Essays on Asset Prices and Macroeconomic Fundamentals

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Diese Dissertation besteht aus vier Arbeitspapieren, von denen drei in Zusammenarbeit mit jeweils einem Koautor entstanden sind.

- Wenjuan Chen (2011)
  On the continuation of the Great Moderation: new evidence from G7 countries
  SFB 649 Discussion Paper 2011-060

- Wenjuan Chen and Anton Velinov (2012)
  Do Japanese stock prices reflect fundamentals?
  SFB 649 Discussion Paper 2012-037

- Wenjuan Chen and Timo Bettendorf (2013)
  Are there bubbles in the Sterling-dollar exchange rates? new evidence from sequential ADF tests
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- Wenjuan Chen and Anton Velinov (2012)
  Testing structural identifications on US monetary policy and stock prices

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Contents

Overview

It is well known that extreme asset price fluctuations not only affect the stability of the whole financial system, but also have negative consequences on the real economy. History has witnessed many sudden falls in the price of a certain asset class, such as the crash of the Dutch tulip bubbles in the 17th century, the crash of the Japanese real estate and stocks bubbles in the early 1990s, and the internet bubble burst in 2001. Recently, a steep decline in the US housing prices also led to a global financial turbulence, and has had long lasting severe consequences on the US and European economies. Therefore it is an essential question to understand how the monetary policy can contribute to the stability of asset price developments.

This thesis is dedicated to study the determinants of asset prices, the detections of asset price bubbles, the relationship between the asset prices and macroeconomic fundamentals, as well as the relevant structural identification issues. The main methodology that has been applied is the Markov regime-switching heteroskedasticity models, and the sequential unit root tests.

The thesis has in total four chapters. Chapter 1 is a simple application of univariate Markov switching models on the discussion of whether the Great Moderation is over after the recent financial crisis. Chapter 2 adopts the bivariate Markov switching heteroskedasticity model on the identification issue of fundamental shocks and nonfundamental shocks that drives the stock prices in Japan. Chapter 3 is an exception as it employs instead the recent sequential unit root tests to test whether speculative bubbles exist in the nominal Sterling-dollar exchange rate. Chapter 4 is an application of Markov switching heteroskedasticity model on testing different identification schemes to identify the effects of US monetary policy shocks on stock prices.

Chapter 1 employs a univariate Markov regime-switching model to investigate whether the Great Moderation is over since the start of the late 2000s recession. The results confirm that the recent financial crisis did cause a simultaneous high-volatility period among the G7 countries. However, the financial crisis may not mark the end of the Great Moderation. There is strong evidence that each G7 country has again returned to the low-variance state since 2009 or the beginning of 2010.

Chapter 2 investigates to what extent the fundamentals of the real economy are reflected in the stock prices of Japan. A Markov switching vector autoregression model with switching variances is used to test the structural identification scheme. Identification of fundamental and nonfundamental shocks is shown to be supported by the data. Based on the appropriate structural restriction, the historical stock prices are decomposed into fundamental components and non-fundamental components. The decomposition shows that the linkage between Japanese stock prices and fundamental shocks has recovered after the burst of the Japanese asset price bubble in the beginning of 1990s.

A seemingly excursion from the empirical application of Markov -switching heteroskedasticity models is Chapter 3 on testing the bubble hypothesis in the nominal Sterling-dollar exchange rate employing recent sequential ADF tests. Although it seems to be divergent from the main theme, it is inspired by work in Chapter 2 and further explores the question: What are the fundamentals that drive asset prices? How could the asset bubbles be detected with econometric tools? This paper introduces recently developed sequential unit root tests into the analysis of exchange rates bubbles. Strong evidence of explosive behavior is found in the nominal Sterling-dollar exchange rate. However, this explosive behavior should not be simply interpreted as evidence of rational bubbles, as we show that it might be driven by the relative prices of traded goods.

Chapter 4 utilizes a Markov-switching structural vector autoregression model to obtain over-identifying information in order to test for the validity of several identification schemes employed in literature. Numerous papers have studied the interaction between the monetary policy and the stock market in a structural VAR framework. However, different ways of structural identifications can lead to dramatically divergent empirical results on the interaction between monetary policy and the stock prices. We find strong evidence against the identification scheme which assumes long run neutrality of monetary policy shocks on stock prices, while the popularly adopted Cholesky decomposition can not be rejected.

Zusammenfassung

Es ist bekannt, dass extreme Schwankungen von Asset-Preisen nicht nur zur Destabilisierung von Finanzsystemen beitragen, sondern auch nachhaltig negative Effekte auf die Realwirtschaft haben. Es gibt zahlreiche historische Beispiele für extreme Preisbewegungen von bestimmten Assets. Bekannt sind unter anderem das plötzliche Platzen der holländischen Tulpenblase im 17. Jahrhundert, der Absturz von Aktienwerten und Immobilienpreisen in Japan in den frühen 1990 Jahren, sowie das Platzen der Dotcom-Blase 2001 mit globalen wirtschaftlichen Auswirkungen. Daher ist die Frage wie Geldpolitik zur Stabilität von Kursbewegungen an den internationalen Anlagemärkten beitragen kann von zentraler Bedeutung.

Diese Arbeit widmet sich den Determinanten von Asset-Preisen, dem Nachweis von Spekulationsblasen, der Beziehung zwischen Vermögenswerten und makroökonomischen Fundamentaldaten, sowie strukturellen Identifizierungsproblemen. Die wichtigsten Methoden, die hierzu Anwendung finden, sind Markov Regime-Switching-Heteroskedastie Modelle und sequentielle Unit Root-Tests.

Diese Arbeit besteht aus vier Kapiteln. Das erste Kapitel ist eine Anwendung eines univariaten Markov-Switching Modells, welches Aufschluss darüber geben soll, ob die sogenannte "Great Moderation" nach der letzten Finanzkrise vorbei ist. Kapitel 2 verwendet ein bivariates Markov-Switching Heteroskedastie Modell zur Identifizierung von Fundamental- und Nicht-Fundamentalschocks, die die Aktienpreise Japans beeinflussen. Kapitel 3, eine Ausnahme innerhalb dieser Arbeit, verwendet den sequentiellen ADF Test, um zu prüfen, ob spekulative Blasen im nominalen Sterling-Dollar Wechselkurs auftreten. Kapitel 4 ist eine Anwendung des Markov-Switching Heteroskedastie Modells zum Testen von verschiedenen Identifizierungsschemata, um die Effekte von US Geldpoli-

tik auf Aktienpreise innerhalb eines vier Variablen VAR Systems zu prüfen.

Kapitel 1 verwendet ein univariates Markov-switching Modell, um zu prüfen, ob die "Great Moderation" seit dem Beginn der Finanzkrise vorbei ist. Die Ergebnisse zeigen, dass die Finanzkrise eine hoch volatile Periode in den G7 Ländern verursacht hat. Jedoch muss diese Krise nicht das Ende der "Great Moderation" bedeuten. Die Ergebnisse zeigen, dass die G7 Länder seit Ende 2009/Anfang 2010 sich wieder in einem Zustand befinden, in der die Volatilität niedrig ist.

Kapitel 2 untersucht inwiefern die Fundamentaldaten der realen Wirtschaft die Aktienpreise in Japan widerspiegeln. Ein Markov-Switching Vektorautoregressionsmodell mit wechselnden Varianzen wird zum Testen des strukturellen Identifikationsschemas verwendet. Es wird gezeigt, dass die Daten eine Identifizierung von Fundamental- und Nicht-Fundamentalschocks unterstützen. Basierend auf passenden strukturellen Restriktionen werden historische Aktienpreise in zwei Komponenten zerlegt: eine fundamentale Komponente und eine nicht-fundamentale Komponente. Diese Zerlegung zeigt, dass die Verbindung zwischen japanischen Aktienpreisen und Fundamentalschocks nach dem Platzen der japanischen Asset-Preisblase Anfang der 1990er wiederhergestellt wurde.

Das dritte Kapitel testet auf Blasen im nominalen Sterling-Dollar Wechselkurs mittels eines sequentiellen ADF Tests. Obwohl dieses Kapitel keine Markov-Switching Modelle anwendet, basiert es auf Kapitel 2 und untersucht die folgenden Fragen. Was sind die Fundamentaldaten, die Asset-Preise treiben? Welche ökonometrischen Werkzeuge können verwendet werden, um Blasen in Asset-Preisen zu entdecken? Diese Arbeit führt den neu entwickelten sequentiellen ADF Test in die Analyse von Wechselkursblasen ein. Der Test zeigt, dass sich der Sterling-Dollar Wechselkurs explosiv entwickelt hat. Dies beweist jedoch nicht, dass der Wechselkurs eine Blase beinhaltet, weil die explosive Entwicklung von den Fundamentalvariablen erklärt werden kann, nämlich dem relativen Preis von handelbaren Güter.

Kapitel 4 verwendet ein Markov-Switching strukturelles Vektorautoregressionsmodell, um die Güte verschiedener Identifizierungsschemata, die in der Literatur verwendet werden, zu testen. Zahlreiche Arbeiten haben die Interaktion zwischen Geldpolitik und dem Aktienmarkt innerhalb des Rahmens eines strukturellen VARs untersucht. Es hat sich gezeigt, dass die empirischen Ergebnisse drastisch von der gewählten Methode zur Identifizierung abhängen. Die Ergebnisse sprechen gegen das Identifizierungsschema, welches die langfristige Neutralität geldpolitischer Schocks auf die Aktienpreise annimmt. Gleichzeitig findet Man starke Evidenz, dass Identifizierungsschemata, die keine unmittelbaren Effekte von Aktienpreisschocks auf die Geldpolitik annehmen, nicht abgelehnt werden können.

Chapter 1

On the Continuation of the Great Moderation: New evidence from G7 Countries

1.1 Introduction

For around two decades, the volatility of aggregate economic variables remained persistently and significantly low in most of the developed economies. This phenomenon has achieved lots of attention and has been called 'the Great Moderation'. However, since the turmoil of the recent financial crisis, it seems that the moderation of economic volatility is coming to an end.

Yet for major industrialized countries official data have shown slow and steady recovery from the crisis since 2009. This might be interpreted as the return of the Great Moderation. It is thus of great interest and importance to update research on the output volatility after the outbreak of the late 2000s financial crisis. This paper explores the behavior of the real quarterly GDP growth rate of the G7 countries, in order to investigate the following question: Could the Great Moderation still continue since the financial crisis occurred?

The Great Moderation in the US has been widely discussed by economists. Kim and Nelson [1999], McConnell and Perez-Quiros [2000], and Blanchard and Simon [2001] are among the first who lead the discussion. Kim and Nelson [1999] find that the US real GDP growth switch towards stabilization at 1984

Q1 in a Markov switching model of the business cycle. Blanchard and Simon [2001] also document the long and large decline in the volatility of US GDP growth in the late 1980s and the 1990s, using a simple AR regression over a 5-year rolling window.

Nevertheless, outside the US there is no consensus on timing of moderation of economic volatility. Papers such as Mills and Wang [2003], Smith and Summers [2009], and Stock and Watson [2005] all find that output volatility in G7 countries has stabilized since the late 1980s and 1990s, however, there are discrepancies among their studies about the timing and magnitude of the Great Moderation. To the best of the author's knowledge, this is the first paper that has included data for the recent financial crisis period and has updated research about the Great Moderation phenomenon.

In the empirical literature on the Great Moderation, Markov switching models are predominant to detect underlying economic regimes. This type of models have the advantage of capturing the timing of structural shifts endogenously. This paper employs the regime switching technique to re-investigate time series of output growth rates of G7 countries till the end of 2010. The estimated timing of switching into the Great Moderation from this paper seems consistent with those from Mills and Wang [2003], Stock and Watson [2005] and Smith and Summers [2009]. In contrast of Canarella et al. [2010], however, my findings indicate that there is a very high probability of being in a low-volatility regime for each G7 country in 2010. The main results suggest that the Great Moderation is probably still continuing after the outbreak of the late 2000s crisis.

Moreover, this paper sheds light on whether shifts in output volatility are originated from switching volatility regime of the economy, or from switching dynamics in absorbing the disturbances. Among the three different specifications of models, the most appropriate model for the majority of G7 countries turns out to be the model with regime switching in only the variances. According to literature such as Blanchard and Simon [2001], these results would imply that there is little role of policy making in causing output fluctuations. In light of the new evidence on the high volatility period during the global economic recession in 2008, this interpretation on the role of luck or policy in causing output fluctuations should be viewed with caution.

The structure of the paper is as follows. Section 1 briefly describes the output growth rates of each G7 country. In Section 2 I introduce the details of the AR model and the three different specifications of Markov-switching AR models that are estimated. Section 3 presents the estimation results and show that the Markov-switching model in variance fits the data best for most G7 countries. Section 5 concludes.

1.2 Output Growth and Volatility in G7 Countries

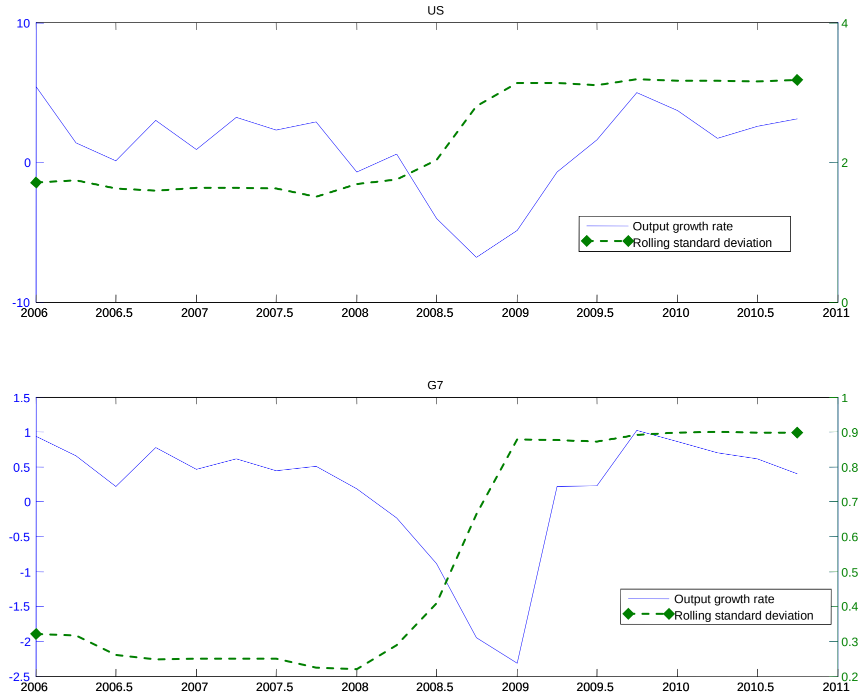
The historical time series of the quarter-to-quarter GDP growth rates for most G7 countries are obtained from the statistical portal of the Organization of Economic Cooperation and Development(OECD). Among the European countries, the French data starts from 1969 Q1 and ends at 2010 Q4, while the Italian data cover a shorter period from 1981 Q1 to 2010 Q4. The UK data starts from 1955 and ends at 2010 Q4. The Canadian data are available from 1961 Q1 to 2010 Q4. For Japan, the data are from 1981 Q1 to 2010 Q4. Data of the United States covers the period from 1969 Q1 to 2010 Q4.

The time series of the German GDP growth rates come from the Bundesbank since the available time series covers longer periods from 1970 Q1 to 2010 Q4. Beside the time series for each individual G7 country, we also consider the aggregate data for all G7 countries. All these series are seasonally adjusted at source and computed as the change from the previous period. The Augmented Dicky-Fuller test is carried out and test statistics show that no unit root exists for each time series.

As a representative example, Figure 1 depicts the process of the quarterly output growth rate and its volatility for the US and the G7 aggregate data from 2006 Q1 to 2010 Q4. The whole data sample for each G7 country that is used in estimation is shown in the appendix. Following Blanchard and Simon [2001], the volatility is measured as the twenty-quarter rolling standard deviation, i.e., the standard deviation for time period t is the estimated standard deviation from nineteenth quarter before till the current quarter.

It is noticeable that the output volatility has sharply increased since the outbreak of the recent financial crisis. At the end of 2010, it seems that most G7

Figure 1.1: Output Growth Rate before and during the Crisis



Notes: This figure depicts the quarter-to quarter GDP growth rates and volatility for the US and the G7 aggregate data. The volatility of output growth is calculated as rolling standard deviation over 20 quarters.

countries still exhibits high volatility in output growth. However, this preliminary look at the output volatility might be misleading since it is only based on a simple moving-average analysis. As a consequence, at the very end of the sample period, a decline in volatility could not be detected. In the next section, I rely on a regime switching framework to have a more precise inspection on the status of the output volatility.

1.3 The Regime Switching Approach to Model Output Volatility

In this section, I introduce the empirical setup to analyze the output growth process. Since Hamilton [1989] proposed a regime switching model in showing shifts between positive and negative output growth, numerous researchers, such as Kim and Nelson [1999] and McConnell and Perez-Quiros [2000], have employed this framework in studying business cycles and the Great Moderation phenomenon.

Following the empirical literature, I rely on the two-state Markov switching framework to detect the underlying states of the economic volatility. Switches between low variance and high variance states are allowed to be recurrent. The focus of this paper is on structural shifts in the changing volatility of the output growth. Therefore the state variables represent volatility regimes instead of business cycle peaks and troughs. In order to assess the performance of the various regime switching models under consideration, a simple AR model without regime shifts is also introduced as a benchmark. Number of lags are chosen according to the Schwarz criterion (see Table 7, 8 and 9 in the Appendix). The following subsections introduce the four different specifications of models on the output growth rates of the G7 countries.

Model 1: The Benchmark AR Model

First I consider a simple AR model with only one regime, where both dynamics and variance are constant over time. Let the benchmark AR model be

$$y_t = \alpha + a_1 y_{t-1} + ... + a_p y_{t-p} + u_t \tag{1.1}$$

where α represents the intercept, $a_1, ..., a_p$ are the autoregressive coefficients. u_t are the *i.i.d.* error terms, with distribution $N(0, \sigma^2)$.

Model 2: The MS-AR Model with Switching Variance

Following Hamilton [2005], Model 2 assumes that the variance of error terms from the process of the output growth depends on an unobserved state variable, whose transition between different states follows a Markov Chain. In this paper it is generally assumed that there exist two states, a high-volatility regime s_1, and a low-volatility regime s_2.

In Model 2, only the variances of the errors are allowed to vary over time. The intercept and the AR coefficients are assumed to stay constant over time:

$$y_t = \alpha + a_1 y_{t-1} + ... + a_p y_{t-p} + u_{s_t} \tag{1.2}$$

where u_{s_t} represents the error terms that depend on a Markov Chain process. When $s_t = 1$, the economy is in the high-volatility state, and $u_t \sim$ i.i.d. $N(0, \sigma_1^2)$. Otherwise, when $s_t = 2$, the economy is supposed to be in the low-volatility state, $u_t \sim$ i.i.d. $N(0, \sigma_2^2)$. The transition probabilities are assumed to be constant over time. They can be presented in a 2×2 transition matrix:

$$P = \begin{bmatrix} P_{HH} & P_{LH} \\ P_{HL} & P_{LL} \end{bmatrix} \tag{1.3}$$

where P_{ij} represents the probability of the economy switching from state i to state j. The expected duration of each regime would be $(1 - P_{HH})^{-1}$ and $(1 - P_{LL})^{-1}$.

