AN EMPIRICAL INVESTIGATION OF THE U.S. GDP GROWTH: A MARKOV SWITCHING APPROACH

Ozge KANDEMIR KOCAASLAN

A thesis submitted to the University of Sheffield for the Degree of Doctor of Philosophy in the Department of Economics

Date Submitted: January 2013

To my parents

Abstract

This thesis is composed of three separate yet related empirical studies. In Chapter 2, we empirically investigate the effects of inflation uncertainty on output growth for the U.S. economy using both monthly and quarterly data over 1960-2009. Employing a Markov regime switching approach, we show that inflation uncertainty obtained from a Markov regime switching GARCH model exerts a negative and regime dependent impact on growth. We show that the negative impact of inflation uncertainty on growth is almost 2 times higher during the low growth regime than that during the high growth regime. We verify the robustness of our findings using quarterly data.

In Chapter 3, we empirically examine whether there are asymmetries in the real effects of monetary policy shocks across business cycle and whether financial depth plays an important role in dampening the effects of monetary policy shocks on output growth using quarterly U.S. data over the period 1981:QI–2009:QII. Applying an instrumental variables estimation in Markov regime switching methodology, we document that the impact of monetary policy changes on growth is stronger during recessions. We also find that financial development is very prominent in dampening the real effects of monetary policy shocks especially during the periods of recession.

In Chapter 4, we empirically search for the causal link between energy consumption and economic growth employing a Markov switching Granger causality analysis. We carry out our investigation using quarterly U.S. real GDP and total energy consumption data over the period 1975:QI–2009:QIV. We find that there are changes in the causal relation between energy consumption and economic growth. Our results show that energy consumption has predictive content for real economic activity. The causality running from energy consumption to output growth seems to be strongly apparent only during the periods of recession and energy crisis. We also reveal that output growth has predictive power for energy consumption and this power evidently arises during the periods of expansion.

Acknowledgements

First of all, I would like to express my sincere gratitude to my supervisors, Mustafa Çağlayan and Kostas Mouratidis whose guidance, support and professionalism have been crucial for the completion of this thesis. This thesis would not have been completed without their motivation and encouragement.

A very warm thank to the Department of Economics of the University of Sheffield especially to Steven McIntosh. I am deeply indebted to him for his help and interest from the start of my PhD and for his useful comments as well.

I would like to thank Abdul Rashid and Zainab Jehan who are not only good friends but also brilliant economists. I thank you for making Sheffield a better place in every aspect.

I would like to thank Murat Kocaaslan for his love, support and encouragement along this challenging process. Thank you for your patience and sacrifices.

I would like to thank my family for their unconditional love and support throughout my life. I will always be most grateful to my family especially to my parents for their understanding and sacrifices.

Contents

List of Tables

List of Figures

List of Abrreviations

AIC	Akaike Information Criterion
AR(p)	Autoregressive Model of Order p
BIC	Bayesian Information Criterion
CPI	Consumer Price Index
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
EGARCH-M	Exponential Generalized Autoregressive Conditional Heteroscedasticity in Mean
EU	European Union
G11	Group of Eleven
G7	Group of Seven
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
GNP	Gross National Product
GRS	Generalized Regime Switching
IEA	International Energy Agency
IFS	International Financial Statistics
IMF	International Monetary Fund
IPI	Industrial Production Index
LM	Lagrange Multiplier
LSTVAR	Logistic Smooth Transition Vector Autoregression
NBER	National Bureau of Economic Research
OECD	Organization for Economic Co-Operation and Development

SIC	Schwarz Information Criterion
TPM	Three-Pattern Method
U.S.	The United States of America
VAR	Vector Autoregression
VEC	Vector Error Correction

Chapter 1

Introduction

Many macroeconomic time series, possibly due to events such as abrupt policy changes, economic crises, oil price shocks exhibit regime shifts in their behavior. In particular, macroeconomic series behave differently in economic downturns, when resources are under-utilized, in contrast to the periods of economic boom as the economic agents use factors of production more efficiently. For instance, output growth is likely to fluctuate around a higher level and tend to be more persistent during expansions while it remains at a lower level with less persistence during contractions.

