one. In order to do this, the underlying states must be pulled out from the particle to filter. In this study, I use the approach described in Fernández-Villaverde and Rubio-Ramírez (2007). This is done for the generated data from the baseline model using the stochastic volatility model with no measurement error. In most cases, there does appear to be an increase in ψ_1, the policy parameter controlling

TABLE 9. Posterior Mean for Drifting Parameter Data

σ_R	ρ_R	η_{σ_R}
0.19	0.67	0.66
σ_g	ρ_g	η_{σ_g}
0.21	0.79	0.46
σ_z	ρ_z	η_{σ_z}
0.99	0.72	0.37

TABLE 10. Posterior Mean for Constant Parameter Data

σ_R	ρ_R	η_{σ_R}
0.14	0.67	0.83
σ_g	ρ_g	η_{σ_g}
0.22	0.78	0.33
σ_z	ρ_z	η_{σ_z}
0.86	0.74	0.37

reactions to inflation, but little change in ψ_2, the policy term related to the output gap. The smoothed underlying states for the monetary policy parameters and the logged deviation from mean of the stochastic volatility terms can be seen in Figures A.1 to A.48 in Appendix A.

A major question this paper asks is whether incorrect specification of the monetary policy parameters can lead to incorrect conclusions about whether there is stochastic volatility or not. One way to look at this is to determine if the standard deviation of shocks change over time. If the policy misspecification led to incorrect conclusions about stochastic volatility, there should be changes in σ_R, σ_g, or σ_z over time. In studying both the baseline case and alternate case, there do not appear to be large swings in stochastic volatility. The stochastic volatility is observed, does not appear to be systematic or related to the changes in monetary policy. This shows that it is unlikely that misspecification of monetary policy, at least the type of misspecification described in this paper, can lead to incorrect conclusions about the stochastic volatility terms changing over time. Therefore, models with parameter drifting and stochastic volatility can be used to estimate models with discretely changing monetary policy, but the researcher must look beyond model fit which can give misleading results.

For the baseline regime switching data, based on the analysis it appears that the Taylor parameter on inflation, ψ_1, appears to increase in the 101^{st} period, which is in line with the underlying data. However, the smoothed state for the Taylor parameter on output gap, ψ_2, does not appear to change much over time, which is slightly concerning since it discretely changes from 0.15 to 0.3 in the underlying data generating process.

Studying the monetary policy parameters in the alternative specification, where policy is allowed to change multiple times, raises more concerns. It appears that the model has a difficult time picking up the frequent changes in monetary policy. In several cases there are extreme values for the monetary policy parameters, as can be seen in the supplementary materials. While this is concerning, it is unlikely that there are frequent, large switches in monetary policy. So, this is unlikely to be a concern when studying real data. Therefore, if the researcher suspects there are several discrete changes in policy, a model with parameter drift may not be able to pick up the policy changes in the underlying states.

Model Comparison

This section will present information on the fit of the models using log marginal likelihoods, which are shown in Tables A.1 and A.2. The model with stochastic volatility that is estimated without measurement error has the largest log marginal likelihood of any specification for all data sets and all specifications. However, this is not an equitable comparison, since the other models include measurement errors. In several of the data sets, models containing stochastic volatility are preferred by the data, despite all of the data containing constant variance shocks.

In both regime switching specifications, many of the data sets preferred the model with stochastic volatility with measurement error when compared to the model without stochastic volatility, but with measurement error. For the baseline regime switching, 9 of the 12 data sets have larger log marginal likelihoods when estimated with stochastic volatility and measurement errors than when estimated without stochastic volatility and measurement errors. When the ρ parameters are set to 0.95, all 12 data sets prefer the model with stochastic volatility. For the alternate regime switching model, 5 of the 12 data sets prefer the stochastic volatility specification and 4 of the 12 data sets prefer the stochastic volatility specification when the ρ parameters are set to 0.95. This shows a strong level of support that the simulated data prefers the stochastic volatility models, despite it being a misspecification.

In order to better understand why the stochastic volatility model seems to be preferred by the regime switching data sets, the marginal likelihoods for the parameter drifting and constant parameter models must be analyzed. For the data sets simulated from the model with parameter drifting, 8 of the 12 data sets prefer the model with stochastic volatility and measurement error to the model without stochastic volatility. For the data sets generated from the model with constant parameters, only one of the 12 data sets prefers the model with stochastic volatility and measurement error over the model without stochastic volatility. Based on these results, it appears that the added flexibility of stochastic volatility helps fit the model better when the underlying data has parameters that change, even if the shocks have constant variances. However, if parameters do not change, the added flexibility of stochastic volatility does not improve model fit.

The evidence supporting the model with stochastic volatility is troubling and surprising. While it is not surprising that adding stochastic volatility to the model would improve model fit, it is surprising that the improvement was enough to overcome relatively diffuse priors. With the diffuse prior on the stochastic volatility parameters, there is a built in penalty for including these parameters. The increase in the likelihood function from including the stochastic volatility was more than enough to overcome this penalty. This is troubling since it shows how a misspecified model with stochastic volatility can be preferred over a model without stochastic volatility, even if the model without stochastic volatility is correctly specified. This is especially troubling, since the data shows a preference for stochastic volatility models even when the process for the monetary policy parameters are correctly specified. Therefore, it is very important for researchers to look beyond model fit when studying stochastic volatility.

Conclusion

In this paper a simple New Keynesian model is augmented with regime switching monetary policy parameters and constant variance shocks is used to generate data. The generated data was then used to estimate a model with stochastic volatility and parameter drifting in the monetary policy rules, as well as a model with drifting in the monetary policy rules and constant variance shocks. The models were estimated using a Metropolis-Hastings algorithm where the likelihood was approximated using a particle filter. These two models were then compared.

I find that the model featuring stochastic volatility is strongly supported by the data in comparison to the model without stochastic volatility. The fact that the model with stochastic volatility is better supported by the data is troubling, since the model the data is generated from has constant variance shocks. This is true, even when estimating data using the correct specification of monetary policy. This should give researchers pause when considering the importance of stochastic volatility in their results. Further research must be done beyond looking at model fit to determine the importance of stochastic volatility, as this might be a misleading measure of the importance of stochastic volatility.

While it is troubling that the model fit is improved in most cases by including stochastic volatility, even with misspecified monetary policy parameters, there do not appear to be any changes in volatility over time when looking at the underlying states. There does appear to be movement in the stochastic volatility terms, but all of it is small in comparison to their standard deviations and it does not systematically change across regimes.

This paper has studied potential problems when estimating misspecified DSGE models. Based on the results discussed in this paper there are concerns when doing model comparison of misspecified models with and without stochastic volatility. However, if the goal of the researchers is to study the changing nature of shocks over time, this paper does not find many concerns. While there appear to be some small changes in the nature of the shocks, these are small in comparison to their standard deviations and do not appear to be changing with the policy. Based on these results, it appears that even with the monetary policy rule being misspecified, at least in the way discussed in this paper, then stochastic volatility can be used to study the changing nature of shocks. However, caution should be used when performing model comparison of models featuring stochastic volatility to those without stochastic volatility.

CHAPTER III

FINANCIAL FRICTIONS AND CHANGING MACROECONOMIC VOLATILITY

Introduction

A key stylized fact about the US economy in the second half of the 20$^{\text{th}}$ century is the dramatic reduction in volatility of real and nominal macroeconomic variables starting in the 1980s, which is commonly called the Great Moderation.[1] Despite much research, it is still unclear what caused the Great Moderation. The debate has focused mainly on whether the moderation can be attributed to good monetary policy or good luck.[2] Changing financial markets have been largely overlooked as a potential factor in the Great Moderation. This paper explores the role that financial frictions play in explaining the Great Moderation using a DSGE model that features time-varying financial frictions. The model is based on the financial accelerator model of Bernanke, Gertler and Gilchrist (1999). The model is augmented with stochastic volatility in the shocks, parameter drifting in the monetary policy coefficients, and drifting financial frictions. I use Bayesian techniques to estimate this model and study whether changing financial frictions, good monetary policy or good luck with shocks caused the Great Moderation.

A major focus of macroeconomics has been to study the effects and causes of business cycle fluctuations and macroeconomic volatility since they can have large welfare effects. Understanding the causes of the Great Moderation is important in guiding future macroeconomic policy that seeks to limit volatility.[3] For this reason, there has been a great deal of research in this area, but there is not a consensus about what caused the reduction in volatility. Clarida, Galí, and Gertler (1999) argue that the Great Inflation, a period of raised inflation during the 1970s, was mainly caused by poor monetary policy. They argue that monetary policy did not react strongly enough to changes in the price level, which allowed prices to continuously climb higher. During the early

---

[1] Kim and Nelson (1999), McConnell and Perez-Quiros (2000), and Stock and Watson (2003) provide an empirical analysis of the change in volatility associated with the Great Moderation.

[2] The good luck story focuses on a decrease in the volatility of the exogenous shocks affecting the economy. There is a significant amount of research that suggests this is the main cause of the Great Moderation. Some other potential causes that have been studied include improvements in inventory management cuased by changes in information technology (McConnell and Perez-Quiros, 2000) and financial innovation (Dynan, Elmendorf, and Sichel, 2006)

[3] Research of optimal monetary policy often focuses on minimizing inflation and output volatility. For a review of optimal monetary policy, see Woodford (2010).

1980s, Clarida et al. (1999) find that the Federal Reserve's interest rate policy had a stronger reaction to inflation than during the 1970s, which led to the Great Moderation.

Others have argued that it has not been good policy, but "good luck" that can be attributed to the decrease in the volatility of exogenous shocks affecting the economy. Sims and Zha (2006) and McConnell and Perez-Quiros (2000) point to smaller exogenous shocks to the economy as the reason for reduced volatility. Much of the previous research was done using vector autoregressions (VAR). However, Benati and Surico (2009) showed that using a VAR in the analysis could lead to incorrect conclusions about the causes of the Great Moderation. They showed that when using a VAR for analysis, changes caused by changing monetary policy might be incorrectly attributed to changes in the variance of structural shocks, even when the variance of the structural shocks did not change. Due to these findings, recent research has used DSGE models in order to identify what caused the Great Moderation. Fernández-Villaverde, Guerrón-Quintana, and Rubio-Ramírez (2010) analyze a New Keynesian model that has stochastic volatility (i.e. the variance of shocks are allowed to smoothly change over time) and drifting coefficients in the Taylor rule that mimics the Federal Reserve's decision-making process when setting interest rates. They find that despite evidence of changes in the coefficients in the Taylor rule, most of the decrease in volatility is explained by changes in the variance of shocks (i.e. good luck) and not due to changes in policy. Still, a consensus has not been reached and little is known about why the nature of the shocks to the economy have changed over time.

Little research has been conducted into what role financial and credit markets may have played in the Great Moderation. This is surprising since Bernanke et al. (1999) showed how financial frictions could affect the size of business cycle fluctuations in their financial accelerator model. Financial frictions can arise due to imperfect information in the lending market or overly restrictive regulations. In the financial accelerator model, banks require collateral when making loans since they are unsure of the productivity level of the firms that are seeking funding. This can lead to productive firms failing to receive financing due to a lack of collateral, especially during a recession when a firm's wealth level is depressed. If this causes less lending during recessions, it can further increase the magnitude of the business cycle. So, if financial frictions changed during the 1980s and 1990s, then these changes could be a very important reason for the reduction in volatility during the Great Moderation.

There is reason to think that financial frictions changed greatly in the 1980s and later years due to deregulation and financial innovation. The 1980s and 1990s saw several changes in bank regulation, including the Depository Deregulations and Monetary Control Act of 1980, Garn-St. Germain Depository Institutions Act in 1982, the Financial Institutions Reform Act in 1989, the Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994 and the Gramm-Leach-Bliley Act in 1999.[4] The 1980s and 1990s also saw financial innovation in the form of interest rate swaps as well as expanded bond option markets. Jermann and Quadrini (2009) develop a model that shows how financial innovation can reduce macroeconomic volatility. In an empirical study, Dynan, Elmendorf and Sichel (2006) find that financial innovation may be an important factor in explaining the decrease in volatility during the Great Moderation.[5] Since Dynan et al. (2006) use a VAR in their study and VARs may give misleading results for the reasons explained above, it is important to further study this using a model with more structure.

In a study similar to this paper, Fuentes-Albero (2011) analyzes the Great Inflation and Great Moderation using a DSGE with New Keynesian style frictions that is augmented with aspects of the financial accelerator model. This model is estimated, allowing structural breaks in the variance of shocks, the monetary policy coefficients and the average level of financial rigidities. Fuentes-Albero (2011) finds that, based on this estimation, the Great Inflation was caused mostly by large shocks (bad luck) while the Great Moderation can be mostly attributed to easier access to credit and better monetary policy, which runs counter to the findings of Fernández-Villaverde et al. (2010). Fuentes-Albero (2011) has to make extreme assumptions in order to estimate this model. The structural breaks are assumed to happen at specific times and agents assume the changes are permanent and the coefficients will remain constant forever following the break. This is hard to reconcile with the rational expectations used in the model since it is unlikely agents would view changes as permanent when they have previously seen changes occur. However, Fuentes-Albero (2011) is very important since it shows the importance of including financial frictions in DSGE models when studying the Great Moderation.

This paper explores the causes of the Great Moderation by analyzing the relative importance of financial frictions, good monetary policy and good luck in explaining changing

[4]For an overview of financial deregulation in the US in recent decades, see Sherman (2009).

[5]These findings were also supported by Guerrón-Quintana (2007).

macroeconomic volatility. A real business cycle (RBC) model is augmented with financial frictions, stochastic volatility and parameter drifting. The parameters governing monetary policy and financial frictions drift, so changing financial frictions or policy can be studied with the model. Incorporating stochastic volatility allows for the model to pick up changes in the standard deviation of the exogenous shocks, which Fernández-Villaverde et al. (2010) show are important to fitting the data. This estimated model is the first, to the best of my knowledge, to incorporate stochastic volatility into a DSGE model with financial frictions.

In order to study observed changes in macroeconomic volatility, the model is estimated using a particle filter and Bayesian econometric methods. To understand the importance of the different features of the model, I do three exercises. First, the fit of models with different specifications are compared to determine the importance of certain features for matching the data. Second, to get an understanding of how unobserved variables have changed over time, a particle filter is used along with the estimation results to pull out the underlying state variables from the model. This shows how the financial frictions, monetary policy and the standard deviation of exogenous shocks have changed over time. The underlying state variables allow for a final exercise, where the importance of drifting parameters can be studied by doing a counterfactaul experiment. This is done by simulating data using the underlying states and holding the parameters being studied, either the financial friction parameter or the monetary policy parameters, constant. The counterfactual data is then compared with the actual data.

I find strong evidence that changing financial frictions are necessary for fitting the data. During the middle of the 1980s, financial frictions fell for an extended period of time before increasing again starting after the year 2000. The decrease in financial frictions observed in the 1980s and 1990s, was an important contributor to the fall in macroeconomic volatility witnessed during the Great Moderation, which is similar to the findings of Fuentes-Albero (2011). This shows the importance of changing financial frictions for explaining the Great Moderation even when allowing for stochastic volatility, which was not included in the model estimated by Fuentes-Albero (2011). In addition to changing financial frictions, there is also evidence that monetary policy changed during the 1980s, with policy becoming more responsive to inflation. While I find that changing monetary policy played a role in the Great Moderation, it does not appear to be the main reason for the reduction of volaitlity. I find a significant amount of stochastic volatility throughout the sample, but this does not appear to be a driver of the Great Moderation, a finding that differs from the conclusions of Fernández-Villaverde et al. (2010). These results suggest that part of the reason for good luck being considered a strong driver of the Great Moderation, may be due to some prior studies ignoring the role that changing financial frictions played in the Great Moderation.

The rest of the paper is organized as follows. Section 2 presents the model to be estimated. Sections 3 and 4 describe the data sources and present the estimation strategy. Section 5 presents the priors and estimation results, while section 6 describes the model fit. Sections 7 and 8 show the underlying states and results from counterfactual experiments. Finally, section 9 provides some concluding remarks and describes some potential future related research.

Model

The model economy is populated by a representative household, financial intermediaries, entrepreneurs, capital producers, final good producers, and a government. The RBC model serves as a basis for the model, with aspects of the financial accelerator model of Bernanke et al. (1999) added. Stochastic volatility is incorporated into the model so the standard deviation of the underlying shocks are allowed to drift over time. The monetary policy rule parameters and the term measuring financial frictions are allowed to drift over time. The model is based on the models of Smets and Wouters (2007), Christiano, Motto and Rostagno (2010), Fernández-Villaverde et al. (2010), and Fuentes-Albero (2012). This model is unique since it combines stochastic volatility, parameter drifting and the financial accelerator in a DSGE model. While this model leaves out some of the features of standard New-Keynesian models, like sticky prices and wages, it serves as a feasible model to estimate and draw initial conclusions.

The main departure from a standard New-Keynesian or RBC model is the inclusion of a financial accelerator. The financial accelerator introduces entrepreneurs who use their own funds and borrow funds in order to purchase capital at the end of every period. After capital is purchased, entrepreneurs are hit with a productivity shock that the entrepreneur costlessly observes, but the financial intermediary must pay a fee in order to observe the entrepreneur's productivity. This asymmetric information introduces new dynamics into the model and can amplify business cycles. In this paper, the monitoring cost paid by banks will be allowed to change over time, which will pick up changes in financial frictions.

Household

There is a representative household that maximizes expected lifetime utility represented by

$$\mathbb{E}_t\Sigma_{s=0}^{\infty}\beta^s d_{t+s}\left[\log c_{t+s}+\log\frac{M_{t+s}}{P_{t+s}}-\psi\frac{l_{t+s}^{1+\gamma}}{1+\gamma}\right] \tag{3.1}$$

subject to the budget constraint

$$\begin{aligned} c_{t+s} \quad & +\frac{D_{t+s+1}}{P_{t+s}}+\frac{NB_{t+s+1}}{P_{t+s}}+\frac{M_{t+s+1}}{P_{t+s}}\leq \\ & w_{t+s}l_{t+s}+R_{t+s-1}\frac{D_{t+s}}{P_{t+s}}+R_{t+s-1}^{N}\frac{NB_{t+s}}{P_{t+s}}+\frac{M_{t+s}}{P_{t+s}}+div_{t+s}-T_{t+s}-Trans_{t+s},\ \ \forall s. \end{aligned}$$

The utility function is separable in consumption, c_t, real money balances, $\frac{M_t}{P_t}$, and hours worked, l_t. β is the discount factor, R_t is the risk-free, gross nominal interest rate paid on deposits, R_t^n is the risk-free nominal interest rate paid on government bonds, NB_t is the nominal value of government bonds held, D_t is the nominal value of deposits at the financial intermediary, div_t is the real value of dividends obtained from ownership of firms, T_t are taxes paid, and $Trans_t$ is the real value of wealth transfers to/from the entrepreneurial sector. The household faces an intertemporal preference shock, d_t, which evolves as

$$\log d_t=\rho_d\log d_{t-1}+\sigma_{d,t}\varepsilon_{d,t}. \tag{3.2}$$

The standard deviation of the innovation is allowed to change over time and follows the process

$$\log\sigma_{d,t}=(1-\rho_{\sigma_d})\log\sigma_d+\rho_{\sigma_d}\log\sigma_{d,t-1}+\eta_d u_{d,t}. \tag{3.3}$$

The exogenous innovations, $\varepsilon_{d,t}$ and $u_{d,t}$, and all other innovations described in the model are i.i.d. $N(0,1)$. Allowing for $\sigma_{d,t}$ to drift through time will allow the model to pick up changes in the nature of underlying shocks over time as in Fernández-Villaverde et al. (2010), if such changes exist. This specification of stochastic volatility will be present for all shocks in the model.

Goods Production

A perfectly competitive, representative goods producer rents capital, k_t, from entrepreneurs and hires labor, l_t, from the representative household to produce goods. The firm uses a Cobb-Douglas technology production function

$$y_{i,t} = (A_t l_t)^{1-\alpha} k_t^{\alpha}. \tag{3.4}$$

The logged productivity term, A_t, follows a random walk with drift and features stochastic volatility. The process is defined as

$$\log A_t = \log A_{t-1} + \Upsilon_A + \sigma_{A,t}\varepsilon_{A,t} \tag{3.5}$$

where the standard deviation of the innovation follows the process

$$\log \sigma_{A,t} = (1-\rho_{\sigma_A}) \log \sigma_A + \rho_{\sigma_A} \log \sigma_{A,t-1} + \eta_d u_{A,t}. \tag{3.6}$$

Capital Producers

Capital producers are perfectly competitive, infinitely lived agents who produce new capital and purchase capital from entrepreneurs. Capital is produced using a linear production function, where one unit of investment in period t produces ζ_t units of time $t+1$ physical capital. The productivity of capital production, ζ_t, is allowed to change over time following the process

$$\log(\zeta_t) = \rho_\zeta \log(\zeta_{t-1}) + \sigma_{\zeta,t}\varepsilon_{\zeta,t} \tag{3.7}$$

where the standard deviation of the innovation follows the process

$$\log \sigma_{\zeta,t} = (1-\rho_{\sigma_\zeta}) \log \sigma_\zeta + \rho_{\sigma_\zeta} \log \sigma_{\zeta,t-1} + \eta_\zeta u_{\zeta,t}. \tag{3.8}$$

Financial Intermediaries and Entrepreneurs

Entrepreneurs are risk-neutral, finitely lived agents who can borrow funds from financial intermediates. Entrepreneurs survive from one period to the next with probability ν. Financial intermediaries attain funds from households. At the end of period t entrepreneurs purchase physical capital. At the beginning of period $t+1$, entrepreneurs observe an idiosyncratic shock that affects the productivity of their capital. Entrepreneurs then determine how much of their capital to rent. At the end of the period entrepreneurs sell off undepreciated capital and pay of debts to the financial intermediary.

Each entrepreneur faces an idiosyncratic productivity shock, ω_t^j, at the beginning of each period which is only observed by the entrepreneur and affects the productivity of his capital holdings. This shock is assumed to have a lognormal distribution with c.d.f. $F(\omega)$ with parameters μ_ω and σ_ω satisfying $\mathbb{E}\left(\omega^j\right) = 1$. Entrepreneurs maximize profits by determining the fraction of capital to utilize, u_t^j, to solve

$$\max_{u_t^j} \left[u_t^j r_t^{j,k} - a\left(u_t^j\right)\right] \omega_t^j K_t^j. \tag{3.9}$$

The rental rate of capital is denoted $r_t^{j,k}$ and $a(\cdot)$ represents the cost of utilizing capital and has the following properties around the steady state: $a(\cdot) = 0$, $a'(\cdot) > 0$, $a''(\cdot) > 0$.

Capital demand for entrepreneur j is determined by the gross nominal returns on holding capital

$$R_{t+1}^{j,k} = \left[\frac{\left(u_{t+1}^j r_{t+1}^{j,k} - a\left(u_{t+1}^j\right)\right) + \omega_{t+1}^j (1-\delta) Q_{t+1}}{Q_t}\right] \frac{P_{t+1}}{P_t}. \tag{3.10}$$

The gross return on capital is denoted $R_{t+1}^{j,k}$ and $\omega_{t+1}^j(1-\delta)Q_{t+1}$ is the return from selling undepreciated capital.

An entrepreneur can use his own net worth, N_{t+1}^j, or external financing to purchase new physical capital. Lenders are unable to observe the returns of entrepreneurs unless they pay an auditing cost. Due to cost minimization, lenders will only audit entrepreneurs when the loan is not fully repaid. The auditing cost is represented by a fraction, μ_{t+1}, being lost in the process of liquidation leaving $(1-\mu_{t+1})P_t \omega_{t+1}^j R_{t+1}^k Q_t K_{t+1}^j$. The auditing cost is allowed to change over time, which is intended to pick up changes in financial frictions. When the auditing cost falls, this is interpreted as a lowering of financial frictions since more entrepreneurs can get access to credit. Since the auditing cost must be between 0 and 1, it is defined as $\mu_t = \frac{1}{1-\mu\check{\mu}_t}$. The process that $\check{\mu}_t$ follows is defined by

$$\log \check{\mu}_t = \rho_\mu \log \check{\mu}_{t-1} + \sigma_\mu \varepsilon_{\mu,t}. \tag{3.11}$$

The debt contract is set to maximize expected entrepreneurial profits subject to a participation constraint. The maximization problem is defined as

$$\max_{\bar{\omega}_{t+1},k_{t+1}} \mathbb{E}_t \left\{ [1-\Gamma(\bar{\omega}_{t+1})] \frac{R^k_{t+1}}{R_t} (B_{t+1}+N_{t+1}) \right\} \tag{3.12}$$

subject to the constraint

$$\mathbb{E}_t \frac{R^k_{t+1}}{R_t} [\Gamma(\bar{\omega}_{t+1}) - \mu_{t+1} G(\bar{\omega}_{t+1})] = \frac{Q_t K_{t+1} - N_{t+1}}{Q_t K_{t+1}} \tag{3.13}$$

where $\Gamma(\bar{\omega}_{t+1})$ is the expected share of gross entrepreneurial earnings going to the lender and $\mu_{t+1}G(\bar{\omega}_{t+1})$ is the expected monitoring cost.[6] The size of the loan is defined as B_{t+1}, the net worth of the borrower is defined as N_{t+1}, Q_t is the shadow cost of capital, and $\bar{\omega}_{t+1}$ represents the productivity that must be drawn in order for the borrower to be able to repay the loan. This results in an external finance premium defined by $\mathbb{E}\frac{R^k_{t+1}}{R_t}$.

The net worth of entrepreneurs evolves as

$$P_t N_{t+1} = x_t \nu V_t + P_t W^e_t \tag{3.14}$$

where x_t represents a wealth shock, V_t represents entrepreneurial equity, and W^e_t is the value of wealth transfers made by exiting firms.[7] The wealth shock changes over time according to $\log x_t = (1-\rho_x)\log x + \rho_x \log x_{t-1} + \sigma_{x,t}\varepsilon_{x,t}$ and $\log \sigma_{x,t} = (1-\rho_{\sigma_x})\log \sigma_x + \rho_{\sigma_x} \log \sigma_{x,t} + \eta_x u_{x,t}$. The entrepreneurial sector provides transfers to/from the private sector equal to $Trans_t = N_{t+1} - \nu V_t - W^e_t$.

Government

The government finances spending by issuing government bonds to households and collecting lump-sum taxes. The government's finances are defined by

$$NB_{t+1} + P_t T_t + M_{t+1} = P_t G_t + R_{t-1} NB_t + M_t. \tag{3.15}$$

[6] $\Gamma(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}_{t+1}} \omega f(\omega) d\omega + \bar{\omega}_{t+1} \int_{\bar{\omega}_{t+1}}^{\infty} f(\omega) d\omega$ and $G(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}_{t+1}} \omega f(\omega) d\omega$.