Model 3: The MS-AR Model with Switching Dynamics

Is regime switching behavior of output originated from switching variances of shocks hitting the economy or switching dynamics of the process in absorbing the shocks? Model 3 is introduced here and its estimation results are compared with Model 2 in the next section. It has the feature of homoscedasticity but changing intercept and autoregressive parameters as follows:

$$y_t = \alpha_{s_t} + a_{1,s_t} y_{t-1} + ... + a_{p,s_t} y_{t-p} + u_t \tag{1.4}$$

Model 4: The MS-AR Model with Switching Dynamics and Variances

A more general specification of Markov switching models is considered here, in which not only the variances of error terms, but also the dynamics are regime dependent, the intercept α_{s_t}, AR coefficients $a_{1,s_t}, ..., a_{p,s_t}$ and σ_{s_t} are all allowed to vary between two regimes.

$$y_t = \alpha_{s_t} + a_{1,s_t} y_{t-1} + ... + a_{p,s_t} y_{t-p} + u_{s_t} \tag{1.5}$$

Better policy making has been often mentioned as a plausible cause of the Great Moderation. If there is less persistence of the output growth process during the Great Moderation, it would be reflected in a smaller sum of the AR coefficients in the low-variance state based on estimation of Model 4.

1.4 Regime Switching in the Output Growth Process

This section presents the empirical results. The Markov switching models are estimated with the iterative Expectation-Maximization algorithm following Krolzig [1997]. In the first step, I use a modified likelihood ratio test to compare Model 1 and Model 4, so as to whether there exists regime switching behavior in the output growth rate. In the second step, estimation results of Model 2, Model 3, and Model 4 are compared to select the most appropriate model for each country. Based on estimation from the most appropriate model, the estimated timing of Great Moderation in each country and pictures of smoothed probabilities are presented.

Table 1.1: Is There Regime Switching in the Output Growth Process?

Countries	P-value of the adjusted-LR test
Canada	0.0000
France	0.0000
Germany	0.0023
Italy	0.0000
Japan	0.0000
UK	0.0000
US	0.0000

Notes: This table reports the test results from comparing the maximum likelihood of the benchmark AR model (Model 1) with the Markov switching AR model with switching dynamics and variance (Model 4).

1.4.1 Single Regime v.s. Two Regimes

Let us first find out whether there is significant regime switching behavior in the output growth process. I compute a modified likelihood ratio statistic proposed by Davies [1977], so as to test whether the difference in the maximum log-likelihood is statistically significant. The standard likelihood ratio test is no longer applicable here because the states are not identifiable in the single-regime AR model, which violates one of the key assumptions of likelihood ratio test. Davies [1977] has proposed the following upper bound for a modified likelihood ratio statistics under the null hypothesis, assuming that a unique global optimum for the likelihood function exists:

$$Pr[(LR(q*)] > M = Pr(\chi^2 > M) + \frac{2M^{(d-1)/2}e^{-M/2}2^{-d/2}}{\Gamma(d/2)} \tag{1.6}$$

where $Pr[(LR(q*)] > M$ is the upper bound critical value, M is the standard likelihood ratio statistics, $q*$ is the vector of transition probabilities under the alternative hypothesis $H1$, and d is the number of restrictions under the null hypothesis.

Table 1.1 presents the p-value of the modified likelihood ratio test for each

Table 1.2: Regime Switching in Dynamics or in Variances?

Countries	Model 2	Model 3
Canada	2.01	2.09
France	1.49	1.50
Germany	2.85	2.92
Italy	1.86	1.83
Japan	2.99	3.04
UK	2.57	2.74
US	5.15	5.38

Notes: This table reports the Schwarz Criterion of the Markov switching AR model with only switching variance (Model 2), the Markov switching AR model with only switching dynamics (Model 3).

G7 country. There is strong evidence of regime switching behavior in the variance of error terms. Smith and Summers [2009] have shown similar findings for the output data of G7 countries before the start of the recent recession.

1.4.2 Switching Variances or Switching Dynamics?

Is regime switching behavior present in the dynamic process of output growth? Or does regime switching exist in the variance of shocks to output? Table 1.2 reports the Schwarz criterion of Model 2 and Model 3, which is commonly used in choosing competing models that are not nested. It is noticeable that for all countries except Italy, Model 2 outperforms Model 3 [1]. Obviously Model 3, the model with only switching dynamics is the less favorite model compared with Model 2. Switching dynamics alone is not sufficient to account for the Markov switching behavior in the output growth process of G7 countries.

Since Model 2 and Model 4 are nested, a likelihood ratio test could be used

[1] Nevertheless, for Italy the Schwarz criterion from Model 4 turns out to be 1.79, lower than the one of Model 3. Further results from a likelihood ratio test to compare Model 3 and Model 4 also rejects Model 3.

Table 1.3: Likelihood Ratio Test for Model 2 and Model 4

Countries	P-value	The Most Appropriate model
Canada	0.431	Model 2
France	0.000	Model 4
Germany	0.463	Model 2
Italy	0.000	Model 4
Japan	0.741	Model 2
UK	0.314	Model 2
US	0.423	Model 2

Notes: This table reports the p-values of the likelihood ratio test to compare the Markov switching AR model with only switching variance (Model 2), and the Markov switching AR model with both switching dynamics and variances (Model 4).

to compare estimation results of Model 2 with those of Model 4 (see Table 3). To sum up, the most appropriate model for Canada, Germany, Japan, the UK and the US turn out to be Model 2, the one with only switching variances. Model 4 fits the best for France and Italy.

Table 4 and Table 5 reports the estimated transition probabilities, the intercept, the sum of AR coefficients and the variances for Model 2 and Model 4. These estimates share a close similarity across the models except for France and Italy [2]. In general, the probability of remaining in the low-volatility is very high, above 95 percent for the majority of the G7 countries. For the United States, the variance of the high-volatility state is about 6 times as high as the one of the low-volatility state, which is in line with the findings of McConnell and Perez-Quiros [2000]. In general, the relative variance ratio of the high-volatility state to the low-volatility state is larger than those found in the traditional literature

[2]For France and Italy, the estimated intercept and the sum of AR coefficients differ more dramatically across the models because switching dynamics is significant for these two countries. Besides, note that for France and Italy, the sum of AR coefficients estimated by Model 4 turns to be negative or explosive in one regime. These complicated properties of regime-dependent AR parameters have also been pointed out by Tjøstheim [1998].

Table 1.4: Maximum Likelihood Estimates of Model 2

Country	P_{HH}	P_{LL}	σ_H^2	σ_L^2	σ_H^2/σ_L^2	I	AR
Canada	0.94	0.96	0.76	0.15	5.07	0.34	0.53
France	0.99	0.92	1.30	0.15	8.67	0.20	0.69
Germany	0.83	0.92	1.99	0.42	4.74	0.42	0.13
Italy	0.74	0.97	1.67	0.21	7.95	0.26	0.37
Japan	0.89	0.97	4.3	0.47	9.15	0.25	0.42
UK	0.87	0.94	2.23	0.26	8.58	0.24	0.06
US	0.97	0.99	21.99	3.62	6.07	1.66	0.45

Notes: P_{HH} represents the probability that the regime transfer from the high-volatility state to the high-volatility state. P_{LL} represents the probability that the regime transfer from the low-volatility state to the low-volatility state. σ_H^2 represents the variance in the high-volatility regime, while σ_L^2 represents the variance in the low-volatility regime. AR stands for the sum of AR coefficients, and I stands for the intercept.

on the Great Moderation. This could be due to the additional extremely volatile period since the end of 2007 included in our data sample.

The above results provide very strong evidence for Markov switching behavior in the variance, which is also found by papers such as Blanchard and Simon [2001], Sims and Zha [2006] and Smith and Summers [2009]. Markov-switching behavior in the dynamics of the output growth seems less relevant, only significant for France and Italy. To sum up, the Markov switching model with switching variance is the most appropriate to model the output growth for most of the G7 countries.

1.4.3 Smoothed Probabilities

Figure 1.2 and Figure 1.3 depict the estimated smoothed probabilities of being in a low-volatility regime from the most appropriate model chosen for each individual country. In general the smoothed probabilities estimated from Model 2 and

Table 1.5: Maximum Likelihood Estimates of Model 4

Country	P_{HH}	P_{LL}	σ_H^2	σ_L^2	I_H	I_L	AR_H	AR_L
Canada	0.94	0.96	0.75	0.15	0.28	0.36	0.50	0.53
France	0.94	0.13	0.15	0.02	0.23	0.35	0.67	-0.01
Germany	0.97	0.96	1.38	0.33	0.55	0.34	0.09	0.11
Italy	0.91	0.38	0.26	0.01	0.31	-0.29	0.23	1.36
Japan	0.85	0.97	4.02	0.52	0.73	0.37	0.15	0.21
UK	0.88	0.94	2.12	0.25	0.39	0.20	-0.08	0.16
US	0.97	0.99	21.43	3.61	1.49	1.64	0.39	0.47

Notes: P_{HH} represents the probability that the regime transfer from the high-variance state to the high-variance state. P_{LL} represents the probability that the regime transfer from the low-variance state to the low-variance state. AR_H stands for the sum of AR coefficients for the high-variance state, while AR_L stands for the sum of AR coefficients for the low-variance state. σ_H^2 represents the variance in the high-volatility regime, while σ_L^2 represents the variance in the low-volatility regime.

Model 4 are very similar [3]. It is noticeable that the US GDP volatility sharply declined in 1984, switched back to a high-volatility regime from the end of 2007 till the mid of 2009, and started stabilizing afterwards. For Canada, France, Germany and the UK, multiple switches happened before the output growth reached a stable period of low variance in the mid 1980s or the beginning of 1990's.

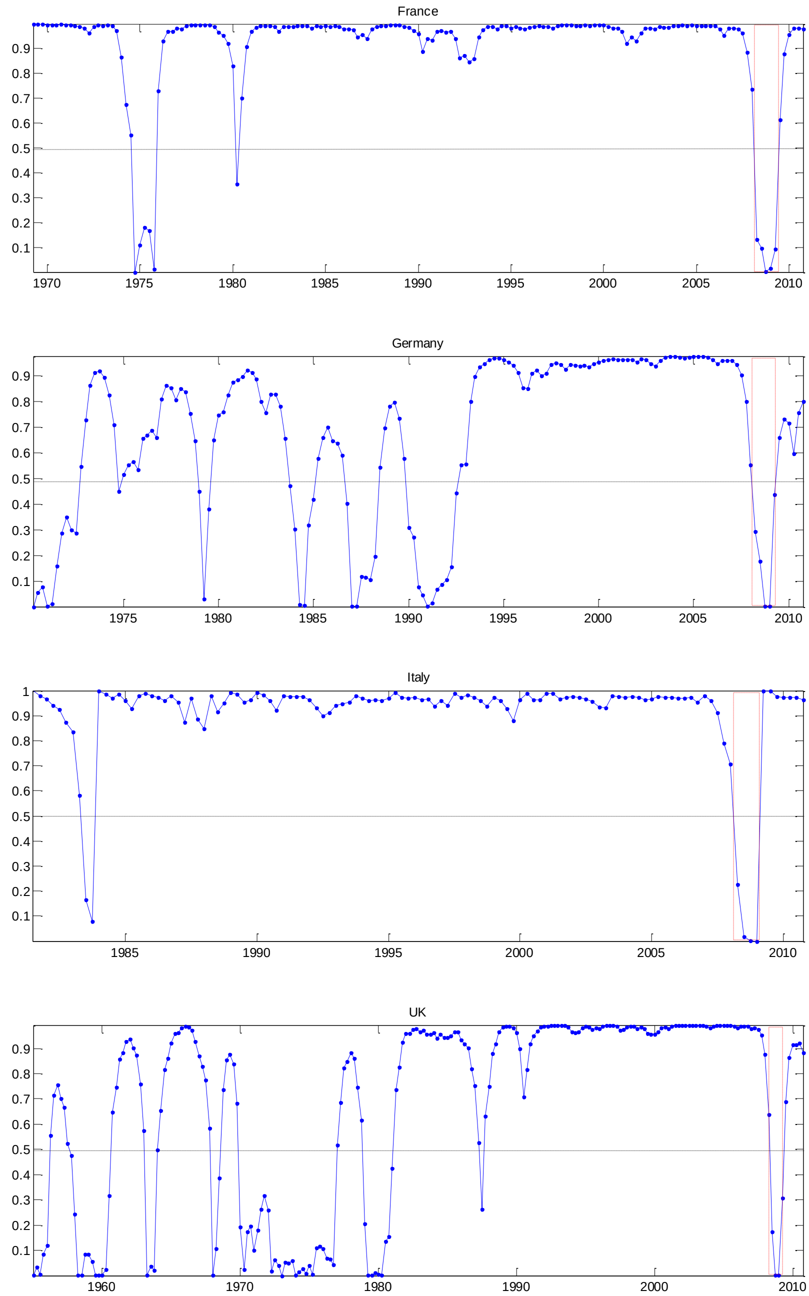
The timing that the economies started switching into the Great Moderation varies across countries, though there is evidence that the switching dates are clustered. Italy, the UK and and the US started the Great Moderation in the 80s, while Canada, Germany and Japan started stabilization in output around the beginning of 1990s. France seems to have an exceptionally earlier start (1976) into a low-volatility state than the rest of the countries. Table 6 compares my estimates of the switching dates with those of Smith and Summers [2009], Mills and Wang [2003] and Stock and Watson [2005].

For France, Germany and US, my estimates are consistent with Smith and Summers [2009]. The date of switch for Italy is later than estimates of other papers, which could result from the shorter sample period of data we have. The start of the Great Moderation for the UK is rather controversial, since the output growth switched multiple times between high-volatility and low-volatility regime before the 1990s. However, combining observations from the volatility path, the output growth has been rather stable since 1980 except for one temporary break shortly before the 1990 recession. Thus I identify the dates of switching into the Great Moderation as 1980, which is consistent with findings from Stock and Watson [2005].

Since the start of the late 2000s financial crisis, all the G7 economies have simultaneously fallen into a state of high volatility. However, in contrast to Canarella et al. [2010], my results suggest that the Great Moderation could probably continue despite the current low confidence of the public on the economic outlook. Actually since 2009 or the beginning of 2010 the probability of returning into low-volatility regime has risen up to the peak of 80 to 95 percent for the output growth rate of each G7 country. These results are robust for either

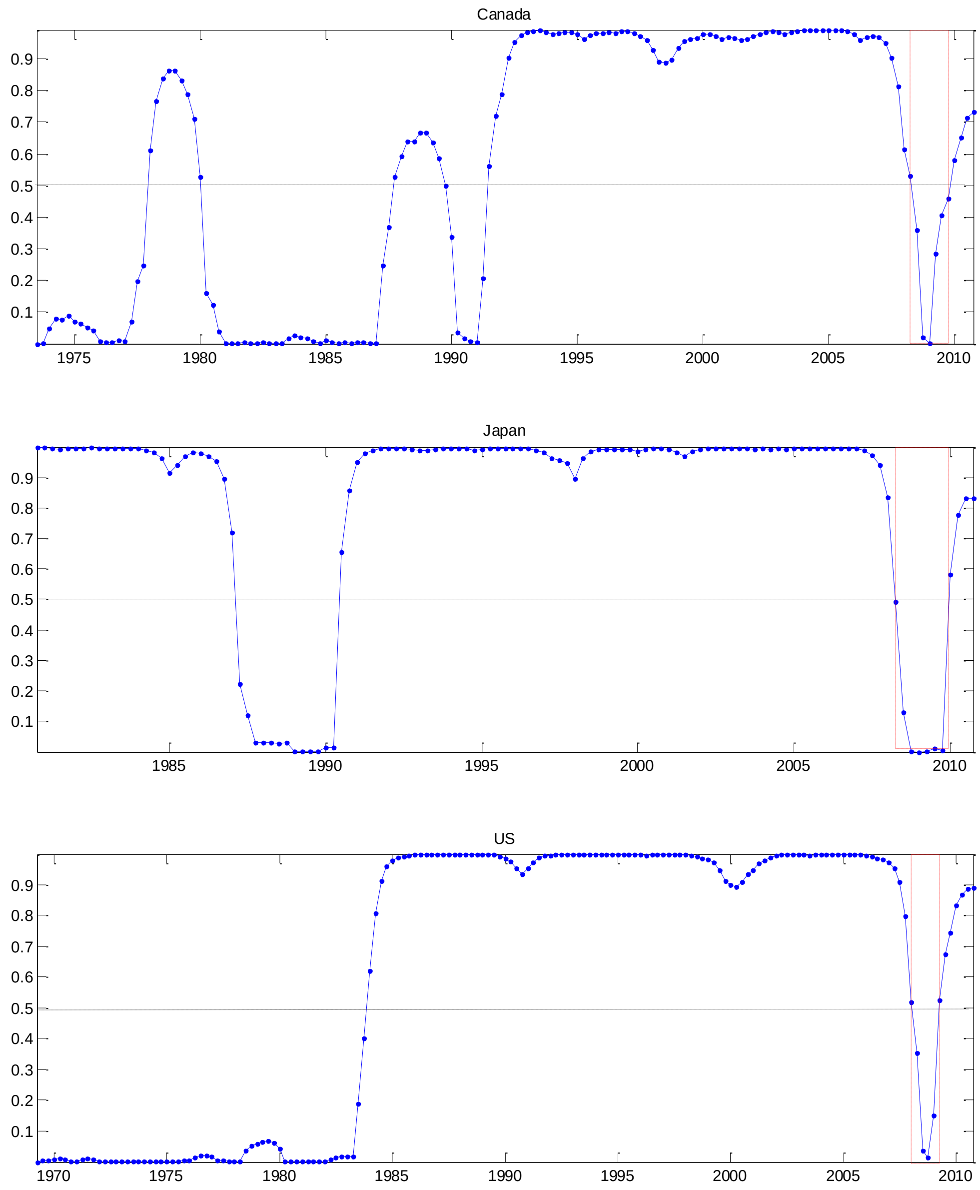
[3] The smoothed probabilities from the second-best model for each G7 country are presented in Figure 6 and Figure 7 in the Appendix. Germany is the only exception where a switch back to the low-variance regime could not be found at the end of the sample period.

Figure 1.2: Smoothed Probabilities for the Low-volatility State of the Output Growth for Countries Inside the EU



Notes: This figure depicts the smoothed probabilities of the low-variance state for France, Germany, Italy and the UK from the chosen most appropriate model, i.e., Model 2 for Germany and the UK, and Model 4 for France and Italy.

Figure 1.3: Smoothed Probabilities for the Low-volatility State of the Output Growth for Countries Outside the EU



Notes: This figure depicts the smoothed probabilities of the low-variance state for Canada, Japan, the US from the most appropriate model, i.e., the Markov switching AR model with only switching variance (Model 2) for Canada, Japan and the US.

Table 1.6: Estimated timing of switching into the Great Moderation

	This paper	Smith and Summers(2009)	Mills and Wang(2003)	Stock and Watson(2005)
Canada	1991	1991	late 1970s	1991
France	1976	1976	1979	1968
Germany	1992	1993	1974	1993
Italy	1984	1980	1982	1980
Japan	1990	1975	1979/1990	n/a
UK	1980	1992	1993	1980
US	1984	1984	1984	1983

Notes: This table reports dates of switches into the low-variance state from various authors. Dates from this paper are the first date for which the smoothed probabilities are larger than 0.5.

Model 2 or for Model 4. The recent economic recession seems to cause only a temporary switch in the variance of output growth. It is likely that the economy will return in the low-volatility regime.

1.5 Conclusion

This paper provides new evidence on the regime switching behavior of the output growth process of G7 countries including the volatile period of the late 2000s financial crisis. Three important switches are documented in the output volatility. The first started from the mid 1980s or the beginning of 1990s, when a significant decline in output volatility has been found for each G7 country. The second prominent switch happened around the end of 2007, when all the G7 economies simultaneously fell into the high-volatility state. However, this is only a temporary switch rather than a structural break. Since the mid of 2009 or the beginning of 2010, all the G7 countries have switched back into the low-volatility regime. These results suggest that the Great Moderation could probably continue despite current pessimism of the public.

According to e.g.Blanchard and Simon [2001], a better policy should imply less persistence in the output growth process, i.e., a smaller sum of AR coefficients. However, the estimation results do not provide evidence that dynamics of the output growth process has changed in most of the G7 countries. This would lead to a puzzling conclusion that policy has played little role in causing output fluctuations for the late 2000s financial crisis. Thus it is recommendable to view this line of interpretation with caution.