Understanding the macroeconomic time series that display different behavior as the economy moves through the business cycle has been a central issue in empirical macroeconomics. Several researchers point out that, models with constant coefficients which do not account for regime changes in the underlying series are likely to perform poorly and yield misleading conclusions. One of the solutions to this problem is the use of Markov regime switching models which researchers implement to scrutinize macroeconomic series exhibiting non-linearities, asymmetries and regime shifts. Markov regime switching models can capture the distinct behavior of time series in different regimes.

The objective of this thesis is to examine in detail the impacts of separate macroeconomic variables on output growth by implementing Markov regime switching models to the U.S. data. Before we discuss each chapter of this thesis in detail, we should note that the U.S. economy has experienced various significant economic events during the last five decades. First of all, a number of economic downturns have taken place over 1960, 1980, 1981/1982, 1990/1991, 2000/2001, 2008/2009. Furthermore, the U.S. economy was affected by several energy crises including the oil crisis started in 1978 caused by the Iranian Revolution, 1980 oil crisis induced by Iran–Iraq War and 1990 oil price shock due to the Gulf War. Ever since the pioneering work of Hamilton (1989) who models the U.S. business cycle, several researchers have examined the macroeconomic fluctuations in the U.S. economy using Markov regime switching models. It is observed that if the macroeconomic time series exhibit regime shifts then the models with constant parameters tend to perform poorly in examining the effects of policy changes. In this respect, Markov regime switching models are one of the most appropriate econometric tools to reveal the dynamic nature of the variables of concern and to analyze how these variables have behaved in the past and how their behavior may change in the future.

The first study of this thesis (Chapter 2) empirically analyze the effects of inflation and inflation uncertainty on output growth for the U.S. economy using both monthly and quarterly data over the period 1960-2009. Unlike most empirical studies in this literature, the first essay contributes to the literature by employing a Markov switching GARCH model which allows for regime shifts in inflation series to obtain a proxy for inflation uncertainty. Understanding the link between inflation, inflation uncertainty and economic growth is important as the decisions that households and policy makers must make are strongly influenced by the changes in the level of inflation and inflation uncertainty. It is widely believed by many economists that sustainable growth and low and stable inflation constitute two of the fundamental objectives of the policymakers. A reason behind this conviction is that high and unstable inflation leads to an increase in inflation uncertainty impeding real economic activity. Not surprisingly, a growing number of both theoretical and empirical studies have scrutinized the linkages between inflation, inflation uncertainty and economic growth in recent years. The origin of this extensive literature lies in the Friedman hypothesis which is based on two arguments. First, Friedman (1977) argues that a rise in inflation level leads to higher inflation uncertainty. Second, he claims that higher inflation uncertainty distorts the information content of prices which plays a fundamental role in the efficient allocation of resources and thereby leads to lower economic growth.

Although several researchers have devoted their time to study the impact of inflation uncertainty on economic growth, the empirical literature does not allow one to arrive at a coherent conclusion. In particular, empirical results seem to be sensitive to various factors including the sample period, model specification and the proxies for inflation uncertainty. Most standard literature has used either the dispersion of inflation forecasts gathered from survey data, standard deviation of the inflation series or ARCH/GARCH models to generate a proxy for inflation uncertainty. A number of criticisms have been leveled at these three methodologies. For instance, uncertainty proxies generated from survey data may not be able to gauge the true level of uncertainty and potentially contain sizable measurement errors. In the case of a standard deviation based measure, it is stated that expected fluctuations in inflation rate will cause an increase in this measure although there is no uncertainty in the economic environment. Moreover, the standard ARCH/GARCH models take the economic structure as given and disregard the potential structural instabilities induced by regime changes over time. However, it is observed that if regime shifts are overlooked, GARCH models tend to overstate the persistence in variance (Lamoureux and Lastrapes (1990); Hamilton and Susmel (1994); Gray (1996)) and understate the level of uncertainty (Giordani and Soderlind (2003)). In this respect, Evans and Wachtel (1993) infer that, models which do not account for regime changes in the inflation process underestimates not only the level of uncertainty but also its impact on economic growth.

This chapter (Chapter 2) adds to the related literature in two ways. First we implement a Markov switching GARCH methodology which allows for the regime shifts in inflation series while generating the proxy for inflation uncertainty. Second, we allow both inflation and inflation uncertainty to exert a regime dependent impact on output growth employing a Markov regime switching model. Our investigation provides evidence that the magnitude of inflation uncertainty on output growth changes significantly across low- and high-growth regimes. Specifically, we find that inflation uncertainty has a greater negative impact on output growth during the low growth regime.