[7] $V_t = P_{t-1} R^k_t Q_{t-1} K_t - R_{t-1} B_t - \mu_t G(\bar{\omega}_t) P_{t-1} R^k_t Q_{t-1} K_t$

Government spending is allowed to change over time and is defined by $G_t = \left(\frac{1}{1+\tilde{g}g_t}\right) Y_t$ where the government spending shock follows

$$\log(g_t) = \rho_g \log(g_{t-1}) + \sigma_{g,t}\varepsilon_{g,t} \tag{3.16}$$

where the standard deviation of the innovation follows the process

$$\log \sigma_{g,t} = (1 - \rho_{\sigma_g}) \log \sigma_g + \rho_{\sigma_g} \log \sigma_{g,t} + \eta_g u_{g,t}. \tag{3.17}$$

The central bank sets the interest rate using a Taylor rule with drifting parameters. The rule is defined as

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{1-\gamma_R} \left(\left(\frac{\Pi_t}{\Pi}\right)^{\psi_{1,t}} \left(\frac{\frac{Y_t}{Y_{t-1}}}{\Upsilon_A}\right)^{\psi_{2,t}} \right)^{1-\gamma_R} m_t. \tag{3.18}$$

The Taylor coefficients drift according to the processes

$$\log(\psi_{1,t}) = \rho_{\psi_1} \log(\psi_{1,t-1}) + (1 - \rho_{\psi_1}) \log(\psi_1) + \eta_{\psi 1}\varepsilon_{\psi_1,t} \tag{3.19}$$

$$\log(\psi_{2,t}) = \rho_{\psi_2} \log(\psi_{2,t-1}) + (1 - \rho_{\psi_2}) \log(\psi_2) + \eta_{\psi 2}\varepsilon_{\psi_2,t}. \tag{3.20}$$

The monetary policy shock is defined as $\log m_t = \sigma_{m,t}\varepsilon_{m,t}$ and $\sigma_{m,t}$ follows the process

$$\log \sigma_{m,t} = (1 - \rho_{\sigma_m}) \log \sigma_m + \rho_{\sigma_m} \log \sigma_{m,t} + \eta_m u_{m,t}. \tag{3.21}$$

Market clearing

The market clearing condition for the goods market is defined by

$$Y_t = C_t + I_t + G_t + a(u_t)K_t + \mu_t G(\bar{\omega}_t) R_t^k Q_{t-1} K_t. \tag{3.22}$$

Credit market clearing is defined by

$$\frac{D_{t+1}}{P_t} = \frac{B_{t+1}}{P_t} = Q_t K_{t+1} - N_{t+1}. \tag{3.23}$$

Equilibrium

The equilibrium can be characterized by the first order conditions, the Taylor rule monetary policy and market clearing conditions. The equilibrium is not stationary due to the unit root in the process for technology, so some variables must be normalized. To do this let $\widetilde{c}_t = \frac{c_t}{A_t}$, $\widetilde{I}_t = \frac{I_t}{A_t}$, $\widetilde{K}_t = \frac{K_t}{A_t}$, $\widetilde{B}_{t+1} = \frac{B_{t+1}}{A_t}$, $\widetilde{NB}_{t+1} = \frac{NB_{t+1}}{A_t}$, $\widetilde{N}_{t+1} = \frac{N_{t+1}}{A_t}$, $\widetilde{div}_t = \frac{div_t}{A_t}$, $\widetilde{T}_t = \frac{T_t}{A_t}$, and $\widetilde{A}_t = \frac{A_t}{\exp(\Upsilon_A)A_{t-1}}$.

Data

The data used to estimate the model spans from 1954.Q4 to 2006.Q4.[8] Seven data series are used: growth rate of real output, growth rate of real per capita investment, growth rate of real per capita consumption, the log of inflation (measured as the ratio of the price level this period and last period), the log of the gross federal funds rate, the log of the Moody's Baa corporate bond interest rate divided by the federal funds rate, and the growth rate of net worth.[9] The data is incorporated into the model by creating a vector of observables defined as

$$\mathbb{Y}_t^{data} = \begin{pmatrix} \widehat{\widetilde{y}}_t - \widehat{\widetilde{y}}_{t-1} + \Upsilon_A \\ \widehat{\widetilde{I}}_t - \widehat{\widetilde{I}}_{t-1} + \Upsilon_A \\ \widehat{\widetilde{c}}_t - \widehat{\widetilde{c}}_{t-1} + \Upsilon_A \\ \widehat{\Pi}_t + \Upsilon_A \\ \widehat{R}_t + R \\ \widehat{R^{Baa}}_t - \widehat{R}_t + R^{Baa} - R \\ \widehat{\widetilde{N}}_t - \widehat{\widetilde{N}}_{t-1} + \Upsilon_A \end{pmatrix}.^{10} \quad (3.24)$$

To simplify notation, terms that are expressed as the log deviation from their steady state are denoted as $\widehat{var}_t = \log var_t - \log var$.

[8] More recent data is not used in order to avoid problems that arise at the zero lower bound.

[9] For more details on how the data is calculated, see Appendix B.

[10] Υ_A represents the drift term in the random walk process for the productivity shock.

Model Solution and Estimation Strategy

Based on the complexity, size and nonlinearities of the model, estimation is difficult. The model does not have a closed-form solution and the likelihood function cannot be analytically solved, so numerical approximations must be used. To achieve this, I first do a second-order approximation of the model around the steady state using perturbation methods and then approximate the likelihood using a particle filter. This is then used in a Metropolis-Hastings algorithm to estimate the posterior.[11] This process is described in more detail below.

Following Fernández-Villaverde et al. (2010), the endogenous states of the economy are stacked into a vector $S_t = \left(\widehat{R}_{t-1}, \widehat{\widetilde{c}}_{t-1}, \widehat{\widetilde{I}}_{t-1}, \widehat{\widetilde{y}}_{t-1}, \widehat{R^k}_{t-1}, \widehat{\widetilde{N}}_{t-1}, \widehat{\widetilde{K}}_{t-1}, \widehat{q}_{t-1}, \widehat{\Pi}_{t-1}\right)'$. In addition to the endogenous states are the exogenous states which are stacked in three different vectors. The exogenous states regulating the parameter drift are stacked into a vector $D_t = \left(\widehat{\mu}_{t-1}, \widehat{\psi_1}_{t-1}, \widehat{\psi_2}_{t-1}\right)'$. The exogenous states for the underlying structural shocks and stochastic volatility are stacked in two separate vectors, $Z_t = \left(\widehat{x}_{t-1}, \widehat{d}_{t-1}, \widehat{g}_{t-1}, \widehat{\zeta}_{t-1}, \widehat{m}_{t-1}, \widehat{\widetilde{A}}_{t-1}\right)'$ and $\Sigma_t = (\widehat{\sigma}_{x,t-1}, \widehat{\sigma}_{d,t-1}, \widehat{\sigma}_{g,t-1}, \widehat{\sigma}_{\zeta,t-1}, \widehat{\sigma}_{m,t-1}, \widehat{\sigma}_{A,t-1},)'$.

There are three sources of variation in the model: structural shocks, parameter drift, and volatility shocks. The innovations to structural shocks are stacked in a vector $\mathcal{E}_t = (\varepsilon_{x,t}, \varepsilon_{d,t}, \varepsilon_{g,t}, \varepsilon_{A,t}, \varepsilon_{\zeta,t}, \varepsilon_{m,t})'$. The innovations to the parameter drift are stacked in a vector $\mathcal{V}_t = \left(\varepsilon_{\mu,t}, \varepsilon_{\psi_{1,t}}, \varepsilon_{\psi_{1,t}}\right)'$. The innovations to the volatility shocks are stacked in a vector defined as $\mathcal{U}_t = (u_{x,t}, u_{d,t}, u_{g,t}, u_{A,t}, u_{\zeta_t}, u_{m,t})'$. All three vectors of shocks are then stacked into one vector, $\mathbb{W}_t = (\mathcal{E}_t', \mathcal{V}_t', \mathcal{U}_t')'$.

The model does not have a closed-form solution, so the solution must be approximated. Due to the large size of the model and the inherent nonlinearity of the model introduced by the stochastic volatility terms, a second order approximation of the model is done around the deterministic steady state using perturbation methods.[12] The model is not linearized since the stochastic volatility terms would disappear and the solution would exhibit certainty equivalence.

[11] This process is standard in the literature and closely follows the process described in Fernández-Villaverde et al. (2010).

[12] For more information on second order perturbation techniques see Kim et al. (2005), Schmitt-Grohe and Uribe (2004) and Klein and Gomme (2011). Aruoba, Fernández-Villaverde, and Rubio-Ramírez (2006) show that perturbation methods are both fast and accurate.

To approximate the model, it must first be put into state space form. The solution can be written, for a vector of parameters θ, as

$$\mathbb{S}_{t+1} = h\left(\mathbb{S}_t, \Lambda; \theta\right) + \Xi \mathbb{W}_{t+1} \tag{3.25}$$

where $\mathbb{S}_t = (S_t, D_t, Z_t, \Sigma_t, \mathbb{W}_t)'$, Λ represents the perturbation parameter and h maps from $\mathbb{R}^{40}$ to $\mathbb{R}^{39}$. In addition to the state transition equations, the observation equation is defined as

$$\mathbb{Y}_t = g\left(\mathbb{S}_t, \Lambda; \theta\right). \tag{3.26}$$

The second order perturbation gives an approximate solution that is defined by transition equations

$$\mathbb{S}_{t+1} = \Psi_c + \begin{pmatrix} \Psi^1_{s1}\mathbb{S}'_t \\ \vdots \\ \Psi^1_{s39}\mathbb{S}'_t \end{pmatrix} + \frac{1}{2}\begin{pmatrix} \mathbb{S}_t\Psi^1_{s1}\mathbb{S}'_t \\ \vdots \\ \mathbb{S}_t\Psi^1_{s39}\mathbb{S}'_t \end{pmatrix} + \Xi\mathbb{W}_{t+1} \tag{3.27}$$

and an observation equation

$$\mathbb{Y}_t = \mathcal{C} + \begin{pmatrix} \Psi^1_{Y1}\mathbb{S}'_t \\ \vdots \\ \Psi^1_{Y7}\mathbb{S}'_t \end{pmatrix} + \frac{1}{2}\begin{pmatrix} \mathbb{S}_t\Psi^2_{Y1}\mathbb{S}'_t \\ \vdots \\ \mathbb{S}_t\Psi^2_{Y7}\mathbb{S}'_t \end{pmatrix} \tag{3.28}$$

where $\mathbb{Y}_t$ represents a vector of observables, which may contain a subset or all of the vector $\mathbb{Y}_t$ from the observation equation. In the equations Ψ^1_{ij} is a 1×39 matrix and Ψ^2_{ij} is a 39×39 matrix, while Ξ is a 39×5. Ψ_c is a vector containing the correction for risk in the state equation and $\mathcal{C}$ is a vector containing the sum of the means of the observables and the correction for risk for the observation equation.

The approximate solution described in equation (3.28) can be used to evaluate the likelihood by using the particle filter, even if some observables are not considered to have measurement error. Define $\mathbb{Y}_{1,t}$ as a vector 6×1 of observations that are assumed to have no measurement error and $\mathbb{Y}_{2,t}$ as the observation with measurment error, which are stacked to make the 7×1 vector $\mathbb{Y}_t = (\mathbb{Y}_{1,t}, \mathbb{Y}_{2,t})'$. As is shown in Fernández-Villaverde et al. (2010), the second derivatives from h and g show that the cross-derivative for $\mathcal{U}_t$ is always equal to zero for all variables except $\mathcal{E}_t$. Based on this, the measurement equation can be rewritten as

$$\mathbb{Y}_t = \mathbb{C} + \begin{pmatrix} \Psi^1_{Y1}\mathbb{S}'_t \\ \vdots \\ \Psi^1_{Y7}\mathbb{S}'_t \end{pmatrix} + \frac{1}{2}\begin{pmatrix} (S'_t, D'_t, Z'_t, \Sigma'_t, \mathcal{E}'_t, \mathcal{V}'_t)\,\Psi^{2,1}_{Y1}\,(S'_t, D'_t, Z'_t, \Sigma'_t, \mathcal{E}'_t, \mathcal{V}'_t)' \\ \vdots \\ (S'_t, D'_t, Z'_t, \Sigma'_t, \mathcal{E}'_t, \mathcal{V}'_t)\,\Psi^{2,1}_{Y7}\,(S'_t, D'_t, Z'_t, \Sigma'_t, \mathcal{E}'_t, \mathcal{V}'_t)' \end{pmatrix} + \begin{pmatrix} \mathcal{E}'_t\Psi^{2,2}_{Y1} \\ \vdots \\ \mathcal{E}'_t\Psi^{2,2}_{Y7} \end{pmatrix}\mathcal{U}_t. \tag{3.29}$$

This can be used to evaluate the likelihood function using the particle filter. Unlike in Fernández-Villaverde et al. (2010), there are more observables, 7, than volatility shocks, 6. So, I assume that there is measurement error, me_t on the growth of net worth observations, which is likely to be the most difficult to accurately measure.[13] To ease notation, define $\mathcal{H}_t = (S'_t, D'_t, Z'_t, \Sigma'_t, \mathcal{E}'_t, \mathcal{V}'_t)'$. To aid with the evaluation, define

$$\mathbb{A}_t\left(\mathcal{H}'_t\right) = \mathbb{Y}^{data}_t - \mathbb{C} - \begin{pmatrix} \Psi^1_{Y1}\mathbb{S}'_t \\ \vdots \\ \Psi^1_{Y7}\mathbb{S}'_t \end{pmatrix} - \frac{1}{2}\begin{pmatrix} (\mathcal{H}_t)\,\Psi^{2,1}_{Y1}\,(\mathcal{H}_t)' \\ \vdots \\ (\mathcal{H}_t)\,\Psi^{2,1}_{Y7}\,(\mathcal{H}_t)' \end{pmatrix}$$

and

$$\mathbb{B}\left(\mathcal{E}_t\right) = \begin{pmatrix} \mathcal{E}_t\Psi^{2,2}_{Y1}, 0 \\ \vdots \\ \mathcal{E}_t\Psi^{2,2}_{Y6}, 0 \\ \mathcal{E}_t\Psi^{2,2}_{Y7}, 1 \end{pmatrix}.$$

The entry of 1 in the seventh row of $\mathbb{B}\left(\mathcal{E}_t\right)$ picks up the measurement error. Using N draws of $\{s^i_t, h^i_t\}^N_{i=1}$ from $p\left(S_t, \mathcal{H}_t|\mathbb{Y}^{data,t-1};\theta\right)$, this equation can be used to directly calculate

$$p\left(\mathbb{Y}_t = \mathbb{Y}^{data}_t|\mathbb{Y}^{data,t-1};\theta\right) \simeq \frac{1}{N}\sum_{i=1}^{N}\left|\det\left(\mathbb{B}^{-1}\left(e^{i'}_t\right)\right)\right| p\left(\left(\mathcal{U}_t, me_t\right) = \mathbb{B}^{-1}\left(e^{i'}_t\right)\mathbb{A}_t\left(h^{i'}_t\right)\right).$$

[13]The measurement error is assumed to be i.i.d. with a mean zero normal distribution with a standard deviation of 0.003. This value is chosen because the measurement error is not well identified in estimation and it assumes only a small measurement error.

From this, importance weights of each draw can be calculated for use in the particle filter:

$$q_t^i = \frac{\left|\det\left(\mathbb{B}^{-1}\left(e_t^{i'}\right)\right)\right| p\left((\mathcal{U}_t, me_t) = \mathbb{B}^{-1}\left(e_t^{i'}\right)\mathbb{A}_t\left(h_t^{i'}\right)\right)}{\sum_{i=1}^{N}\left|\det\left(\mathbb{B}^{-1}\left(e_t^{i'}\right)\right)\right| p\left((\mathcal{U}_t, me_t) = \mathbb{B}^{-1}\left(e_t^{i'}\right)\mathbb{A}_t\left(h_t^{i'}\right)\right)}.$$

The particle filter used follows Fernández-Villaverde et al. (2010) and Fernández-Villaverde and Rubio-Ramírez (2007). The steps followed are:

1. Set $t \rightsquigarrow 1$ and sample N values $\{s_{t-1|t-1}^i, h_{t-1|t-1}^i\}_{i=1}^N$ from $p\left(S_t, \mathcal{H}_t | \mathbb{Y}^{data,t-1}; \theta\right)$.
2. Sample N values $\{s_{t|t-1}^i, h_{t|t-1}^i\}_{i=1}^N$ from $p\left(S_t, \mathcal{H}_t | \mathbb{Y}^{data,t-1}; \theta\right)$ by using $\{s_{t-1|t-1}^i, h_{t-1|t-1}^i\}_{i=1}^N$, the law of motion for the states and the distribution of the shocks $\{\mathcal{H}_t|\theta\}$.
3. Assign the weight q_t^i to each draw $\left(s_{t|t-1}^i, h_{t|t-1}^i\right)$.
4. Sample N times with replacement from $\{s_{t|t-1}^i, h_{t|t-1}^i\}_{i=1}^N$ using the weights q_t^i. Call each draw $\left(s_{t|t}^i, h_{t|t}^i\right)$. If $t < T$ set $t \rightsquigarrow t+1$ and go to step 2, otherwise stop.

Using the output of the particle filter the likelihood can be calculated as

$$P\left(\mathbb{Y}^T|\theta\right) \simeq \prod_{t=1}^{T} p\left(\mathbb{Y}_t = \mathbb{Y}_t^{data} | \mathbb{Y}^{data,t-1}; \theta\right). \tag{3.30}$$

In order to feasibly estimate the model when there is no stochastic volatility, I must assume measurement error for all observables. I also estimate the model with stochastic volatility and measurement error for all observables to have a more fair comparison for the two models. In these specifications, I assume the measurement error is defined as a 7 × 1 vector $\mathcal{M}_t$. With slight modifications, the particle filter can be used to approximate the likelihood function for this specification as well. The particle filter proceeds as follows

1. Set $t \rightsquigarrow 1$ and sample N values $\{s_{t-1|t-1}^i, w_{t-1|t-1}^i\}_{i=1}^N$ from $p\left(S_t, \mathbb{W}_t | \mathbb{Y}^{data,t-1}; \theta\right)$.
2. Sample N values $\{s_{t|t-1}^i, w_{t|t-1}^i\}_{i=1}^N$ from $p\left(S_t, \mathbb{W}_t | \mathbb{Y}^{data,t-1}; \theta\right)$ by using $\{s_{t-1|t-1}, w_{t-1|t-1}\}_{i=1}^N$, the law of motion for the states and the distribution of $\mathbb{W}_t$.
3. Assign the weight $q_t^i = \frac{p\left(\mathcal{M}_t = \mathbb{Y}_t - \mathbb{Y}_t^{data} | \mathbb{Y}^{t-1}, s_{t|t-1}^i, w_{t|t-1}^i\right)}{\sum_{i=1}^N p\left(\mathcal{M}_t = \mathbb{Y}_t - \mathbb{Y}_t^{data} | \mathbb{Y}^{t-1}, s_{t|t-1}^i, w_{t|t-1}^i\right)}$ to each draw $\left(s_t^i, h_t^i\right)$.
4. Sample N times with replacement from $\{s_{t|t-1}, w_{t|t-1}\}_{i=1}^N$ using the weights q_t^i. Call each draw $\left(s_{t|t}^i, w_{t|t}^i\right)$. If $t < T$ set $t \rightsquigarrow t+1$ and go to step 2, otherwise stop.

The output of the particle filter can be used to calculate the likelihood as

$$P\left(\mathbb{Y}^T|\theta\right) \simeq \prod_{t=1}^{T} \frac{1}{N} \sum_{i=1}^{N} p\left(\mathcal{M}_t = \mathbb{Y}_t - \mathbb{Y}_t^{data}|\mathbb{Y}^{t-1}, s_{t|t-1}^i, w_{t|t-1}^i\right). \tag{3.31}$$

Once the likelihood is approximated, it can be combined with a prior distribution and used to estimate the model. To do so, I use a random walk Metropolis-Hastings algorithm.[14] The algorithm proceeds as follows:

1. Choose a starting vector, $\theta^{(0)}$, of size n_θ of coefficients and set $s \rightsquigarrow 1$
2. Take a candidate draw, $\theta^* = \theta^{(s-1)} + \xi$, where ξ is a random normal vector of dimension n_θ.
3. Set $\theta^{(s)} = \theta^*$ with probability $\min\left[\frac{p(\mathcal{Y}^T|\theta^*)p(\theta^*)}{p(\mathcal{Y}^T|\theta^{(s-1)})p(\theta^{(s-1)})}, 1\right]$
4. If $s < S$, set $s \rightsquigarrow s+1$ and go to step 2, otherwise stop.

In this paper, I set S=20,000 in the Metropolis-Hastings algorithm and discard the first 5,000 draws as a burn-in sampling.

Priors and Estimation Results

Priors

The model is estimated using flat priors, which are described in Table B.1 in Appendix B. Flat priors are chosen in order to minimize the impact of pre-sample information. While this differs from some previous studies, it is difficult to know what reasonable priors are for the stochastic volatility terms. Flat priors do not come without concerns, as they can make identification difficult. To avoid potential identification issues and ease the computational burden, some parameters are fixed to certain values. As is common in the literature, I fix $\delta = 0.25$, $\psi = 8$, $F(\bar{\omega}_{ss}) = 0.0075$, $\sigma_\omega^2 = 0.24$, $\beta = 0.998$, and $\nu = 0.9762$.[15] In addition to this, I also fix the persistence terms, ρ, for the stochastic volatility and parameter drift processes to 0.95. While this is quite restrictive, it helps with identification and imparts a large degree of persistence, which would be expected of changes that caused the Great Moderation.[16] While I am fixing

[14]Bayesian methods are used instead of maximum likelihood estimation in order to be consistent with other studies and to restrict the model to parameterizations that are reasonable.

[15]These numbers are used by either Fernández-Villaverde et al. (2010) or Christiano et al. (2010) in similar studies.

[16]This is not very different from specifying that a process follows a unit root, which is frequently done in empirical studies.

the persistence, the standard deviation of the exogenous shocks to the stochastic volatility and parameter drifting is freely estimated. If there is little movement in the parameters or if there is little stochastic volatility, this can still be determined in the estimation and would show the estimated standard deviation of the innovations to be near zero.

Results

The posteriors of many key variables from the partial measurement error estimation will be described here, while all results can be found in Appendix B in Tables B.2 to B.5. The results are presented with the means of the posterior distribution along with their standard deviation.

The posterior results for the coefficients controlling the parameter drift of the bankruptcy cost, which can be considered a measure of financial frictions, are shown in Table 11. The steady state marginal bankruptcy cost is estimated to be around 0.28, which would mean that 28% of an entrepreneur's assets would be lost due to auditing costs if the entrepreneur went bankrupt. This estimate is much lower than the calibration used by Christiano et al. (2010), but is slightly higher than the findings in Fuentes-Albero (2010). The bankruptcy cost does not appear to be constant, as the mean posterior of σ_μ is 0.11, so financial frictions do appear to be changing during the sample.

TABLE 11. Posterior, Bankruptcy Cost Parameters

μ_{ss}	σ_μ
0.279	0.11
(0.043)	(0.027)

The posterior results for the monetary policy parameters are shown in Table 12. The steady-state Taylor rule parameter governing the response to inflation in much larger than in Fernández-Villaverde et al. (2010) which does not have financial frictions, but is in line with the estimates from similar models with financial frictions. Policy is quite responsive to deviations of inflation from the Fed's target, as is shown by the posterior distribution of ψ_1. Based on the distributions of σ_{ψ_1} and σ_{ψ_2}, it appears that policy has not be constant throughout the sample.

The posterior results for the stochastic volatility parameters are shown in Table 13. Similar to the findings in Fernández-Villaverde et al. (2010)., there appears to be a large degree of

TABLE 12. Posterior, Monetary Policy

ψ_1	ψ_2	Π
2.370 (0.026)	0.279 (0.043)	1.010 (0.005)
σ_{ψ_1}	σ_{ψ_2}	γ_R
0.070 (0.029)	0.293 (0.020)	0.027 (0.016)

stochastic volatility, as all of the standard deviations to the innovation are significantly above zero.

TABLE 13. Posterior, Stochastic Volatility

σ_m	σ_d	σ_x	σ_ζ	σ_z	σ_g
0.105 (0.009)	0.080 (0.006)	0.195 (0.013)	0.063 (0.012)	0.003 (0.001)	0.144 (0.008)
σ_{σ_m}	σ_{σ_d}	σ_{σ_x}	σ_{σ_ζ}	σ_{σ_z}	σ_{σ_g}
0.637 (0.120)	0.120 (0.021)	0.825 (0.037)	0.978 (0.023)	0.257 (0.020)	0.470 (0.040)

Based on the posterior distributions from the estimation, I find that financial frictions, monetary policy and the standard deviation of the exogenous shocks are not constant over time. These results show that any of these model features could play a large role in explaining the Great Moderation.

Model Fit

To better understand the role that stochastic volatility and parameter drifting play, I will first study the fit of the model by comparing log marginal data densities, which are shown in Table 14.[17] There are four models that are compared. The "Full Model" and "Constant μ" both have no measurement error, except in the log growth of net worth, but one model allows μ_t to drift as described above and the other fixes μ_t. The model listed as " No s.v., w/full measurement error" holds estimates a variation of the model described above where the standard deviation of all shocks is held constant (i.e. no stochastic volatility) and all observables are assumed to have measurement error. To best compare the importance of stochastic volatility, the model

[17]The log marginal data densities are calculated using the method presented by Chib and Jeliazkov (2001).

called "Full Model, w/full measurement error" estimates the full model described above with measurement error for all observables and includes stochastic volatility.[18]

TABLE 14. Model Fit

Model	$\log p\left(\mathbb{Y}^T = \mathbb{Y}^{data,T} \vert m_i\right)$
Full Model	2,156
Constant μ	1,861
Full Model, w/full measurement error	-3,897
No s.v., w/full measurement error	-5,640

Based on Table 14, allowing for μ to drift over time greatly improves model fit, the log Bayes Factor comparing the "Full Model" and the "Constant μ" model is 295. This is overwhelming evidence in favor of the model with changing financial frictions. Both of these specifications fit the data much better than either of the models with measurement error for all observables. However, when comparing the models with and without stochastic volatility, there is overwhelming evidence that stochastic volatility improves model fit as the log Bayes Factor comparing the two models is 1,743.

Underlying States

In order to get a better understanding of how parameters have changed over time, the smoothed shocks are presented in this section. There is considerable movement in the marginal bankruptcy cost term as well as the monetary policy parameters. There also is a significant amount of stochastic volatility, especially when looking at the standard deviation of productivity shocks.

Based on Figure 1, there is substantial movement in the marginal bankruptcy cost term, μ_t, over time. This is a measure of financial frictions, as it plays a role in determining how many entrepreneurs receive loans and what the credit spread is. It falls from a high around 0.3 to a low around 0.12, which represents a fall in auditing costs of about 40%. The fall began in the early to mid-1980s, around the start of the Great Moderation. The lowering of μ_t would allow freer access

[18]The inclusion of measurement error decreases the marginal data densities, so it is difficult to compare models if one contains measurement error and the other does not.