This paper is only a first step to document the endogenous switches in the variances of output growth in G7 countries based on a univariate framework. It is therefore interesting to extend the current study to include more variables such as inflation and interest rate in a multivariate structural model to find the causing factors behind the switching disturbances to the economy.

Appendix

Table 1.7: Schwarz criterion and Choice of Lags for Model 2

Countries	preferred number of Lags	Schwarz criterion	Maximum Likelihood
Canada	1	2.01	-134.81
France	2	1.48	-105.10
Germany	1	2.85	-215.60
Italy	1	1.86	-95.45
Japan	3	2.99	-160.03
UK	1	2.57	-270.18
US	2	5.15	-409.25

Notes: Schwarz criterion is calculated as $-2(l/T) + klog(T)/T$, where l is the log likelihood, k is the number of parameters, and T is the sample size.

Table 1.8: Schwarz criterion and Choice of Lags for Model 3

Country	Lag	Schwarz criterion	Log likelihood
Canada	2	2.09	-131.82
France	3	1.50	-95.65
Germany	1	2.92	-218.60
Italy	1	1.83	-91.37
Japan	1	3.04	-168.65
UK	3	2.74	-272.40
US	1	5.38	-430.95

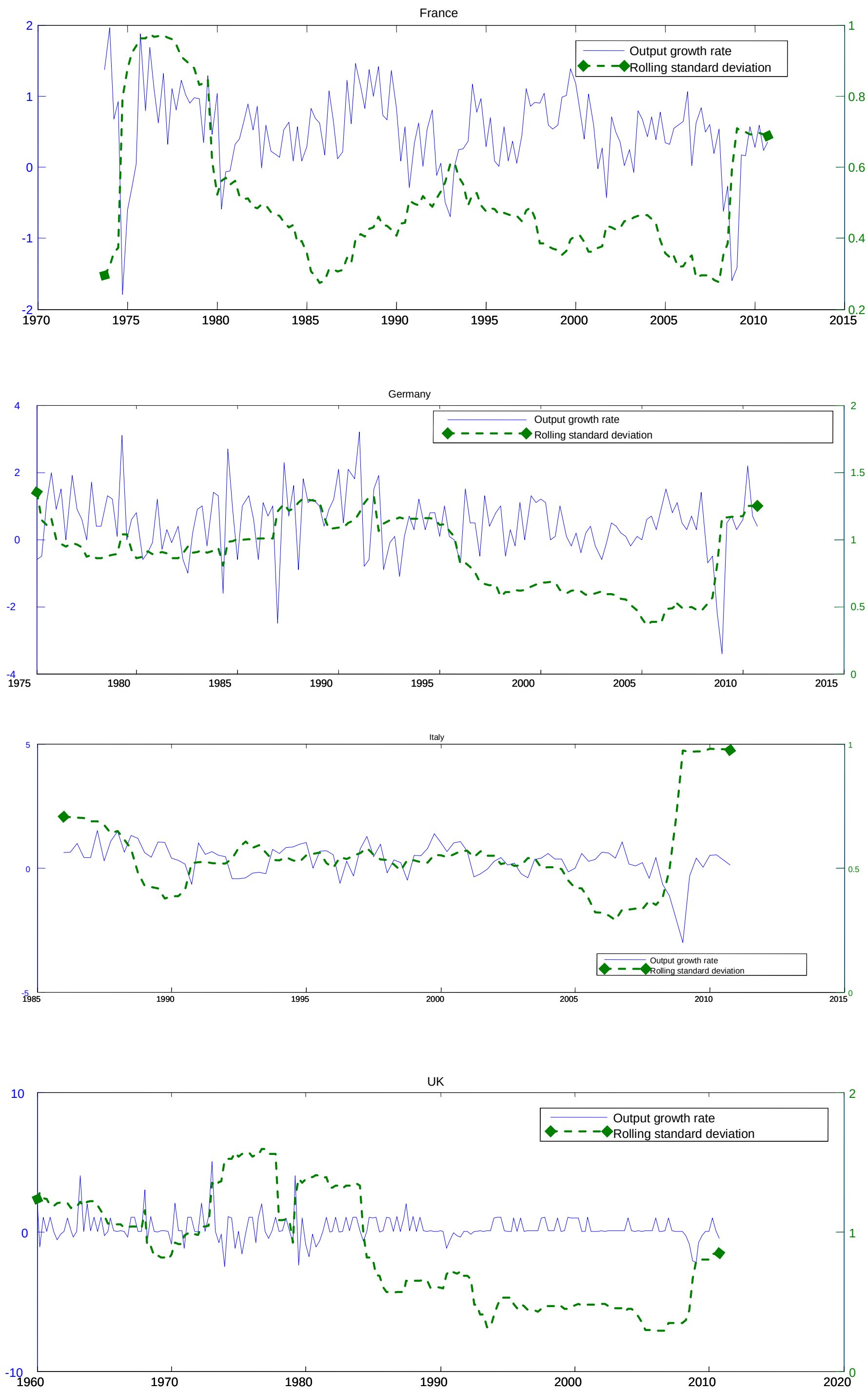
Notes: Schwarz criterion is calculated as $-2(l/T) + klog(T)/T$, where l is the log likelihood, k is the number of parameters, and T is the sample size.

Table 1.9: Schwarz criterion and Choice of Lags for Model 4

Country	Lag	Schwarz criterion	LogL
Canada	1	2.07	-134.50
France	3	1.51	-93.73
Germany	1	2.91	-215.00
Italy	1	1.79	-86.46
Japan	1	3.09	-168.98
UK	1	2.61	-269.02
US	2	5.23	-408.39

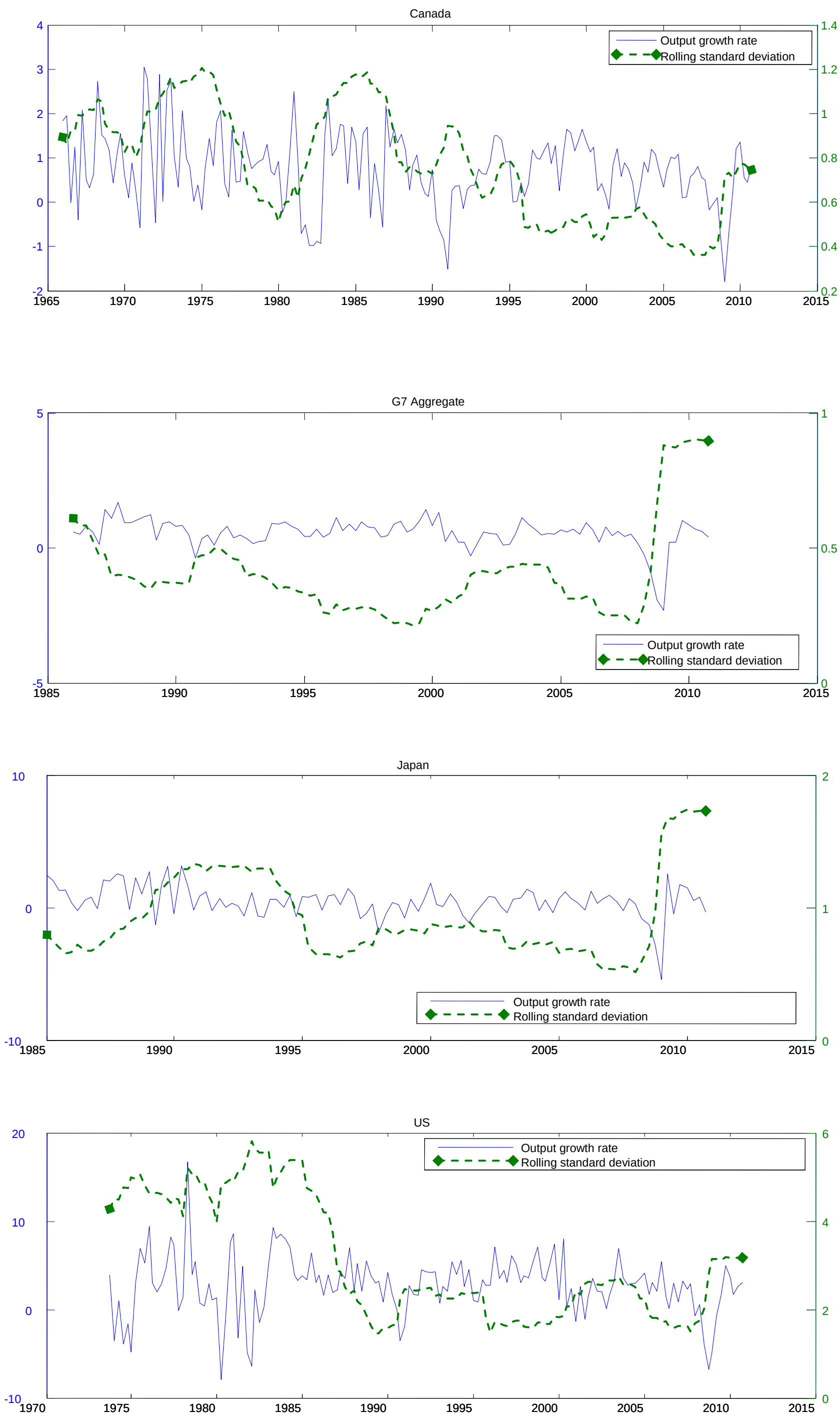
Notes: Schwarz criterion is calculated as $-2(l/T) + klog(T)/T$, where l is the log likelihood, k is the number of parameters, and T is the sample size.

Figure 1.4: Output Growth Rate of G7 countries Inside the EU



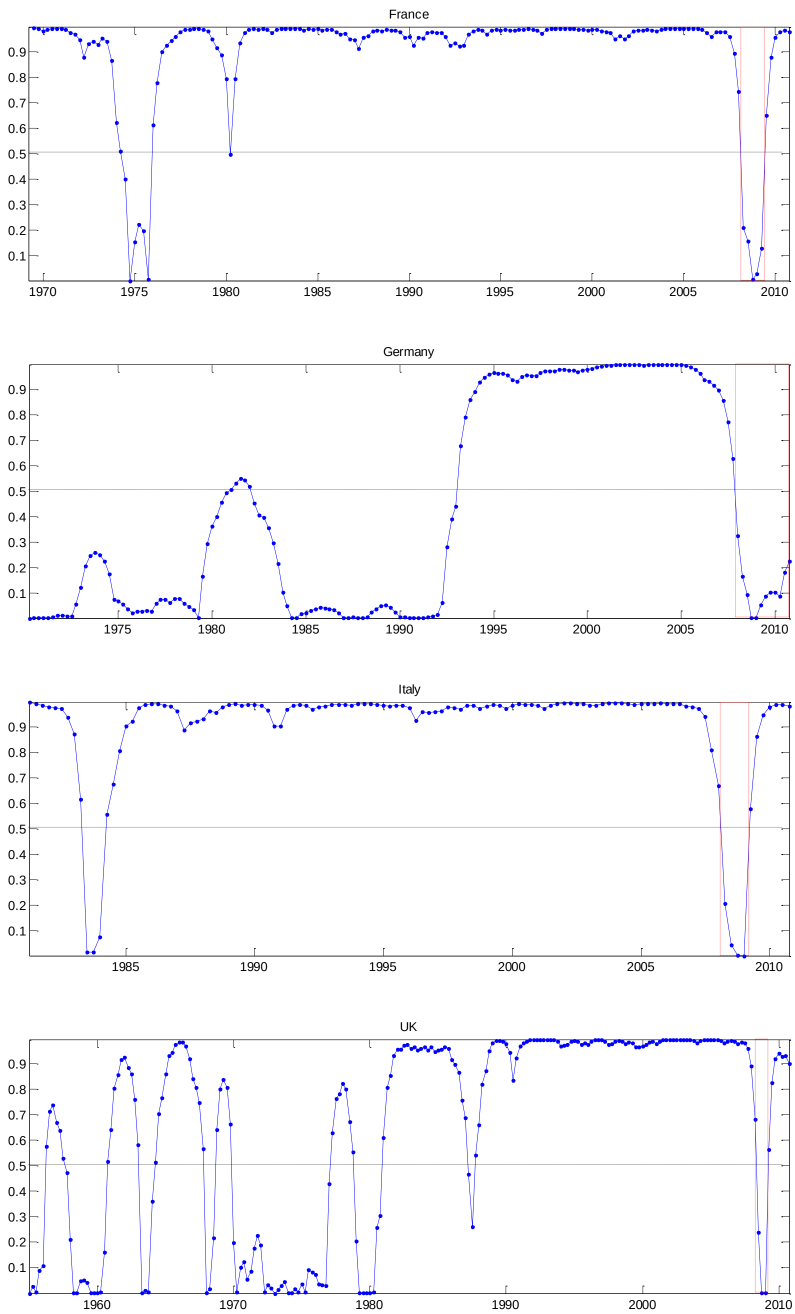
Notes: This figure depicts the GDP quarter-to quarter growth rate of G7 countries Inside the EU. The volatility of output growth is measured as rolling standard deviation over 20 quarters.

Figure 1.5: Output Growth Rate of G7 countries Outside the EU



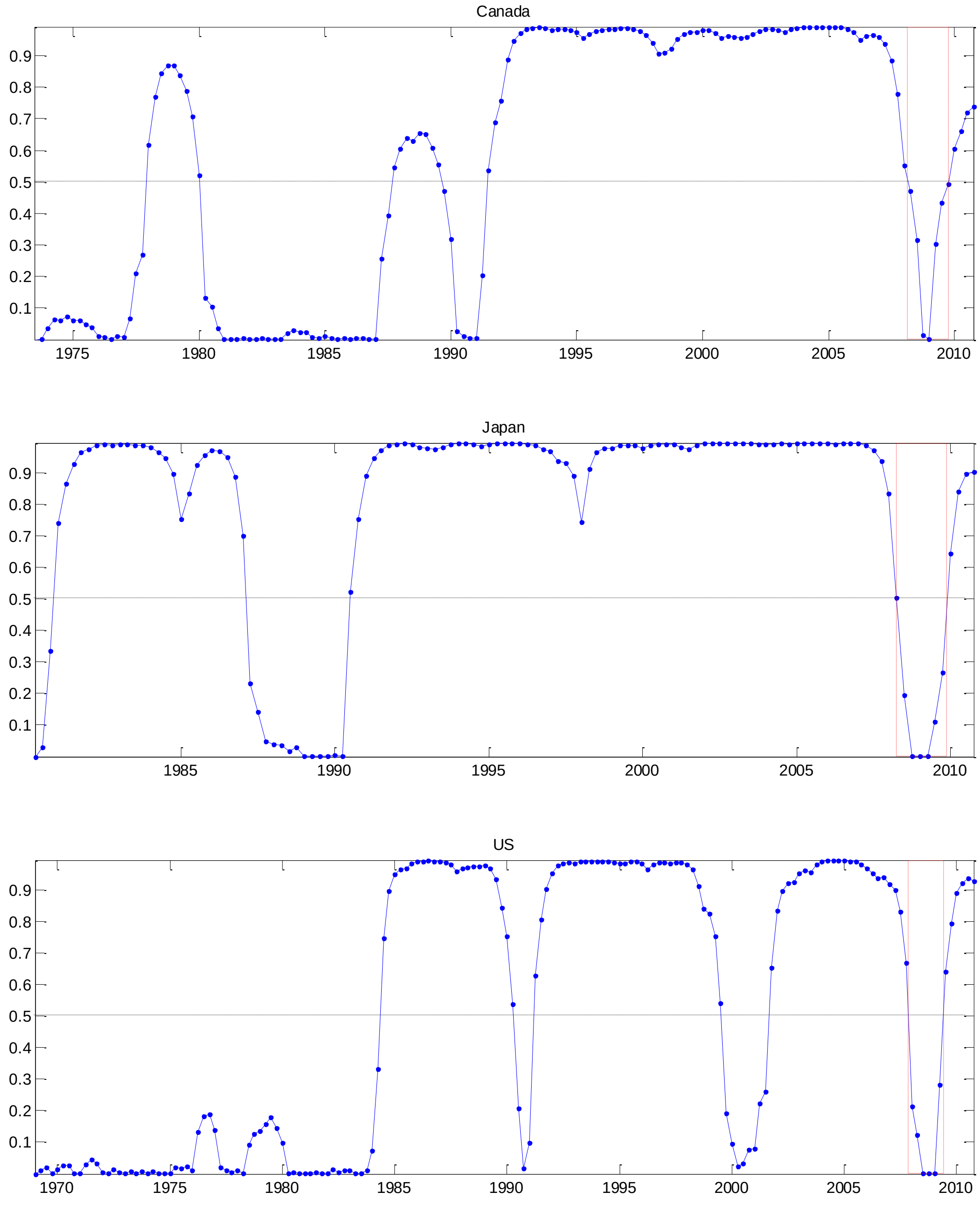
Notes: This figure depicts the GDP quarter-to quarter growth rate of G7 countries Outside the EU. The volatility of output growth is measured as rolling standard deviation over 20 quarters.

Figure 1.6: Smoothed Probabilities for the Low-volatility State of the Output Growth for Countries Inside the EU



Notes: This figure depicts the smoothed probabilities of the low-variance state for France, Germany, Italy and the UK from the second most appropriate model, i.e., Model 4 for Germany and the UK, and Model 2 for France and Italy.

Figure 1.7: Smoothed Probabilities for the Low-volatility State of the Output Growth for Countries Outside the EU



Notes: This figure depicts the smoothed probabilities of the low-variance state for Canada, Japan, the US from the second most appropriate model, i.e., the Markov switching AR model with only switching variance (Model 4) for Canada, Japan and the US.

Chapter 2

Do Japanese Stock Prices Reflect Fundamentals?

2.1 Introduction

There is an ongoing controversy regarding the extent to which stock prices reflect fundamental values.[1] Earlier literature such as Shiller [1981] found that the U.S. stock prices were much more volatile than their subsequent changes in dividends. More recently, Binswanger [2004] shows evidence that stock prices are priced substantially above their fundamentals since the early 1980s for the U.S., Japan and Europe. On the contrary, other literature such as Chung and Lee [1998] found that the stock prices hardly deviate from their fundamental value in Hong Kong and Singapore.[2]

Among the developed countries, Japan is worth special investigation. From 1986 to 1991, the stock prices and the real estate prices were greatly inflated, a period well known as the Japanese asset price bubble. The bubble started collapsing since the beginning of the 1990s, contributing to the start of the so-called 'lost decades' and the end of the Japanese economic growth. This paper reinvestigates how the linkage between the Japanese stock prices and the real

[1] This Chapter is based on the SFB working paper 2012-037 'Do Japanese stock prices reflect fundamentals' written by Chen, W. and Velinov, A..

[2] Chung and Lee [1998] use earnings and dividends as fundamental variables, while GNP and industrial production are used by Groenewold [2004] and Huang and Guo [2008] as fundamental variables.

activities has changed before, in-between and after the collapse of the asset price bubble.

Mixed results along the time line of Japan have been shown in existing literature. Chung and Lee [1998] found that Japanese stock prices were substantially overvalued from 1984 to 1990. When the market started to collapse from 1991, the stock prices were undervalued for several years and their deviation from the fundamental became much smaller. In contrast, Binswanger [2004] claims that the Japanese stock prices have been priced far above their fundamental values ever since the mid-1980s.

In order to disentangle the fundamental shocks and non-fundamental shocks, a long-run identification strategy in the spirit of Blanchard and Quah [1989] is often applied. Specifically, it is assumed that the nonfundamental shocks have no long-run effect on the output. This type of identification framework has been employed by Chung and Lee [1998], Rapach [2001], Binswanger [2004], Groenewold [2004], and Huang and Guo [2008]. In a just-identified structural VAR model, these restrictions can only be assumed. However, as pointed by Uhlig [2005], the appropriateness of the structural information used for identification could be questionable.