The second study of the thesis (Chapter 3) aims to explore whether monetary policy shocks have an asymmetric impact on output growth over the business cycle. The ongoing debate regarding the asymmetric effects of monetary policy shocks that occur due to the credit channel or the convexity of supply curves has ended with the conclusion that monetary policy shocks are likely to have a stronger real impact in the low growth periods (see, among others, Weise (1999), Garcia and Schaller (2002), Lo and Piger (2005)). This study revisits the empirical literature on asymmetric effects of monetary policy shocks on output across expansion and recession periods by using an instrumental variables estimation in Markov regime switching framework. In particular, we apply the instrumental variables estimation in Markov regime switching model proposed by Spagnolo et al. (2005) to get around the endogeneity problem between the measure of monetary policy and output growth. In this context, we simultaneously estimate the output growth equation and the instrumenting equation for the endogenous regressor which both have state-dependent parameters using the U.S. data over the period from 1981:QI to 2009:QII.

The second contribution of this chapter is that we recognize the importance of financial depth in the transmission of monetary policy. In this sense, we aim to shed light on the question whether the effects of monetary policy shocks on output growth vary with the level of financial depth. Simply put, we examine whether the level of financial depth dampens or amplifies the impact of monetary policy shocks on the economic growth. Moreover, the use of a Markov regime switching framework enables us to examine whether the interaction between monetary policy shocks and financial depth is regime-dependent and it would change across recession and expansion regimes.

We expect that the magnitude of the impact of monetary policy shocks on real economic activity should be related to the depth of financial markets. The main motivation behind this view is that deeper financial markets are subjected to less credit market imperfections which are considered as a propagator of shocks to the economy. That is, given all things equal, we anticipate that the negative impact of contractionary monetary policy shocks on economic growth is likely to be less pronounced during a recession should the private sector have easier access to credit.

We add fresh evidence to the existing empirical literature by showing that the magnitude of the negative impact of a monetary contraction on economic growth is greater in the periods of recession as compared to that in the periods of expansion. We also document that higher financial depth fosters output growth when the recession regime persists while it does not exert any impact on economic activity during the expansion regime. Importantly, a deeper financial market is found to dampen the real effects of monetary policy shocks in both regimes but this impact seems to be particularly prominent in the periods of recession.

The third study of the thesis (Chapter 4) examines the causal link between energy consumption and economic growth. The nature of the causal relation between energy consumption and output growth has been one of the issues which have attracted considerable attention recently. To a great extent, the growing interest in the energy consumption and economic growth nexus has been prompted by the rising demand for energy due to the increasing economic activities across countries. However so far, a consensus has not been reached regarding the presence or the direction of the causality between energy and output.

Similar to many other macroeconomic time series, energy data may exhibit nonlinear behavior due to different factors such as policy changes, economic or energy crises. The third empirical study is motivated by the fact that if output and energy data exhibit regime shifts then a model assuming constant parameters is likely to yield misleading results. Furthermore, it is well recognized that the empirical results of the causality tests may significantly depend on the selection of the sample period due to the possible regime shifts in output growth and energy series. Thus, the direction of the causal link between energy and output may change or the causal link even may not be present in certain periods over time. On this account, this empirical study fills the void in the existing empirical literature by providing evidence of a temporal causal relation between energy and output. To do so, we employ a Markov switching Granger causality analysis introduced by Psaradakis et al. (2005). This framework is well-suited to deal with such instabilities and to model the changing causality patterns over the sample period.

The Granger causality analysis in the third empirical study is based on a VAR model with time varying parameters. In particular, the VAR model is specifically designed to show the changes in the causality patterns between energy and output growth. The number and timing of the changes in the causal relation between the energy consumption and economic growth are unknown a priori. However, this methodology enables the data to capture the time points at which the changes in the causality pattern occur. The changes in the causal link between energy consumption and economic growth are assumed to follow a Markov chain with unknown transition probabilities.