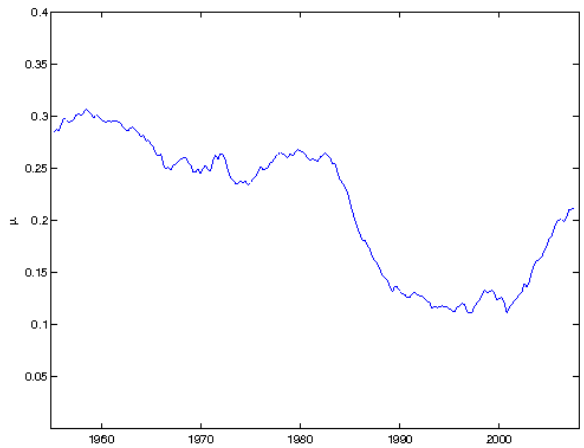

FIGURE 1. Bankruptcy Cost: μ_t

to credit by entrepreneurs and a lowering of the credit spread. This would lower macroeconomic volatility, since investment would be more stable throughout the business cycle.[19]

The underlying states of $\psi_{1,t}$ and $\psi_{2,t}$, which represent Federal Reserve interest rate policy regarding inflation and output, are shown in Figure 2. The Fed's reaction to inflation becomes much stronger, as shown by the increase in $\psi_{1,t}$ starting in the mid-1980s, around the time of the beginning of the Great Moderation. The response to the output growth gap is relatively constant throughout much of the sample. Based on the movements of $\psi_{1,t}$ and $\psi_{2,t}$, it does appear that changes in the Fed's response to inflation might play a role in the Great Moderation, but it does not appear that changes in the response to output growth could play a role.

The underlying states of the stochastic volatility parameters are shown in Figure 3. In each series there is substantial variation; however, none of the movements appear to be supportive of good luck causing the Great Moderation. The only stochastic volatility terms that show a pattern to their drift are the standard deviations of the monetary policy shock, $\sigma_{m,t}$, and the government spending shock, $\sigma_{g,t}$. However, both of these show that the underlying shocks became more volatile starting in the 1980s, rather than less. This would actually cause more macroeconomic volatility to increase and is the opposite of the good luck story. These findings differ from Fernández-Villaverde et al. (2010), who find that the standard deviations of some

[19]As can be seen below in Table 15, investment did indeed become more stable during the Great Moderation.

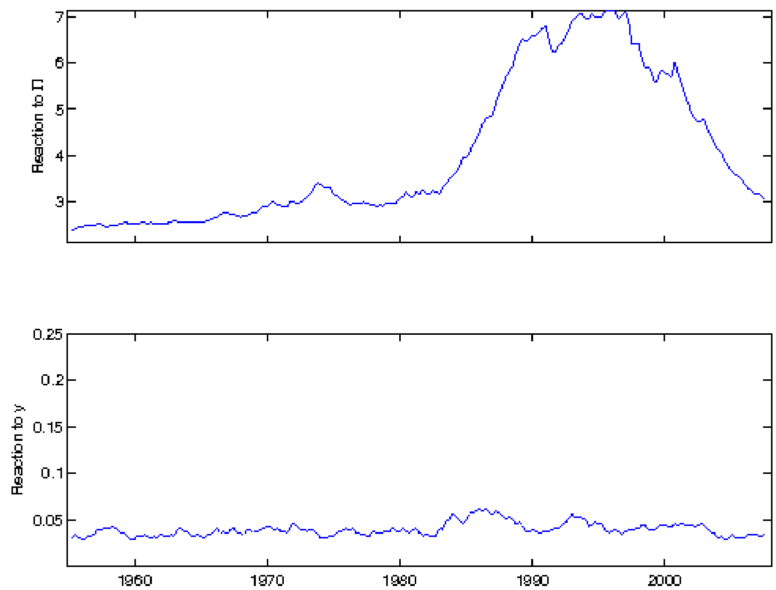

FIGURE 2. Monetary Policy Parameters: $\psi_{1,t}$, $\psi_{2,t}$

shocks fall, specifically the intertemporal shock which is similar to the shock described above as d_t, during the 1980s and this a key contributor to the Great Moderation.[20]

Counterfactuals

In order to study the role that changing financial frictions and stochastic volatility play in reducing macroeconomic volatility, counterfactual studies must be done. To do this, some variables in the model are constrained and then the model is simulated using the same underlying shocks that are pulled out from the original estimation. One variation holds the marginal bankruptcy/auditing cost parameter, μ, constant throughout the sample to judge it's role in the change in volatility. Another counterfactual study is done by holding the monetary policy parameters constant. If the drifting of financial frictions or the changing of monetary policy is important to decreasing the volatility of the observed data, I would expect there to be a smaller drop in the standard deviations of the simulated data when these features are removed from the model.

[20]It is important to note that not all of the shocks are shared across the model described above and the model used by Fernández-Villaverde et al. (2010), which may account for some of the differences in the findings regarding stochastic volatility.

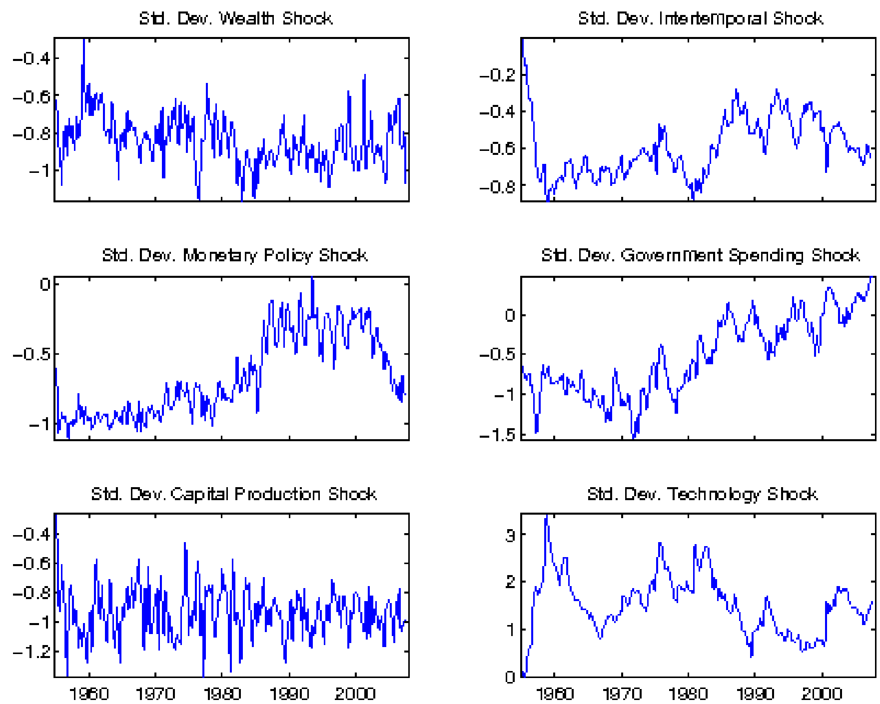

FIGURE 3. Stochastic Volatility (Log Deviation from S.S) of: Weath Shock ($\sigma_{x,t}$), Intertemporal Shock ($\sigma_{d,t}$), Monetary Policy Shock($\sigma_{m,t}$), Governemtne Spending Shock ($\sigma_{g,t}$), Capital Production Shock ($\sigma_{\zeta,t}$), Technology Shock ($\sigma_{A,t}$)

The results of these countefactuals can be found in Table 15. The first section of the table shows how the standard deviation of the annualized growth rate of output, inflation and the annualized growth rate of investment, the annual credit spread, measured as $\frac{R^{Baa}}{R}$, the annual federal funds rate, the annualized growth rate of net worth, as well as the annualized growth rate of consumption changed before and after the first quarter of 1984, which is considered to be the approximate start of the Great Moderation.[21] The data shows a clear drop in the standard deviation across all data types, except net worth which actually becomes more volatile.

TABLE 15. Standard Deviation of Data from Counterfactuals

	Standard Deviation						
	Y	Π	I	$\frac{R^{Baa}}{R}$	R	N	C
Data, pre 1984Q1	6.14	3.42	18.6	0.0042	4.01	2.89	3.14
Data, post 1984Q1	3.17	1.16	9.79	0.0035	2.47	8.55	2.36
Data, post/pre	0.52	0.34	0.53	0.83	0.62	2.96	0.75
Constant μ, pre 1984Q1	6.92	3.65	29.5	0.0065	4.34	4.79	3.69
Constant μ, post 1984Q1	7.52	2.95	36.1	0.0080	3.21	9.89	4.19
Constant μ, post/pre	1.09	0.81	1.22	1.23	0.74	2.07	1.14
Constant ψ_1, ψ_2, pre 1984Q1	6.14	12.1	19.0	0.0288	4.30	4.40	3.18
Constant ψ_1, ψ_2, post 1984Q1	4.08	14.5	17.8	0.0355	3.19	8.58	2.67
Constant ψ_1, ψ_2, post/pre	0.66	1.20	0.94	1.23	0.74	1.95	0.84

The second section of Table 15 shows the counterfactual data's standard deviations that would have been observed if μ_t was constant throughout the sample. For all data types, except net worth, if financial frictions were constant then the decrease in volatility observed during the Great Moderation would have been much smaller or nonexistent. The standard deviation of output growth, investment growth, consumption growth and the credit spread would have actually increased after 1984 if financial frictions were constant, instead of decreasing as is observed in the data. With financial frictions held constant, the decrease in the variability of inflation would have been much smaller than the observed drop, with the standard deviation only falling by about 19% instead of falling by 66%.

The third section of Table 15 shows the counterfactual data's standard deviations that would have been observed had monetary policy been constant throughout the sample. Not

[21] The simulated data pulled from the estimation, with no constraints added, perfectly matches all the observed data except for the net worth observations. The net worth data does not match due to measurement error and the estimated data, with no constraints, finds the standard deviation of the growth of net worth to increase from 4.01 to 8.28, which is similar to the actual data.

surprisingly, the standard deviation of inflation changes greatly when monetary policy is held constant. The standard deviation of the credit spread is also greatly affected. Based on the results presented above, it appears that changing monetary policy is important for explaining the moderation in inflation and investment. It also appears that changing monetary policy is important for explaining the change in the volatility of the federal funds rate and the credit spread. When holding monetary policy constant, there is still a decrease in the standard deviation of output and consumption growth. This decrease in standard deviations is similar to that observed in the data, so it does not appear that changing monetary policy is an important driver of the moderation of output and consumption. Based on this counterfactual study, changing monetary policy played a role in the Great Moderation, but it was a much smaller role than the role played by changing financial frictions.[22]

Conclusion

In this paper I estimate a medium-scale DSGE model featuring financial frictions, parameter drifting and stochastic volatility. The model is estimated using Bayesian techniques and the particle filter. To understand the importance of the features of the model, I study the underlying states and run counterfactual tests, in addition to analyzing model fit. I find that changing financial frictions play a large role in explaining the reduction in volatility observed during the Great Moderation. I also find that changing monetary policy played a limited role in the Great Moderation. While stochastic volatility is important to fitting the data, good luck does not appear to be an important cause of the Great Moderation. This differs from Fernández-Villaverde et al. (2010), who point to decreases in the variance of shocks and good luck as being the main cause of the Great Moderation. Part of the differing importance of stochastic volatility may be due to the inclusion of financial frictions.

While this paper finds support for changing financial frictions contributing to the Great Moderation, it is important to remember that the model does not feature sticky wage or sticky price mechanisms found in New-Keynesian models. In future research, I plan to augment this model with sticky wages and sticky prices. This should further clarify the role that financial

[22] It is important to remember that there are no price and no wage rigidities. I plan to study a similar model featuring these in future work.

frictions played in the Great Moderation. Another extension to this paper would be to add learning to the model to further study the role that changing parameters can have on dynamics.

CHAPTER IV

CHANGING MACROECONOMIC VOLATILITY IN A NEW KEYNESIAN MODEL WITH FINANCIAL FRICTIONS

Introduction

A key feature of the post-war US economy is the Great Moderation, where there was a dramatic reduction in volatility of real and nominal macroeconomic variables starting in the 1980s.[1] The causes of the Great Moderation have been greatly debated and there is no definitive answer as to what brought about the reduction in volatility. Much of the research has focused on changing monetary policy and good luck. Chapter III finds that reductions in financial frictions played a key role in the Great Moderation using a Real Business Cycle (RBC) model with changing financial frictions and stochastic volatility. I further that work by using Bayesian techniques to estimate a New Keynesian model featuring aspects of the financial accelerator model of Bernanke, Gertler and Gilchrist (1999). The model features stochastic volatility, changing financial frictions and changing monetary policy. This model is used to study whether changing financial frictions, good monetary policy or good luck with shocks caused the Great Moderation.

A major focus of macroeconomics is understanding the causes of business cycle fluctuations and macroeconomic volatility. Macroeconomic volatility can have large welfare effects and may even impact economic growth.[2] A great deal of research has focused on the Great Moderation since it provides a natural setting to study the causes of macroeconomic volatility. Some have argued that the Great Moderation was brought about by improved monetary policy that was more responsive to inflation.[3] The other main explanation for the Great Moderation was "good luck," where the exogenous shocks became less volatile.[4] Another explanation is provided by

[1]Kim and Nelson (1999), McConnell and Perez-Quiros (2000), and Stock and Watson (2003) provide an empirical analysis of the change in volatility associated with the Great Moderation.

[2]For estimates of the welfare cost of volatility, see Reis (2009). For an estimate of the effect on growth, see Barlevy(2004).

[3]For example, see Clarida, Galí, and Gertler (1999).

[4]For examples, see Sims and Zha (2006), McConnell and Perez-Quiros (2000), and Fernández-Villaverde, Guerrón-Quintana, and Rubio-Ramírez (2010).

Dynan, Elmendorf and Sichel (2006), who find that financial innovation may be an important factor in explaining the decrease in volatility during the Great Moderation.[5]

A reduction of financial frictions may also explain the Great Moderation. Bernanke et al. (1999) showed that financial frictions could affect the size of business cycle fluctuations by developing the financial accelerator model, so a reduction in financial frictions could lower macroeconomic volatility. There is reason to believe that financial frictions may have fallen during the 1980s as this was a time of financial innovation and deregulation.[6] Fuentes-Albero (2011) and Chapter III find evidence that financial frictions fell during the 1980s and this drop in frictions was a key driver in moderating the business cycle.

This paper studies the causes of the Great Moderation by estimating a large structural model that allows for changing monetary policy, stochastic volatility, and changing financial frictions. The estimated model is based on a New Keynesian model that features a financial accelerator mechanism. The model allows for financial frictions and monetary policy to drift over time. This model differs from Chapter III since it includes nominal rigidities and differs from Fuentes-Albero (2011) since it includes stochastic volatility. The inclusion of stochastic volatility lets the standard deviation of the exogenous shocks in the model change over time. These features allow the model to be used to study the importance of good luck, good policy and changing financial frictions in the Great Moderation.[7]

In order to study observed changes in macroeconomic volatility, the model is estimated using a particle filter and Bayesian econometric methods. To understand the importance of the different features of the model, I do three exercises. First, the fit of models with different specifications are compared to determine the importance of certain features for matching the data. Second, to get an understanding of how unobserved variables have changed over time, a particle filter is used along with the estimation results to pull out the underlying state variables from the model. This shows how the financial frictions, monetary policy and the standard deviation

[5] These findings were also supported by Guerrón-Quintana (2007).

[6] Examples of changes in regulation include the Bankruptcy Reform Act of 1978, Depository Deregulations and Monetary Control Act of 1980, Garn-St. Germain Depository Institutions Act in 1982, the Financial Institutions Reform Act in 1989, the Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994 and the Gramm-Leach-Bliley Act in 1999. For an overview of financial deregulation in the US in recent decades, see Sherman (2009).

[7] It is important to study these explanations from within the same model as this will make for a more fair comparison.

of exogenous shocks have changed over time. The underlying state variables allow for a final exercise, where the importance of drifting parameters can be studied by doing a counterfactaul experiment. This is done by simulating data using the underlying states and holding the financial frictions constant or setting them equal to the pre-1984 levels during the Great Moderation. The counterfactual data is then compared with the actual data.

I find strong evidence that financial frictions fell during the early 1980s and this reduction in financial frictions was an important reason for the reduction in volatility observed during the Great Moderation. This supports the findings of Fuentes-Albero (2011) and Chapter III. Based on a study of the underlying states there appears to be some changes in monetary policy during the time studied, but there doesn't appear to be any systematic change in policy. Specifically, there does not appear to an increase in responsiveness to inflation during the 1980s like the "good policy" story suggests. I find mixed support of "good luck" during the Great Moderation. There does not appear to be a reduction in the standard deviation of the exogenous shocks during the 1980s as is found in Fernández-Villaverde et al. (2010). However, when studying the underlying shocks that hit the economy, there do appear to be some changes in the way the economy behaved. It appears that the shocks facing households systematically changed during the 1980s. These shocks appear to be important in explaining the reduction in consumption volatility observed during the Great Moderation. Based on these findings, it appears that changing financial frictions and good luck were both important in bringing about the Great Moderation. This differs from the third chapter, which found no rle for good luck. This is may be attributed to the inclusion of habit persistance and intratemporal shocks into the model

The rest of the paper is organized as follows. Section 2 presents the model to be estimated. Sections 3 and 4 describe the data sources and present the estimation strategy. Section 5 presents the priors and estimation results, while section 6 describes the model fit. Sections 7 and 8 show the underlying states and results from counterfactual experiments. Finally, section 9 provides some concluding remarks and describes some potential future related research.

Model

The model economy is populated by a continuum of households, financial intermediaries, entrepreneurs, capital producers, final good producers, and a government. A New Keynsian model serves as the basis for the model, with aspects of the financial accelerator model that Bernanke et al. (1999) added. Stochastic volatility is incorporated into the model so the standard deviation of the underlying shocks are allowed to drift over time. The monetary policy rule parameters and the term measuring financial frictions are allowed to drift over time. The model is based on the models of Smets and Wouters (2007), Christiano, Motto and Rostagno (2010), Fernández-Villaverde et al. (2010), and Fuentes-Albero (2012). This model is unique since it combines stochastic volatility, parameter drifting and the financial accelerator in a DSGE model.

The main departure from a standard New-Keynesian or RBC model is the inclusion of a financial accelerator. The financial accelerator introduces entrepreneurs who use their own funds and borrow funds in order to purchase capital at the end of every period. After capital is purchased, entrepreneurs are hit with a productivity shock that the entrepreneur costlessly observes, but the financial intermediary must pay a fee in order to observe the entrepreneurs productivity. This asymmetric information introduces new dynamics into the model and can amplify business cycles. In this paper, the monitoring cost paid by banks will be allowed to change over time, which will pick up changes in financial frictions.

Household

There is a continuum of households indexed by j who maximize expected utility represented by

$$\mathbb{E}_t \Sigma_{s=0}^{\infty} \beta^s d_{t+s} \left[\log \left(c_{j,t+s} - h c_{j,t+s-1} \right) + \log \frac{M_{j,t+s}}{P_{t+s}} - \varphi_t \psi \frac{l_{j,t+s}^{1+\vartheta}}{1+\vartheta} \right] \tag{4.1}$$

subject to the budget constraint

$$\begin{aligned} c_{j,t+s} \quad & + \frac{D_{j,t+s+1}}{P_{t+s}} + \frac{NB_{j,t+s+1}}{P_{t+s}} + \frac{M_{j,t+s+1}}{P_{t+s}} \leq \\ & w_{j,t+s} l_{t+s} + R_{t+s-1} \frac{D_{j,t+s}}{P_{t+s}} + R_{t+s-1}^N \frac{NB_{j,t+s}}{P_{t+s}} + \frac{M_{j,t+s}}{P_{t+s}} + div_{t+s} - T_{t+s} - Trans_{t+s}, \ \ \forall s. \end{aligned}$$

The utility function is separable in consumption, $c_{j,t}$, real money balances, $\frac{M_{j,t}}{P_t}$, and hours worked, $l_{j,t}$. β is the discount factor, R_t is the risk-free, gross nominal interest rate paid on deposits, R_t^n is the risk-free nominal interest rate paid on government bonds, $NB_{j,t}$ is the nominal value of government bonds held, $D_{j,t}$ is the nominal value of deposits at the financial intermediary, div_t is the real value of dividends obtained from ownership of firms, T_t are taxes paid, and $Trans_t$ is the real value of wealth transfers to/from the entrepreneurial sector. The household faces an intertemporal preference shock, d_t, and an intratemporal preference shock, φ_t, that evolves as

$$\log d_t = \rho_d \log d_{t-1} + \sigma_{d,t}\varepsilon_{d,t} \tag{4.2}$$

$$\log \varphi_t = \rho_\varphi \log \varphi_{t-1} + \sigma_{\varphi,t}\varepsilon_{\varphi,t}. \tag{4.3}$$

The standard deviation of the innovation is allowed to change over time and follows the process

$$\log \sigma_{d,t} = (1-\rho_{\sigma_d}) \log \sigma_d + \rho_{\sigma_d} \log \sigma_{d,t-1} + \eta_d u_{d,t} \tag{4.4}$$

$$\log \sigma_{\varphi,t} = (1-\rho_{\sigma_\varphi}) \log \sigma_\varphi + \rho_{\sigma_\varphi} \log \sigma_{\varphi,t-1} + \eta_\varphi u_{\varphi,t}. \tag{4.5}$$

The exogenous innovations, $\varepsilon_{d,t}$, $\varepsilon_{\varphi,t}$, $u_{d,t}$, and $u_{\varphi,t}$, and all other innovations described in the model are i.i.d. $N(0,1)$. Allowing for $\sigma_{d,t}$ and $\sigma_{\varphi,t}$ to drift through time will allow the model to pick up changes in the nature of underlying shocks over time as in Fernández-Villaverde et al. (2010), if such changes exist. This specification of stochastic volatility will be present for all shocks in the model.

Households provide differentiated labor to a labor packer in a monopolistically competitive market. The perfectly competitive labor packer aggregates labor using the following production function

$$l_t^d = \left(\int_0^1 l_{j,t}^{\frac{\eta-1}{\eta}} dj \right)^{\frac{\eta}{\eta-1}}. \tag{4.6}$$

The labor packer maximizes profits given the wage, w_t, and the differentiated wage, $w_{j,t}$ using the following equation

$$\max_{l_{j,t}} w_t l_t^d - \int_0^1 w_{j,t} l_{j,t} dj. \tag{4.7}$$

Households face a Calvo pricing mechanism for their wages. Each period, a fraction $1 - \theta_w$, of households are able to optimize their prices. Households that are not able to optimize their wages partially index wages based on previous inflation using the indexation parameter χ_w, setting prices as $w_{i,t} = \Pi_{t-1}^{\chi_w} w_{i,t-1}$.

Final Good Production

A perfectly competitive final good producer aggregates a continuum of intermediate goods using the production function

$$y_t^d = \left(\int_0^1 y_{i,t}^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}} \tag{4.8}$$

where ϵ is the elasticity of substitution for the intermediate goods. The final goods producer minimizes costs given this production function, the price of intermediate goods, $p_{i,t}$, and the price of the final good, p_t. This minimization leads to the following demand function

$$y_{i,t} = \left(\frac{p_{i,t}}{p_t} \right)^{-\epsilon} y_t^d \qquad \forall i$$

where the price of the final good is defined by

$$p_t = \left(\int_0^1 p_{i,t}^{1-\epsilon} di \right)^{\frac{1}{1-\epsilon}}.$$

Intermediate Good Production

Intermediate goods are produced by a monopolistic competitor with a Cobb-Douglas production function defined as

$$y_{i,t} = A_t k_{i,t}^{\alpha} \left(l_{i,t}^d \right)^{1-\alpha} \tag{4.9}$$

where $k_{i,t}$ is the capital rented and $l_{i,t}^d$ is the "packed" labor rented by firm i. The log of the productivity term, A_t, follows a random walk and features stochastic volatility. The process is defined as

$$\log A_t = \log A_{t-1} + \Upsilon_A + \sigma_{A,t} \varepsilon_{A,t} \tag{4.10}$$

where the standard deviation of the innovation follows the process

$$\log \sigma_{A,t} = (1 - \rho_{\sigma_A}) \log \sigma_A + \rho_{\sigma_A} \log \sigma_{A,t-1} + \eta_d u_{A,t}. \tag{4.11}$$

Intermediate good producers face a Calvo pricing mechanism. Each period, a fraction $1-\theta_p$, of firms are able to optimize their prices. Firms that are not able to optimize their prices partially index their prices based on previous inflation using the indexation parameter χ, setting prices as $p_{j,t} = \Pi_{t-1}^{\chi} p_{j,t-1}$.

Capital Producers

Capital producers are perfectly competitive, infinitely lived agents who produce new capital and purchase capital from entrepreneurs. Capital is produced using a linear production function, where one unit of investment in period t produces ζ_t units of time $t+1$ physical capital. The log of the productivity of capital production, ζ_t, follows a random walk with drift defined by the process

$$\log \zeta_t = \log \zeta_{t-1} + \Upsilon_\zeta + \sigma_{\zeta,t} \varepsilon_{\zeta,t} \tag{4.12}$$

where the standard deviation of the innovation follows the process

$$\log \sigma_{\zeta,t} = (1 - \rho_{\sigma_\zeta}) \log \sigma_\zeta + \rho_{\sigma_\zeta} \log \sigma_{\zeta,t-1} + \eta_\zeta u_{\zeta,t}.^{8} \tag{4.13}$$

Financial Intermediaries and Entrepreneurs

Entrepreneurs are risk-neutral, finitely lived agents who can borrow funds from financial intermediates. Entrepreneurs survive from one period to the next with probability ν. Financial intermediaries attain funds from households. At the end of period t, entrepreneurs purchase physical capital. At the beginning of period $t+1$, entrepreneurs observe an idiosyncratic shock that affects the productivity of their capital. Entrepreneurs then determine how much of their capital to rent. At the end of the period entrepreneurs sell off undepreciated capital and pay of debts to the financial intermediary.

Each entrepreneur faces an idiosyncratic productivity shock, ω_t^j, at the beginning of each period which is only observed by the entrepreneur and affects the productivity of his capital holdings. This shock is assumed to have a lognormal distribution with c.d.f. $F(\omega)$ with parameters μ_ω and σ_ω satisfying $\mathbb{E}\left(\omega^j\right) = 1$. Entrepreneurs maximize profits by determining the fraction of

[8] To ease notation later, define $z_t = A_t^{\frac{1}{1-\alpha}} \zeta_t^{\frac{\alpha}{1-\alpha}}$ and $\Upsilon_z = \frac{\Upsilon_A + \Upsilon_\zeta}{1-\alpha}$.

capital to utilize, u_t^j, to solve

$$\max_{u_t^j} \left[u_t^j r_t^{j,k} - \zeta_t^{-1} a\left(u_t^j\right) \right] \omega_t^j K_t^j. \tag{4.14}$$

The rental rate of capital is denoted $r_t^{j,k}$. $a(\cdot)$ represents the cost of utilizing capital and is defined as $a(u_t) = \gamma_1 (u_t - 1) + \frac{1}{2}\gamma_2 (u_t - 1)^2$.