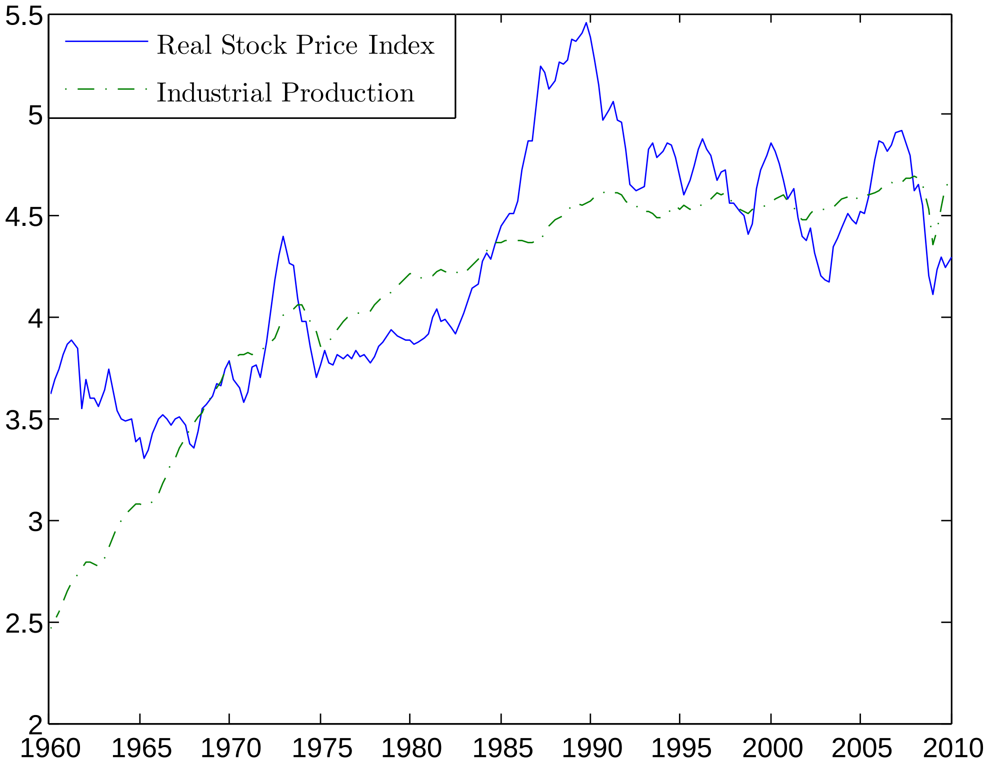
In this paper, we follow Lanne et al. [2010], and obtain over-identifying information from Markov switching variance models to test whether the assumed long run structural restrictions are appropriate or not. Markov switching variance VAR models provide over-identifying information from decomposition of covariance matrices across states to test the assumed structural restrictions, which is essential for the correct identification of fundamental and nonfundamental shocks.

Our results indicate that the assumed structural identification scheme is compatible with the data. Based on the confirmed identification of fundamental and nonfundamental shocks, the historical stock prices are decomposed into fundamental components and nonfundamental components. In contrast to Binswanger [2004], the decomposition shows that the linkage between Japanese stock prices and real activity shocks became strengthened since the bubble collapsed in the beginning of 1990s. In line with Chung and Lee [1998], our results suggest that the deviation of Japanese stock prices from the fundamentals has not been substantial in the two decades following the burst of the asset price bubble.

This paper is structured as follows: Section 2 describes the data. Section 3 introduces how fundamental shocks are identified, and how the Markov switching VAR model with switching variances can help to test the assumed identification. Section 4 discusses the test results regarding the structural identification scheme, and the empirical findings on the extent to which fundamental shocks explain stock price fluctuations. Section 5 concludes.

2.2 The Data

Figure 2.1: Japanese Stock Prices and Industrial Production



Notes: This graph depicts the series of the industrial production and the real stock prices of Japan in log levels from 1960 to 2010.

The data are obtained from the International Financial Statistics (IFS) of the International Monetary Fund. The series consist of seasonally adjusted industrial production y_t, a stock price index $Nikkei_t$, and Consumer Price Index

(CPI).[3] All three series are normalized to a base year of 2005. The stock price series is converted to real terms by dividing by the Consumer Price Index. Figure 2.1 plots the deflated stock prices and the industrial production in log levels. The data range is from 1960 Q1 to 2010 Q1, implying that the period of the late 2000s financial crisis is also included.

To examine the stationarity of the data, ADF unit root tests are conducted. Results strongly suggest that the log-level series for both output and real stock prices are of order $I(1)$. When testing for cointegration relationships for the unrestricted levels VAR model, the Saikkonen and Lütkepohl test rejects the null hypothesis that there is no cointegration relation between output and real stock prices.[4] As a consequence, the empirical analysis is based on a VAR in first differences.

2.3 Identification of Fundamental and Nonfundamental Shocks

2.3.1 The Long-run Restriction à la Blanchard and Quah

Following earlier empirical literature, we adopt the following bivariate VAR model to study the interdependence of stock prices and the real activities:

$$\Delta x_t = \nu + A_1 \Delta x_{t-1} + A_2 \Delta x_{t-2} + \cdots + A_p \Delta x_{t-p} + u_t, \tag{2.1}$$

where Δx_t is a 2×1 vector of the endogenous variables representing logs of industrial production and logs of real stock prices in first differences. A_i's are 2×2 parameter matrices, with $i = 1, \ldots, p$. u_t is a 2×1 vector of unobservable error terms with $E[u_t] = 0$ and $E[u_t u_t'] = \Sigma_u$.

The structural shocks ε_t hitting the system can not be identified in the above reduced form VAR model. One popular way to identify the shocks is to impose restrictions on the long-run impact matrix as in Blanchard and Quah [1989]. The long-run impact matrix can be represented as follows:

[3] The Nikkei index represents more than half of the total market capitalization in the Tokyo Stock Exchange.

[4] Results of the ADF tests and the cointegration test are shown in Table 2.4 and Table 2.5 in Appendix B.

$$\Psi = (I - A_1 - ... - A_p)^{-1} B \tag{2.2}$$

where I stands for the identity matrix, and $u_t = B\varepsilon_t$, and $\Sigma_u = BB'$. B transforms the reduced form residuals into structural innovations.

Following Binswanger [2004] and Groenewold [2004], we set the upper right element, $\Psi_{1,2}$, of the long-run impact matrix to zero making it lower triangular. The other elements of the Ψ matrix, denoted by $*$, can take on any value.

$$\Psi = \begin{bmatrix} * & 0 \\ * & * \end{bmatrix} \tag{2.3}$$

Under this identification scheme, the structural shocks, $\varepsilon_t = [\varepsilon_t^F, \varepsilon_t^{NF}]'$, can be interpreted as fundamental and non-fundamental shocks respectively. By assumption, fundamental shocks can have a permanent effect on the real economy and on the stock market, while non-fundamental shocks can only have a transitory effect on the real economy and a permanent effect on the stock price.

However, the structural identification scheme introduced above can only be assumed and can not be tested in a linear VAR model. Therefore, in the next subsection we introduce a Markov switching model with time-varying variances. This type of model is capable of providing over-identifying information to test structural restrictions.

2.3.2 Testing the Identification Scheme of Fundamental Shocks

Many researchers including Uhlig [2005] have criticized that the assumed structural restrictions could be too restrictive. Following Lanne et al. [2010], a Markov Switching model is used to validate the identification strategy. This model allows for heteroscedasticity of the residuals as follows:

$$\Delta x_t = \nu + A_1 \Delta x_{t-1} + A_2 \Delta x_{t-2} + \cdots + A_p \Delta x_{t-p} + u_t | s_t. \tag{2.4}$$

where the distribution of the residuals is assumed to be governed by a Markov process, s_t and it is assumed that the residuals are normally distributed conditional on the given state, i.e., $u_t | s_t \sim N(0, \Sigma_{s_t})$.

The discrete stochastic process s_t assumes M regimes with transition probabilities given by

$$p_{ij} = P(s_t = j | s_{t-1} = i), \quad i, j = 1, \ldots, M$$

with a $M \times M$ matrix of transitional probabilities. Note that the probabilities add up to one row-wise, hence $p_{iM} = 1 - p_{i1} - p_{i2} - \cdots - p_{iM-1}$.

In the above framework, if there exist at least two different covariance states, shocks can be identified without assuming further restrictions. Special features of (2.4) provide over-identifying information to test the appropriateness of structural restrictions, if the covariance matrices could be uniquely decomposed in the following way:

$$\Sigma_1 = BB', \quad \Sigma_2 = B\Lambda_2 B', \quad \ldots, \quad \Sigma_M = B\Lambda_M B', \tag{2.5}$$

where B is the contemporaneous impact matrix which is used to transform reduced form shocks into structural shocks. Λ_i can be interpreted as the relative-variance matrix of the structural shocks in Regime i versus Regime 1. In the empirical example, $M = 3$ is chosen. For State 1, Λ_1 is normalized as a 2×2 identity matrix. For the second and the third state, Λ_i is a 2×2 diagonal matrix with the following representation:

$$\Lambda_i = \begin{bmatrix} \lambda_{i1} & 0 \\ 0 & \lambda_{i2} \end{bmatrix} \tag{2.6}$$

If diagonal elements in either Regime 2 or Regime 3 are distinct, i.e., $\lambda_{i1} \neq \lambda_{i2}$, the transformation matrix B is identified without further structural assumptions. The decomposition in (2.5) is unique up to sign changes in the B matrix. In accordance with Lanne et al. [2010], sign changes in the columns of B are no problem for our analysis of structural identification since it corresponds to whether negative structural shocks or positive structural shocks are of interest.

Whether the structural restrictions are compatible with the data is verified through a likelihood ratio test. The maximum log-likelihood from the just-identified Markov switching VAR model can be compared with the maximum log-likelihood from the over-identified Markov switching VAR model including the structural restrictions. If the likelihood ratio test is rejected, it is evidence against the presumed structural restrictions.

The Markov switching VAR models are solved by the Expectation Maximization algorithm. Details of the algorithm are given in the appendix. The next section describes the data and the empirical results on the relation between stock prices and industrial production of Japan.

2.4 Empirical Results

Based on the information criteria, a three-state one-lag Markov switching structural VAR model is selected for Japan. In the following, the test results regarding the long-run structural restrictions are first illustrated. Then details are revealed about the extent to which the Japanese stock prices have been driven by the fundamental shocks.

2.4.1 Estimates from the Markov Switching VAR models

Table 2.1: Estimates of the relative variances of shocks across states

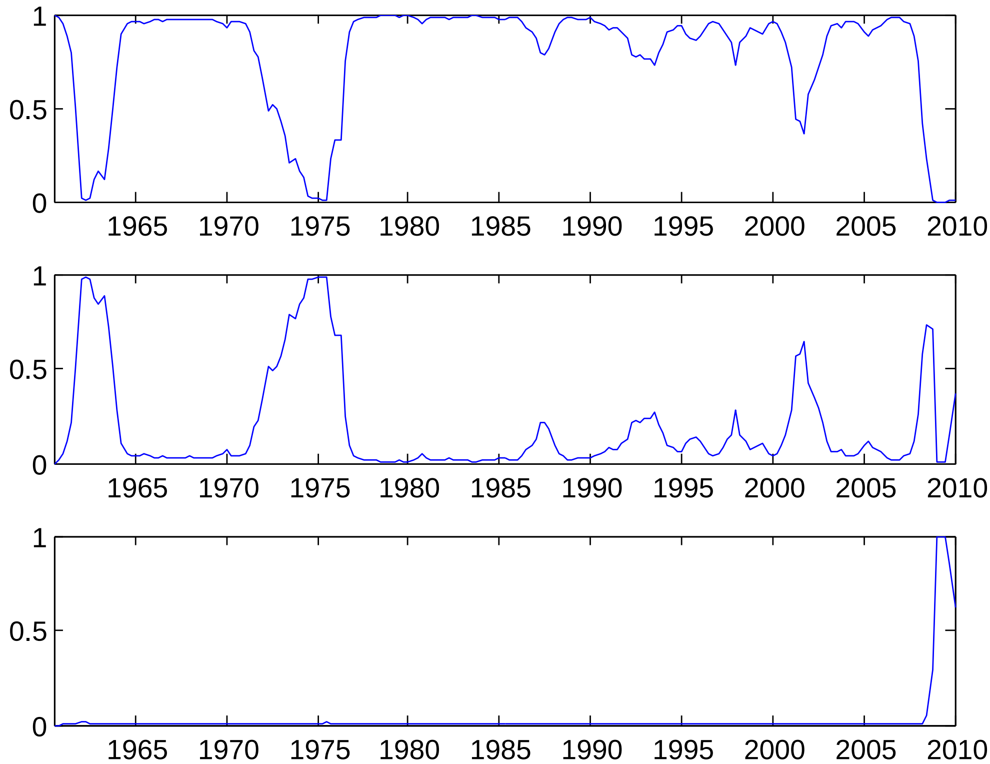
	estimates	standard errors
λ_{21}	2.912	1.186
λ_{22}	2.411	0.802
λ_{31}	55.637	41.765
λ_{32}	3.109	2.046

Notes: This table presents the estimates of diagonal elements of the relative-variance matrix Λ_i for $i = 2, 3$, and their corresponding standard errors from the Markov switching VAR models without further structural restrictions. λ_{i1} is the first element along the diagonal of Λ_i, while λ_{i2} represents the second element along the diagonal of Λ_i. λ_{i1} can be interpreted as the relative variance of fundamental shocks in Regime i versus Regime 1.

Lanne et al. [2010] have shown that, in a three-state Markov switching VAR model, the necessary condition in achieving over-identifying information is that diagonal elements of Λ_i either in the second or the third state should be distinct from each other. Table 2.1 reports the estimated diagonal elements of Λ_2 and

Λ_3. Since Λ is normalized to be the identity matrix in State 1, the relative ratios of variances show that the volatility is increasing in states. Figures 2.2 plots the smoothed probabilities for the Markov switching VAR model. The first state is the one with low volatility. The second one stands for the medium-volatility regime. The 1975 recession in Japan has been captured as the medium-volatility regime. The third state is the most volatile one, which coincides with the time of the late 2000s financial crisis. As shown in Table 2.1, the relative variance of the fundamental shocks in the state of the recent financial crisis relative to the low-volatility state is around 56.

Figure 2.2: Smoothed probabilities for different volatility regimes in Japan



Notes: This graph depicts the smoothed probabilities estimated from the Markov Switching VAR model with three states and one lag with structural restrictions. The top panel shows the probability of the system being in a low-volatility regime. The panel in the middle represents the probability of being in a medium-volatility regime, while the bottom panel represents the probability of being in a high-volatility regime.

The standard errors of Λ_3 diagonal elements are noticeably large. It is very likely a result of the few observations for the recent financial crisis period. Due to concerns regarding robustness, we estimate also on the subsample that excludes the late 2000s financial crisis. A two-state two-lag model is selected, and the results regarding the test of the appropriateness of the structural identifications remain robust(see Appendix).

2.4.2 Are the Structural Restrictions Appropriate?

In order to test whether the relative variance of the fundamental shocks in Regime 2 versus Regime 1 is indeed different from that of the non-fundamental shocks, a likelihood ratio test is performed. The likelihood ratio test statistics is 8.281 and the corresponding p-value obtained from a χ^2 distribution is 0.016. Hence there is evidence that $\lambda_{21} \neq \lambda_{22}$. Consequently, the decomposition in Equation (2.5) is unique up to sign changes in the B matrix.

Are the assumed structural restrictions on the long-run impact matrix Ψ in Equation (2.3) too restrictive? Let us now apply the likelihood ratio test to find out whether the imposed long run restriction is supported by the data or not. The likelihood ratio test compares the maximum log-likelihood achieved from the Markov switching VAR model without the long run structural restrictions to the maximum log-likelihood achieved from the Markov switching VAR model with the long run structural restrictions. As shown in Table 2.2, the test statistics is 2.449 with a corresponding p-value 0.118. Therefore, the identification of the structural innovations as fundamental shocks and non-fundamental shocks is compatible with the data.

Table 2.2: Likelihood ratio test for the structural restrictions

data	test statistic	p-value
1960-2010	2.449	0.118
Pre-crisis period	0.200	0.655

Notes: This table shows results of the likelihood ratio test that compares the maximum likelihood from the Markov switching VAR model without the structural restriction to the one from the Markov switching VAR model with the structural restriction imposed. P-values indicate that the long run restriction is compatible with the data.

2.4.3 The Role of Fundamental Shocks for Japanese Stock Prices

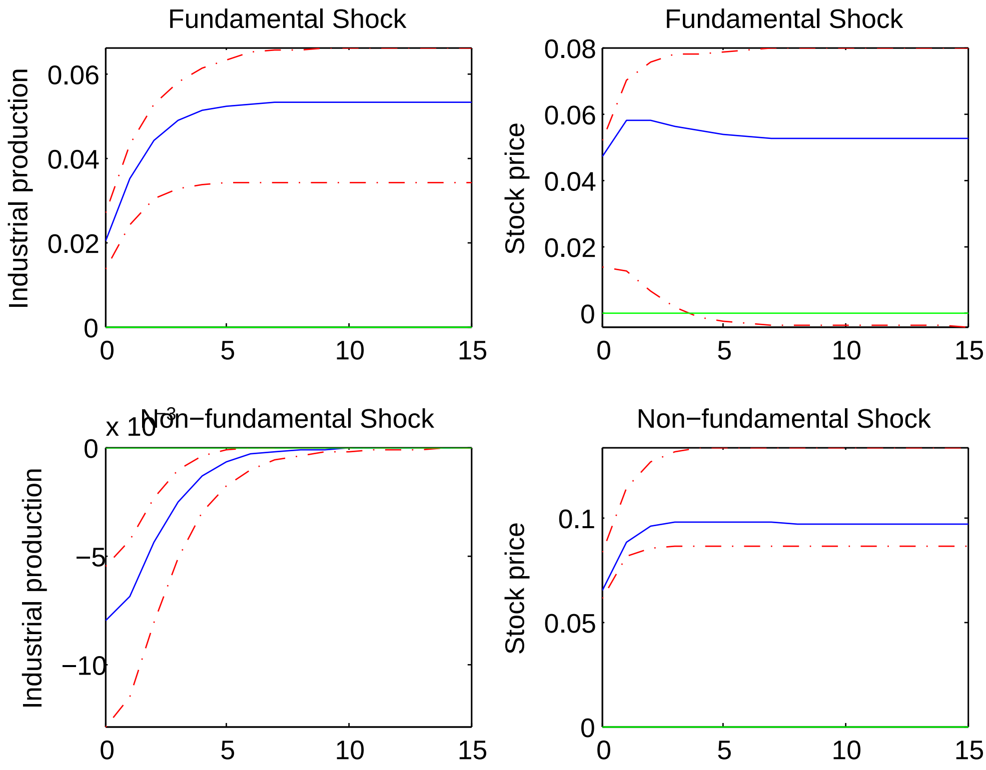
The above subsection demonstrates that the assumed long run restriction to disentangle fundamental shocks and non-fundamental shocks is validated by over-identifying information achieved from a three-state Markov switching variance model. The appropriate structural identification allows us to conduct further structural analysis on the extent to which Japanese stock prices are driven by the fundamental shocks. As the estimates from the structural model with and without switching variances are very close, we present the following findings based on the linear structural VAR model for comparable analysis with former empirical literature. Moreover, the financial crisis period is excluded due to stability concerns.

Figure 2.3 presents the accumulated impulse responses of each variable to a one-standard-deviation structural shock. The responses to a fundamental shock are shown in the first row. Industrial production increases after a fundamental shock, converging to a permanently higher level after around five quarters. Real stock prices are also pushed up permanently after a fundamental shock.

The impulse responses to a nonfundamental shock are found in the second row. There is a temporary decline in industrial production after a nonfundamental shock. After around eight quarters, industrial production returns to its original level before the shock, as implied by the identifying long-run restriction. The short-run negative effects on industrial production may result from the changing sentiments of investors, who will shift funds into the stock market instead of financing new investment projects. The response of real stock prices to a nonfundamental shock is positive and permanent. In general, the impulse responses pictures seem much in line with the former empirical literature such as Rapach [2001] and Binswanger [2004].