The specification of the model allows for four alternative states in which energy consumption is Granger-causal for output growth, output growth is Granger-causal for energy consumption, both variables are Granger causal for each other and both variables are Granger non-causal for each other, respectively. The empirical investigation is carried out using quarterly U.S. real GDP and total final energy consumption data which cover the period between 1975:QI–2009:QIV. Our results from standard Granger causality test based on a linear VAR model show that total energy consumption does not have any predictive power for output growth. However, our findings from the estimation of the Markov switching VAR model provide evidence that total energy consumption has predictive content for real economic activity. More importantly, the causality running from total energy consumption to output growth appears to exist only during the periods of economic downturn and energy crisis.

Looking at the reverse causality that runs from output growth to energy consumption, we find that the output growth has predictive power for total energy consumption and this predictive ability clearly disappears during the periods of recession and rises again during the periods of expansion. Different from the empirical studies which report that there is an absence of causality between the related series, overall we find that both series have predictive power for each other during different regimes over the sample period under study. As a matter of fact, the smoothed probability of each series being Granger non-causal for the other one is found to be quite low almost over the whole sample period.

The remainder of the thesis consists of three separate yet related empirical studies: Chapter 2: Real Effects of Inflation Uncertainty in the U.S., Chapter 3: The Asymmetric Effects of Monetary Policy in the U.S.: An Instrumental Variables Estimation in Markov Switching Model and Chapter 4: Markov Switching Causality and the Energy-Output Relation in the U.S.. Conclusions and implications of each chapter and conclusions of the thesis are addressed in Chapter 5: Conclusion.

Chapter 2

Real Effects of Inflation Uncertainty in the U.S.

2.1 Key Findings

In this chapter, we empirically investigate the effects of inflation uncertainty on output growth for the U.S. using both monthly and quarterly data over 1960-2009. Employing a Markov regime switching approach to model output dynamics, we show that inflation uncertainty obtained from a Markov regime switching GARCH model exerts a negative and regime dependent impact on output growth. In particular, we show that the negative impact of inflation uncertainty on output growth is almost 2 times higher during the low growth regime than that during the high growth regime. We verify the robustness of our findings using quarterly data.

2.2 Introduction

Many economists agree that sustainable growth and low and stable inflation constitute two of the fundamental objectives of the macroeconomic policymakers. A reason behind this conviction is that high and unstable inflation leads to an increase in inflation uncertainty distorting the efficient allocation of resources. Hence, it is not surprising that the linkages between inflation, inflation uncertainty and economic growth have been extensively investigated on theoretical and empirical grounds.

Friedman (1977) emphases two arguments. First, he claims that an increase in the inflation level raises inflation uncertainty.[1] The rationale behind this view is the actions of the policymakers who use discretionary policy tools in pursuit

[1] However, Cukierman and Meltzer (1986) assume a reverse causation between inflation rate and inflation uncertainty.

of lowering inflation end up widening the gap between actual and anticipated inflation generating inflation uncertainty.[2] Second, he indicates that higher uncertainty distorts the information content of prices which plays a fundamental role in efficient allocation of resources.[3] In particular, it is argued that during the periods of high inflation volatility it is harder to extract information about the relative prices of goods rendering managers unable to detect profitable investment opportunities. Furthermore, during the periods of high uncertainty, external funds become prohibitively expensive due to the heightened asymmetric information problems causing managers to delay or cancel fixed investment projects. Lower investment, in turn, hinders output growth. In summary, high inflation and high inflation uncertainty affect the economy adversely.

However, despite all the efforts expended by the researchers, the empirical literature does not allow us to arrive at a firm conclusion on the association between inflation uncertainty and output growth. While some researchers provide evidence that inflation uncertainty affects output growth negatively, some others show that there is no or even a positive association. In general, it appears that empirical results are sensitive to various factors including the sample period, model specification and the proxies for inflation uncertainty that researchers use.

A review of the literature shows that some studies take advantage of survey data and employ the dispersion across forecasters' forecasts as a measure of uncertainty while others use a simple moving standard deviation of the inflation series at the same frequency as the data. Alternatively, researchers implement a GARCH model to mimic the volatility clustering often found in high-frequency

[2] Ball (1992) formalizes the relation between inflation and inflation uncertainty with a model in which a rise in inflation raises uncertainty about future monetary policy, and thereby increases uncertainty about future inflation. He points out that when inflation is high, policymakers may apply disinflation policies or they fear of the recession that would result and may not trigger such policies. Since economic agents do not know the future preferences of policymakers, they do not know whether disinflation will occur.