Capital demand for entrepreneur j is determined by the gross nominal returns on holding capital

$$R_{t+1}^{j,k} = \left[\frac{\left(u_{t+1}^j r_{t+1}^{j,k} - \zeta_t a\left(u_{t+1}^j\right)\right) + \omega_{t+1}^j (1-\delta) Q_{t+1}}{Q_t} \right] \frac{P_{t+1}}{P_t}. \tag{4.15}$$

The gross return on capital is denoted $R_{t+1}^{j,k}$ and $\omega_{t+1}^j(1-\delta)Q_{t+1}$ is the return from selling undepreciated capital.

An entrepreneur can use his own net worth, N_{t+1}^j, or external financing to purchase new physical capital. Lenders are unable to observe the returns of entrepreneurs unless they pay an auditing cost. Due to cost minimization, lenders will only audit entrepreneurs when the loan is not fully repaid. The auditing cost is represented by a fraction, μ_{t+1}, being lost in the process of liquidation leaving $(1-\mu_{t+1})P_t \omega_{t+1}^j R_{t+1}^k Q_t K_{t+1}^j$. The auditing cost is allowed to change over time, which is intended to pick up changes in financial frictions. When the auditing cost falls, this is interpreted as a lowering of financial frictions since more entrepreneurs can get access to credit. Since the auditing cost must be between 0 and 1, it is defined as $\mu_t = \frac{1}{1-\mu\check{\mu}_t}$. The process that $\check{\mu}_t$ follows is defined by

$$\log \check{\mu}_t = \rho_\mu \log \check{\mu}_{t-1} + \sigma_\mu \varepsilon_{\mu,t}. \tag{4.16}$$

The debt contract is set to maximize expected entrepreneurial profits subject to a participation constraint. The maximization problem is defined as

$$\max_{\bar{\omega}_{t+1}, k_{t+1}} \mathbb{E}_t \left\{ [1 - \Gamma(\bar{\omega}_{t+1})] \frac{R_{t+1}^k}{R_t} (B_{t+1} + N_{t+1}) \right\} \tag{4.17}$$

subject to the constraint

$$\mathbb{E}_t \frac{R_{t+1}^k}{R_t} [\Gamma(\bar{\omega}_{t+1}) - \mu_{t+1} G(\bar{\omega}_{t+1})] = \frac{Q_t K_{t+1} - N_{t+1}}{Q_t K_{t+1}} \tag{4.18}$$

where $\Gamma(\bar{\omega}_{t+1})$ is the expected share of gross entrepreneurial earnings going to the lender and $\mu_{t+1}G(\bar{\omega}_{t+1})$ is the expected monitoring cost.[9] The size of the loan is defined as B_{t+1}, the net worth of the borrower is defined as N_{t+1}, Q_t is the shadow cost of capital, and $\bar{\omega}_{t+1}$ represents the productivity that must be drawn in order for the borrower to be able to repay the loan. This results in an external finance premium defined by $\mathbb{E}\frac{R^k_{t+1}}{R_t}$.

The net worth of entrepreneurs evolves as

$$P_t N_{t+1} = x_t \nu V_t + P_t W^e_t \tag{4.19}$$

where x_t represents a wealth shock, V_t represents entrepreneurial equity, and W^e_t is the value of wealth transfers made by exiting firms.[10] The wealth shock changes over time according to $\log x_t = (1-\rho_x)\log x + \rho_x \log x_{t-1} + \sigma_{x,t}\varepsilon_{x,t}$ and $\log\sigma_{x,t} = (1-\rho_{\sigma_x})\log\sigma_x + \rho_{\sigma_x}\log\sigma_{x,t} + \eta_x u_{x,t}$. The entrepreneurial sector provides transfers to/from the private sector equal to $Trans_t = N_{t+1} - \nu V_t - W^e_t$.

Government

The government finances spending by issuing government bonds to households and collecting lump-sum taxes. The government's finances are defined by

$$NB_{t+1} + P_t T_t + M_{t+1} = P_t G_t + R_{t-1} NB_t + M_t. \tag{4.20}$$

Government spending is allowed to change over time and is defined by $G_t = \left(\frac{1}{1+\breve{g}g_t}\right) Y_t$ where the government spending shock follows

$$\log(g_t) = \rho_g \log(g_{t-1}) + \sigma_{g,t}\varepsilon_{g,t} \tag{4.21}$$

where the standard deviation of the innovation follows the process

$$\log\sigma_{g,t} = (1-\rho_{\sigma_g})\log\sigma_g + \rho_{\sigma_g}\log\sigma_{g,t} + \eta_g u_{g,t}. \tag{4.22}$$

[9] $\Gamma(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}_{t+1}} \omega f(\omega)d\omega + \bar{\omega}_{t+1}\int_{\bar{\omega}_{t+1}}^{\infty} f(\omega)d\omega$ and $G(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}_{t+1}} \omega f(\omega)d\omega$.

[10] $V_t = P_{t-1}R^k_t Q_{t-1}K_t - R_{t-1}B_t - \mu_t G(\bar{\omega}_t)P_{t-1}R^k_t Q_{t-1}K_t$

The central bank sets the interest rate using a Taylor rule with drifting parameters. The rule is defined as

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{1-\gamma_R} \left(\left(\frac{\Pi_t}{\Pi}\right)^{\psi_{1,t}} \left(\frac{\frac{Y_t}{Y_{t-1}}}{\Upsilon_A}\right)^{\psi_2}\right)^{1-\gamma_R} m_t \tag{4.23}$$

where $\Pi_t = \frac{P_t}{P_{t-1}}$. The Taylor coefficient on inflation drifts according to the processes

$$\log(\psi_{1,t}) = \rho_{\psi_1} \log(\psi_{1,t-1}) + (1 - \rho_{\psi_1}) \log(\psi_1) + \eta_{\psi 1} \varepsilon_{\psi_1,t} \tag{4.24}$$

The monetary policy shock is defined as $\log m_t = \sigma_{m,t} \varepsilon_{m,t}$ and $\sigma_{m,t}$ follows the process

$$\log \sigma_{m,t} = (1 - \rho_{\sigma_m}) \log \sigma_m + \rho_{\sigma_m} \log \sigma_{m,t} + \eta_m u_{m,t}. \tag{4.25}$$

Market clearing

The market clearing condition for the goods market is defined by

$$Y_t = C_t + I_t + G_t + a(u_t) K_t + \mu_t G(\bar{\omega}_t) R_t^k Q_{t-1} K_t. \tag{4.26}$$

Credit market clearing is defined by

$$\frac{D_{t+1}}{P_t} = \frac{B_{t+1}}{P_t} = Q_t K_{t+1} - N_{t+1}. \tag{4.27}$$

Equilibrium

The equilibrium can be characterized by the first order conditions, the Taylor rule monetary policy and market clearing conditions. The equilibrium is not stationary due to the unit root in the process for technology, so some variables must be normalized. To do this let $\widetilde{c}_t = \frac{c_t}{z_t}$, $\widetilde{I}_t = \frac{I_t}{z_t}$, $\widetilde{K}_t = \frac{K_t}{z_t \zeta_t}$, $\widetilde{B}_{t+1} = \frac{B_{t+1}}{z_t}$, $\widetilde{NB}_{t+1} = \frac{NB_{t+1}}{z_t}$, $\widetilde{N}_{t+1} = \frac{N_{t+1}}{z_t}$, $\widetilde{div}_t = \frac{div_t}{z_t}$, $\widetilde{T}_t = \frac{T_t}{z_t}$, $\widetilde{\lambda}_t = \lambda_t z_t$, $\widetilde{r}_t = r_t \zeta_t$, $\widetilde{Q}_t = Q_t \zeta_t$, $\widetilde{w}_t = \frac{w_t}{z_t}$, $\widetilde{w^*}_t = \frac{w_t^*}{z_t}$, and $\widetilde{y}_t = \frac{y_t}{z_t}$.[11]

[11]The first order conditions can be found in the supplementary materials.

Data

The data used to estimate the model spans from 1954.Q4 to 2006.Q4.[12] Eight data series are used: growth rate of real output, growth rate of real per capita investment, growth rate of real per capita consumption, the growth rate of real wages, inflation (measured as the logged ratio of the price level this period and last period), the gross federal funds rate, the spread between the Moody's Baa corporate bond interest rate and the 10 year treasury yield, and the growth rate of net worth.[13] All observables, except the growth rate of net worth, are assumed to be measured without measurement error. While measurement error may be a feature of the data, not using measurement error sharpens the estimation strategy and makes for cleaner counterfactual studies.

Estimation Strategy

Based on the complexity, size and nonlinearities of the model, estimation is difficult. The model does not have a closed-form solution and the likelihood function cannot be analytically solved, so numerical approximations must be used. To achieve this, I do a second-order approximation of the model around the steady state using perturbation methods. Aruoba, Fernández-Villaverde, and Rubio-Ramírez (2006) show that perturbation methods are both fast and accurate.[14] A second order approximation is necessary since a first order approximation would be certainty equivalent and the stochastic volatility terms would disappear.

After the approximation is done, the model is estimated using Bayesian techniques. After an initial grid search, the model is estimated using a random walk Metropolis-Hastings algorithm.[15] The algorithm is run over 14,000 draws and discard the first 5,000 draws.[16] In order to run the Metropolis-Hastings algorithm, the likelihood must be calculated. Due to the nonlinearities of the model, the Kalman filter cannot be accurately used. Therefore, the likelihood is approximated using a particle filter using 10,000 particles. The methodology of both

[12] More recent data is not used in order to avoid problems that arise at the zero lower bound.

[13] For more details on how the data is calculated, see the supplementary materials.

[14] For more information on second order perturbation techniques see Kim et al. (2005), Schmitt-Grohe and Uribe (2004) and Klein and Gomme (2011).

[15] The grid search is necessary in order to find an area of the model where the likelihood is numerically different from zero.

[16] See Chapter III for more details on the estimation strategy, as the strategy is very similar to the one used in this paper.

the particle filter used the Metropolis-Hastings algorithm are very similar to those described in Chapter III.

Priors and Estimation Results

Priors

The model is estimated using flat priors in order to minimize the impact of pre-sample information.[17] Flat priors are also chosen since it is difficult to know what reasonable priors are for the stochastic volatility terms. Flat priors do not come without concerns, as they can make identification difficult. To avoid potential identification issues and ease the computational burden, some parameters are fixed to certain values. As is common in the literature, I fix $\delta = 0.25$, $\psi = 8$, $F(\bar{\omega}_{ss}) = 0.003$, $\sigma_{\omega}^2 = 0.24$, $\beta = 0.99$, $\psi = 8$, $h = 0.9$, $\alpha = 0.3$, $\varepsilon = 10$, $\eta = 10$, $\vartheta = 1.17$, $\gamma_2 = 0.001$, and $\nu = 0.974$.[18] In addition to this, I also fix the persistence terms, ρ, for the stochastic volatility and parameter drift processes to 0.95. While this is quite restrictive, it helps with identification and imparts a large degree of persistence, which would be expected of changes that caused the Great Moderation.[19] While I am fixing the persistence, the standard deviation of the exogenous shocks to the stochastic volatility and parameter drifting is freely estimated. If there is little movement in the parameters or if there is little stochastic volatility, this can still be determined in the estimation and would show the estimated standard deviation of the innovations to be near zero.

Results

The posteriors of many key variables from the partial measurement error estimation will be described here, while all results can be found in the Table C.2 in Appendix C. The results are presented with the means of the posterior distribution along with their standard deviation.

[17]The priors are described in Appendix C and can be seen in Table C.1.

[18]These numbers are similar to those used by either Fernández-Villaverde et al. (2010) or Christiano et al. (2010) in similar studies. Based on some preliminary studies, selecting different calibrations results in changes in the levels of the parameter drifting and stochastic volatility terms, but do not change the general pattern of their underlying time series.

[19]This is not very different from specifying that a process follows a unit root, which is frequently done in empirical studies.

The posterior results for the coefficients controlling the parameter drift of the bankruptcy cost, which can be considered a measure of financial frictions, are shown in Table 16. The steady state marginal bankruptcy cost is estimated to be around 0.51, which would mean that 51% of an entrepreneur's assets would be lost due to auditing costs if the entrepreneur went bankrupt. This estimate is higher than the estimate from Chapter III, but is still below than the calibration used by Christiano et al. (2010). The bankruptcy cost does not appear to be constant, as the mean posterior of σ_μ is 0.41, so financial frictions do appear to be changing during the sample.

TABLE 16. Posterior, Bankruptcy Cost Parameters

μ_{ss}	σ_μ
0.51 (0.088)	0.41 (0.064)

The posterior results for the monetary policy parameters are shown in Table 17. The steady state Taylor rule parameter governing the response to inflation is much larger than in Fernández-Villaverde et al. (2010) which does not have financial frictions, but is in line with the estimates from similar models with financial frictions. Policy is quite responsive to deviations of inflation from the Fed's target, as is shown by the posterior distribution of ψ_1. Based on the distributions of σ_{ψ_1} and σ_{ψ_2}, it appears that policy has not be constant throughout the sample.

TABLE 17. Posterior, Monetary Policy

ψ_1	ψ_2	Π
1.95 (0.34)	0.47 (0.013)	1.021 (0.004)
σ_{ψ_1}		γ_R
0.510 (0.20)		0.54 (0.12)

The posterior results for the stochastic volatility parameters are shown in Table 18. Similar to the findings in Fernández-Villaverde et al. (2010)., there appears to be a large degree of stochastic volatility, as all of the standard deviations to the innovation are significantly above zero.

Based on the posterior distributions from the estimation, I find that financial frictions, monetary policy and the standard deviation of the exogenous shocks are not constant over

TABLE 18. Posterior, Stochastic Volatility

σ_m	σ_d	σ_x	σ_ζ	σ_z	σ_g	σ_φ
0.052	0.155	0.042	0.037	0.022	0.015	0.111
(0.023)	(0.033)	(0.021)	(0.017)	(0.004)	(0.043)	(0.053)
σ_{σ_m}	σ_{σ_d}	σ_{σ_x}	σ_{σ_ζ}	σ_{σ_z}	σ_{σ_g}	σ_{σ_φ}
0.297	0.582	0.445	0.48	0.571	0.595	0.58
(0.107)	(0.245)	(0.105)	(0.158)	(0.316)	(0.203)	(0.2)

time. These results show that any of these model features could potentially play a large role in explaining the Great Moderation.

Model Fit

In this section I will discuss model fit and the log marginal data densities (log MDD) of the different models estimated. The log MDD of the model with a constant and a drifting marginal bankruptcy cost parameter, μ, are shown in Table 19. Comparing these results with those found in Chapter III, it is clear that the inclusion of nominal rigidities greatly improves model fit. Based on the the results in Table 19, allowing μ to drift greatly improves model fit as the log Bayes Factor comparing the models is 156. This is overwhelming evidence that changing financial frictions are important for fitting the data.

TABLE 19. Model Fit

Model	$\log p\left(\mathbb{Y}^T = \mathbb{Y}^{data,T} \vert m_i\right)$
Full Model	3,270
Constant μ	3,114

Underlying States

In order to get a better understanding of how parameters have changed over time, the smoothed shocks are presented in this section. There is considerable movement in the marginal bankruptcy cost term as well as the monetary policy parameters. There also is a significant amount of stochastic volatility, especially when looking at the standard deviation of productivity shocks.

Based on Figure 4, there is substantial movement in the marginal bankruptcy cost term, μ_t, over time. This is a measure of financial frictions, as it plays a role in determining how many entrepreneurs receive loans and what the credit spread is. It falls from a high around 0.55 to a low around 0.2, which represents a fall in auditing costs of about 35%. The fall began in the early to mid-1980s around the start of the Great Moderation. The lowering of μ_t would allow freer access to credit by entrepreneurs and a lowering of the credit spread. This would lower macroeconomic volatility, since investment would be more stable throughout the business cycle.[20]

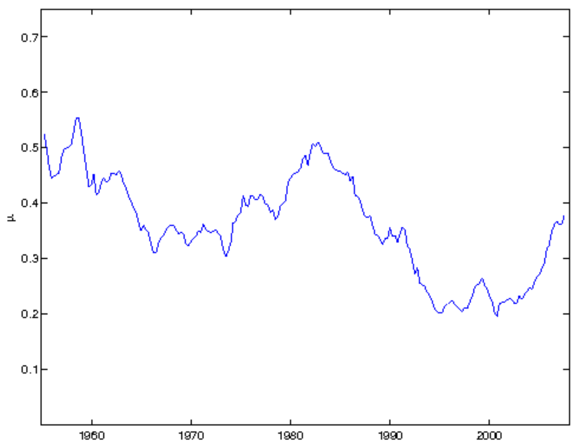

FIGURE 4. Bankruptcy Cost: μ_t

The underlying states of $\psi_{1,t}$, which represents the Federal Reserve interest rate policy regarding inflation, is shown in Figure 5. Unlike in Chapter III and Fernández-Villaverde et al. (2010), there does not appear to be any distinctive change in monetary policy during the 1980s. Therefore, it does not appear that a stronger stance against inflation is a possible explanation for the Great Moderation.

[20]As can be seen below in Table 20, investment did indeed become more stable during the Great Moderation.

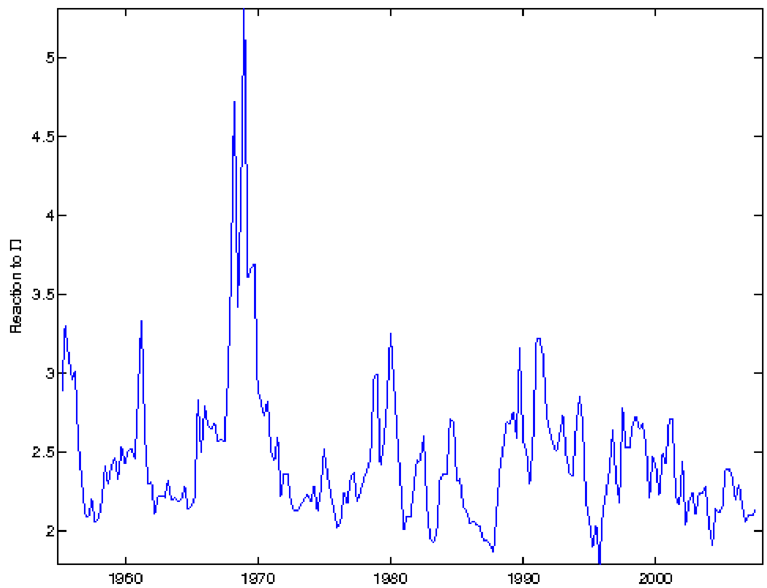

FIGURE 5. Monetary Policy Parameter: $\psi_{1,t}$

The underlying states of the stochastic volatility parameters are shown in Figure 6. In each series there is substantial variation; however, none of the movements appear to be supportive of good luck causing the Great Moderation. The standard deviation of the capital productivity shock, ($\sigma_{\varphi,t}$), appears to jump during the 1970s, but this appears to be a temporary movement. It also appears that there is an increase in the standard deviation of the wealth shock, ($\sigma_{x,t}$), during the 1970s that lasts for much of the remainder of the sample. However, increased variability in wealth would run counter to the good luck story, but is not surprising given the immoderation of financial markets and net worth during this time. As a whole, Figure 6 lends no support to the idea that the exogenous shocks faced by the economy became less volatile during the Great Moderation.

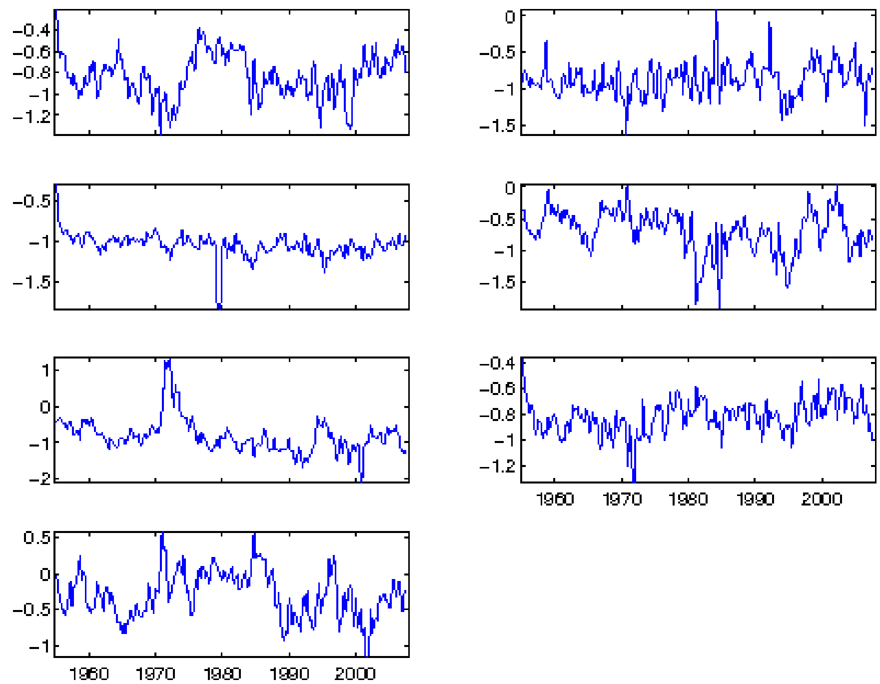

FIGURE 6. Stochastic Volatility (Log Deviation from S.S) of: Weath Shock ($\sigma_{x,t}$), Intertemporal Shock ($\sigma_{d,t}$), Monetary Policy Shock($\sigma_{m,t}$), Governemtne Spending Shock ($\sigma_{g,t}$), Capital Production Shock ($\sigma_{\zeta,t}$), Technology Shock ($\sigma_{A,t}$), Intratemmporal Shock ($\sigma_{\varphi,t}$)

The underlying exogenous shocks are shown in Figure 7. There appears to be a series of positive intertemporal shocks and negative intratemporal shocks starting in the 1980s and continuing to the end of the sample. These shocks point to a change in household behavior and are likely important in explaining changes in consumption overtime. The other set of shocks that show patterns over time are the government spending and technology shocks. During the 1990s and into the the 2000s, there is a string of positive government spending shocks. During the 1990s, there is also a string of negative technology shocks and positive capital productivity shocks. While these are noteworthy, it is unlikely that they would be important factors in reducing macroeconomic volatility.

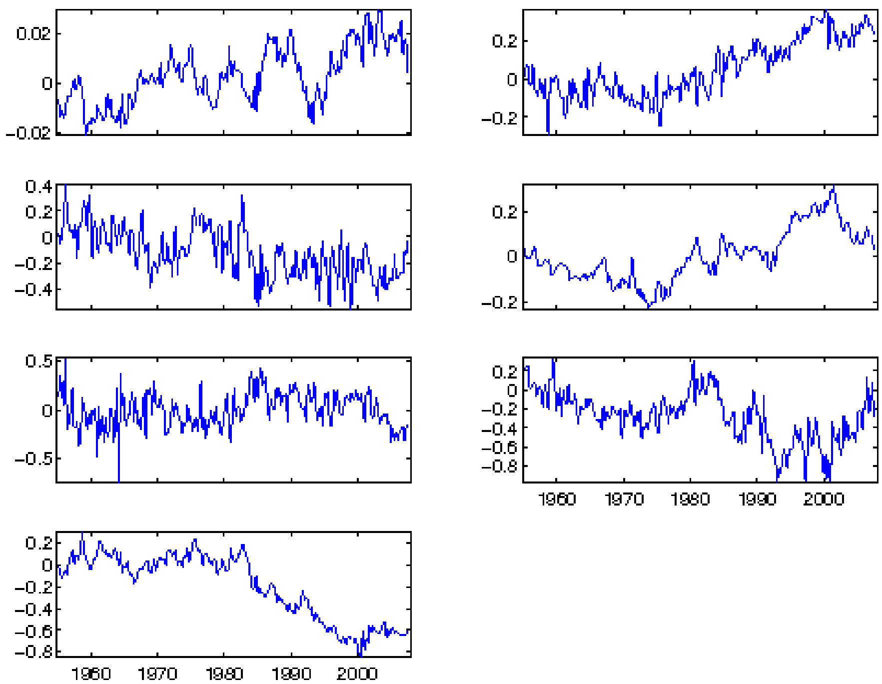

FIGURE 7. Innovations to Shocks (Log Deviation from S.S) of: Weath Shock ($\varepsilon_{x,t}$), Intertemporal Shock ($\varepsilon_{d,t}$), Monetary Policy Shock($\varepsilon_{m,t}$), Governemtne Spending Shock ($\varepsilon_{g,t}$), Capital Production Shock ($\varepsilon_{\zeta,t}$), Technology Shock ($\varepsilon_{A,t}$), Intratemmporal Shock ($\varepsilon_{\varphi,t}$)

Counterfactuals

To get a better understanding of the role that changing financial frictions played in reducing macroeconomic volatility, two counterfactual studies are done. The first counterfactual study holds μ at its steady state level throughout the sample. The second counterfactual study lets μ change until 1984. After 1984, in the counterfactual study μ is set equal to the mean level of μ from the sample before 1984. In both counterfactual studies, the model is simulated using the underlying shocks, except for those affecting μ, pulled from the data using the particle filter. If the drifting financial frictions were important in decreasing financial frictions during the Great Moderation, we wouldn't expect to observe a reduction in the standard deviation of the simulated data for the post 1984 time period.

The results of these counterfactual studies can be found in Table 20. The first section of the table shows the actual standard deviations of the annualized growth rate of output, annualized

TABLE 20. Counterfactual Studies

	Standard Deviation				
	Output	Inflation	Investment	Net Worth	Consumption
Data, pre 1984Q1	6.14	3.42	18.60	2.89	3.14
Data, post 1984Q1	3.17	1.16	9.79	8.55	2.36
Data, post/pre	0.52	0.34	0.53	2.96	0.75
Constant μ, pre 1984Q1	7.68	3.12	28.24	4.46	3.12
Constant μ, post 1984Q1	11.41	2.92	58.66	14.40	2.41
Constant μ, post/pre	1.49	0.94	2.08	3.23	0.77
Pre 1984Q1 μ, pre 1984Q1	6.14	3.42	18.60	3.74	3.14
Pre 1984Q1 μ, post 1984Q1	11.80	5.05	59.77	14.20	2.39
Pre 1984Q1 μ, post/pre	1.92	1.47	3.21	3.80	0.76

quarterly inflation, the annualized growth rate of investment, the annualized growth rate of net worth, as well as the annualized growth rate of consumption. The data shows a clear drop in the standard deviation across all data types, except net worth which actually becomes more volatile.

The second section of Table 20 shows the counterfactual data's standard deviations that would have been observed if μ_t was constant throughout the sample. Based on these results, it appears that if μ was held constant throughout the sample there would only have been a moderation in consumption. The third section of the table shows what would happen had μ been held constant after 1984 at the mean level of the underlying μ from before 1984.[21] The results are similar, with a moderation only being observed in consumption. Based on these findings, the observed fall in financial frictions was a key factor in reducing volatility for most of the key observables except consumption.