What would the Japanese stock prices have been if they had only been driven by the fundamental shocks? To answer this question, a historical decomposition is conducted following the method proposed in Burbidge and Harrison [1985]. Based on estimation on the pre-crisis data sample, the fundamental series is constructed by setting the value of nonfundamental shocks to zero and simulating the historical values of the Japanese stock prices in the presence of only funda-

Figure 2.3: Accumulated impulse responses



Notes: This graph depicts the accumulated impulse responses to one-standard-deviation structural shocks. Confidence intervals denoted by dashed lines are according to fixed design wild bootstrap at the 95% level.

mental shocks. The actual series shown in Figure 2.4 represents the historical stock prices in the presence of both the fundamental shocks and the nonfundamental shocks. The dashed line depicts the fundamentals values that represent the series influenced only by the fundamental shocks. In accordance with Binswanger [2004], it is important to look at the degree to which the fundamental series follow stock prices instead of the absolute value of the simulated series.

One crucial step of the historical decomposition method is the choice of the starting value, as it is implicitly assumed that the real stock prices coincide with the fundamental series at the starting date. However, the chosen starting date at 1983 in Binswanger [2004] could be misleading, as it is identified as the preasset inflation period when the monetary policy is easy in Japan.[5] Therefore we choose the stock price at 1975 Q1 as the starting value for the simulation of the historical stock prices and the fundamental values following Chung and Lee [1998].

The panel in the middle of Figure 2.4 displays the graph of the historical decomposition for the Japanese stock prices from 1975 Q1 to 2007 Q1 based on estimation in this paper. The deviation of stock prices from the fundamental values is the most substantial for the Japanese asset price bubble period. However after the crash in 1991, the stock prices started moving close with the fundamentals. The stock prices floated the furthest away from the fundamentals, when the series reached a bottom in 2003. In general, it is observable that the linkage between the Japanese stock prices and the fundamentals has been restored after the burst of the asset bubble.

Let us now compare the historical decomposition in this paper to the simulation presented in Chung and Lee [1998] and Binswanger [2004]. As depicted the upper panel in Figure 2.4, Binswanger [2004] shows that the stock prices are floating far above the fundamentals from 1983 to 1999. In contrast, the lower panel from Chung and Lee [1998] demonstrates that though the stock prices were substantially overvalued from 1986 to 1990, the deviation of the stock prices from the fundamentals declined below zero and stayed small after the bubble collapsed in 1991. The historical decomposition in our paper shown in the lower panel of Figure 2.4 seems more in line with those of Chung and Lee [1998], supporting their view that the dependence of stock prices on real activities has recovered after the burst of the Japanese stock price bubble.

A forecast error variance decomposition analysis further confirms the results of Chung and Lee [1998]. As shown in Table 2.3, based on the sub-sample from 1960 to 2007, the fundamental shocks explain around 20 percent of the stock price fluctuations. Similarly, Chung and Lee [1998] found that around 30 percent of the stock price fluctuations are due to fundamental shocks. In contrast, Binswanger [2004] shows that only 3 percent of stock price fluctuations are explained by the fundamentals from the mid-1980s to 1999.[6]

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[5] See details of the Japanese asset bubble period in literature such as Goyal and Yamada [2004] and Shiller et al. [1996].

[6] The Chow tests and the Cusum tests also show no evidence of structural breaks in the mid

Table 2.3: Variance decomposition of the Japanese stock prices

	Percentage of variance attributable to:	
	Fundamental shocks	Non-fundamental shocks
1 quarter	22	78
5 quarters	21	79
10 quarters	21	79
15 quarters	21	79
20 quarters	21	79

Notes: This table presents percentage of the 20-month forecast error variance explained respectively by fundamental shocks and nonfundamental shocks to real stock prices.

To sum up, the empirical analysis in our paper suggests that since the Japanese asset price bubble collapsed in 1991, the linkage between the stock price and fundamentals has been restored.

2.5 Conclusion

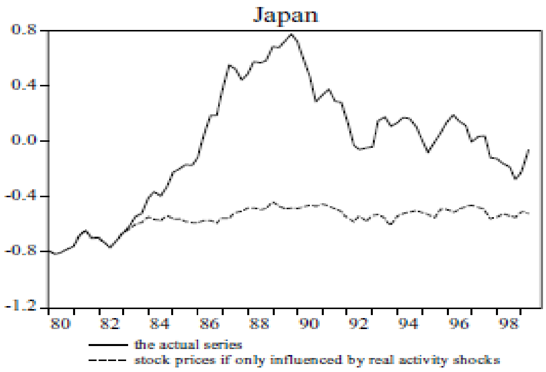
This paper has investigated the extent to which stock prices in Japan are explained by their fundamental values. First, a bivariate Markov switching VAR model with Markov switching variances is employed to test the appropriateness of the long run structural restrictions, which assumes that the nonfundamental shocks have no long-run effect on output.

We found that the identification of fundamental shocks and nonfundamental shocks using long run structural restrictions is supported by the data. Based on the proper identification scheme, stock prices are decomposed into fundamental components and nonfundamental components for the period from 1991 Q4 to 2007 Q1. In contrast to Binswanger [2004], but in line with Chung and Lee [1998], our results suggest that the linkage between stock prices and fundamental components has recovered since the collapse of the Japanese asset price bubble in the beginning of 1990s.

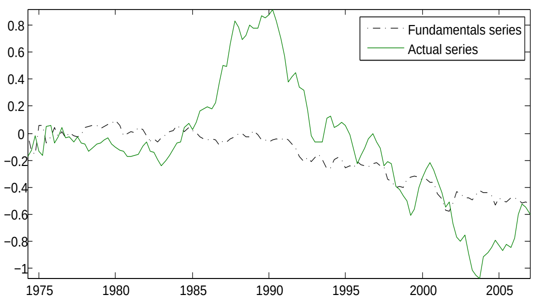
1980s.

Figure 2.4: Fundamentals and Japanese stock prices: a comparison of historical decompositions from different papers

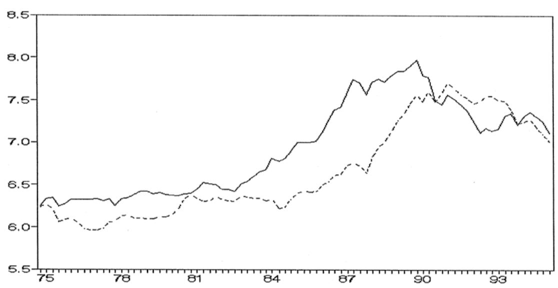
(a) The historical decomposition in Binswanger (2004)



(b) The historical decomposition in our paper



(c) The historical decomposition in Chung and Lee (1998)



Notes: The upper panel in this figure shows the historical decomposition for the Japanese stock prices in Binswanger [2004]. The middel panel presents the historical decomposition made in this paper for the Japanese stock prices from 1975 until 2007. The lower panel presents the historical decomposition in Chung and Lee [1998]. For all panels, the solid lines represent the actual series, while the dashed lines stand for the fundamental series.

Appendix

The EM Algorithm

This is a technical appendix explaining the EM algorithm used in this paper based on Krolzig [1997]. The same approach has been also applied by Lanne et al. [2010].

Starting with the regression equation

$$\Delta x = (\bar{Z} \otimes I_K)\beta + u,$$

where Δx is a $(TK \times 1)$ vector or the vectorization of $\Delta X = [\Delta x_1, \ldots, \Delta x_T]$, and where T is the sample size and K the number of variables. Here $\bar{Z} = [\mathbf{1}_T, \Delta X_{-1}, \ldots, \Delta X_{-p}]$, where $\mathbf{1}_T$ is a $(T \times 1)$ vector of ones and $\Delta X_{-i} = [\Delta x_{1-i}, \ldots, \Delta x_{T-i}]'$ is a $(T \times K)$ matrix of lagged regressors, for $i = 1, \ldots, p$ and p being the number of lags of the MS-VAR model. The $(K(Kp+1) \times 1)$ vector β contains the vectorized intercept and slope parameters, i.e. $\mathrm{vec}[\nu, A_1, \ldots, A_p]$ as defined in (2.1). Finally u is the $(TK \times 1)$ vectorization of the matrix of residuals, $U = [u_1, \ldots, u_T]'$, where the distribution of each residual, $u_i, i = 1, \ldots, T$ is given according to (2.4).

The EM algorithm is initiated by defining the starting values of the intercept, slope and contemporaneous impact matrix, B parameters as well as the transition probabilities and initial states. For the intercept and slope parameters the starting values are given by $\beta_0 = [\bar{Z}'\bar{Z} \otimes I_K]^{-1}(\bar{Z}' \otimes I_K)\Delta x$. The initial value of the contemporaneous impact matrix is $B_0 = (UU'/T)^{1/2}$, where U is obtained from $u = \Delta x - (\bar{Z} \otimes I_K)\beta_0$. The transition probabilities are set at $P_0 = \mathbf{1}_M \mathbf{1}_M'/M$, where $\mathbf{1}_M$ is an $(M \times 1)$ vector of ones and M are the number of states in the model. The initial states (defined below) are defined as $\xi_{0|0} = \mathbf{1}_M/M$. Finally, the starting values of the covariance matrices need to be determined as defined in the decomposition in (2.5). This is done by setting the values of the Λ_i matrices, $i = 2, \ldots, M$. I use a loop of different starting values for these matrices by starting with $\Lambda_2 = 2 * I_K, \ldots, \Lambda_M = 2^{M-1} * I_K$ and replacing the 2 with higher values and in the end seeing which starting value gives the highest log-likelihood.

The vector of conditional probabilities for the unobserved states is denoted as $\hat{\xi}_{t|t}$ and it indicates the probability of a given state in a given time period conditional on all observations up to time period t, ΔX_t and all intercept, slope, covariance parameters and transition probabilities stored in, θ. Hence

$$\hat{\xi}_{t|t} = \begin{bmatrix} P(s_t = 1|\Delta X_t, \theta) \\ P(s_t = 2|\Delta X_t, \theta) \\ \vdots \\ P(s_t = M|\Delta X_t, \theta) \end{bmatrix}. \tag{2.7}$$

It is also necessary to define the conditional densities of an observation given a particular state, all past observations and θ as

$$\eta_t = \begin{bmatrix} P\Delta x_t|s_t = 1, \Delta X_{t-1}, \theta) \\ P\Delta x_t|s_t = 2, \Delta X_{t-1}, \theta) \\ \vdots \\ P(\Delta x_t|s_t = M, \Delta X_{t-1}, \theta) \end{bmatrix} = \begin{bmatrix} \frac{1}{2\pi|\Sigma_1|^{1/2}} \exp\left\{-\frac{u_t'\Sigma_1^{-1}u_t}{2}\right\} \\ \frac{1}{2\pi|\Sigma_2|^{1/2}} \exp\left\{-\frac{u_t'\Sigma_2^{-1}u_t}{2}\right\} \\ \vdots \\ \frac{1}{2\pi|\Sigma_M|^{1/2}} \exp\left\{-\frac{u_t'\Sigma_M^{-1}u_t}{2}\right\} \end{bmatrix}. \tag{2.8}$$

Expectation Step

Now follows the expectation step where the filtered probabilities from (2.7) are calculated as

$$\hat{\xi}_{t|t} = \frac{\eta_t \odot \hat{\xi}_{t|t-1}}{\mathbf{1'}(\eta_t \odot \hat{\xi}_{t|t-1})}, \tag{2.9}$$

and

$$\hat{\xi}_{t|t-1} = P'\hat{\xi}_{t-1|t-1}, \tag{2.10}$$

for $t = 1, \ldots, T$. This generates an $(M \times 1)$ vector of conditional probabilities for each time period. Here $\odot$ denotes element-by-element multiplication and P is defined as in (2.6). Next using the values of the filtered probabilities, the smoothed probabilities, $P(s_t = i|\Delta X_T, \theta), i = 1, \ldots, M$ are estimated as

$$\hat{\xi}_{t|T} = [P(\hat{\xi}_{t+1|T} \oslash \hat{\xi}_{t+1|t})] \odot \hat{\xi}_{t|t}, \tag{2.11}$$

for $t = T-1, \ldots, 0$. The symbol $\oslash$ denotes element-by-element division. Note that the filtered probabilities from the current iteration are used to estimate the smoothed probabilities.

Maximization Step

After the expectation step in the maximization step first the vector of transition probabilities $\hat{\rho}$ is estimated as

$$\hat{\rho} = \hat{\xi}^{(2)} \oslash (\mathbf{1}_M \otimes \hat{\xi}^{(1)}), \tag{2.12}$$

where $\hat{\xi}^{(2)} = \sum_{t=0}^{T-1} \hat{\xi}_{t|T}^{(2)}$ and

$$\hat{\xi}_{t|T}^{(2)} = \text{vec}(P) \odot \left[\left(\hat{\xi}_{t+1|T}^{(1)} \oslash \hat{\xi}_{t+1|t}^{(1)} \right) \otimes \hat{\xi}_{t|t}^{(1)} \right],$$

for $t = 0, \dots, T-1$. Here $\otimes$ denotes the Kronecker product. Finally, $\hat{\xi}_{t|T}^{(1)}$ is the vector of smoothed probabilities from (2.9) and $\hat{\xi}_{t|t}^{(1)}$ is the vector of filtered probabilities from (2.7). Also note that $\hat{\xi}^{(1)} = (\mathbf{1}_M' \otimes I_M)\hat{\xi}^{(2)}$, where $\mathbf{1}_M$ is an $(M \times 1)$ vector of ones and I_M is the $(M \times M)$ identity matrix.

The B and Λ matrices are then estimated by optimizing

$$\begin{aligned} l(B, \Lambda_2, \dots, \Lambda_M) &= T \log|\det(B)| + \frac{1}{2}\text{tr}\Big((BB')^{-1}\hat{U}\hat{\Xi}_1\hat{U}'\Big) \\ &+ \sum_{m=2}^{M} \Big[\frac{\hat{T}_m}{2} \log(\det(\Lambda_m)) + \frac{1}{2}\text{tr}\Big((B\Lambda_m B')^{-1}\hat{U}\hat{\Xi}_m\hat{U}'\Big)\Big], \end{aligned} \tag{2.13}$$

where $\hat{U}$ is obtained from $\hat{u} = \Delta x - (\bar{Z} \otimes I_K)\hat{\beta}$, $\hat{\Xi}_m$ =diag$(\hat{\xi}_{m1|T}, \dots, \hat{\xi}_{mT|T})$,the smoothed probabilities of regime m and $\hat{T}_m = \sum_{t=1}^{T} \hat{\xi}_{mt|T}$ is a summation of the smoothed probabilities. To avoid singularity a lower bound of 0.001 is imposed on the diagonal elements of the $\Lambda_m, m = 2, \dots, M$ matrices. The updated covariance matrices are given from the decomposition

$$\hat{\Sigma}_1 = \hat{B}\hat{B}', \quad \hat{\Sigma}_2 = \hat{B}\hat{\Lambda}_2\hat{B}', \quad \dots \quad \hat{\Sigma}_M = \hat{B}\hat{\Lambda}_M\hat{B}'.$$

Next the intercept and slope parameters are obtained as

$$\hat{\beta} = \Big[\sum_{m=1}^{M} (\bar{Z}'\hat{\Xi}_m\bar{Z}) \otimes \hat{\Sigma}_m^{-1} \Big]^{-1} \Big[\sum_{m=1}^{M} (\bar{Z}'\hat{\Xi}_m) \otimes \hat{\Sigma}_m^{-1} \Big] \Delta x. \tag{2.14}$$

Note, that to estimate $\hat{\beta}$ the covariances of the previous iteration were used. These parameters are then plugged back into (2.13) and new estimates of the covariance matrices are obtained which are then used in (2.14). All this is iterated until convergence. The convergence criteria used is the absolute change in the log-likelihood given in (2.13), i.e.

$$\Delta = |l(\theta^{j+1}|\Delta X_T) - l(\theta^j|\Delta X_T)|, \tag{2.15}$$

where $l(\bullet)$ is the log-likelihood and θ^j denotes the parameters of the j-th iteration. Convergence is satisfied when $\Delta \leq 10^{-6}$ or after a specified maximum number of iterations.

The EM algorithm terminates as well after a similar convergence criteria as in (2.15). As shown in Hamilton [1994] the log-likelihood is given by $\log(\mathbf{1}'(\eta_t \odot \hat{\xi}_{t|t-1}))$.

The restricted MS-SVAR model is estimated in a similar way, recall that the long-run impact matrix, Ψ is related to the B matrix by $\Psi = A(1)^{-1}B$.

Standard Errors

Once the EM algorithm has converged and the point estimates of the parameters are obtained it is necessary to calculate their standard errors in order to carry out statistical tests. The optimal values of $P, \beta, B, \Lambda_m, m = 2, \ldots, M$ and $\xi_{0|0}$ are used in $\log(\mathbf{1}'(\eta_t \odot \hat{\xi}_{t|t-1}))$. Standard errors are then obtained by the inverse of the negative of the Hessian matrix.

Tables for the Full Sample

Table 2.4: Augmented Dickey-Fuller test

variable	test statistic	1% critical value	5% critical value	10% critical value
output	-2.47	-3.96	-3.41	-3.13
stock price	-1.56	-3.43	-2.86	-2.57

Notes: This table shows results of the ADF test for the series of output and real stock prices. In both cases, the null hypothesis that there is a unit root is not rejected at 10% significance level since the test statistic is larger than the critical value.

Table 2.5: Test for cointegration

test statistic	p-value
10.28	0.11

Notes: This table shows results of the Saikkonen-Lütkepohl test. The null hypothesis that there is no cointegration relationship between output and real stock prices can not be rejected at 10% significance level.

Table 2.6: Estimates of the transition probabilities

	estimates	standard errors
p_{11}	0.963	0.031
p_{12}	0.037	0.027
p_{21}	0.155	0.106
p_{22}	0.812	0.092
p_{32}	0.134	0.347
p_{33}	0.866	0.479

Notes: This table presents the estimates of transition probabilities and their corresponding standard errors from the three-state Markov switching VAR models without further structural restrictions based on data from 1960 to 2010. p_{ij} represents the probability that the regime in the next period switches into j given that the current regime is i.

Other Results for the Pre-crisis Period

Table 2.7: Estimates of the transition probabilities

	estimates	standard errors
p_{11}	0.971	0.025
p_{22}	0.865	0.081

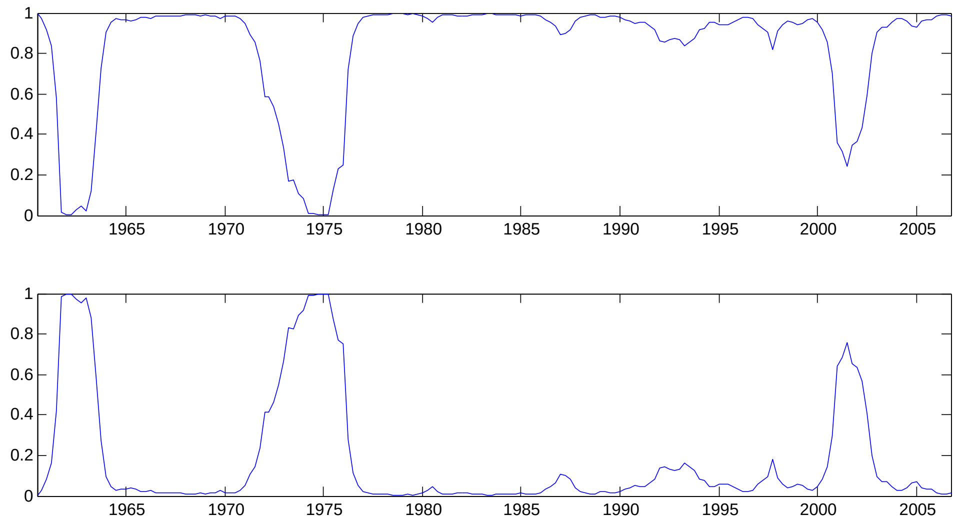
Notes: This table presents the estimates of transition probabilities and their corresponding standard errors from the two-state Markov switching VAR models without further structural restrictions for the period from 1960 to 2007. p_{ij} represents the probability that the regime in the next period switches into j given that the current regime is i.