[3] Beaudry et al. (2001) show that monetary instability exerts a negative effect on the allocation of resources across firms via price uncertainty channel.

series and use the generated conditional variance as a proxy for uncertainty. All these three methodologies are criticized on various grounds. For instance, uncertainty proxies generated from survey data may not be able to gauge the true level of uncertainty and potentially contain sizable measurement errors. In the case of standard deviation based measures, it is pointed out that expected fluctuations in inflation rate will cause an increase in this measure although there is no uncertainty in the economic environment (Jansen (1989), Grier and Perry (2000)).[4]

Despite the attractiveness of GARCH methodology as a tool to generate a measure of uncertainty, it is well known that the standard ARCH/GARCH models take the economic structure as given and disregard the potential structural instabilities induced by regime changes over time. For instance, several researchers point out that when regime shifts are overlooked standard GARCH models may overstate the persistence in variance (Lamoureux and Lastrapes (1990); Hamilton and Susmel (1994); Gray (1996)) and understate the level of uncertainty (Giordani and Soderlind (2003)).[5] To that end, Evans and Wachtel (1993) infer that, models which do not account for regime changes in the inflation process underestimate not only the level of uncertainty but also its effect on economic growth.

In the light of the above discussion and the previous empirical evidence which shows that both output growth and inflation series are subject to regime shifts, we start our investigation by testing for the presence of regime shifts in the inflation series prior to committing to a particular approach to generate our measure of uncertainty. We also carefully investigate the properties of the output growth series because the true impact of inflation uncertainty on economic growth cannot be properly captured should we fail to account for the presence of regime shifts

[4] Cukierman and Wachtel (1979), Cukierman (1983) show that inflation uncertainty measured by the dispersion of inflation forecasts gathered from survey data and standard deviation of inflation are highly correlated.

[5] To capture regime shifts in the conditional variance one can also apply smooth transition GARCH models (see for example Silvennoinen and Teräsvirta (2009)).

in output growth. We carry out our investigation using monthly U.S. industrial production and inflation data which cover the period between 1960:01–2009:12. We also use quarterly GDP series over 1960:QI–2009:QIV to check for the robustness of our findings.

Our results can be summarized as follows. We find that both inflation and output series exhibit regime dependence. Hence, we first generate inflation uncertainty using a Markov switching GARCH model and in the second stage we allow both inflation and inflation uncertainty to exert a regime dependent impact on output growth.[6] As a result, we find that inflation uncertainty has a negative impact on output growth during both regimes. Our investigation also shows that the magnitude of inflation uncertainty on output growth changes significantly across low- and high-growth regimes. In particular, we find that inflation uncertainty has a greater negative impact on output growth during the low growth regime. In fact, the impact of inflation uncertainty on output growth in a low growth regime is about 2 times greater than that in a high growth regime. We examine the robustness of our results by estimating a similar model using quarterly GDP growth series. Controlling for the state of the business cycles, we observe that inflation uncertainty exerts a negative and significant impact on economic growth during the periods of contraction. However, we find that the impact of inflation uncertainty on economic growth is negative but insignificant in the periods of expansion. Furthermore, we observe that the regimes captured by the model on quarterly data fit well with the periods of contraction and expansion as defined by NBER. This finding provides further support to our empirical approach.

The remainder of the chapter is organized as follows. Section 2.3 provides a brief summary of the empirical literature. Section 2.4 presents the Markov

[6] Evans and Wachtel (1993) show that inflation forecasts based on survey data were not significantly different from forecasts generated by a Markov switching model. Also, Chua et al. (2011) suggest that models that account for heteroscedastic errors in inflation produce uncertainty proxies which track the behavior of the survey measure well.

switching GARCH methodology, the empirical model and the data. The empirical results are discussed and some specification tests are presented in Section 2.5. Section 2.6 concludes the chapter. The results are presented in the Appendix.