Conclusion

In this chapter I estimate a New Keynesian model featuring financial frictions, parameter drifting and stochastic volatility. The model is estimated using Bayesian techniques and the particle filter. To understand the importance of the features of the model, I study the underlying states and run counterfactual tests. I find that changing financial frictions played a large role in explaining the reduction in volatility observed during the Great Moderation. However, changing financial frictions cannot explain the reduction in observed consumption volatility. Based on a

[21] Since μ and all of the underlying shocks are pulled from the data, the simulations exactly match the data for all observables except net worth, which is assumed to have measurement error.

study of the underlying states, there appears to be a change in household behavior during the 1980s. This change in household behavior is shown by changes in intertemporal and intratemporal shocks. These changes likely explains the reduction in consumption volatility observed during the Great Moderation.

While this paper finds support for changing financial frictions contributing to the Great Moderation, it is important to remember that the model does not explain why financial frictions fell. It is important to understand why financial frictions fell and to study which policies might reduce financial frictions. It is possible that financial markets may also play a role in describing why household behavior changed. While it does not feature into the model, access to credit for households may have improved during the Great Moderation. This is a potential explanation for why a reduction in consumption volatility. In future work I plan to study these questions.

CHAPTER V

CONCLUSION

Understanding the causes of time variation in macroeconomic volatility is an important area of study. Most research on this topic has focused on the causes of the Great Moderation. I further the literature in this dissertation in two different ways. First, I provide evidence about the importance of specification during the estimation of DSGE models designed to study macroeconomic volatility. Second, I provide empirical evidence about the drivers of the Great Moderation.

The first contribution of this dissertation is to provide some practical evidence for researchers using structural models to study changing macroeconomic volatility. For a variety of reasons, large DSGE models are often estimated for these studies. These models often study the importance of changing variance exogenous shocks and changing monetary policy. Due to technical limitations, these changes are typically modeled to drift smoothly over time. However, it is possible that these changes are actually discrete, especially considering how discretely volatility changed during the Great Moderation. This might make results from models with parameter drift misleading. To study this, I run multiple estimations of simulated data that feature this misspecification. I find that the inclusion of stochastic volatility can give misleading results when studying model fit. Therefore, it is important for researchers to look beyond model fit to understand what is causing changes in volatility. One way to do this is to look at the underlying states of the model. Based on the results from this dissertation, the underlying states can be accurately estimated using a model with parameter drifting, even if it is misspecified.

The second contribution of this dissertation is evidence about the causes of the Great Moderation. The two most widely studied explanations of the Great Moderation are “good luck” and “good policy.” I study these explanations and look at a third explanation: changing financial frictions. I find that changing financial frictions was the key driver in causing the Great Moderation. Financial frictions fell during the 1980s and without this drop in financial frictions, there would not have been a fall in volatility like the one observed during the Great Moderation. While the fall in financial frictions does appear to be the main driver in moderating the business cycle, there also appears to be a role for luck. During the Great Moderation, household behavior changed, which is shown by the intratemporal and intertemporal shocks. This change in household behavior is important for explaining the observed reduction in consumption volatility.

This dissertation also provides some interesting avenues for future research. I find that a reduction in financial frictions is important to explain the Great Moderation; however this dissertation cannot explain why financial frictions fell. In future research I plan to study why financial frictions fell. It is also not clear why household behavior changed in the 1980s. It would be interesting to further study why this is the case. Understanding what is causing these changes is important since it might be relevant for policymakers trying to reduce volatility.

APPENDIX A

SUPPLEMENTARY MATERIALS FOR CHAPTER II

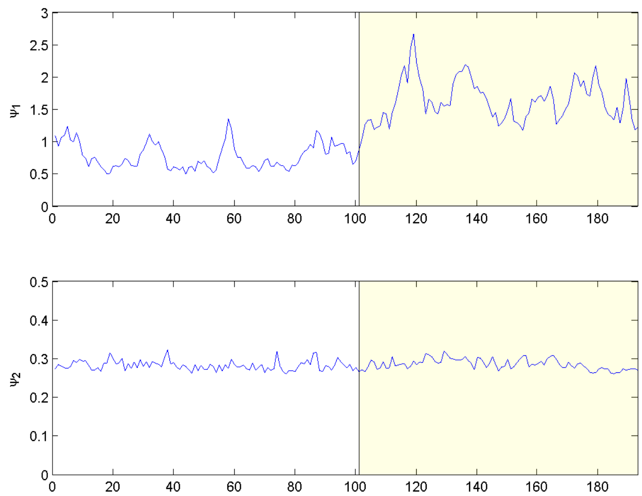

FIGURE A.1. Smoothed Taylor rule parameters ψ_1 and ψ_2, for first baseline data set

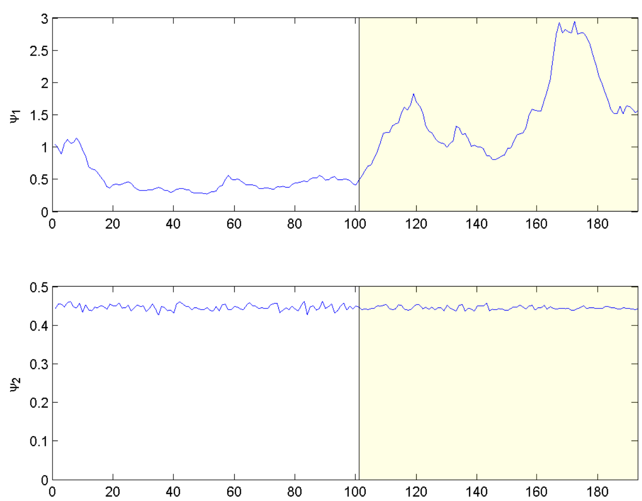

FIGURE A.2. Smoothed Taylor rule parameters ψ_1 and ψ_2, for second baseline data set

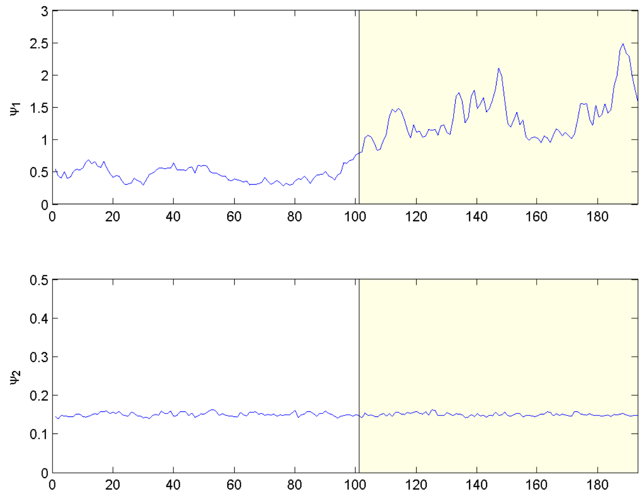

FIGURE A.3. Smoothed Taylor rule parameters ψ_1 and ψ_2, for third baseline data set

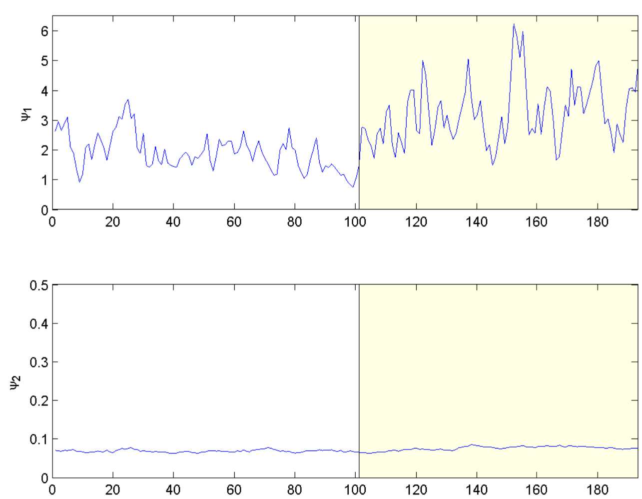

FIGURE A.4. Smoothed Taylor rule parameters ψ_1 and ψ_2, for fourth baseline data set

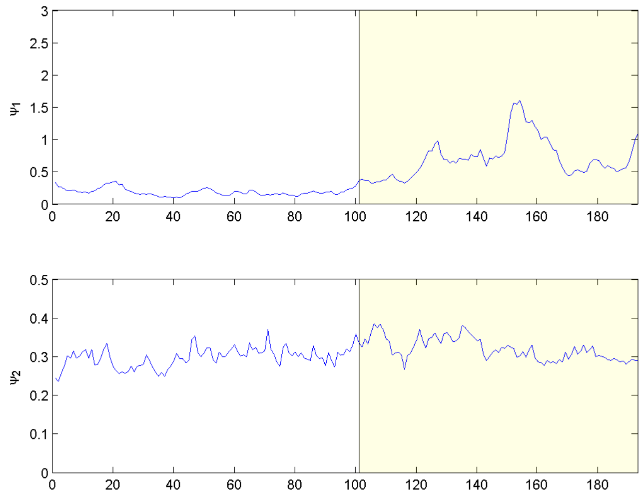

FIGURE A.5. Smoothed Taylor rule parameters ψ_1 and ψ_2, for fifth baseline data set

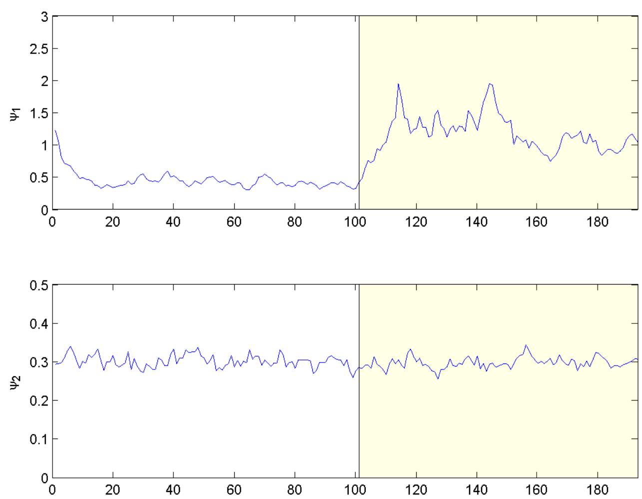

FIGURE A.6. Smoothed Taylor rule parameters ψ_1 and ψ_2, for sixth baseline data set

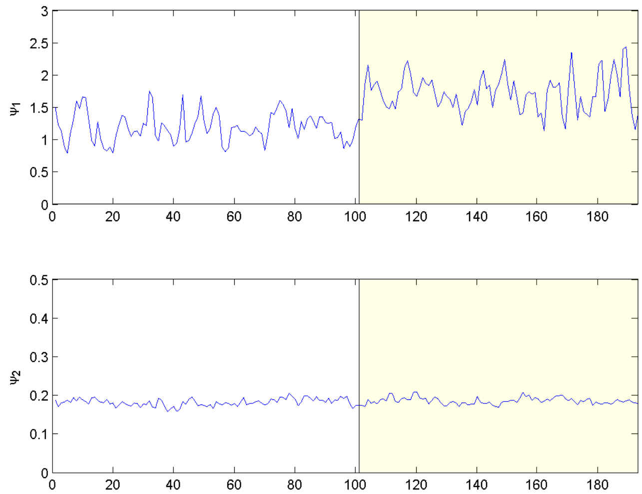

FIGURE A.7. Smoothed Taylor rule parameters ψ_1 and ψ_2, for seventh baseline data set

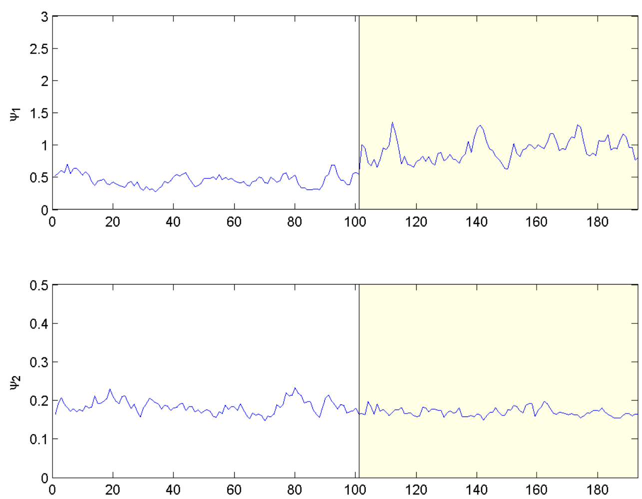

FIGURE A.8. Smoothed Taylor rule parameters ψ_1 and ψ_2, for eighth baseline data set

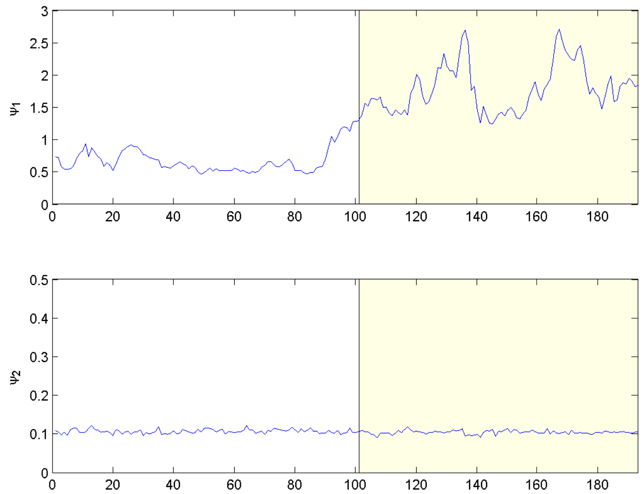

FIGURE A.9. Smoothed Taylor rule parameters ψ_1 and ψ_2, for ninth baseline data set

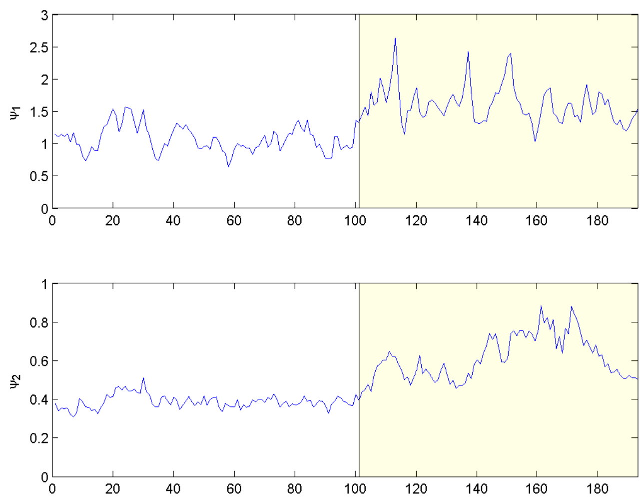

FIGURE A.10. Smoothed Taylor rule parameters ψ_1 and ψ_2, for tenth baseline data sets

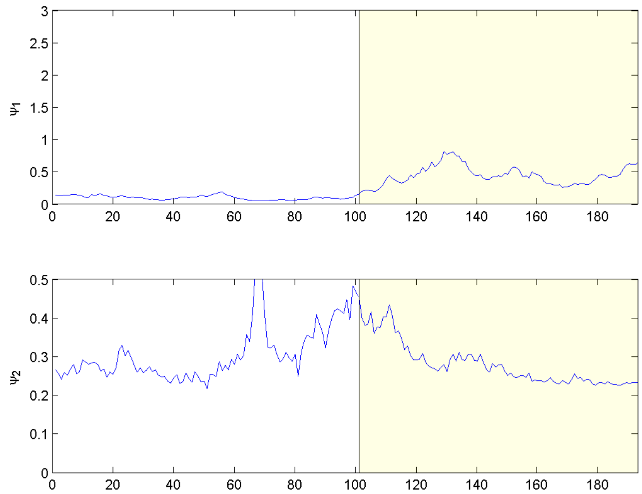

FIGURE A.11. Smoothed Taylor rule parameters ψ_1 and ψ_2, for eleventh baseline data sets

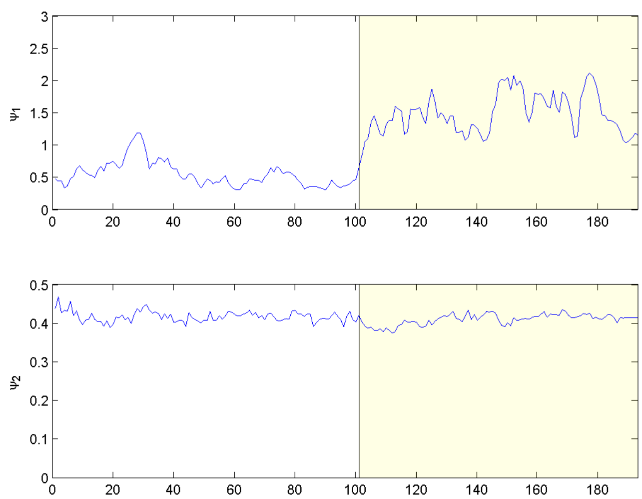

FIGURE A.12. Smoothed Taylor rule parameters ψ_1 and ψ_2, for twelfth baseline data sets

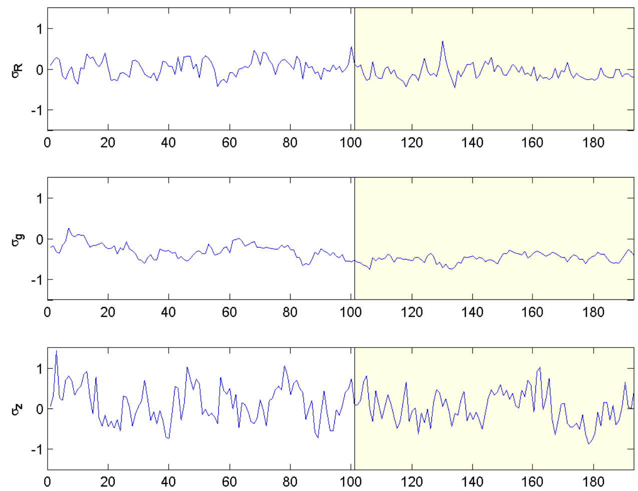

FIGURE A.13. Smoothed logged deviation from mean of standard deviation of shocks for first baseline data set: σ_R, σ_g, σ_z

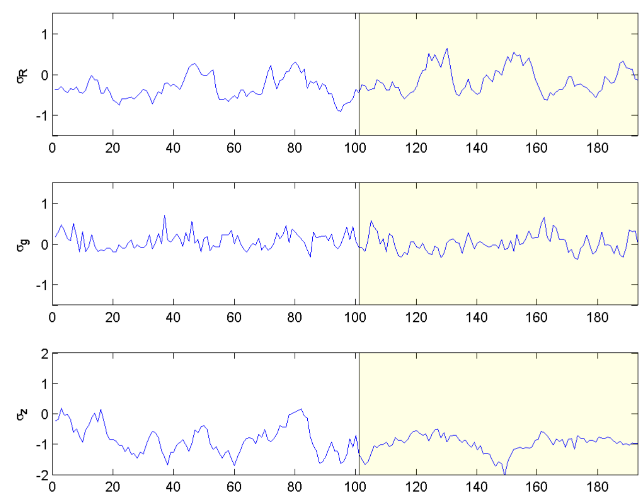

FIGURE A.14. Smoothed logged deviation from mean of standard deviation of shocks for second baseline data set: σ_R, σ_g, σ_z

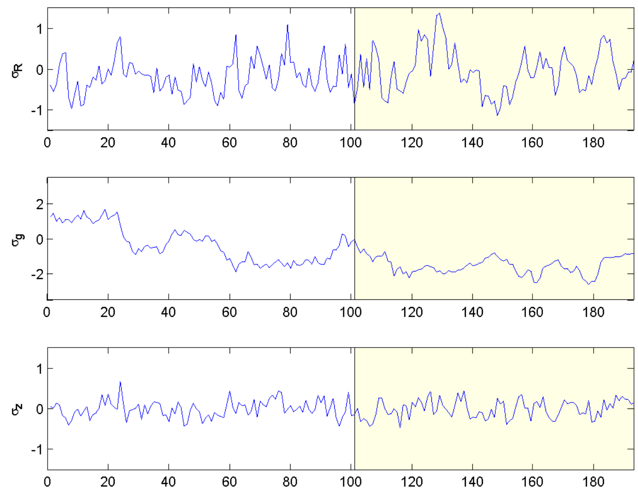

FIGURE A.15. Smoothed logged deviation from mean of standard deviation of shocks for third baseline data set: σ_R, σ_g, σ_z

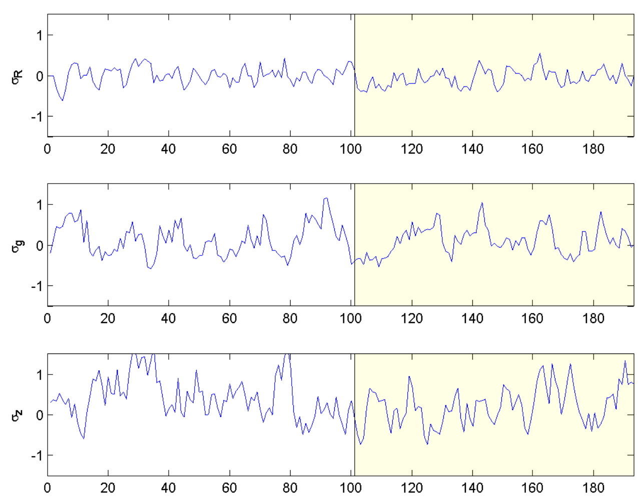

FIGURE A.16. Smoothed logged deviation from mean of standard deviation of shocks for fourth baseline data set: σ_R, σ_g, σ_z

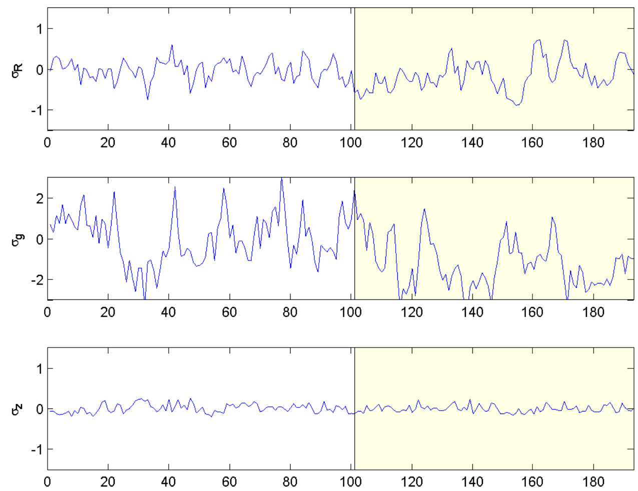

FIGURE A.17. Smoothed logged deviation from mean of standard deviation of shocks for fifth baseline data set: σ_R, σ_g, σ_z

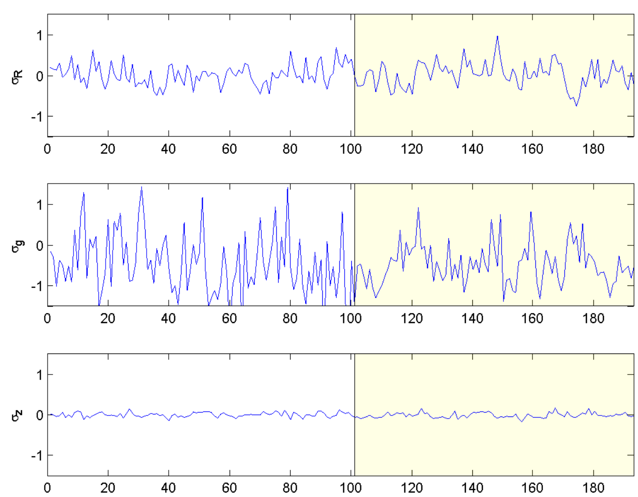

FIGURE A.18. Smoothed logged deviation from mean of standard deviation of shocks for sixth baseline data set: σ_R, σ_g, σ_z

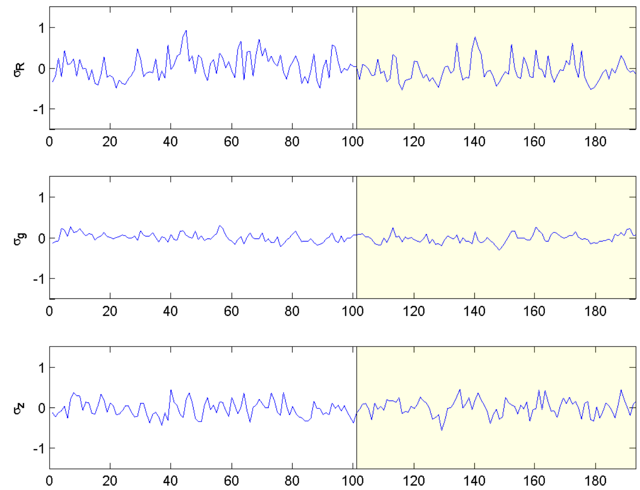

FIGURE A.19. Smoothed logged deviation from mean of standard deviation of shocks for seventh baseline data set: σ_R, σ_g, σ_z

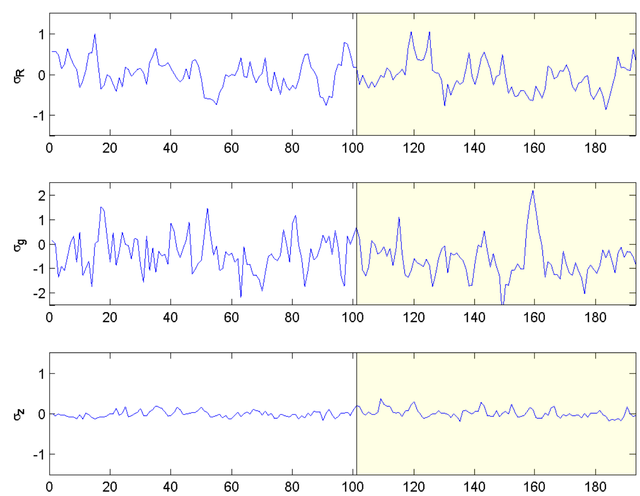

FIGURE A.20. Smoothed logged deviation from mean of standard deviation of shocks for eighth baseline data set: σ_R, σ_g, σ_z

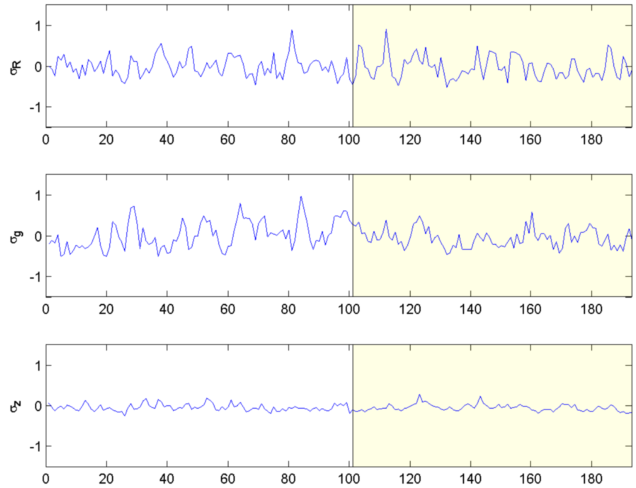

FIGURE A.21. Smoothed logged deviation from mean of standard deviation of shocks for ninth baseline data set: σ_R, σ_g, σ_z

FIGURE A.22. Smoothed logged deviation from mean of standard deviation of shocks for tenth baseline data set: σ_R, σ_g, σ_z