Table 2.8: Estimates of the relative variances of shocks across states

	estimates	standard errors
λ_{21}	3.596	1.170
λ_{22}	2.184	0.808

Notes: This table presents the estimates of diagonal elements of the relative-variance matrix Λ_2 and their corresponding standard errors from the Markov switching VAR models without further structural restrictions based on data from the pre-crisis period. λ_{21} can be interpreted as the relative variance of fundamental shocks in Regime 2 versus Regime 1, while λ_{22} can be interpreted as the relative variance of nonfundamental shocks in Regime 2 versus Regime 1.

Figure 2.5: Smoothed probabilities for different volatility regimes for the Pre-crisis Period



Notes: This graph depicts the smoothed probabilities estimated from the Markov Switching VAR model with two states and two lags based on data from 1960 to 2007. The top panel shows the probability of the system being in a low-volatility regime, while the bottom panel represents the probability of being in a high-volatility regime. It is noticeable that this graphs resemble closely with the first two subplots in Figure 2.2, which is based on estimation on the full sample.

Chapter 3

Are There Bubbles in the Sterling-dollar Exchange Rate? New Evidence from Sequential ADF Tests

3.1 Introduction

Following the breakdown of the Bretton-Woods system of fixed exchange rates in the early 1970s, major developed countries switched from fixed into a floating exchange rate regime.[1] History has witnessed many episodes of crises in the Sterling-dollar exchange market, such as the 1976 Sterling crisis, the strong depreciation in the mid-1980s, the 1992 Black Wednesday UK currency crisis, and the recent 2008 financial crisis. Dramatic depreciation of the Sterling-dollar rate during these crisis periods has puzzled practitioners as well as researchers. Some economists conjecture that speculative bubbles were driving the market during these periods. For example, Evans [1986] finds significant evidence of bubbles in the Sterling-dollar exchange rate in the early 1980s, while Meese [1986], West [1987] and Wu [1995] yield mixed results.

Recently, various new tests have been developed to detect speculative bub-

[1] This Chapter is based on the joint paper 'Are there bubbles in the Sterling-dollar exchange rates? new evidence from sequential ADF tets' written by Chen, W. and Bettendorf, T..

bles in asset prices, including Al-Anaswah and Wilfling [2011], Lammerding et al. [2013], Phillips et al. [2011b] and Phillips et al. [2011a]. We employ the sequential unit root tests proposed by Phillips et al. [2011b] and Phillips et al. [2011a], which are based on the type of indirect stationarity tests initiated by Diba and Grossman [1984] and Hamilton and Whiteman [1985]. These indirect tests have the advantage of detecting speculative bubbles despite a potential misspecification of the market fundamental process.

This paper applies the sequential unit root tests so as to shed new light on the debate on the existence of rational bubbles in exchange rates [2]. We find strong evidence for explosive behavior in the nominal Sterling-dollar exchange rates. In order to shed light on the causes of the explosiveness, we also test for explosive behavior in the underlying fundamentals. Engel [1999] points out that movements in the US exchange rate are mainly driven by the relative prices of traded goods and not those of nontraded goods. Following Engel [1999], we construct the relative prices of traded and nontraded goods as fundamentals for exchange rates. Results show that the traded goods fundamental may explain the explosiveness in the Sterling-dollar exchange rate. Our findings thus shed doubt on claims that the Sterling-dollar exchange has been driven by speculative bubbles.

The remainder of the article is organized as follows: Section 2 describes the rational bubble model of the foreign exchange rate. Section 3 briefly introduces the econometric methods that we have applied. Section 4 presents the evidence on the explosiveness of the Sterling-dollar exchange rate and Section 5 concludes.

3.2 Rational Bubbles in Exchange Rate Dynamics

As stated by Obstfeld and Rogoff [1996, p. 529], "*the nominal exchange rate must be viewed as an asset price*", which implies that it is determined by current

[2] Another interesting application of the sequential unit root tests is the recent study by Pavlidis et al. [2012] who test the Efficient Market Hypothesis with forward exchange rates. The tests have also been applied to study the existence of speculative bubbles in commodity price and housing prices by Gutierrez [forthcoming], Phillips and Yu [2011] and Bohl et al. [forthcoming].

and expected values of fundamentals. We thus assume the following present value model of exchange rate in line with Engel and West [2005] and León-Ledesma and Mihailov [forthcoming]:

$$s_t = (1-\gamma)\sum_{j=0}^{k}\gamma^j E_t[f_{t+j}] + \gamma^{k+1}E_t[s_{t+k+1}], \tag{3.1}$$

where s_t is the nominal exchange rate, and f_t is the market fundamental at time period t. γ denotes the discount factor. By imposing the transversality condition

$$\lim_{k\to\infty}\gamma^k E_t[s_{t+k}] = 0,$$

we assure that the exchange rate will only depend on future expected fundamentals in the long run. However, if the transversality condition does not hold, the exchange rate may be subject to an explosive rational bubble. Assuming that the bubble follows an AR(1) process, it can be written as

$$b_t = \frac{1}{\gamma}b_{t-1} + \varepsilon_t, \tag{3.2}$$

where the first-order autoregressive coefficient $\frac{1}{\gamma}$ is greater than 1, as the bubble is an explosive process. Errors are captured by $\varepsilon_t \sim NID(0,\sigma^2)$. Therefore, we can write the exchange rate as

$$s_t = s_t^f + b_t \qquad \text{or} \qquad s_t - s_t^f = b_t, \tag{3.3}$$

where s_t^f denotes the discounted sum of all future economic fundamentals and b_t the bubble component. We assume that s_t^f is linearly dependent on the economic fundamental f_t. In accordance to Engel and West [2005] we also assume that f_t is I(1). According to the Purchasing Power Parity model, the economic fundamental for the nominal exchange rate is the price differential:

$$f_t = p_t - p_t^*, \tag{3.4}$$

where p_t denotes the log level of the domestic price index. Asterisks denote foreign counterparts. For decomposing the price index into indexes of non-traded and traded goods, Engel [1999] considers a price index for a country as a weighted average of traded- and nontraded- goods prices $p_t = (1-\alpha)p_t^T + \alpha p_t^N$. p_t^T denotes the log of the traded goods price index, p_t^N the log of the nontraded goods price index and α the share of the nontraded goods component. For the foreign country, one can also write $p_t^* = (1-\beta)p_t^{T*} + \beta p_t^{N*}$. It follows that the price differential (f_t) can be decomposed into two components, the traded goods component (f_t^T), and the nontraded goods component (f_t^N).

$$\underbrace{(p_t - p_t^*))}_{f_t} = \underbrace{(p_t^T - p_t^{T*})}_{f_t^T} + \underbrace{\alpha(p_t^N - p_t^T) - \beta(p_t^{N*} - p_t^{T*})}_{f_t^N}. \tag{3.5}$$

The producer price index (PPI) is the most broadly available and frequently used index to represent the price level of traded goods. Though there are some producer goods that are not traded, PPI is measured at the production site and thus exclude marketing and other nontraded consumer services. Thus we construct the traded goods component using the PPI following Engel [1999]:

$$f_t^T = ln(PPI_t) - ln(PPI_t^*), \tag{3.6}$$

The relative nontraded goods component is constructed from the aggregate consumer price indexes (CPI) relative to aggregate PPI [3]:

$$f_t^N = ln(CPI_t) - ln(PPI_t) - (ln(CPI_t^*) - ln(PPI_t^*)). \tag{3.7}$$

In the following section, we demonstrate how explosiveness can be detected in the nominal Sterling-dollar exchange rates s_t, and the ratio of the exchange rate relative to the two types of economic fundamentals, using recursive right-tailed unit root tests by Phillips et al. [2011b] and Phillips et al. [2011a].

3.3 The Sequential ADF Tests

Phillips et al. [2011b] provide a new framework to test for bubble phenomena in asset prices. Homm and Breitung [2012] show that this sup ADF (SADF) test is capable of detecting periodically collapsing bubbles and is robust against multiple breaks due to a possible burst of the bubble. The test procedure is based on the autoregressive process

$$x_t = \mu + \delta x_{t-1} + \sum_{j=1}^{J} \phi_j \Delta x_{t-j} + \varepsilon_t, \tag{3.8}$$

[3] Note that no assumption is made about α or β. Through transformation it is easy to show that $f_t^N = \alpha(p_t^N - p_t^T) - \beta(p_t^{N*} - p_t^{T*}) = (p_t - p_t^T) - (p_t^* - p_t^{T*})$.

where x_t is the time series of interest, $E(\varepsilon_t) = 0$ and $E(\varepsilon_t^2) = \sigma^2$. The unit root null hypothesis is $H_0 : \delta = 1$ and the right-tailed alternative hypothesis is $H_1 : \delta > 1$.

Given a fraction r_0 of the total sample as an initial window size, Equation (3.8) is estimated recursively fixing the first observation as the starting point, and using the subsets of sample data increased by one observation stepwise.

For a subsample starting from the first observation and at a fractional size of the full sample r_2, where $r_0 < r_2 \leq 1$, the corresponding ADF test statistic can be denoted by ADF_{r_2}. Hence ADF_1 corresponds to the ADF test statistic of the full sample. The SADF test statistic is thus the supremum value of ADF_{r_2}, for $r_0 < r_2 \leq 1$.

$$SADF(r_0) = \sup_{r_2 \in [r_0, 1]} \{ADF_{r_2}\}, \tag{3.9}$$

Evidence of explosive behavior is obtained on certain time series if the SADF statistic is larger than the right-side critical values for a chosen nominal size.

One limitation of the SADF test is that the starting point is fixed as the first observation of the sample. This implies that in the presence of two bubbles, the second bubble may not be detected if it is dominated by the first bubble. Therefore, Phillips et al. [2011b] also apply a rolling version of the SADF test, where the starting window moves over the sample. However, the size of the starting window is still fixed, which limits the power of the test. Phillips et al. [2011a] extend the SADF test by nesting it in a loop, which increments the starting point ($r_1 \in [0, r_2 - r_0]$) each run. The generalized SADF test (GSADF) is able to detect potential multiple bubbles in the data and thus overcomes the weakness of the SADF test:

$$GSADF(r_0) = \sup_{r_2 \in [r_0, 1], r_1 \in [0, r_2 - r_0]} \{ADF_{r_1}^{r_2}\}. \tag{3.10}$$

Consequently, both the SADF test and the rolling SADF test are nested in the GSADF test. It is important to note that the tests may fail to detect an early bubble if the starting window size is too large.

3.4 Explosive Behavior in the Sterling-dollar Exchange Rates

Our study focuses on the bilateral exchange rates between the United States and Great Britain. We obtained time series of the British Pound/ US dollar exchange rate from the OECD database. The time series of the consumer price index (US) and retailer price index (UK) as well as the producer price index (PPI) are obtain from the IMF International Financial Statistics and used for constructing the fundamentals of the exchange rates. All times series are transformed into logarithm. We work with monthly data, because a higher frequency of price data is not available. The data sample ranges from 1972 M1 to 2012 M6 and covers 486 monthly observations. Hence, our sample covers the period after the breakdown of the Bretton-Woods system of fixed exchange rates. We set the lag order to zero for all time series, because Phillips et al. [2011a] demonstrate with Monte-Carlo simulations that lag selection criteria such as Campbell and Perron [1991] result in significant size distortion and lower power of both the SADF and the GSADF tests.

Results for the nominal Sterling-dollar exchange rate s_t are shown at the third row of Table 3.1. The standard right-sided ADF test statistic seems to suggest no explosive behavior in the nominal exchange rate. However, this result could be misleading if periodically collapsing bubbles occur during the given period (see Evans [1991]). The SADF and the GSADF tests are capable of overcoming this shortcoming. The null hypothesis that there is no explosive behavior in the nominal Sterling-dollar exchange rate is rejected at the 1% significance level for the SADF test. Non-explosiveness is also rejected at the 5% significance level according to the GSADF test. Figure 3.1 shows the time series of the log nominal exchange rate and the corresponding sequence of ADF_t statistics. The ADF_t sequence displays clear evidence of multiple periods of explosiveness. First, the test reports explosiveness in 1976, which corresponds to the 1976 Sterling crisis. Secondly, we find explosiveness in 1985. At that time, the US dollar appreciated heavily against several currencies.

The explosiveness in the nominal exchange rate could be driven either by rational bubbles or explosive fundamentals. The fourth row of Table 3.1 shows

Table 3.1: Tests for Explosive Behavior in the Sterling-dollar Exchange Rate

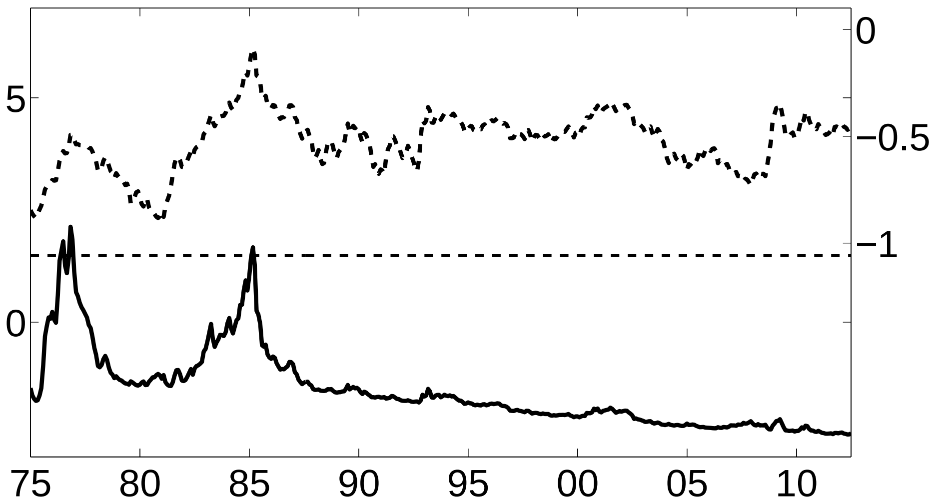
	Sample: 1972 M1-2012 M6		
Variable	ADF	SADF	GSADF
s_t	-2.478	2.128**	2.416*
$s_t - f_t^N$	-1.934	2.630**	2.794*
$s_t - f_t^T$	-1.827	0.374	1.623
CV 1%	0.614	1.984	2.860
CV 5%	-0.091	1.490	2.340
CV 10%	-0.451	1.218	2.106

This table shows the various test statistics of the nominal exchange rates s_t, the ratio of the exchange rate to the nontraded goods fundamental $s_t - f_t^N$, and the ratio of the exchange rate to the traded goods fundamental $s_t - f_t^T$ (see Equation (3.6) *and Equation* (3.7)*). The initial window size r_0 is set as three years (36 observations) for the SADF and GSADF tests. Critical Values are obtained from Monte-Carlo simulations with 5000 replications for the ADF, SADF and GSADF tests. The items marked with * are significant at 5% significance level, and the items market with ** are significant at 1% significance level.*

the test results for the ratio of the exchange rate to the nontraded goods fundamental $s_t - f_t^N$. The exchange rate remains explosive after the relative prices of nontraded goods are accounted for. Figure 3.2(a) displays the sequence of the ADF_t statistics for the exchange rate to the nontraded goods fundamental ratio, which behaves very similar to those of the nominal exchange rate s_t in Figure 3.1. Thus the relative prices of nontraded goods f_t^N play no role in explaining the explosiveness in the nominal exchange rate.

In contrast, no evidence of explosive behavior is found in the relative ratio of the exchange rate to the traded goods fundamental $s_t - f_t^T$. The null hypothesis that the series is nonexplosive can not be rejected at the 10% significance level for either the SADF or the GSADF test. Figure 3.2(b) displays the result of the SADF test graphically. The GSADF statistics show exactly the same pattern (see appendix). Therefore, the explosive behavior in the nominal Sterling-dollar exchange rate may be driven by the relative prices of traded goods between the

Figure 3.1: The Nominal Sterling-dollar Exchange Rate



Note: This graph shows the series of the nominal Sterling dollar exchange rate s_t (right, dotted) and its corresponding sequence of ADF statistics (left, solid). The dashed line represents the 5% critical values of the SADF test.

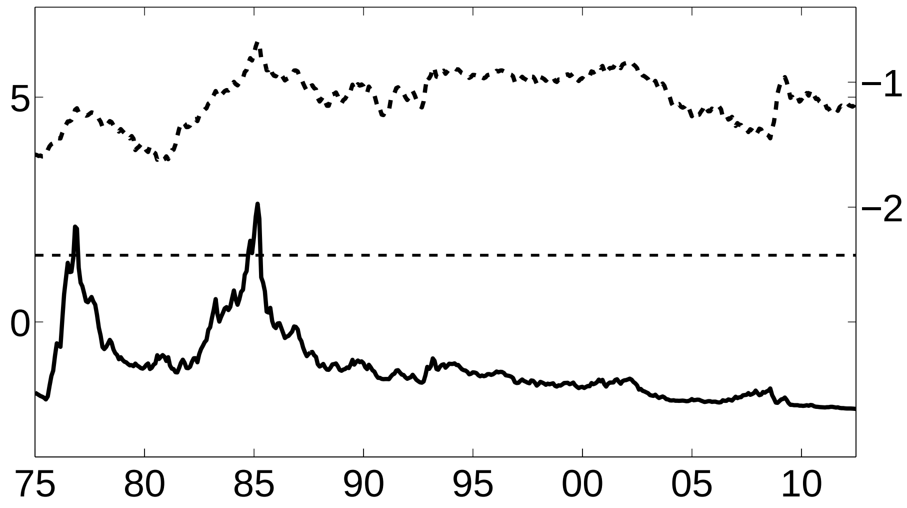
US and Great Britain.[4] The two periods where the explosiveness diminishes are characterised by large commodity shocks. Moreover, manufacturing and mining, two large sectors in the UK until the mid-1980s, were heavily unionised, creating large wage-price spirals. Both effects may have driven up UK PPI inflation causing the observed pattern.

These findings are not in favor of the speculative bubble hypothesis in the nominal Sterling-dollar exchange rate, because the explosive behavior in the exchange rate may be driven by the relative prices of trades goods. Our results are in accordance with those of Engel [1999] and Betts and Kehoe [2005] who show that the relative prices of traded goods explain most of the movements in exchange rates.

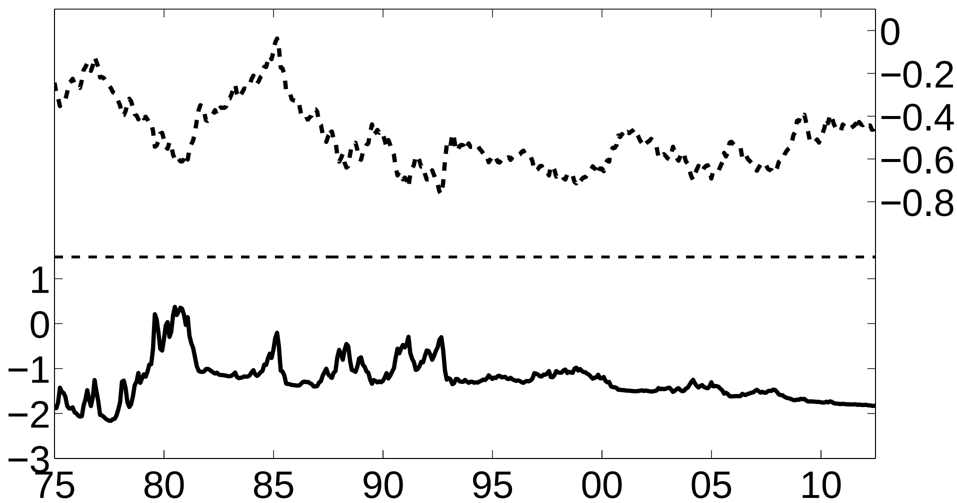
[4]As a robustness check, we test the price ratios separately. The series f_t^T exhibits explosiveness during the two periods where the explosiveness in the ratio of the exchange rate to the traded goods fundamental diminishes. Results are available on request.