2.3 Literature Review

Following Okun (1971) and Friedman (1977), several researchers have examined the impact of inflation uncertainty on output growth for different countries. For example, Darrat and Lopez (1989) investigate the relation between inflation uncertainty and output growth for Latin American countries. Ma (1998) scrutinizes the same question for Colombia, Bohara and Sauer (1994) and Grier and Grier (2006) examine it for Germany and Mexico, respectively. Fountas et al. (2002) and Wilson (2006) examine the data from Japan. Fountas et al. (2006) investigate the link between inflation uncertainty and output growth for the G7 countries. Conrad et al. (2010) examines the link between inflation, output growth and their corresponding volatilities using the United Kingdom data. Several other researchers, including Judson and Orphanides (1999), Elder (2004), Conrad and Karanasos (2010) scrutinize the U.S. data in search for understanding the effects of inflation uncertainty on output growth.

However, results seem to depend both on the method used to generate a measure of inflation uncertainty and on the model employed to examine the impact of uncertainty on output growth. In what follows, we first discuss the alternative methods that researchers use to generate a proxy for inflation uncertainty and then we briefly comment on how to model the association between inflation uncertainty and output growth.

2.3.1 Measuring inflation uncertainty

Researchers implement different strategies to measure inflation uncertainty. One approach is to exploit survey data and use the dispersion of inflation forecasts across the estimates of the surveyed forecasters as a measure of inflation uncertainty. Researchers using survey based uncertainty proxies in general, report that real economic activity is negatively affected by inflation uncertainty. For instance Hafer (1986) provides evidence that the dispersion across the individual forecasts has a negative effect on output for the U.S.. Hayford (2000) and Davis and Kanago (1996) show that the dispersion of inflation and unemployment forecast reduce output growth, at least temporarily. Holland (1988), using survey data, concludes that the adverse effects of inflation uncertainty on real GNP may be permanent. Although this approach is appealing, a survey based uncertainty measure may not gauge the true level of uncertainty as such a measure potentially contains sizable measurement errors.

Alternatively, researchers use the standard deviation or moving standard deviation of the inflation series, at the same frequency as the data, to proxy for inflation uncertainty. However, this approach imposes equal weights on all past observations and gives rise to substantial serial correlation in the summary measure. It is also pointed out that standard deviation is a measure of variability and expected fluctuations in inflation rate will cause an increase in this uncertainty measure although there is no uncertainty. This method, due to its simplicity, is often implemented in the literature with mixed results. Barro (1996) using standard deviation of inflation as a measure of inflation uncertainty on a data set that includes over 100 countries from 1960 to 1990 fails to provide any significant effects of inflation uncertainty on growth. Similarly, Clark (1997) with cross-country growth regression analysis reports that there is no robust relation between inflation uncertainty and growth. In contrast, using a cross country panel data, Judson and Orphanides (1999) stress that inflation and inflation uncertainty are both significantly and negatively correlated with output growth.

Researchers also extensively use ARCH/GARCH methodology and exploit the ability of these models to mimic the volatility clustering often found in the high-frequency series. In fact several researchers use ARCH/GARCH models to examine the impact of inflation uncertainty on output growth. For instance, Fountas et al. (2004) generate a proxy for inflation uncertainty by employing an EGARCH model and they show that inflation uncertainty exerts no significant negative output effects for Germany, the Netherlands, Italy, Spain and France except for the United Kingdom. An important caveat against the use of proxies obtained from ARCH/GARCH methodology is the model dependence of the generated series. Hence, if the underlying series were to exhibit structural breaks, the model must be modified to incorporate these shifts in the series. Otherwise the generated uncertainty proxy would be measured with error and would lead to wrong conclusions.

Another possible approach is to employ bivariate GARCH models so that one examines the behavior of inflation and output series simultaneously eliminating the need for a generated regressor. For instance, Fountas et al. (2006), using a bivariate GARCH model of inflation and output growth, show that nominal uncertainty deters output growth in almost all of the G7 countries. Jansen (1989), implements a bivariate ARCH-M model for inflation and real output growth, and his results cannot refute an adverse effect of nominal uncertainty on growth. Grier et al. (2004) employ bivariate GARCH-M models for inflation and output growth series and show that an increase in inflation uncertainty significantly reduces real output growth in the U.S.. Elder (2004) confirms this result for the U.S. by using a multivariate GARCH-M model and adds that an average shock to inflation uncertainty lowers output growth over three months by about 22 basis points.