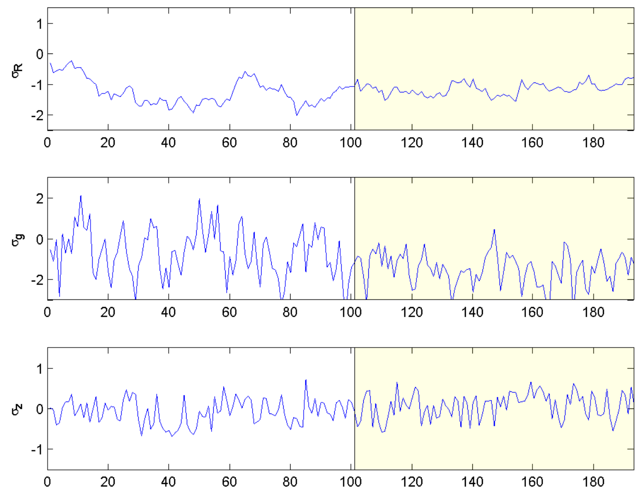

FIGURE A.23. Smoothed logged deviation from mean of standard deviation of shocks for eleventh baseline data set: σ_R, σ_g, σ_z

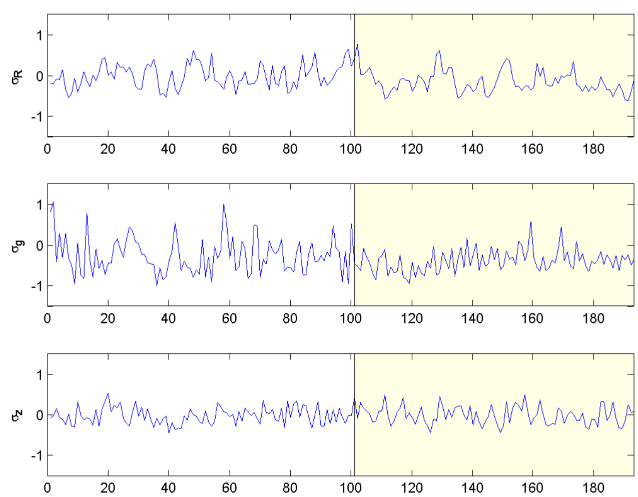

FIGURE A.24. Smoothed logged deviation from mean of standard deviation of shocks for twelfth baseline data set: σ_R, σ_g, σ_z

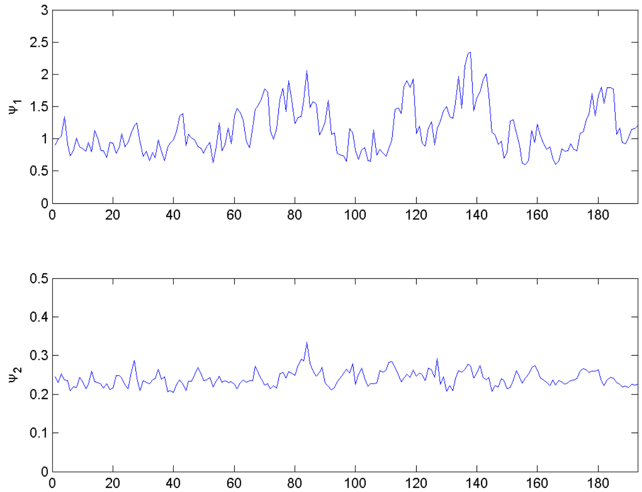

FIGURE A.25. Smoothed Taylor rule parameters ψ_1 and ψ_2, for first alternative data set

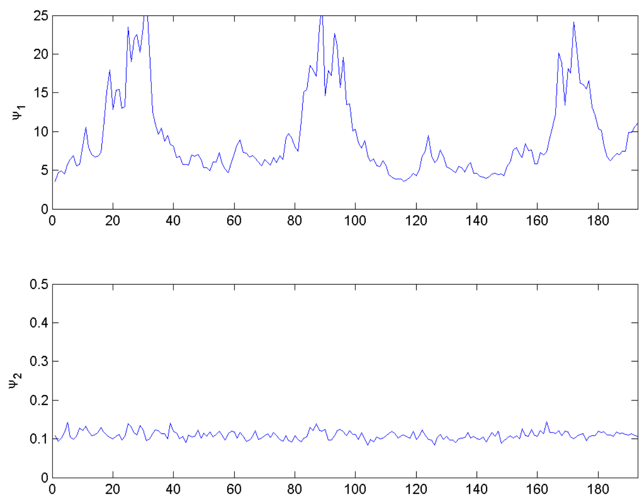

FIGURE A.26. Smoothed Taylor rule parameters ψ_1 and ψ_2, for second alternative data set

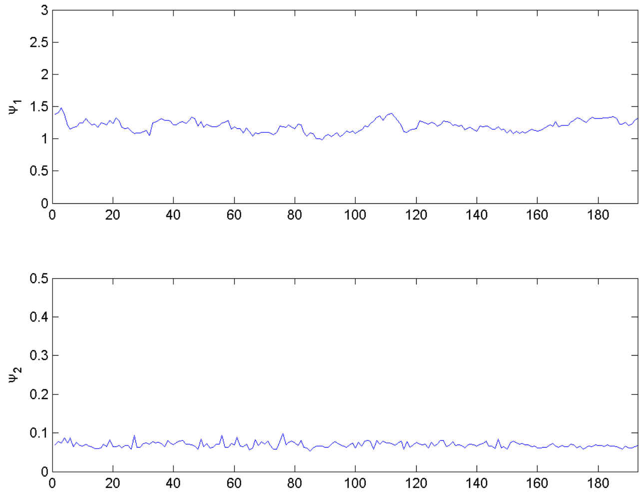

FIGURE A.27. Smoothed Taylor rule parameters ψ_1 and ψ_2, for third alternative data set

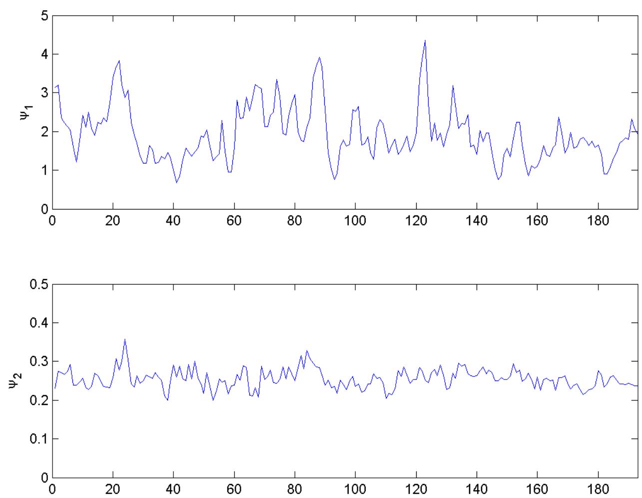

FIGURE A.28. Smoothed Taylor rule parameters ψ_1 and ψ_2, for fourth alternative data set

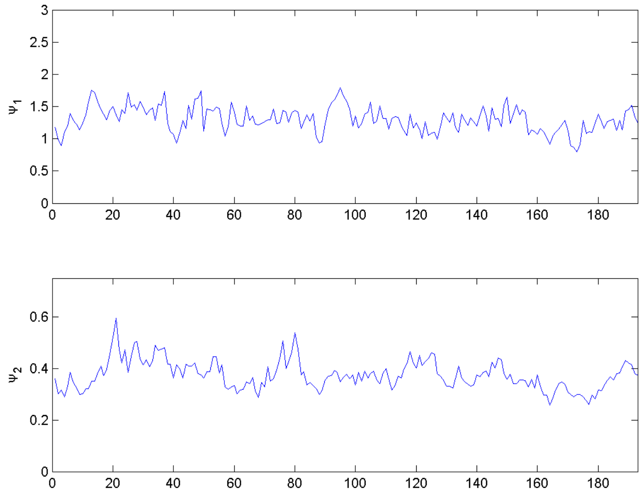

FIGURE A.29. Smoothed Taylor rule parameters ψ_1 and ψ_2, for fifth alternative data set

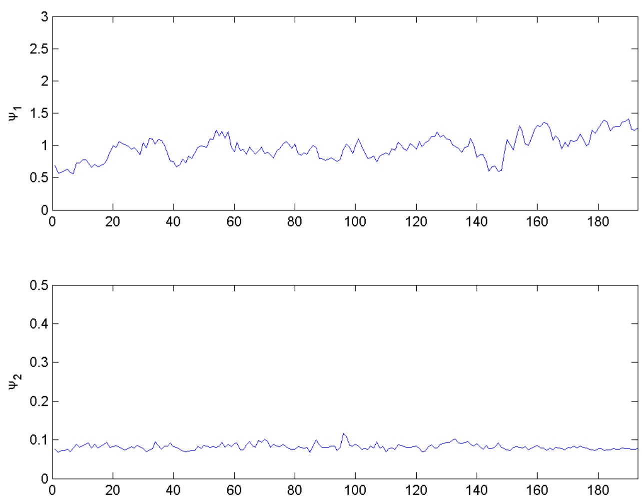

FIGURE A.30. Smoothed Taylor rule parameters ψ_1 and ψ_2, for sixth alternative data set

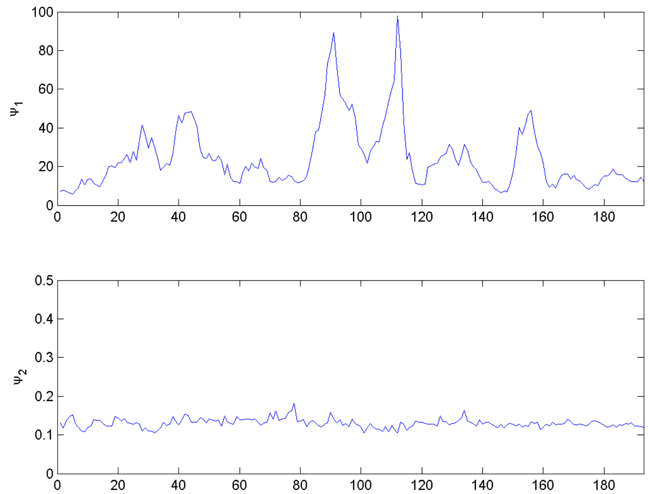

FIGURE A.31. Smoothed Taylor rule parameters ψ_1 and ψ_2, for seventh alternative data set

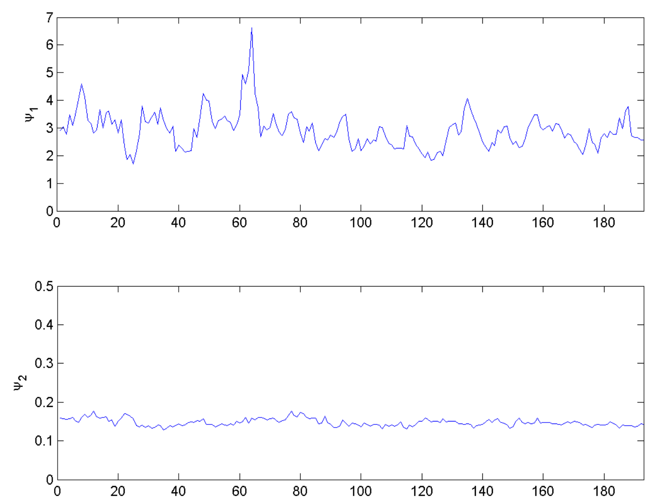

FIGURE A.32. Smoothed Taylor rule parameters ψ_1 and ψ_2, for eighth alternative data set

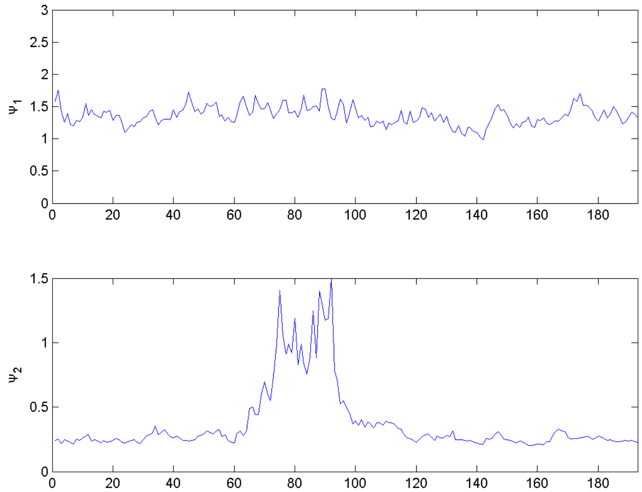

FIGURE A.33. Smoothed Taylor rule parameters ψ_1 and ψ_2, for ninth alternative data set

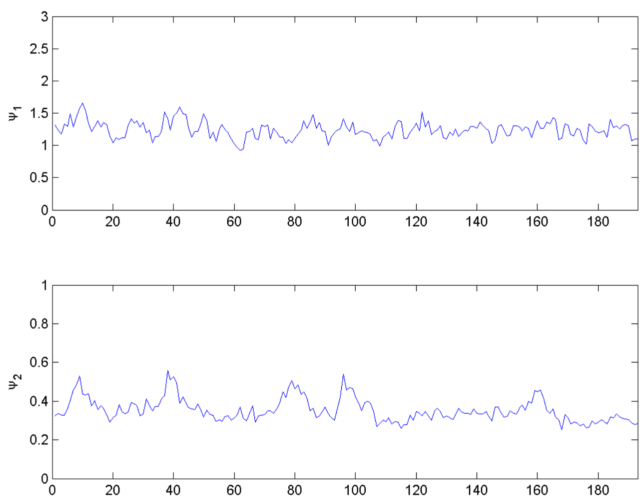

FIGURE A.34. Smoothed Taylor rule parameters ψ_1 and ψ_2, for tenth alternative data sets

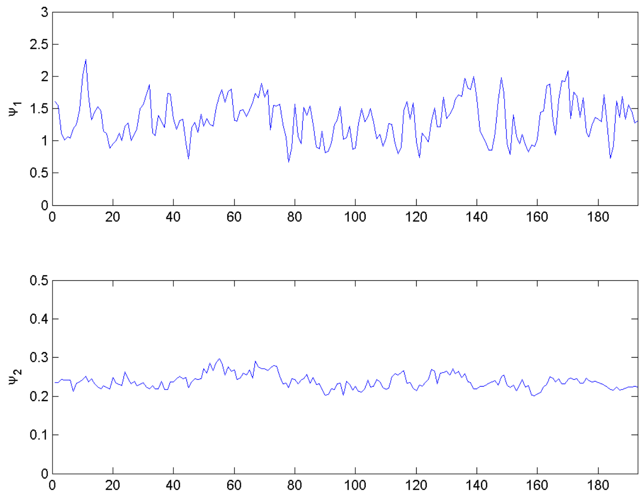

FIGURE A.35. Smoothed Taylor rule parameters ψ_1 and ψ_2, for eleventh alternative data sets

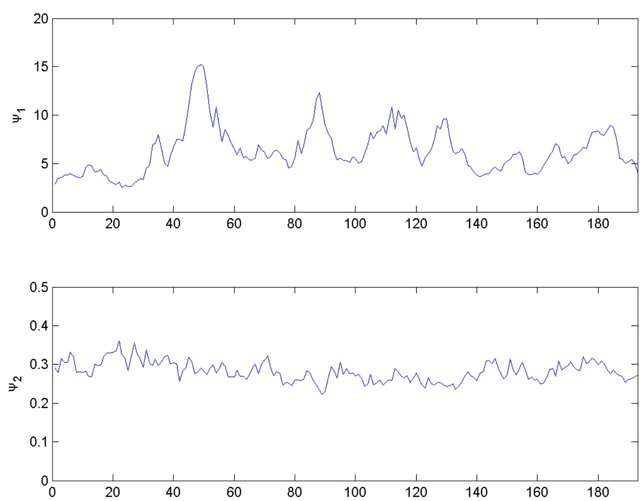

FIGURE A.36. Smoothed Taylor rule parameters ψ_1 and ψ_2, for twelfth alternative data sets

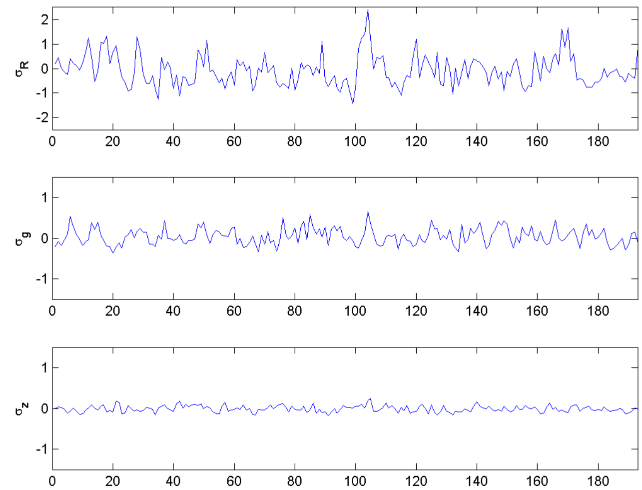

FIGURE A.37. Smoothed logged deviation from mean of standard deviation of shocks for first alternative data set: σ_R, σ_g, σ_z

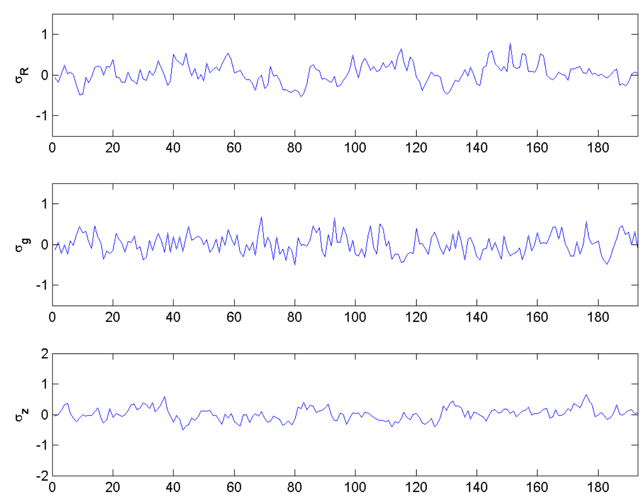

FIGURE A.38. Smoothed logged deviation from mean of standard deviation of shocks for second alternative data set: σ_R, σ_g, σ_z

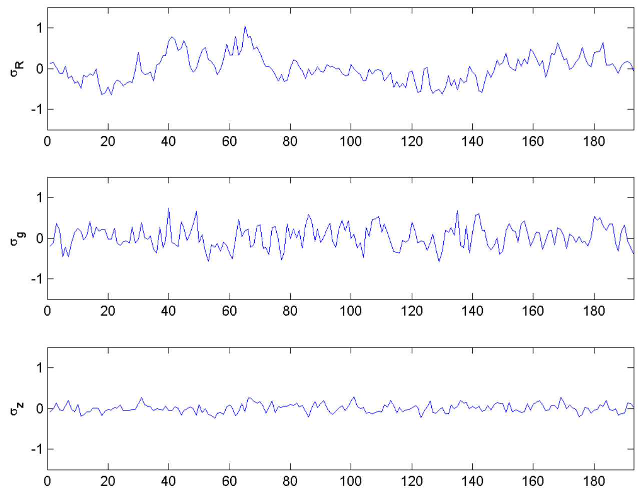

FIGURE A.39. Smoothed logged deviation from mean of standard deviation of shocks for third alternative data set: σ_R, σ_g, σ_z

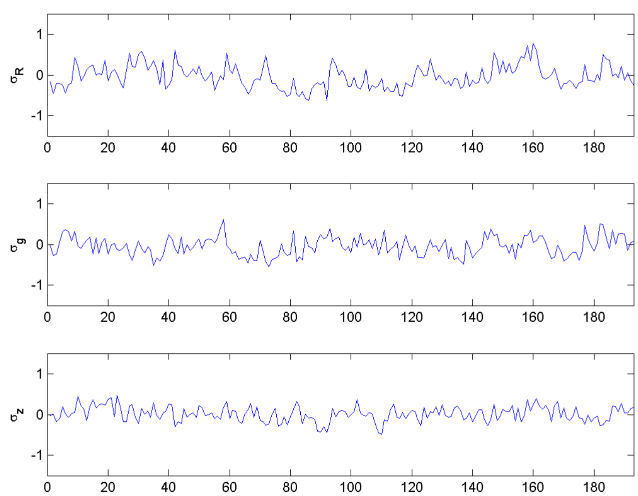

FIGURE A.40. Smoothed logged deviation from mean of standard deviation of shocks for fourth alternative data set: σ_R, σ_g, σ_z

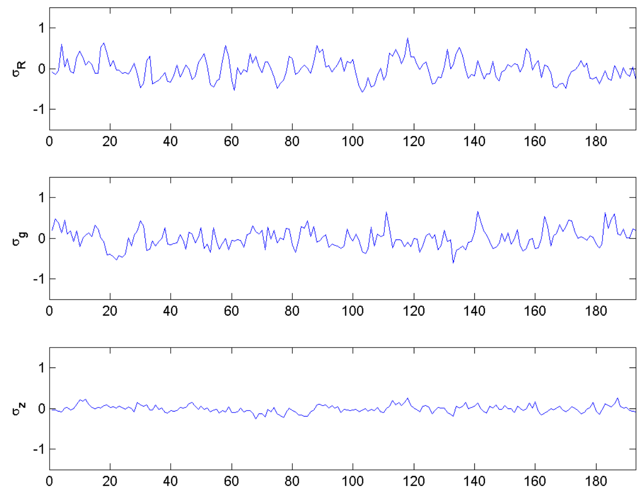

FIGURE A.41. Smoothed logged deviation from mean of standard deviation of shocks for fifth alternative data set: σ_R, σ_g, σ_z

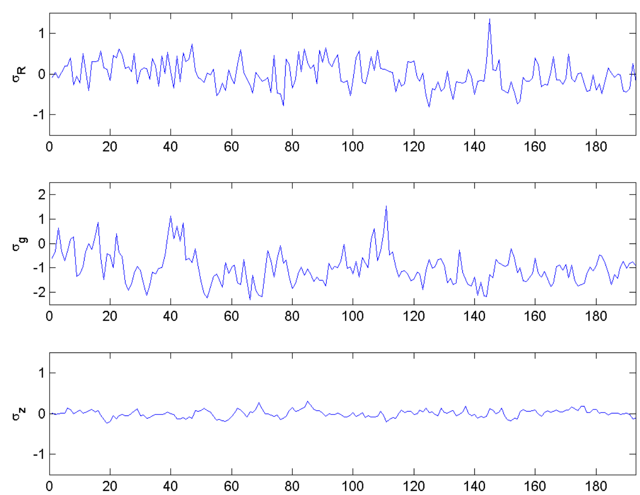

FIGURE A.42. Smoothed logged deviation from mean of standard deviation of shocks for sixth alternative data set: σ_R, σ_g, σ_z

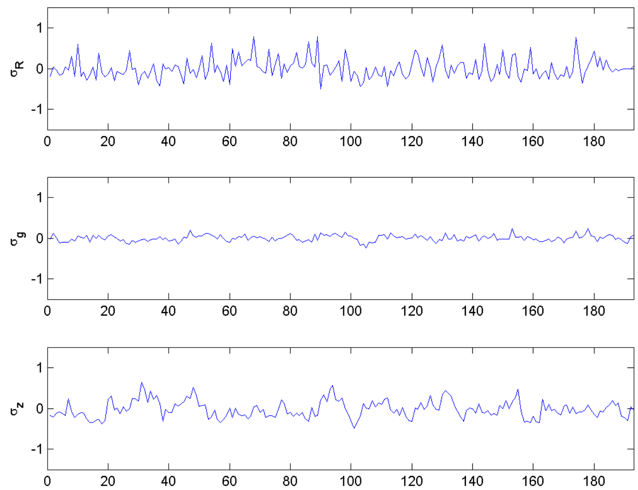

FIGURE A.43. Smoothed logged deviation from mean of standard deviation of shocks for seventh alternative data set: σ_R, σ_g, σ_z

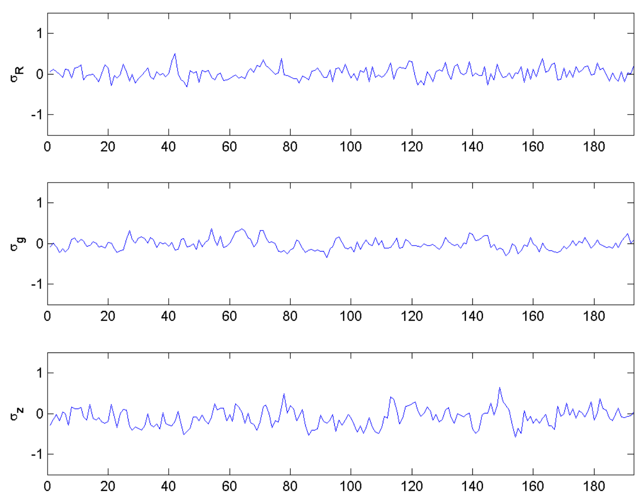

FIGURE A.44. Smoothed logged deviation from mean of standard deviation of shocks for eighth alternative data set: σ_R, σ_g, σ_z

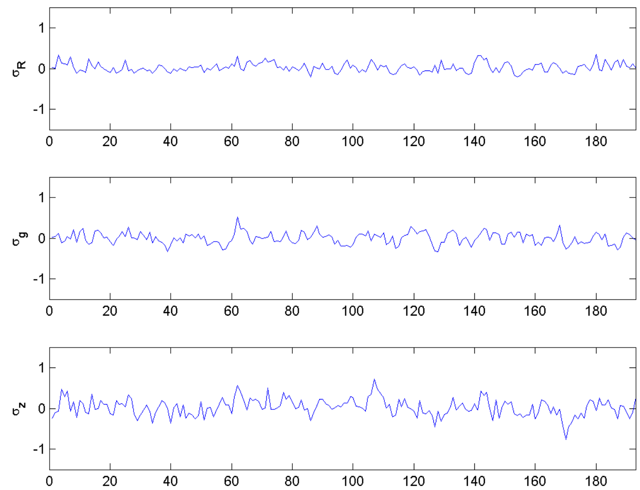

FIGURE A.45. Smoothed logged deviation from mean of standard deviation of shocks for ninth alternative data set: σ_R, σ_g, σ_z

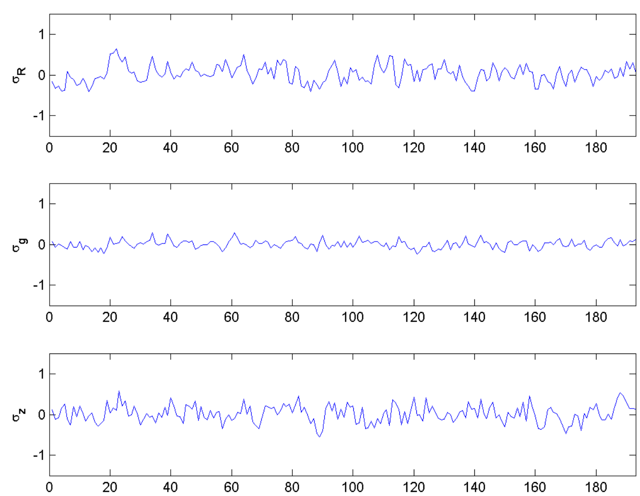

FIGURE A.46. Smoothed logged deviation from mean of standard deviation of shocks for tenth alternative data set: σ_R, σ_g, σ_z