Figure 3.2: The Sterling-dollar Exchange Rate to Fundamental Ratios

(a) The Ratio of the Exchange Rate to the Nontraded Goods Fundamental



(b) The Ratio of the Exchange Rate to the Traded Goods Fundamental



Note: The upper panel shows the series of the ratio of the exchange rate to the nontraded goods fundamental $s_t - f_t^N$ (right, dotted) and its corresponding sequence of ADF statistics (left, solid). The lower panel shows the series of the ratio of the exchange rate to the traded goods fundamental $s_t - f_t^T$ (right, dotted) and its corresponding sequence of ADF statistics (left, solid). The dashed line represents the 5% critical values of the SADF test.

3.5 Conclusion

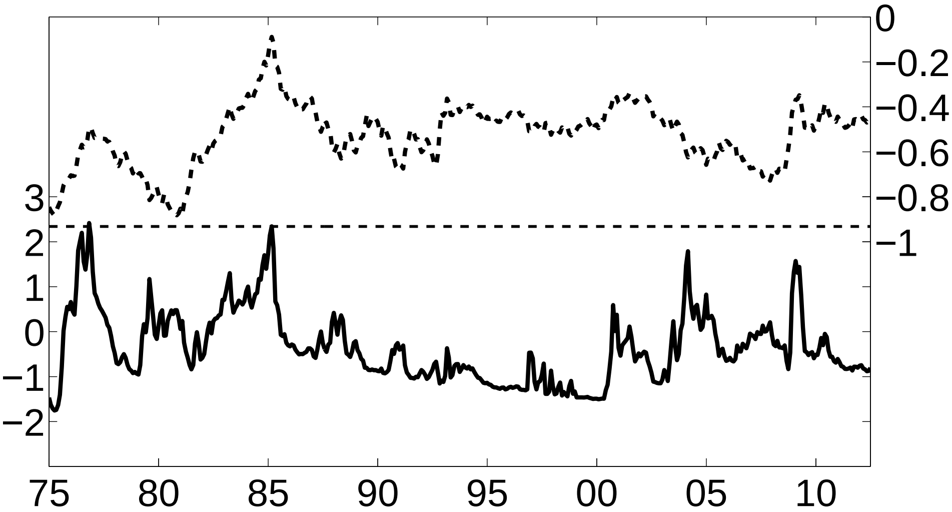
In this paper we provide new evidence casting doubt on the bubble hypothesis in the nominal Sterling-dollar exchange rate by employing recent sequential ADF tests developed by Phillips et al. [2011b] and Phillips et al. [2011a]. Though we find explosive behavior in the nominal exchange rate, the explosiveness coincides with explosive behavior in the relative prices of traded goods. Hence, our findings are not in favor of the bubble hypothesis. In line with Engel (1999) and Betts and Kehoe (2005), our results demonstrate that the relative prices of non-traded goods play little role in the movements of exchange rates, while the relative prices of traded goods seem to be an important determinant. Consequently, we show that it is crucial to take the underlying fundamentals into account when identifying rational bubbles in asset prices, because explosiveness in the asset price alone is not a sufficient condition. This is an important insight for policy makers and practitioners as well.

Appendix

GSADF test statistics

Here, we present the results of the GSADF tests graphically. Figure 3.3 and 3.4 show that the results obtained from the GSADF test are in line with those obtained from the SADF test.

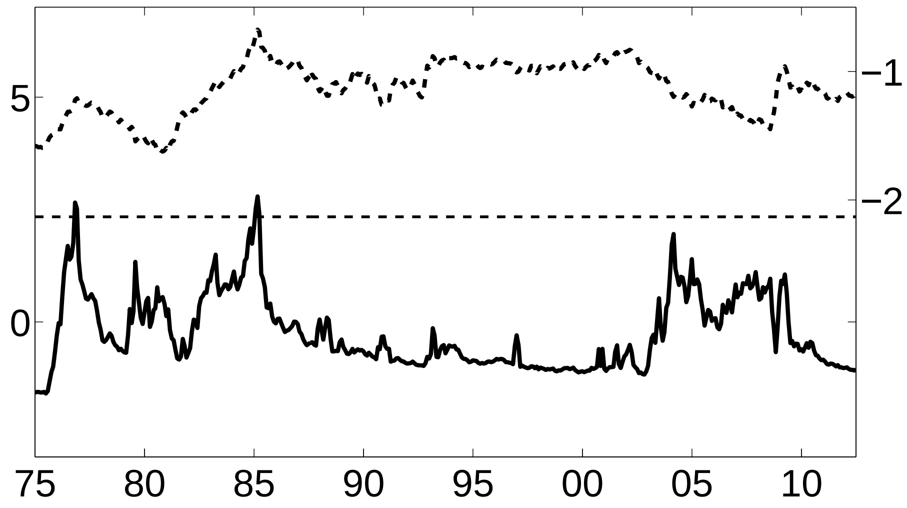
Figure 3.3: The Nominal Sterling-dollar Exchange Rate



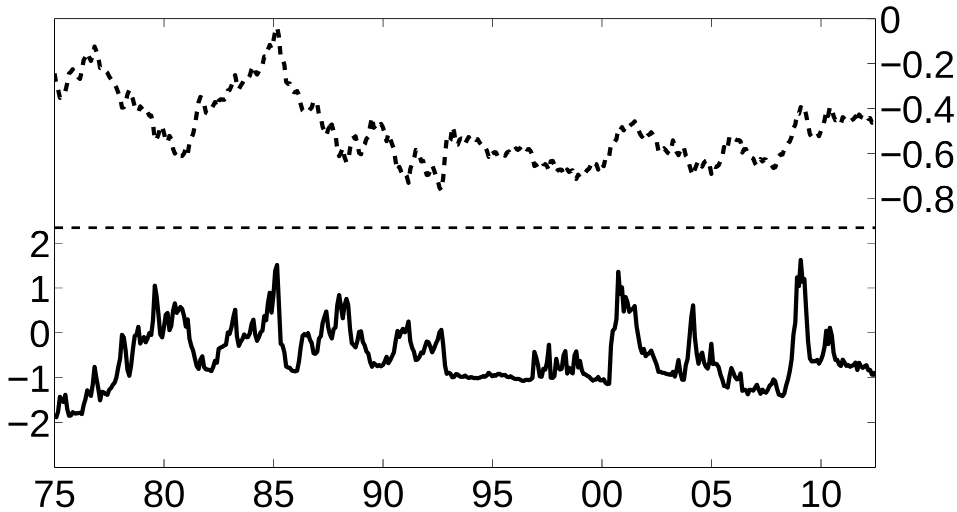
Note: This graph shows the series of the nominal Sterling dollar exchange rate s_t (right, dotted) and its corresponding sequence of ADF statistics (left, solid). The dashed line represents the 5% GSADF critical values.

Figure 3.4: The Sterling-dollar Exchange Rate to Fundamental Ratios

(a) The Ratio of the Exchange Rate to the Nontraded Goods Fundamental



(b) The Ratio of the Exchange Rate to the Traded Goods Fundamental



Note: The upper panel shows the series of the ratio of the exchange rate to the nontraded goods fundamental $s_t - f_t^N$ (right, dotted) and its corresponding sequence of ADF statistics (left, solid). The lower panel shows the series of the ratio of the exchange rate to the traded goods fundamental $s_t - f_t^T$ and its corresponding sequence of ADF statistics. The dashed line represents the 5% GSADF critical values.

Chapter 4

Testing Structural Identifications on US Monetary Policy and Stock Prices

4.1 Introduction

The stock market is one of the most important channels of monetary transmission mechanism.[1] The interactions between monetary policy and stock markets have been studied via various methods [2], among which the structural vector autoregressions (VAR) models are frequently used in order to provide a plausible description of the monetary policy transmission mechanism. However, discrepancies on how to identify structural shocks are noticed among the existing structural VAR literature studying the effect of monetary policy shock on the stock market.

This paper tests the various identification schemes from above mentioned literature using a recently developed method via heteroskedasticity by Lanne and Lütkepohl [2008] and Lanne et al. [2010]. As first shown in Rigobon [2003], a change in volatility in the shocks can provide identifying information. Lanne

[1] This Chapter is based on the joint working paper 'Testing structural identifications on US monetary policy and stock prices' written by Chen, W. and Velinov, A..

[2] Event study approach has been adopted by Ehrmann and Fratzscher [2004] and Bernanke and Kuttner [2005]. Alternatively, Rigobon and Sack [2004] employed a heteroskedasticity-based approach to analyze the effects of monetary policy on stock prices.

and Lütkepohl [2008] has adapted the formulation in Rigobon [2003] in order to discriminate competing models used to identify monetary policy shocks. We apply this method to testing the various structural VAR models on the relations between US monetary policy and stock prices.

One of the most widely used identification schemes is the Cholesky decomposition following the lead of Christiano et al. [2000]. Neri [2004], Li et al. [2010] and Cheng and Jin [2013] have all based their analysis on this type of short-run restrictions. Zero restrictions on the long run impact matrix to identify structural shocks in the spirit of Blanchard and Quah [1989] have also been adopted by papers such as Lastrapes [1998] and Rapach [2001]. Recently, a combination of both short-run and long-run restrictions has been proposed by Bjørnland and Leitemo [2009]. This identification scheme leads to an immediate and unusually large decline of stock prices in response to a contractionary monetary policy shock compared with findings from the standard literature. Results by Bjørnland and Leitemo [2009] highlight the importance of identification schemes in understanding how monetary policy affects the stock market.

We will consider a US monetary system comprised of real output, inflation, the federal funds rate, and real stock prices for the period from 1964 to 2007[3]. Stability tests demonstrate that the structural parameters are stable during the sample period while there is evidence for changes in volatility. Therefore we assume the data generating process is a VAR with constant parameters apart from changes in variances.

Our estimates from the Markov switching heterskedasticity model provide over-identifying information to identify shocks. Based on the estimation results, statistical tests can be performed to compare various identification schemes used in the literature. We find that the Cholesky decomposition adopted by Neri [2004], Li et al. [2010] and Cheng and Jin [2013] assuming no instantaneous effects of stock price shocks on monetary policy can not be rejected by data. However, strong evidence is found against the structural identification by Bjørn-

[3]Compared with Neri [2004] and Bjørnland and Leitemo [2009], we have one variable less in our system, the commodity price index. This commodity price index is often included to solve the price puzzle. However, since the price puzzle is not the main focus of our paper, we conduct our analysis without the commodity price index. In Section 4.2 we show that main results by Bjørnland and Leitemo [2009] can be replicated in the four-variable VAR system.

land and Leitemo [2009] that assumes the long-run neutrality of monetary policy shocks on real stock prices.

This paper is structured as follows: Section 2 introduces how fundamental shocks are identified with various structural restrictions and the heteroskedasticity-based method to obtain over-identifying information from the data. Section 3 describes the data and discusses the empirical findings on the interaction between US monetary policy and the stock market. Section 4 concludes.

4.2 The Model Setup

4.2.1 Economic Setup

The Cholesky decomposition has been widely utilized in the existing literature such as Neri [2004], Li et al. [2010], and Cheng and Jin [2013]. It is assumed that there are no instantaneous effects of stock price shocks on macro variables and monetary policy variables. Similarly zero short-run restrictions are imposed on monetary policy shocks and the macroeconomic variables. Most of these studies find that monetary policy shocks account for only a small part of the variation in stock returns. In our framework, such Cholesky decomposition is implemented by restricting the upper diagonal elements of B matrix as zero as follows:

$$\begin{bmatrix} U_t^y \\ U_t^\pi \\ U_t^{FFR} \\ U_t^{sp} \end{bmatrix} = \begin{bmatrix} B_{11} & 0 & 0 & 0 \\ B_{21} & B_{22} & 0 & 0 \\ B_{31} & B_{32} & B_{33} & 0 \\ B_{41} & B_{42} & B_{43} & B_{44} \end{bmatrix} \times \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^\pi \\ \varepsilon_t^{FFR} \\ \varepsilon_t^{sp} \end{bmatrix}$$

where $U_t^y, U_t^\pi, U_t^{FFR}, U_t^{sp}$ stands for the reduced form residuals of respectively, output, inflation, the Federal Funds rate, and the stock price, while $\varepsilon_t^y, \varepsilon_t^\pi, \varepsilon_t^{FFR}, \varepsilon_t^{sp}$ stands for the structural shocks, i.e., the output shock, the inflation shock, the monetary policy shock and the stock price shock.

Bjørnland and Leitemo [2009] proposed an alternative way of structural identification through a combination of short-run and long-run restrictions. Instead of assuming zero instantaneous effect of the monetary policy to the stock price shocks, Bjørnland and Leitemo [2009] assume that the monetary policy shocks have no effect in the long run on the real stock prices. That is, in the following B matrix, there is one less zero short-run restriction. Instead, one additional zero restriction is set on C_{34} in the long run impact matrix:

$$\begin{bmatrix} U_t^y \\ U_t^\pi \\ U_t^{sp} \\ U_t^{FFR} \end{bmatrix} = \begin{bmatrix} B_{11} & 0 & 0 & 0 \\ B_{21} & B_{22} & 0 & 0 \\ B_{31} & B_{32} & B_{33} & B_{34} \\ B_{41} & B_{42} & B_{43} & B_{44} \end{bmatrix} \times \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^\pi \\ \varepsilon_t^{sp} \\ \varepsilon_t^{FFR} \end{bmatrix}$$

A third identification strategy is also mentioned by Bjørnland and Leitemo [2009], which assumes that there is no instantaneous effect of monetary policy shocks on stock price. It can be implemented by shifting the order of the Federal Funds rate and stock prices in the model with Cholesky decomposition as shown in the following matrix. We also test for the validity of this structural identification in Section 4.

$$\begin{bmatrix} U_t^y \\ U_t^\pi \\ U_t^{sp} \\ U_t^{FFR} \end{bmatrix} = \begin{bmatrix} B_{11} & 0 & 0 & 0 \\ B_{21} & B_{22} & 0 & 0 \\ B_{31} & B_{32} & B_{33} & 0 \\ B_{41} & B_{42} & B_{43} & B_{44} \end{bmatrix} \times \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^\pi \\ \varepsilon_t^{sp} \\ \varepsilon_t^{FFR} \end{bmatrix}$$

The Markov switching heteroscedasticity VAR models are capable of providing additional statistical information to identify shocks. In the following subsection we describe in detail how the Markov switching heteroscedasticity VAR model can provide over-identifying information so as to test the above mentioned identification schemes from existing literature.

4.2.2 Identification of shocks via heteroskedasticity

Many researchers including Uhlig [2005] have criticized that the assumed structural restrictions could be too restrictive. Following Lanne and Lütkepohl [2008] and Lanne et al. [2010], a Markov Switching model is used to validate the identification strategy. This model allows for heteroscedasticity of the residuals as follows:

$$\Delta x_t = \nu + A_1 \Delta x_{t-1} + A_2 \Delta x_{t-2} + \cdots + A_p \Delta x_{t-p} + u_t | s_t. \tag{4.1}$$

where the distribution of the residuals is assumed to be governed by a Markov process, s_t and it is assumed that the residuals are normally distributed conditional on the given state, i.e., $u_t|s_t \sim N(0, \Sigma_{s_t})$.

The discrete stochastic process s_t assumes M regimes with transition probabilities given by

$$p_{ij} = P(s_t = j|s_{t-1} = i), \quad i, j = 1, \ldots, M$$

with a $M \times M$ matrix of transitional probabilities. Note that the probabilities add up to one row-wise, hence $p_{iM} = 1 - p_{i1} - p_{i2} - \cdots - p_{iM-1}$.

In the above framework, if there exist at least two different covariance states, shocks can be identified without assuming further restrictions. Special features of (4.1) provide over-identifying information to test the appropriateness of structural restrictions, if the covariance matrices could be uniquely decomposed in the following way:

$$\Sigma_1 = BB', \quad \Sigma_2 = B\Lambda_2 B', \quad \ldots, \quad \Sigma_M = B\Lambda_M B', \tag{4.2}$$

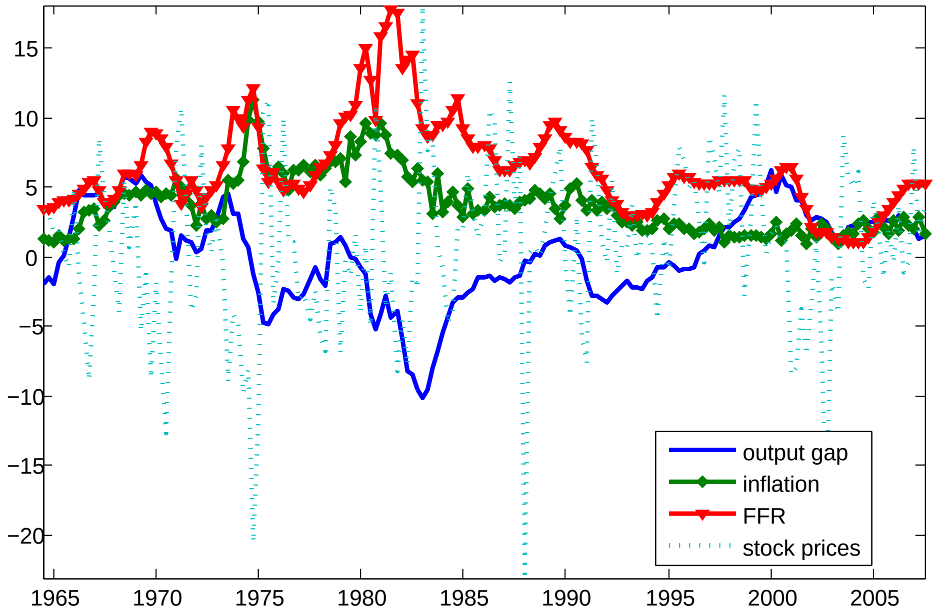
where B is the contemporaneous impact matrix which is used to transform reduced form shocks into structural shocks. Λ_i can be interpreted as the relative-variance matrix of the structural shocks in Regime i versus Regime 1. In the empirical example, $M = 2$ is chosen. For State 1, Λ_1 is normalized as a 2×2 identity matrix. For the second state, Λ_i is a 2×2 diagonal matrix with the following representation:

$$\Lambda_i = \begin{bmatrix} \lambda_{i1} & 0 \\ 0 & \lambda_{i2} \end{bmatrix} \tag{4.3}$$

If diagonal elements in either Regime 2 are distinct from each other, i.e., $\lambda_{i1} \neq \lambda_{i2}$, the transformation matrix B is identified without further structural assumptions. The decomposition in (4.2) is unique up to sign changes in the B matrix. In accordance with Lanne et al. [2010], sign changes in the columns of B are no problem for our analysis of structural identification since it corresponds to whether negative structural shocks or positive structural shocks are of interest.

Whether the structural restrictions are compatible with the data is verified through a likelihood ratio test. The maximum loglikelihood from the just-identified

Figure 4.1: Time series of output, inflation, stock prices and the Federal funds rate from 1964 Q2 to 2007Q2



Note: This figure shows the log output after taking linear trend, the log inflation, the deflated log stock prices in first differences, and the Federal funds rate.

Markov switching VAR model can be compared with the maximum loglikelihood from the over-identified Markov switching VAR model including the structural restrictions. If the likelihood ratio test is rejected, it is evidence against the presumed structural restrictions.

4.3 Empirical Analysis

4.3.1 The Data

The data set includes the quarterly times series of US output, CPI, the Federal funds rate and stock prices from 1964 Q1 to 2007 Q2. They are obtained from the database provided by the Federal Reserve Bank of St. Louis. All time series except for the Federal funds rate have been taken as logarithm. The stock prices have been deflated by the CPI index and have been taken first differences. The inflation series come from the first-differenced CPI index. Figure 4.1 plots the four series over the sample period.