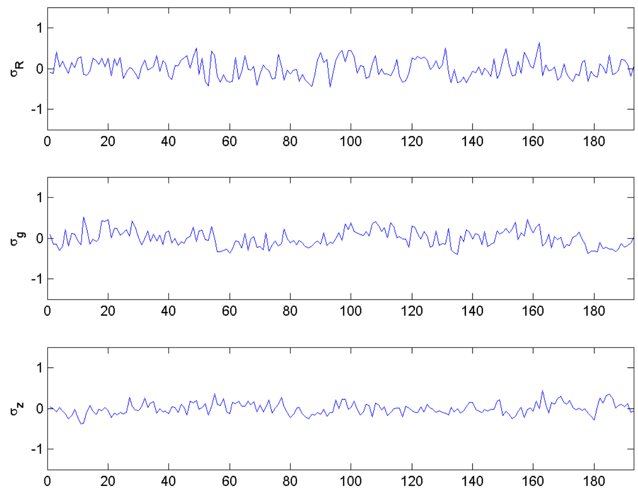

FIGURE A.47. Smoothed logged deviation from mean of standard deviation of shocks for eleventh alternative data set: σ_R, σ_g, σ_z

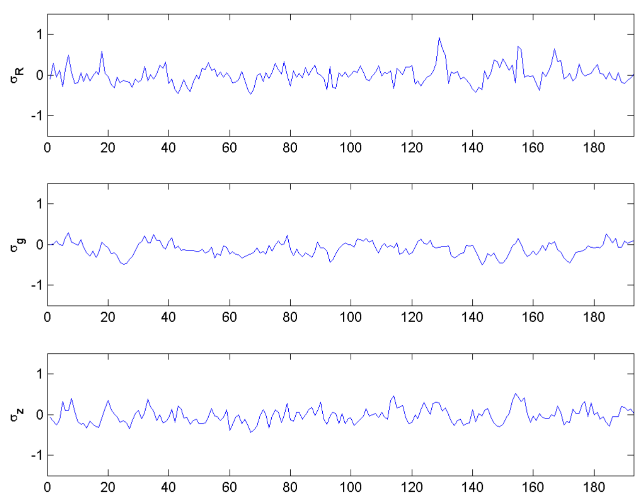

FIGURE A.48. Smoothed logged deviation from mean of standard deviation of shocks for twelfth alternative data set: σ_R, σ_g, σ_z

TABLE A.1. Log Marginal Likelihood

Data Set	SV, No Meas. Error	SV	No SV
Baseline Regime Switching			
1	-673.9	-699.9	-688.1
2	-644.6	-673.3	-705.2
3	-648.3	-657.0	-684.3
4	-618.9	-703.3	-690.2
5	-629.9	-657.9	-760.0
6	-672.3	-755.9	-996.3
7	-653.3	-707.0	-744.4
8	-588.3	-680.2	-706.8
9	-648.5	-742.1	-787.4
10	-634.6	-692.9	-710.1
11	-633.2	-658.6	-725.7
12	-633.7	-690.7	-678.0
Alternate Regime Switching			
1	-641.9	-700.2	-679.0
2	-621.9	-655.6	-657.6
3	-635.7	-692.8	-656.9
4	-597.1	-664.6	-643.3
5	-625.4	-637.0	-665.7
6	-606.7	-677.8	-666.8
7	-588.5	-660.1	-735.5
8	-638.0	-708.7	-668.1
9	-611.1	-667.9	-665.3
10	-671.0	-714.8	-726.6
11	-654.8	-705.4	-682.6
12	-680.3	-718.8	-731.1

TABLE A.2. Log Marginal Likelihood

Data Set	SV, No Meas. Error	SV	No SV
Parameter Drifting			
1	-446.9	-552.2	-534.6
2	-388.0	-441.9	-401.3
3	-486.6	-542.6	-545.1
4	-525.9	-582.0	-585.3
5	-433.0	-493.2	-490.8
6	-521.5	-557.3	-631.9
7	-438.4	-438.4	-546.2
8	-448.3	-504.3	-510.3
9	-612.3	-675.2	-627.2
10	-518.4	-535.6	-542.4
11	-525.9	-565.6	-582.8
12	-394.7	-505.7	-627.8
Constant Parameter			
1	-392.4	-447.3	-410.0
2	-431.0	-441.0	-423.0
3	-417.0	-470.6	-432.2
4	-429.3	-498.6	-457.0
5	-431.3	-455.2	-435.8
6	-429.1	-473.4	-460.7
7	-382.2	-524.0	-448.2
8	-382.2	-414.4	-415.9
9	-436.4	-535.2	-466.6
10	-406.8	-472.2	-446.9
11	-421.2	-451.6	-430.3
12	-384.5	-441.3	-407.4

TABLE A.3. Posterior for Baseline Regime Switching Data, Part 1

Data Set	1	2	3	4	5	6
τ	0.37	0.64	0.44	0.32	0.32	0.75
	(0.30)	(0.18)	(0.23)	(0.14)	(0.19)	(0.12)
κ	0.35	0.69	0.64	0.67	0.74	0.76
	(0.32)	(0.19)	(0.20)	(0.19)	(0.21)	(0.19)
ψ_1	1.59	1.92	1.36	2.55	2.20	1.29
	(0.48)	(0.50)	(0.38)	(0.51)	(0.57)	(0.17)
ψ_2	0.13	0.16	0.23	0.39	0.22	0.17
	(0.08)	(0.12)	(0.12)	(0.11)	(0.10)	(0.11)
ρ_{ψ_1}	0.94	0.90	0.63	0.96	0.98	0.30
	(0.05)	(0.12)	(0.25)	(0.05)	(0.02)	(0.20)
ρ_{ψ_2}	0.67	0.43	0.32	0.72	0.50	0.67
	(0.25)	(0.31)	(0.22)	(0.21)	(0.28)	(0.34)
η_{ψ_1}	0.23	0.36	0.35	0.34	0.31	0.42
	(0.12)	(0.06)	(0.10)	(0.10)	(0.08)	(0.08)
η_{ψ_2}	0.37	0.30	0.20	0.34	0.17	0.39
	(0.10)	(0.12)	(0.14)	(0.12)	(0.12)	(0.10)
σ_R	0.40	0.30	0.45	0.31	0.18	0.44
	(0.12)	(0.10)	(0.19)	(0.08)	(0.06)	(0.15)
σ_g	0.16	0.15	0.22	0.27	0.46	0.16
	(0.08)	(0.10)	(0.09)	(0.14)	(0.11)	(0.06)
σ_z	1.82	0.91	0.73	0.69	0.61	0.81
	(0.64)	(0.17)	(0.13)	(0.17)	(0.10)	(0.21)
ρ_R	0.65	0.57	0.63	0.89	0.90	0.56
	(0.10)	(0.11)	(0.09)	(0.05)	(0.03)	(0.09)
ρ_g	0.75	0.77	0.74	0.77	0.59	0.89
	(0.09)	(0.09)	(0.10)	(0.08)	(0.11)	(0.06)
ρ_z	0.70	0.65	0.87	0.82	0.75	0.75
	(0.12)	(0.09)	(0.06)	(0.07)	(0.05)	(0.09)
η_{σ_R}	0.47	0.98	0.50	0.76	1.27	0.70
	(0.18)	(0.50)	(0.24)	(0.15)	(0.31)	(0.31)
η_{σ_g}	1.09	1.68	0.66	0.61	0.28	0.53
	(0.35)	(0.75)	(0.18)	(0.52)	(0.11)	(0.22)
η_{σ_z}	0.33	0.44	0.34	0.65	0.63	0.60
	(0.09)	(0.08)	(0.10)	(0.05)	(0.08)	(0.12)
Accept. Rate	24%	26%	28%	18%	20%	23%

Note: Posteriors from stochastic volatility with no measurement error estimation. Standard deviations in parentheses.

TABLE A.4. Posterior for Baseline Regime Switching Data, Part 2

Data Set	7	8	9	10	11	12
τ	0.37	0.44	0.45	0.29	0.57	0.78
	(0.13)	(0.19)	(0.27)	(0.11)	(0.23)	(0.14)
κ	0.81	0.87	0.51	0.73	0.68	0.84
	(0.18)	(0.13)	(0.26)	(0.18)	(0.23)	(0.11)
ψ_1	1.29	3.21	1.37	3.21	1.30	1.35
	(0.15)	(0.55)	(0.24)	(0.51)	(0.20)	(0.22)
ψ_2	0.19	0.17	0.38	0.20	0.14	0.28
	(0.09)	(0.10)	(0.08)	(0.11)	(0.09)	(0.15)
ρ_{ψ_1}	0.68	0.98	0.92	0.97	0.84	0.90
	(0.13)	(0.02)	(0.08)	(0.03)	(0.17)	(0.06)
ρ_{ψ_2}	0.70	0.66	0.55	0.44	0.32	0.53
	(0.26)	(0.30)	(0.27)	(0.26)	(0.20)	(0.30)
η_{ψ_1}	0.30	0.31	0.32	0.33	0.26	0.27
	(0.07)	(0.06)	(0.09)	(0.10)	(0.13)	(0.11)
η_{ψ_2}	0.26	0.24	0.11	0.29	0.31	0.25
	(0.12)	(0.19)	(0.08)	(0.11)	(0.13)	(0.15)
σ_R	0.20	0.43	0.26	0.35	0.37	0.32
	(0.05)	(0.11)	(0.06)	(0.11)	(0.09)	(0.07)
σ_g	0.14	0.38	0.27	0.39	0.24	0.27
	(0.06)	(0.14)	(0.10)	(0.13)	(0.08)	(0.07)
σ_z	0.68	0.62	0.95	0.67	0.79	0.60
	(0.14)	(0.15)	(0.27)	(0.16)	(0.16)	(0.10)
ρ_R	0.56	0.91	0.61	0.92	0.56	0.49
	(0.08)	(0.02)	(0.07)	(0.02)	(0.09)	(0.08)
ρ_g	0.81	0.68	0.70	0.61	0.72	0.76
	(0.08)	(0.10)	(0.07)	(0.11)	(0.09)	(0.06)
ρ_z	0.89	0.80	0.76	0.80	0.83	0.83
	(0.08)	(0.08)	(0.07)	(0.06)	(0.06)	(0.06)
η_{σ_R}	2.25	0.49	1.56	0.70	0.72	1.37
	(0.42)	(0.14)	(0.33)	(0.16)	(0.25)	(0.30)
η_{σ_g}	0.46	0.36	0.60	0.45	0.44	0.44
	(0.25)	(0.13)	(0.25)	(0.21)	(0.15)	(0.14)
η_{σ_z}	0.38	0.43	0.20	0.32	0.21	0.63
	(0.09)	(0.04)	(0.07)	(0.05)	(0.04)	(0.08)
Accept. Rate	22%	21%	30%	22%	34%	29%

Note: Posteriors from stochastic volatility with no measurement error estimation. Standard deviations in parentheses.

TABLE A.5. Posterior for Alternative Regime Switching Data, Part 1

Data Set	1	2	3	4	5	6
τ	0.49	0.61	0.52	0.81	0.86	0.61
	(0.30)	(0.18)	(0.23)	(0.14)	(0.11)	(0.19)
κ	0.77	0.80	0.86	0.90	0.88	0.88
	(0.16)	(0.18)	(0.09)	(0.09)	(0.09)	(0.12)
ψ_1	2.74	1.49	1.20	1.48	1.36	1.32
	(0.86)	(0.17)	(0.12)	(0.17)	(0.16)	(0.15)
ψ_2	0.24	0.20	0.18	0.35	0.22	0.33
	(0.13)	(0.12)	(0.13)	(0.10)	(0.13)	(0.11)
ρ_{ψ_1}	0.97	0.71	0.43	0.53	0.63	0.47
	(0.03)	(0.14)	(0.17)	(0.23)	(0.21)	(0.17)
ρ_{ψ_2}	0.79	0.83	0.53	0.51	0.36	0.61
	(0.17)	(0.12)	(0.23)	(0.30)	(0.20)	(0.24)
η_{ψ_1}	0.34	0.35	0.30	0.35	0.28	0.38
	(0.12)	(0.10)	(0.09)	(0.12)	(0.11)	(0.08)
η_{ψ_2}	0.20	0.20	0.16	0.26	0.24	0.18
	(0.12)	(0.10)	(0.16)	(0.13)	(0.13)	(0.11)
σ_R	0.25	0.22	0.21	0.37	0.32	0.23
	(0.08)	(0.05)	(0.06)	(0.07)	(0.07)	(0.05)
σ_g	0.51	0.17	0.08	0.18	0.18	0.23
	(0.12)	(0.06)	(0.04)	(0.06)	(0.06)	(0.07)
σ_z	0.69	0.76	0.60	0.74	0.79	0.72
	(0.14)	(0.10)	(0.12)	(0.10)	(0.10)	(0.10)
ρ_R	0.89	0.62	0.67	0.58	0.55	0.53
	(0.04)	(0.05)	(0.07)	(0.08)	(0.08)	(0.06)
ρ_g	0.61	0.82	0.90	0.83	0.82	0.74
	(0.10)	(0.07)	(0.04)	(0.07)	(0.07)	(0.08)
ρ_z	0.73	0.84	0.96	0.88	0.80	0.85
	(0.08)	(0.07)	(0.05)	(0.05)	(0.07)	(0.06)
η_{σ_R}	1.05	1.53	1.67	0.82	1.14	2.43
	(0.19)	(0.09)	(0.33)	(0.39)	(0.16)	(0.52)
η_{σ_g}	0.33	0.86	1.05	0.85	0.94	0.41
	(0.14)	(0.13)	(0.25)	(0.19)	(0.19)	(0.14)
η_{σ_z}	0.36	0.28	0.57	0.28	0.26	0.29
	(0.12)	(0.08)	(0.18)	(0.14)	(0.11)	(0.09)
Accept. Rate	24%	26%	28%	18%	20%	23%

Note: Posteriors from stochastic volatility with no measurement error estimation. Standard deviations in parentheses.

TABLE A.6. Posterior for Alternative Regime Switching Data, Part 2

Data Set	7	8	9	10	11	12
τ	0.62	0.07	0.59	0.68	0.62	0.33
	(0.24)	(0.06)	(0.33)	(0.18)	(0.18)	(0.15)
κ	0.78	0.30	0.62	0.88	0.78	0.74
	(0.18)	(0.12)	(0.31)	(0.10)	(0.19)	(0.18)
ψ_1	1.27	1.54	1.45	1.14	1.31	1.27
	(0.17)	(0.32)	(0.28)	(0.10)	(0.16)	(0.20)
ψ_2	0.38	0.11	0.14	0.17	0.12	0.26
	(0.10)	(0.09)	(0.12)	(0.14)	(0.09)	(0.07)
ρ_{ψ_1}	0.59	0.30	0.49	0.47	0.43	0.96
	(0.23)	(0.19)	(0.26)	(0.21)	(0.26)	(0.03)
ρ_{ψ_2}	0.47	0.47	0.56	0.68	0.60	0.70
	(0.29)	(0.22)	(0.24)	(0.24)	(0.24)	(0.23)
η_{ψ_1}	0.40	0.22	0.34	0.28	0.41	0.37
	(0.07)	(0.12)	(0.14)	(0.15)	(0.06)	(0.08)
η_{ψ_2}	0.20	0.32	0.23	0.14	0.17	0.12
	(0.14)	(0.11)	(0.15)	(0.11)	(0.12)	(0.09)
σ_R	0.38	0.39	0.36	0.43	0.33	0.24
	(0.10)	(0.09)	(0.12)	(0.11)	(0.06)	(0.10)
σ_g	0.28	0.24	0.23	0.40	0.09	0.38
	(0.07)	(0.08)	(0.06)	(0.09)	(0.03)	(0.08)
σ_z	0.79	0.56	0.96	0.78	0.76	0.65
	(0.17)	(0.18)	(0.31)	(0.13)	(0.18)	(0.15)
ρ_R	0.52	0.87	0.64	0.52	0.62	0.87
	(0.09)	(0.07)	(0.09)	(0.08)	(0.07)	(0.03)
ρ_g	0.70	0.68	0.79	0.61	0.86	0.68
	(0.08)	(0.10)	(0.10)	(0.09)	(0.07)	(0.08)
ρ_z	0.76	0.88	0.75	0.76	0.82	0.73
	(0.12)	(0.05)	(0.07)	(0.09)	(0.07)	(0.04)
η_{σ_R}	1.14	0.37	0.84	0.85	0.66	1.05
	(0.26)	(0.18)	(0.38)	(0.32)	(0.16)	(0.29)
η_{σ_g}	0.26	0.32	0.49	0.34	1.77	0.26
	(0.11)	(0.11)	(0.12)	(0.15)	(0.16)	(0.08)
η_{σ_z}	0.33	0.83	0.38	0.31	0.31	0.75
	(0.10)	(0.11)	(0.11)	(0.09)	(0.08)	(0.22)
Accept. Rate	22%	21%	30%	22%	34%	29%

Note: Posteriors from stochastic volatility with no measurement error estimation. Standard deviations in parentheses.

TABLE A.7. Posterior for Parameter Drift Data, Part 1

Data Set	1	2	3	4	5	6
τ	0.50	0.83	0.37	0.59	0.70	0.45
	(0.10)	(0.08)	(0.14)	(0.20)	(0.18)	(0.17)
κ	0.52	0.62	0.57	0.71	0.42	0.54
	(0.12)	(0.16)	(0.17)	(0.16)	(0.10)	(0.20)
ψ_1	1.71	2.65	1.55	1.14	2.24	1.28
	(0.45)	(0.45)	(0.41)	(0.11)	(0.34)	(0.22)
ψ_2	0.36	0.08	0.42	0.38	0.16	0.31
	(0.08)	(0.06)	(0.06)	(0.09)	(0.07)	(0.10)
ρ_{ψ_1}	0.81	0.93	0.92	0.45	0.88	0.80
	(0.10)	(0.04)	(0.06)	(0.23)	(0.07)	(0.21)
ρ_{ψ_2}	0.29	0.65	0.48	0.50	0.37	0.47
	(0.22)	(0.23)	(0.24)	(0.28)	(0.18)	(0.27)
η_{ψ_1}	0.43	0.38	0.35	0.31	0.32	0.29
	(0.05)	(0.06)	(0.09)	(0.13)	(0.09)	(0.08)
η_{ψ_2}	0.33	0.29	0.27	0.18	0.32	0.11
	(0.13)	(0.17)	(0.11)	(0.07)	(0.08)	(0.06)
σ_R	0.18	0.17	0.18	0.18	0.22	0.17
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)
σ_g	0.19	0.25	0.16	0.23	0.23	0.16
	(0.05)	(0.04)	(0.05)	(0.08)	(0.06)	(0.07)
σ_z	0.87	0.84	0.82	0.66	1.17	0.75
	(0.15)	(0.16)	(0.15)	(0.10)	(0.32)	(0.23)
ρ_R	0.68	0.62	0.70	0.69	0.65	0.70
	(0.05)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)
ρ_g	0.80	0.83	0.82	0.83	0.84	0.81
	(0.07)	(0.04)	(0.05)	(0.06)	(0.06)	(0.08)
ρ_z	0.78	0.70	0.77	0.82	0.61	0.80
	(0.06)	(0.04)	(0.07)	(0.08)	(0.11)	(0.08)
η_{σ_R}	0.89	1.03	0.76	0.51	0.55	0.58
	(0.17)	(0.24)	(0.16)	(0.22)	(0.20)	(0.25)
η_{σ_g}	0.36	0.30	0.43	0.33	0.36	0.94
	(0.15)	(0.14)	(0.14)	(0.10)	(0.15)	(0.46)
η_{σ_z}	0.34	0.34	0.34	0.41	0.35	0.49
	(0.13)	(0.11)	(0.09)	(0.10)	(0.11)	(0.08)
Accept. Rate	24%	26%	28%	18%	20%	23%

Note: Posteriors from stochastic volatility with no measurement error estimation. Standard deviations in parentheses.

TABLE A.8. Posterior for Parameter Drift Data, Part 2

Data Set	7	8	9	10	11	12
τ	0.62	0.07	0.59	0.68	0.62	0.33
	(0.24)	(0.06)	(0.33)	(0.18)	(0.18)	(0.15)
κ	0.78	0.30	0.62	0.88	0.78	0.74
	(0.18)	(0.12)	(0.31)	(0.10)	(0.19)	(0.18)
ψ_1	1.27	1.54	1.45	1.14	1.31	1.27
	(0.17)	(0.32)	(0.28)	(0.10)	(0.16)	(0.20)
ψ_2	0.38	0.11	0.14	0.17	0.12	0.26
	(0.10)	(0.09)	(0.12)	(0.14)	(0.09)	(0.07)
ρ_{ψ_1}	0.59	0.30	0.49	0.47	0.43	0.96
	(0.23)	(0.19)	(0.26)	(0.21)	(0.26)	(0.03)
ρ_{ψ_2}	0.47	0.47	0.56	0.68	0.60	0.70
	(0.29)	(0.22)	(0.24)	(0.24)	(0.24)	(0.23)
η_{ψ_1}	0.40	0.22	0.34	0.28	0.41	0.37
	(0.07)	(0.12)	(0.14)	(0.15)	(0.06)	(0.08)
η_{ψ_2}	0.20	0.32	0.23	0.14	0.17	0.12
	(0.14)	(0.11)	(0.15)	(0.11)	(0.12)	(0.09)
σ_R	0.38	0.39	0.36	0.43	0.33	0.24
	(0.10)	(0.09)	(0.12)	(0.11)	(0.06)	(0.10)
σ_g	0.28	0.24	0.23	0.40	0.09	0.38
	(0.07)	(0.08)	(0.06)	(0.09)	(0.03)	(0.08)
σ_z	0.79	0.56	0.96	0.78	0.76	0.65
	(0.17)	(0.18)	(0.31)	(0.13)	(0.18)	(0.15)
ρ_R	0.52	0.87	0.64	0.52	0.62	0.87
	(0.09)	(0.07)	(0.09)	(0.08)	(0.07)	(0.03)
ρ_g	0.70	0.68	0.79	0.61	0.86	0.68
	(0.08)	(0.10)	(0.10)	(0.09)	(0.07)	(0.08)
ρ_z	0.76	0.88	0.75	0.76	0.82	0.73
	(0.12)	(0.05)	(0.07)	(0.09)	(0.07)	(0.04)
η_{σ_R}	1.14	0.37	0.84	0.85	0.66	1.05
	(0.26)	(0.18)	(0.38)	(0.32)	(0.16)	(0.29)
η_{σ_g}	0.26	0.32	0.49	0.34	1.77	0.26
	(0.11)	(0.11)	(0.12)	(0.15)	(0.16)	(0.08)
η_{σ_z}	0.33	0.83	0.38	0.31	0.31	0.75
	(0.10)	(0.11)	(0.11)	(0.09)	(0.08)	(0.22)
Accept. Rate	22%	21%	30%	22%	34%	29%

Note: Posteriors from stochastic volatility with no measurement error estimation. Standard deviations in parentheses.

TABLE A.9. Posterior for Constant Parameter Data, Part 1

Data Set	1	2	3	4	5	6
τ	0.29	0.56	0.51	0.63	0.54	0.46
	(0.08)	(0.18)	(0.12)	(0.10)	(0.19)	(0.15)
κ	0.45	0.63	0.75	0.82	0.68	0.54
	(0.14)	(0.16)	(0.20)	(0.17)	(0.16)	(0.09)
ψ_1	1.33	1.46	1.57	1.72	1.58	1.26
	(0.18)	(0.20)	(0.21)	(0.48)	(0.15)	(0.13)
ψ_2	0.15	0.38	0.29	0.16	0.25	0.29
	(0.10)	(0.08)	(0.10)	(0.13)	(0.10)	(0.12)
ρ_{ψ_1}	0.75	0.18	0.39	0.58	0.33	0.28
	(0.15)	(0.13)	(0.23)	(0.17)	(0.20)	(0.20)
ρ_{ψ_2}	0.51	0.46	0.53	0.76	0.36	0.32
	(0.26)	(0.18)	(0.30)	(0.16)	(0.25)	(0.25)
η_{ψ_1}	0.09	0.27	0.13	0.13	0.10	0.15
	(0.07)	(0.10)	(0.09)	(0.11)	(0.08)	(0.12)
η_{ψ_2}	0.14	0.28	0.42	0.21	0.39	0.20
	(0.10)	(0.09)	(0.04)	(0.13)	(0.07)	(0.14)
σ_R	0.16	0.15	0.15	0.19	0.13	0.16
	(0.03)	(0.04)	(0.10)	(0.04)	(0.03)	(0.04)
σ_g	0.25	0.23	0.21	0.31	0.20	0.22
	(0.07)	(0.07)	(0.05)	(0.13)	(0.04)	(0.08)
σ_z	0.94	0.56	0.82	0.80	0.73	0.96
	(0.18)	(0.14)	(0.17)	(0.17)	(0.13)	(0.16)
ρ_R	0.67	0.66	0.68	0.67	0.69	0.65
	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.03)
ρ_g	0.59	0.81	0.82	0.71	0.84	0.73
	(0.09)	(0.08)	(0.06)	(0.12)	(0.07)	(0.14)
ρ_z	0.74	0.80	0.79	0.74	0.74	0.67
	(0.06)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)
η_{σ_R}	0.48	0.67	0.69	0.55	0.76	0.84
	(0.20)	(0.26)	(0.31)	(0.19)	(0.22)	(0.40)
η_{σ_g}	0.39	0.21	0.33	0.31	0.37	0.32
	(0.15)	(0.12)	(0.11)	(0.11)	(0.15)	(0.13)
η_{σ_z}	0.28	0.87	0.31	0.34	0.47	0.21
	(0.09)	(0.22)	(0.09)	(0.10)	(0.18)	(0.09)
Accept. Rate	21%	22%	22%	21%	28%	30%

Note: Posteriors from stochastic volatility with no measurement error estimation. Standard deviations in parentheses.

TABLE A.10. Posterior for Constant Parameter Data, Part 2

Data Set	7	8	9	10	11	12
τ	0.47	0.60	0.51	0.57	0.27	0.51
	(0.15)	(0.17)	(0.19)	(0.17)	(0.11)	(0.20)
κ	0.76	0.53	0.79	0.60	0.30	0.53
	(0.20)	(0.12)	(0.13)	(0.14)	(0.21)	(0.17)
ψ_1	1.46	1.31	1.57	1.58	1.48	1.48
	(0.18)	(0.15)	(0.23)	(0.24)	(0.28)	(0.15)
ψ_2	0.16	0.24	0.22	0.16	0.14	0.31
	(0.10)	(0.10)	(0.11)	(0.14)	(0.09)	(0.15)
ρ_{ψ_1}	0.83	0.24	0.68	0.78	0.83	0.38
	(0.11)	(0.12)	(0.28)	(0.12)	(0.10)	(0.27)
ρ_{ψ_2}	0.61	0.28	0.62	0.38	0.30	0.59
	(0.24)	(0.18)	(0.33)	(0.21)	(0.16)	(0.23)
η_{ψ_1}	0.09	0.15	0.09	0.13	0.08	0.08
	(0.06)	(0.09)	(0.10)	(0.07)	(0.06)	(0.06)
η_{ψ_2}	0.25	0.18	0.31	0.23	0.20	0.09
	(0.16)	(0.12)	(0.12)	(0.11)	(0.06)	(0.06)
σ_R	0.14	0.10	0.12	0.15	0.19	0.09
	(0.03)	(0.03)	(0.04)	(0.04)	(0.09)	(0.03)
σ_g	0.21	0.18	0.25	0.20	0.14	0.19
	(0.05)	(0.04)	(0.07)	(0.05)	(0.06)	(0.05)
σ_z	0.75	0.80	0.74	0.87	1.56	0.83
	(0.13)	(0.14)	(0.14)	(0.18)	(0.68)	(0.18)
ρ_R	0.65	0.67	0.68	0.69	0.65	0.68
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
ρ_g	0.75	0.83	0.77	0.83	0.79	0.84
	(0.08)	(0.06)	(0.08)	(0.10)	(0.11)	(0.06)
ρ_z	0.74	0.74	0.80	0.67	0.73	0.76
	(0.07)	(0.07)	(0.07)	(0.09)	(0.09)	(0.09)
η_{σ_R}	1.08	1.40	0.96	0.76	0.42	1.38
	(0.19)	(0.34)	(0.28)	(0.22)	(0.17)	(0.30)
η_{σ_g}	0.38	0.35	0.25	0.29	0.50	0.28
	(0.18)	(0.17)	(0.10)	(0.14)	(0.21)	(0.12)
η_{σ_z}	0.28	0.34	0.41	0.32	0.30	0.32
	(0.11)	(0.12)	(0.14)	(0.10)	(0.14)	(0.12)
Accept. Rate	22%	21%	30%	22%	34%	29%

Note: Posteriors from stochastic volatility with no measurement error estimation. Standard deviations in parentheses.

APPENDIX B

SUPPLEMENTARY MATERIALS FOR CHAPTER III

Data

Data is from NIPA-BEA,CPS-BLS, the FRED database, and the Flow of Funds accounts from the Federal Reserve Board for the period 1954.Q4 to 2006.Q4. Data is chosen to conform with the literature and is similar to the data used in Fuentes-Albero (2011). The data used is:

- Real output: data from NIPA table 1.3.5 on nominal gross value added by the nonfarm business sector is deflated the implicit price deflator from table 1.3.4. This data is annualized, so these are divided by four. This is divided by the civilian noninstitutional population aged 16 and over from the BLS.

- Real investment: the sum of personal consumption expenditures of durables and gross private domestic investment from NIPA table 1.1.5 is deflated using the GDP deflator from table 1.1.4. This is weighted by the relative significance in total GDP and divided by the civilian noninstitutional population aged 16 and over from the BLS.

- Real net worth: the weighted average of net worth for corporate and noncorporate nonfarm business sectors. It is defined as tangible assets minus credit market instruments at market value. Tangible assets are defined as the weighted (based on the sector's contribution to gross value added) sum of series FL102010005.Q from Table B.102 and series FL112010005.Q from table B.103 of the Flow of Funds account. Liabilities are the defined as the weighted sum of series FL1041014005.Q from Table B.102 and series FL114102005.Q from Table B.103 from the Flow of Funds account. The data is converted to real and per capita data the same way output is converted.

- Real consumption: the sum of personal consumption expenditures of nondurables and services from NIPA table 1.1.5 deflated by the GDP deflator from table 1.14. This weighted and corrected to per capita terms the same way as investment.

- Inflation: the log difference of the price index for gross value added by the nonfarm business sector from NIPA table (1.3.4).

- Federal funds rate: this is from the FRED database and is converted to quarterly rates.
- Credit spread: the log difference between the gross Moody's Seasoned Baa Corporate Bond Yield found on FRED and the federal funds rate (both rates are converted to quarterly rates).

Estimation Results

TABLE B.1. Priors

Parameter	Distribution	Lower Bound	Upper Bound
χ	Uniform	0	2
γ	Uniform	0	1
γ_2	Uniform	0	1
α	Uniform	0	1
Π_{ss}	Uniform	1	1.03
μ_{ss}	Uniform	0	1
$\psi_{1,ss}$	Uniform	1	3
$\psi_{2,ss}$	Uniform	0	1
υ_A	Uniform	0	0.03
ρ_d	Uniform	0	1
ρ_m	Uniform	0	1
ρ_x	Uniform	0	1
ρ_ζ	Uniform	0	1
σ_μ	Uniform	0	1.5
σ_{ψ_1}	Uniform	0	1.5
σ_{ψ_2}	Uniform	0	1.5
$\sigma_{d,ss}$	Uniform	0	1
$\sigma_{m,ss}$	Uniform	0	1
$\sigma_{x,ss}$	Uniform	0	1
$\sigma_{\zeta,ss}$	Uniform	0	1
$\sigma_{g,ss}$	Uniform	0	1
$\sigma_{A,ss}$	Uniform	0	1
σ_{σ_d}	Uniform	0	1.5
σ_{σ_m}	Uniform	0	1.5
σ_{σ_x}	Uniform	0	1.5
σ_{σ_ζ}	Uniform	0	1.5
σ_{σ_A}	Uniform	0	1.5
σ_{σ_g}	Uniform	0	1.5

TABLE B.2. Posterior, Full Model

	Mean	Standard Deviation
χ	0.8304	0.0932
γ	0.0568	0.0062
γ_2	0.7106	0.0305
Π_{ss}	1.01	0.0049
μ_{ss}	0.279	0.0425
ψ_1	2.3704	0.0264
ψ_2	0.0268	0.0163
γ_R	0.4808	0.0409
ρ_d	0.9451	0.0079
ρ_x	0.3731	0.0522
ρ_ζ	0.9548	0.0183
ρ_g	0.5052	0.0406
σ_μ	0.1102	0.0271
σ_{ψ_1}	0.0702	0.0292
σ_{ψ_2}	0.2929	0.02
σ_m	0.1047	0.0089
σ_d	0.0797	0.0063
σ_x	0.195	0.0128
σ_ζ	0.0633	0.0124
σ_z	0.0027	0.0009
σ_g	0.1436	0.0084
σ_{σ_d}	0.1202	0.0207
σ_{σ_m}	0.6366	0.1198
σ_{σ_x}	0.8251	0.0366
σ_{σ_ζ}	0.9776	0.0233
σ_{σ_z}	0.2572	0.0198
σ_{σ_g}	0.4698	0.0401
Υ_A	0.02	0.0058
Acceptance Rate	27.6%	

TABLE B.3. Posterior, Constant μ

	Mean	Standard Deviation
χ	0.7169	0.0263
γ	0.0621	0.0019
γ_2	0.6903	0.0178
Π_{ss}	1.0109	0.002
μ_{ss}	0.2668	0.0246
ψ_1	2.3108	0.0514
ψ_2	0.0897	0.0084
γ_R	0.4972	0.0052
Υ_A	0.0211	0.0065
ρ_d	0.9432	0.0041
ρ_x	0.3874	0.0084
ρ_ζ	0.8889	0.0313
ρ_g	0.4761	0.0377
σ_μ	0	0
σ_{ψ_1}	0.0703	0.0128
σ_{ψ_2}	0.3255	0.0064
σ_m	0.0924	0.0046
σ_d	0.0767	0.003
σ_x	0.192	0.0022
σ_ζ	0.0451	0.0035
σ_z	0.0032	0.0011
σ_g	0.1367	0.0033
σ_{σ_d}	0.2067	0.0097
σ_{σ_m}	0.724	0.0316
σ_{σ_x}	0.7907	0.0078
σ_{σ_ζ}	1.0605	0.0265
σ_{σ_z}	0.2866	0.0118
σ_{σ_g}	0.535	0.0151
Acceptance Rate	27.8%	

TABLE B.4. Posterior, Full Measurement Error

	Mean	Standard Deviation
χ	0.1343	0.0504
γ	0.4036	0.0478
γ_2	0.3496	0.0614
Π_{ss}	1.0062	0.004
μ_{ss}	0.2447	0.0088
ψ_1	1.68	0.0493
ψ_2	0.3759	0.0116
γ_R	0.0475	0.025
ρ_d	0.4442	0.0407
ρ_x	0.1798	0.0539
ρ_ζ	0.7684	0.1383
ρ_g	0.9157	0.0367
σ_μ	0.1145	0.0697
σ_{ψ_1}	0.537	0.1227
σ_{ψ_2}	0.2743	0.0428
σ_m	0.143	0.0101
σ_d	0.0098	0.0089
σ_x	0.118	0.0107
σ_ζ	0.088	0.0146
σ_z	0.0011	0.0008
σ_g	0.0071	0.005
σ_{σ_d}	0.191	0.0264
σ_{σ_m}	0.3441	0.0885
σ_{σ_x}	0.5134	0.0436
σ_{σ_ζ}	0.2296	0.1148
σ_{σ_z}	0.1529	0.0603
σ_{σ_g}	0.3016	0.0595
Υ_A	0.0051	0.0025
Acceptance Rate	17.8%	

TABLE B.5. Posterior, No Stochastic Volatility

	Mean	Standard Deviation
χ	0.7651	0.0935
γ	0.4426	0.0818
γ_2	0.6215	0.048
Π_{ss}	1.0074	0.0033
μ_{ss}	0.2271	0.0069
ψ_1	1.8403	0.0495
ψ_2	0.329	0.0136
γ_R	0.1158	0.0426
Υ_A	0.0072	0.0022
ρ_d	0.6727	0.0311
ρ_x	0.6814	0.0347
ρ_ζ	0.4976	0.0733
ρ_g	0.3781	0.0752
σ_μ	0.3805	0.0082
σ_{ψ_1}	0.6666	0.0335
σ_{ψ_2}	0.353	0.0568
σ_m	0.2069	0.0158
σ_d	0.0153	0.0056
σ_x	0.0789	0.0077
σ_ζ	0.0125	0.0058
σ_z	0.0014	0.0011
σ_g	0.0268	0.0132
Υ_A	0.0072	0.0022
Acceptance Rate	27.3%	

APPENDIX C

SUPPLEMENTARY MATERIALS FOR CHAPTER IV

Data

Data is from NIPA-BEA,CPS-BLS, the FRED database, and the Flow of Funds accounts from the Federal Reserve Board for the period 1954.Q4 to 2006.Q4. Data is chosen to conform with the literature and is similar to the data used in Fuentes-Albero (2011). The data used is:

– Real output: data from NIPA table 1.3.5 on nominal gross value added by the nonfarm business sector is deflated the implicit price deflator from table 1.3.4. This data is annualized, so these are divided by four. This is divided by the civilian noninstitutional population aged 16 and over from the BLS.

– Real investment: the sum of personal consumption expenditures of durables and gross private domestic investment from NIPA table 1.1.5 is deflated using the GDP deflator from table 1.1.4. This is weighted by the relative significance in total GDP and divided by the civilian noninstitutional population aged 16 and over from the BLS.

– Real net worth: the weighted average of net worth for corporate and noncorporate nonfarm business sectors. It is defined as tangible assets minus credit market instruments at market value. Tangible assets are defined as the weighted (based on the sector's contribution to gross value added) sum of series FL102010005.Q from Table B.102 and series FL112010005.Q from table B.103 of the Flow of Funds account. Liabilities are the defined as the weighted sum of series FL1041014005.Q from Table B.102 and series FL114102005.Q from Table B.103 from the Flow of Funds account. The data is converted to real and per capita data the same way output is converted.

– Real consumption: the sum of personal consumption expenditures of nondurables and services from NIPA table 1.1.5 deflated by the GDP deflator from table 1.14. This weighted and corrected to per capita terms the same way as investment.

– Real wages: real compensation per hour in the nonfarm business sector (COMPRNFB) provided by the BLS

– Inflation: the log difference of the price index for gross value added by the nonfarm business sector from NIPA table (1.3.4).

– Federal funds rate: this is from the FRED database and is converted to quarterly rates.

– Credit spread: the difference between the gross Moody's Seasoned Baa Corporate Bond Yield found on FRED and the federal funds rate (both rates are converted to quarterly rates).

First Order Conditions

$$\widetilde{\lambda}_t = \frac{d_t}{\widetilde{c}_t - h\widetilde{c}_{t-1}\frac{z_{t-1}}{z_t}} - \beta h \mathbb{E}_t \frac{d_{t+1}}{\widetilde{c}_{t+1} - h\widetilde{c}_t \frac{z_t}{z_{t+1}}} \tag{C.1}$$

$$\widetilde{\lambda}_t = \beta \mathbb{E}_t \frac{R_t \widetilde{\lambda}_{t+1}\frac{z_t}{z_{t+1}}}{\Pi_{t+1}} \tag{C.2}$$

$$mc_t = (1-\alpha)^{\alpha-1}\alpha^{-\alpha}\widetilde{w} > t^{1-\alpha}\widetilde{r}_t^{\alpha} \tag{C.3}$$

$$f_t = \frac{\eta-1}{\eta}\left(\widetilde{w}_t^*\right)^{1-\eta}\widetilde{\lambda}_t \widetilde{w}_t^{\eta} l_t^d + \beta\theta_w \mathbb{E}_t \left(\frac{\Pi_t^{\chi_w}}{\Pi_{t+1}}\right)^{-\eta(1+\gamma)}\left(\frac{\widetilde{w}_{t+1}^*}{\widetilde{w}_t^*}\frac{z_{t+1}}{z_t}\right)^{\eta-1} f_{t+1} \tag{C.4}$$

$$f_t = \psi d_t \varphi_t \left(\frac{\widetilde{w}_t}{\widetilde{w}_t^*}\right)^{\eta(1+\gamma)}\left(l_t^d\right)^{1+\gamma} + \beta\theta_w \mathbb{E}_t \left(\frac{\Pi_t^{\chi_w}}{\Pi_{t+1}}\right)^{-\eta(1+\gamma)}\left(\frac{\widetilde{w}_{t+1}^*}{\widetilde{w}_t^*}\frac{z_{t+1}}{z_t}\right)^{\eta(1+\gamma)} f_{t+1} \tag{C.5}$$

$$\widetilde{w}_t^{1-\eta} = \theta_w \left(\frac{\Pi_{t-1}^{\chi_w}}{\Pi_t}\right)^{1-\eta}\left(\widetilde{w}_{t-1}\frac{z_{t-1}}{z_t}\right)^{1-\eta} + (1-\theta_w)\left(\widetilde{w}^*\right)^{1-\eta} \tag{C.6}$$

$$\epsilon g_t^1 = (\epsilon - 1)\, g_t^2 \tag{C.7}$$

$$g_t^1 = \widetilde{\lambda}_t mc_t y_t^d + \beta\theta_p \mathbb{E}_t \left(\frac{\Pi_t^{\chi}}{\Pi_{t+1}}\right)^{-\epsilon} g_{t+1}^1 \tag{C.8}$$

$$g_t^2 = \widetilde{\lambda}_t \Pi_t^* \widetilde{y}_t^d + \beta\theta_p \mathbb{E}_t \frac{\Pi_t^{\chi}}{\Pi_{t+1}} \frac{\Pi_t^*}{\Pi_{t+1}^*} g_{t+1}^* \tag{C.9}$$

$$1 = \theta_p \left(\frac{\Pi_{t-1}^{\chi}}{\Pi_t} \right)^{1-\epsilon} + (1-\theta_p) (\Pi_t^*)^{1-\epsilon} \tag{C.10}$$

$$v_t^p = \theta_p \left(\frac{\Pi_{t-1}^{\chi}}{\Pi_t} \right)^{-\epsilon} v_{t-1}^p + (1-\theta_p) (\Pi_t^*)^{-\epsilon} \tag{C.11}$$

$$\widetilde{y}_t^d = \frac{\widetilde{k}_t^{\alpha} \left(\widetilde{l}_t^d \right)^{1-\alpha}}{v_t^p} \tag{C.12}$$

$$\frac{\widetilde{k}_t}{l_t^d} = \frac{\alpha}{1-\alpha} \frac{\widetilde{w}_t}{\widetilde{r}_t} \tag{C.13}$$

$$\widetilde{r}_t = \gamma_1 + \gamma_2 (u_t - 1) \tag{C.14}$$

$$\widetilde{Q}_t = 1 + \xi \left(\frac{\widetilde{I}_t}{\widetilde{K}_t} - (\delta - 1 + \Upsilon_z \Upsilon_\zeta) \right) \tag{C.15}$$

$$R_{t+1}^k = \left[\frac{\left(u_{t+1} \widetilde{r}_{t+1}^k - a(u_{t+1}) \right) + \bar{\omega}_{t+1}(1-\delta)\widetilde{Q}_{t+1}}{\widetilde{Q}_t \frac{\zeta_{t+1}}{\zeta_t}} \right] \Pi_{t+1} \tag{C.16}$$

$$\mathbb{E}_t \frac{R_{t+1}^k}{R_t} \left[\Gamma(\bar{\omega}_{t+1}) - \mu_{t+1} G(\bar{\omega}_{t+1}) \right] = \frac{\widetilde{Q}_t \widetilde{K}_{t+1} \frac{\zeta_{t+1}}{\zeta_t} - \widetilde{N}_{t+1} \frac{z_t}{z_{t+1}}}{\widetilde{Q}_t \widetilde{K}_{t+1} \frac{\zeta_{t+1}}{\zeta_t}} \tag{C.17}$$

$$\mathbb{E}_t \Bigg\{ \left[1 - \Gamma(\bar{\omega}_{t+1}) \right] \frac{R_{t+1}^k}{R_{t+1}} + \frac{\Gamma'(\bar{\omega}_{t+1})}{\Gamma'(\bar{\omega}_{t+1}) - \mu_{t+1} G'(\bar{\omega}_{t+1})} \left[\frac{R_{t+1}^k}{R_{t+1}} \left(\Gamma(\bar{\omega}_{t+1}) - \mu_{t+1} G(\bar{\omega}_{t+1}) \right) - 1 \right] \Bigg\} = 0 \tag{C.18}$$

$$spread_t = \frac{\mu_t G(\bar{\omega}_t) \widetilde{K}_t \widetilde{Q}_t \frac{\zeta_t}{\zeta_{t-1}}}{\widetilde{K}_t \widetilde{Q}_{t-1} \frac{\zeta_t}{\zeta_{t-1}} - \widetilde{N}_t \frac{z_{t-1}}{z_t}} \tag{C.19}$$

$$P_t N_{t+1} = x_t \nu \left(P_{t-1} R_t^k \widetilde{Q}_{t-1} \widetilde{K}_t \frac{\zeta_t}{\zeta_{t-1}} - R_{t-1} \left(\widetilde{Q}_{t-1} \widetilde{K}_t \frac{\zeta_t}{\zeta_{t-1}} - \widetilde{N}_t \frac{z_t}{z_{t-1}} \right) \right.$$
$$\left. - \mu_t G(\bar{\omega}_t) P_{t-1} R_t^k Q_{t-1} K_t \right) + P_t W_t^e \tag{C.20}$$

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R} \right)^{1-\gamma_R} \left(\left(\frac{\Pi_t}{\Pi} \right)^{\psi_{1,t}} \left(\frac{\frac{\widetilde{Y}_t}{\widetilde{Y}_{t-1}} \frac{z_t}{z_{t-1}}}{\Upsilon_Z} \right)^{\psi_{2,t}} \right)^{1-\gamma_R} m_t. \tag{C.21}$$

$$\widetilde{K}_{t+1} = (1-\delta) \widetilde{K}_t \frac{z_t \zeta_t}{z_{t+1} \zeta_{t+1}} + \frac{z_t \zeta_t}{z_{t+1} \zeta_{t+1}} \widetilde{I}_t \tag{C.22}$$

TABLE C.1. Priors

	Distribution	Lower Bound	Upper Bound
Υ_A	Uniform	0	0.03
Υ_ζ	Uniform	0	0.03
Π	Uniform	1	1.03
χ	Uniform	0	1
χ_1	Uniform	0	1
γ_R	Uniform	0	1
ψ_2	Uniform	0	0.5
ξ	Uniform	0	5
μ	Uniform	0	1
ψ_1	Uniform	1	3
θ_p	Uniform	0	1
θ_w	Uniform	0	1
ρ_d	Uniform	0	1
ρ_φ	Uniform	0	1
ρ_g	Uniform	0	1
ρ_x	Uniform	0	1
σ_d	Uniform	0	1
σ_φ	Uniform	0	1
σ_g	Uniform	0	1
σ_m	Uniform	0	1
σ_x	Uniform	0	1
σ_ζ	Uniform	0	1
σ_z	Uniform	0	1
η_d	Uniform	0	1
η_φ	Uniform	0	1
η_g	Uniform	0	1
η_m	Uniform	0	1
η_x	Uniform	0	1
η_ζ	Uniform	0	1
η_z	Uniform	0	1
η_μ	Uniform	0	1
η_{ψ_1}	Uniform	0	1

TABLE C.2. Posterior

	Mean	Std. Dev.
Υ_A	0.001	(0.001)
Υ_ζ	0.002	(0.001)
Π	1.022	(0.004)
χ	0.239	(0.160)
χ_1	0.778	(0.119)
γ_R	0.545	(0.124)
ψ_2	0.472	(0.013)
ξ	4.136	(0.658)
μ	0.515	(0.088)
ψ_1	1.951	(0.335)
θ_p	0.277	(0.256)
θ_w	0.162	(0.065)
ρ_d	0.417	(0.177)
ρ_φ	0.539	(0.173)
ρ_g	0.582	(0.253)
ρ_x	0.694	(0.201)
σ_d	0.155	(0.033)
σ_φ	0.111	(0.053)
σ_g	0.143	(0.043)
σ_m	0.052	(0.023)
σ_x	0.042	(0.021)
σ_ζ	0.037	(0.017)
σ_z	0.022	(0.004)
η_d	0.582	(0.245)
η_φ	0.580	(0.201)
η_g	0.595	(0.203)
η_m	0.297	(0.107)
η_x	0.445	(0.105)
η_ζ	0.571	(0.316)
η_z	0.480	(0.158)
η_μ	0.407	(0.064)
η_{ψ_1}	0.508	(0.201)
Acceptance Rate		35.9%

REFERENCES CITED

ARUOBA, S., J. FERNÁNDEZ-VILLAVERDE, AND J. RUBIO-RAMÍREZ (2006): "Comparing Solution Methods for Dynamic Equilibrium Economies," *Journal of Economic Dynamics and Control*, 30, 2477–2508.

BARLEVY, G. (2004): "The Cost of Business Cycles Under Endogenous Growth," *American Economic Review*, 94, 964–990.

BENATI, L. AND P. SURICO (2009): "VAR Analysis and the Great Moderation," *American Economic Review*, 99, 1632–1652.

BERNANKE, B., M. GERTLER, AND S. GILCHRIST (1999): "The Financial Accelerator in a Quantitative Business Cycle Framework," in *Handbook of Macroeconomics*, ed. by J. Taylor and M. Woodford, 1341–1393.

BIANCHI, F. (2009): "Regime Switches, Agents Beliefs, and Post-World War II U.S." *mimeo*.

CHIB, S. AND I. JELIAZKOV (2001): "Marginal Likelihood from the Metropolis-Hastings Output," *Journal of the American Statistical Association*, 96, 270–281.

CHRISTIANO, L., R. MOTTO, AND M. ROSTAGNO (2010): "Financial Factors in Economic Fluctuations," *ECB Working Paper Series No. 1192*.

CLARIDA, R., J. GALLÍ, AND M. GERTLER (2000): "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 115, 147–180.

DAVIG, T. AND T. DOH (2008): "Monetary policy regime shifts and inflation persistence," Tech. rep.

DYNAN, K., D. ELMENDORF, AND D.SICHEL (2006): "Can Financial Innovation Help to Explain the Reduced Volatility of Economic Activity," *Journal of Monetary Economics*, 53, 123–150.

FARMER, R., D. WAGGONER, AND T. ZHA (2000): "Understanding Markov-Switching Rational Expectations Models," *Journal of Economic Theory*, 144, 1849–1867.

——— (2009): "Understanding Markov-Switching Rational Expectations Models," *Journal of Economic Theory*, 144, 1849–1867.

FERNÁNDEZ-VILLAVERDE, J., P. GUERRÓN-QUINTANA, AND J. RUBIO-RAMÍREZ (2010): "Fortune or Virtue: Time-Variant Volatilities Versus Parameter Drifting in U.S. Data," *mimeo*.

FERNÁNDEZ-VILLAVERDE, J. AND J. RUBIO-RAMÍREZ (2007): "Estimating Macroeconomic Models: A Likelihood Approach," *Review of Economic Studies*, 74, 1059–1087.

FOERSTER, A., J. RUBIO-RAMÍREZ, D. WAGGONER, AND T. ZHA (2011): "Perturbation Methods for Markov-Switching Models," *mimeo*.

FUENTES-ALBERO, C. (2011): "Financial Frictions, Financial Shocks and Aggregate Volatility," *mimeo*.

GOMME, P. AND P. KLEIN (2011): "Second-order approximation of dynamic models without the use of tensors," *Journal of Economic Dynamics and Control*, 37, 535–542.

Guerrón-Quintana, P. (2007): "Financial Innovations: An Alternative Explanation of the Great Moderation," *mimeo.*

Jermann, U. and V. Quadrini (2009): "Financial Innovations and Macroeconomic Volatility," *mimeo.*

Kim, C. and C. Nelson (1999): "Has the U.S. Economy Become More Stable? A Bayesian Approach Based on A Markov-Switching Model of the Business Cycle," *Review of Economics and Statistics*, 81, 608–616.

Kim, J., S. Kim, E. Schaumburg, and C. A. Sims (2005): "Calculating and Using Second Order Accurate Solutions of Discrete Time Dynamic Equilibrium Models," *mimeo.*

Lubik, T. and F. Schorfheide (2004): "Testing for Indeterminacy: An Application to U.S. Monetary Policy," *American Economic Review*, 94, 190–217.

McConnell, M. and G. Perez-Quiros (2000): "Output Fluctuations in the United States: What has Changed Since the Early 1980s?" *American Economic Review*, 90, 1464–1476.

Reis, R. (2009): "The Time-Series Properties of Aggregate Consumption: Implications for the Costs of Fluctuations," *Journal of the European Economic Association*, 7, 722–753.

Schmitt-Grohé, S. and M. Uribe (2004): "Solving Dynamic General Equilibrium Models Using a Second-order Approximation of the Policy Function," *Journal of Economic Dynamics & Control*, 28, 755–775.

Sherman, M. (2009): "A Short History of Financial Deregulation in the United States," *mimeo.*

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

Smets, F. and R. Wouters (2007): "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review*, 97, 586–606.

Stock, J. and M. Watson (2002): "Has the Business Cycle Changed and Why?" *NBER Macroeconomics Annual*, 159–218.

Woodford, M. (2010): "Optimal Monetary Stabilization Policy," in *Handbook of Monetary Economics*, ed. by B. M. Friedman and M. Woodford.