In order to test for stabilities of the system, the CUSUM test and the CUSUM SQ test are conducted. Figure 5 in Appendix depicts the CUSUM test statistics with the corresponding 5% confidence bands. It is noticeable that none of the series wanders beyond the confidence bands. Hence there is some evidence for stability in the structural parameters over our data sample period. However, the CUSUM SQ test statistics depicted in Figure 6 demonstrate that there is instability in the variances. Thus we assume the data generating process is a VAR with constant parameters but varying variances.

4.3.2 Replication of Bjørnland and Leitemo (2009)

We first estimate the four-variable structural VAR model following the identification strategy by Bjørnland and Leitemo [2009][4]. Results show that following 100 basis point monetary policy shock, the stock prices decrease immediately to around 7 percent. Though we have one time series (the commodity price index) less than the original model by Bjørnland and Leitemo [2009], we could replicate their main results regarding the interaction between monetary policy and stock prices. Figure 7 in Appendix shows the replication results with regard to responses of the Federal funds rate and the stock prices following a 100 basis point monetary policy shock.

[4] In order to be consistent, we also use the same sample period of data as in Bjørnland and Leitemo [2009] in the replication, i.e., the data for the replication starts from the beginning of 1983 to the end of 2002. Using our full data sample generates qualitatively consistent results.

4.3.3 Estimates from the unrestricted Markov switching model

This subsection presents estimation results from the Markov switching model without any standard structural assumptions.The lag length of the Markov switching VAR models is chosen to be two according to the Schwarz criterion[5]. Figure 4.2 shows the estimated smoothed probabilities over time. The low-volatility regime shown in the upper panel clearly covers the period from the mid-1980s till 2007, which is well known as the period of the Great Moderation. The high-volatility regime is dominant through the majority of the 1970s and the first half of the 1980s, including the well-known period of the Federal Reserve's monetarist experiment.

Table 4.1 shows the estimated λ parameters that can be interpreted as the relative variances across states. The λ parameters look different from each other since the one standard error intervals around the estimated parameters do not overlap. However, more accurate tests could be conducted to test for the equality between each pair of the relative variance parameters. Table 4.2 shows the LR statistics and corresponding p-values for the LR tests for the equality relations between each possible pair of λ parameters. The null hypothesis that a certain pair of λ elements are equal is rejected at the 5% significance level for all pairs except for λ_{22} compared with λ_{23}. The equality of λ_{22} and λ_{23} is rejected at the 10% significance level. Therefore there is evidence that all λ elements are distinct from each other.

4.3.4 LR tests for different identification schemes

LR tests could be conducted to test against the data the validity of the two types of Cholesky decomposition, as well as the identification strategy proposed by Bjørnland and Leitemo [2009]. Table 4.3 shows the details of the LR test results. The identification scheme by Bjørnland and Leitemo [2009] is strongly rejected by the data. In contrast, both types of the Cholesky decomposition can not be rejected at the 5% significance level or at the 10% significance level. The identification scheme assuming the long run neutrality of monetary policy shock on real stock prices turns out to be in odds with data, while the identification

[5] The lag choice criteria for models with different lags are presented in the Appendix.

Table 4.1: Estimated relative-variance parameters of unrestricted model

Parameter	Estimate(Std.)
λ_{21}	0.83(0.22)
λ_{22}	2.77(0.73)
λ_{23}	5.12(1.29)
λ_{24}	26.61(6.93)

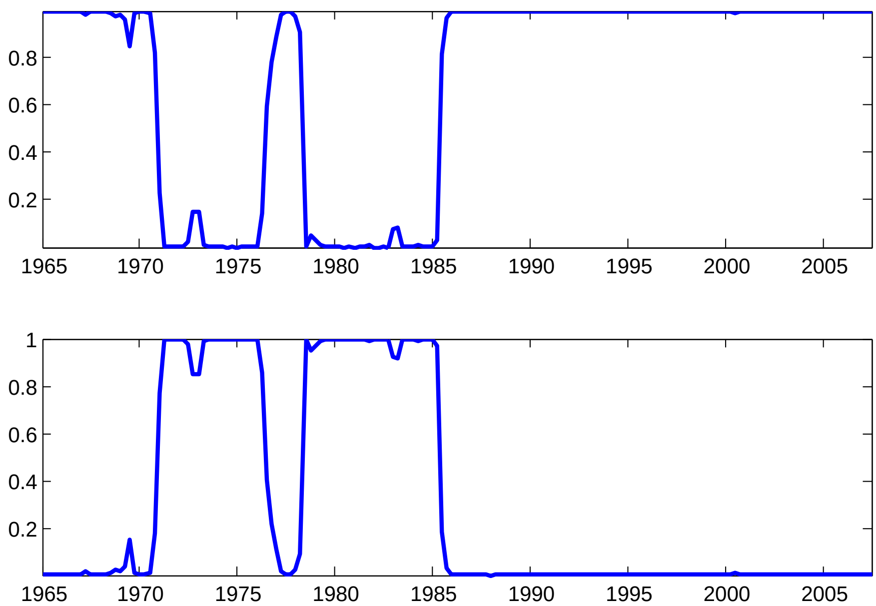
Note: this table shows the estimated λ elements from the 2-state 2-lag Markov switching heteroskedasticity model without any structural restrictions. The standard errors of the estimates are presented in brackets.

Table 4.2: LR tests for equality of λ elements

H_0	LR statistic	p-value
$\lambda_{21} = \lambda_{22}$	6.67	0.009
$\lambda_{21} = \lambda_{23}$	11.72	0.0006
$\lambda_{21} = \lambda_{24}$	11.65	0.0006
$\lambda_{22} = \lambda_{23}$	2.90	0.089
$\lambda_{22} = \lambda_{24}$	4.04	0.044
$\lambda_{23} = \lambda_{24}$	19.98	7.81×10^{-6}

Note: this table presents the LR test statistics and corresponding p-values for testing the equality of each pair of λ elements.

Figure 4.2: Smoothed state probabilities from Markov switching model without structural restrictions



Note: This figure depicts the smoothed state probabilities of unrestricted MS(2)-VAR(2) model. The upper panel shows the probability of the system being in the low-volatility state, while the lower panel shows the probability of the system being in the high-volatility state.

schemes assuming no instantaneous effects of stock prices shocks on monetary policy or assuming no instantaneous effects of monetary policy shocks on stock prices are consistent with the data.

4.3.5 Estimated monetary policy shocks and impulse responses

Figure 4.3 plots the monetary policy shocks from the model without any structural restriction. The identified shocks are consistent in patterns compared with those in Lanne and Lütkepohl [2008] and Romer and Romer [2004]. Moreover, Figure 4.4 presents the responses of stock prices in response to a 100-basis-point

Table 4.3: LR tests of identification schemes

Models compared	LR statistic	p-value
Cholesky I v.s. Unrestricted	8.4	0.21
Cholesky II v.s. Unrestricted	5.8	0.45
Bjornland and Leitemo v.s. Unrestricted	43.2	1.06×10^{-7}

Note: Cholesky I stands for the Choleski decomposition with the order of variables as $[y', \pi', FFR', \Delta sp']$, *while Cholesky II stands for the Choleski decomposition with the order of variables as* $[y', \pi', \Delta sp', FFR']$.

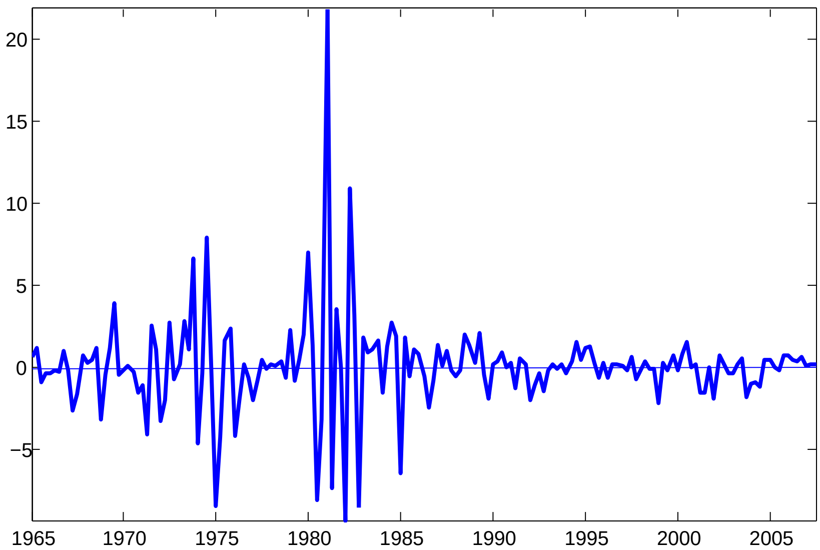
expansionary monetary policy shock from the unrestricted model. It is noticeable that the impulse response curve estimated from the unrestricted exhibits a smooth inverse hump shape, reaching its minimum after around one year, while the impulse response curve in Figure 7 following the identification scheme by Bjørnland and Leitemo [2009] looks more like an upward slope. It brings further doubt on whether the identification scheme by Bjørnland and Leitemo [2009] has led to plausible impulse responses.

4.4 Conclusion

Many literature have studied the interaction between US monetary policy and stock prices. Among them controversy has arisen regarding the identification of structural shocks. This paper has followed recent methodology proposed by Lanne and Lütkepohl [2008] and Lanne et al. [2010] to utilize the changes in volatility in order to test different identification schemes. In particular, we have tested the combination of short-run restrictions and long-run restrictions proposed by Bjørnland and Leitemo [2009], and the Cholesky decomposition used by Neri [2004], Li et al. [2010] and Cheng and Jin [2013].

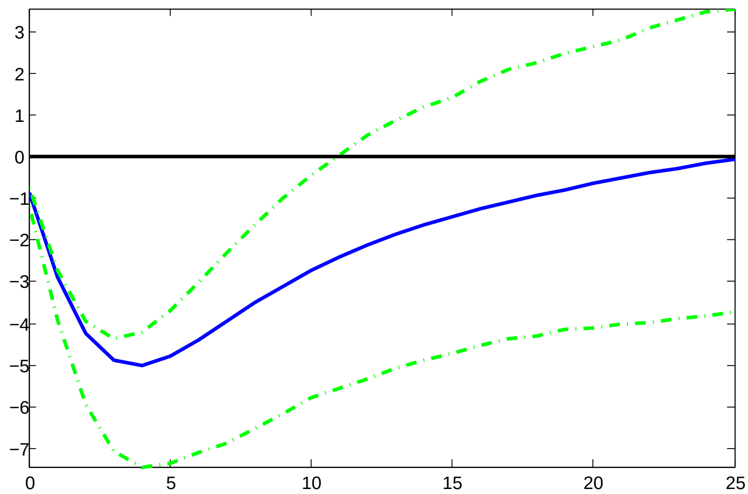
Using the statistical information on the volatility of the shocks provides over-identifying information to test for the above mentioned identification schemes against the data. We found that the identification by Bjørnland and Leitemo

Figure 4.3: Estimated monetary policy shocks from the unrestricted model



Note: This figure plots the estimated monetary policy shocks from the 2-state 2-state Markov switching model without any imposed structural restrictions.

Figure 4.4: Response of stock prices to unit monetary policy shock with 68 % confidence bounds



Note: This figure plots the accumulated responses of stock prices to one unit monetary policy shock from the estimates of the unrestricted Markov switching heteroskedasticity model. The confidence intervals are obtains by 500 bootstrap replications.

[2009] assuming the long-run neutrality of monetary policy shocks on real stock prices is strongly rejected by the data. The impulse response analysis based on this identification could be problematic. In contrast, the Cholesky decomposition assuming no instantaneous effects of stock price shocks on monetary policy is accepted by the data.

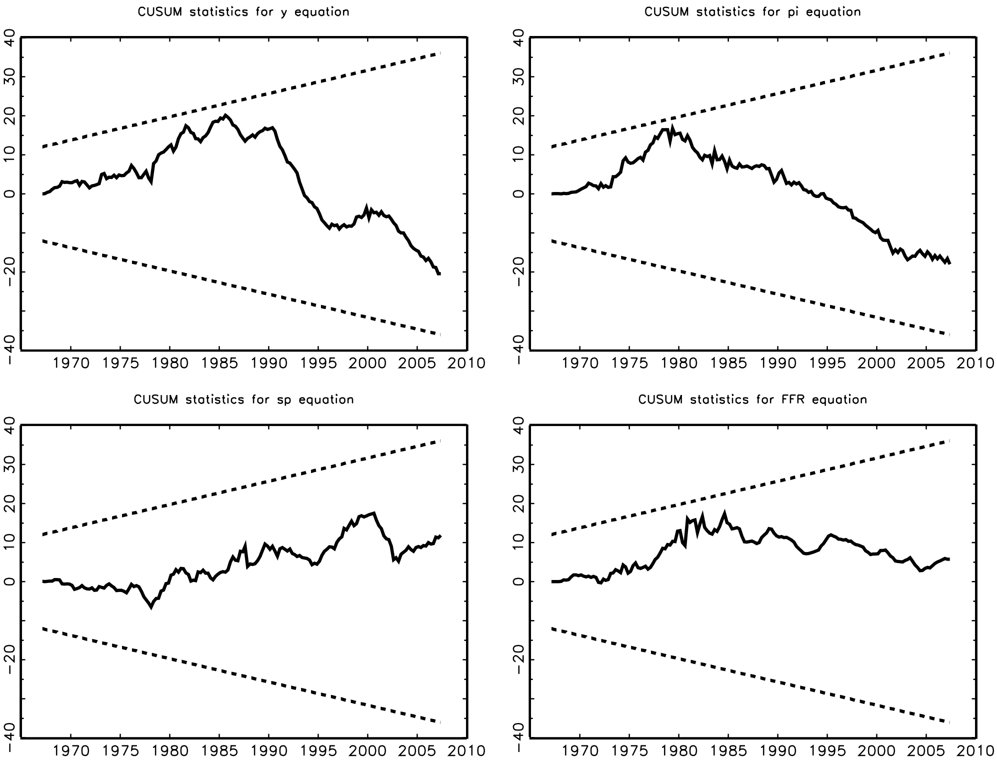
Appendices

Table 4: Information criteria for 2-state MS VAR models with different lags

Model	AIC	SIC
MS(2)-VAR(1)	2252.33	2384.52
MS(2)-VAR(2)	2175.04	2357.25
MS(2)-VAR(3)	2174.63	2406.68

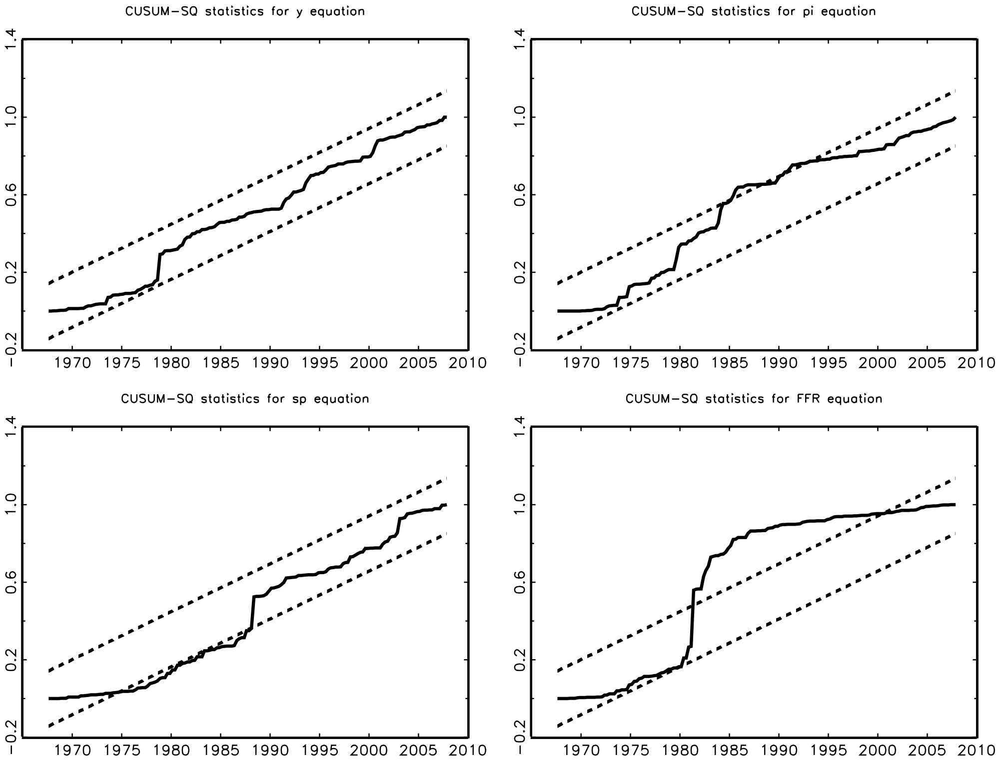
Note: This table presents the AIC criteria and Schwarz criteria for the unrestricted 2-state Markov switching models with different lags.

Figure 5: Test for stability in parameters



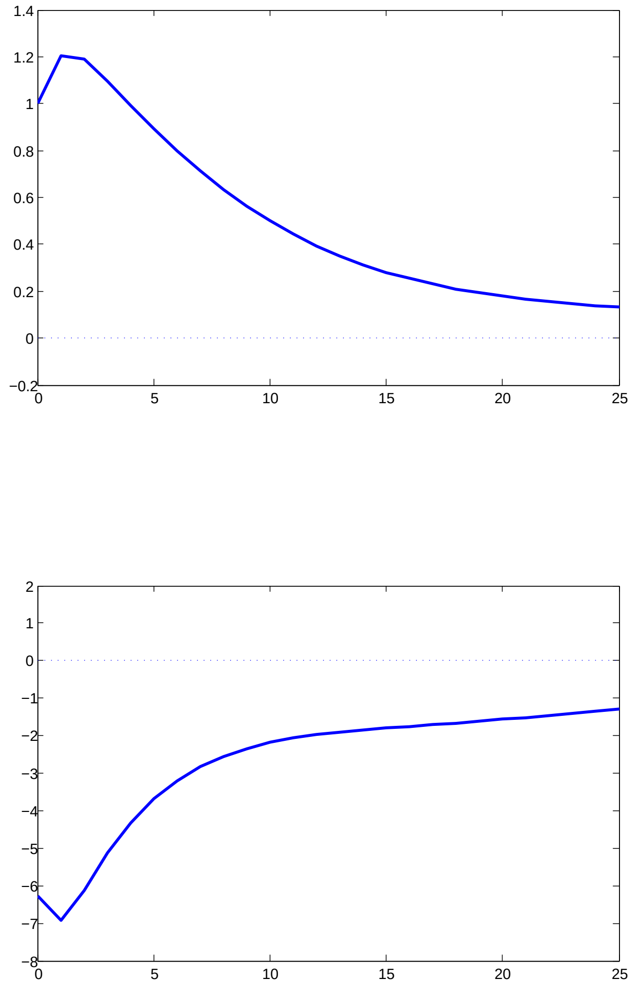
Note: This figure shows the CUSUM test statistics and the corresponding 5% confidence bands.

Figure 6: Test for stability in variances



Note: This figure shows the CUSUM SQ test statistics and the corresponding 5% confidence bands.

Figure 7: Replication of monetary policy shocks by Bjï£¡rnland and Leitemo (2009)



Note: This figure shows responses of variables following a 100-basis-point monetary policy shock estimated in the four-variable structural VAR model employing the identification strategy by Bjørnland and Leitemo (2009). The upper panel shows the response of the Federal funds rate, while the lower panel shows the accumulated responses of the stock prices.

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Ehrenwörtliche Erklärung

Ich habe die vorgelegte Dissertation selbst verfasst und dabei nur die von mir angegebenen Quellen und Hilfsmittel benutzt. Alle Textstellen, die wörtlich oder sinngemäß aus veröffentlichten oder nicht veröffentlichten Schriften entnommen sind, sowie alle Angaben, die auf mündlichen Auskï£¡nften beruhen, sind als solche kenntlich gemacht.

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