Several other researchers use more sophisticated versions of ARCH/GARCH models. Wilson (2006) performs a bivariate EGARCH-M model while allowing the conditional variance to react to the direction of change in inflation and shows that increased inflation uncertainty is detrimental to the growth in Japanese economy.[7] Nevertheless, there are various problems associated with the use of bivariate GARCH models. For instance, modeling is complicated and there are convergence problems which leads one to use parsimonious models. There is also the question of identification because, eventually, a bivariate model is a reduced form equation so that the conditional variance of inflation might embody the volatility that arises from output growth.[8]

One common weakness of all the approaches that we discussed above is that none of the uncertainty measures (measures based on surveys, standard deviation or ARCH/GARCH models) of inflation uncertainty are sensitive to the direction of changes in inflation. In particular, if the underlying series contain regime shifts, these methods would not capture the true nature of the impact of inflation uncertainty on growth. In fact many macroeconomic time series, possibly due to abrupt policy changes, exhibit regime shifts in their behavior and they behave differently during economic downturns, when resources are under-utilized, in contrast to expansionary periods as the economic agents use factors of production more efficiently. This is an important issue and several researchers point out that models which do not account for regime changes in the underlying series lead to wrong conclusions.

To scrutinize the economic series that display different behavior as the economy moves through the business cycle, researchers developed the so-called regime switching models. This class of models are developed in Goldfeld and Quandt (1973) which later led to the introduction of the Markov switching models by

[7] Fountas et al. (2002) also conclude that inflation uncertainty impedes output growth in Japan using a bivariate GARCH model.

[8] Harvey et al. (1994) argue that multivariate generalization of ARCH model can be difficult to estimate and interpret. They suggest a multivariate stochastic volatility model where factor loading matrix was identified by rotating the estimated factors. Arestis and Mouratidis (2005) adopted the methodology suggested by Harvey et al. (1994) to model the trade-off between inflation and output-gap variability for ten European Union countries.

Hamilton (1989). Subsequently, Hamilton and Susmel (1994) and Cai (1994) proposed models which allow the error component to follow Markov switching ARCH effects. These models and their variants are extensively used in the literature to examine the behavior of macroeconomic series which often contain non-linearities, asymmetries and regime shifts.

Within the context of our investigation, some studies raised this problem. For instance, Evans and Wachtel (1993), develop a Markov switching model that explains the behavior of inflation. They decompose inflation uncertainty into two components where the first one portrays the certainty equivalence component reflecting the variance of future shocks to the inflation process and the second one captures uncertainty about the future changes in the inflation regime. They then show that the second component of uncertainty which is regime dependent lowers real economic activity. Wu et al. (2003) employ the time varying parameter model of Kim (1993) with Markov-switching heteroscedasticity for the U.S. economy. Their results suggest that uncertainty due to the changing coefficients hinders growth of real GDP but uncertainty concerning heteroscedasticity in disturbances has an insignificant effect on growth.[9]

In this study, observing that the underlying inflation series embody regime shifts, we choose to implement a two stage modeling approach due to reasons raised above. We apply the Markov switching GARCH methodology which allows for regime shifts in inflation series to capture a proxy for inflation uncertainty as proposed by Gray (1996). We do so because the generalized regime switching (GRS) model suggested by Gray (1996) is superior to other approaches as it allows one to estimate an uncertainty series independent of the entire history of the unobserved state variable. In section 2.4.2 we provide the details of our

[9]Similarly, using state-dependent conditional variance model of Brunner and Hess (1993), Lee and Ni (1995) also conclude that inflation uncertainty significantly negatively correlated with economic activities in the U.S. economy.

approach.

2.3.2 Modeling output growth and inflation variability

There is a similar problem regarding the model that one employs to capture the impact of inflation uncertainty on output growth. If the output growth series follows a regime switching process, a linear reduced form regression model will not capture the true account of the association between the variables. In that sense, it is likely that those studies in the literature which do not explore the possibility of changing output regimes may have arrived at misleading conclusions. Hence, prior to investigating the growth uncertainty relation, we test the null hypothesis of linearity of output growth against the regime switching alternative. Observing that the output series is characterized by regime shifts, we resort to a Markov regime switching model. The advantage of this model is that it allows us to determine the effects of inflation uncertainty across high and low growth regimes as we discuss in our empirical section below.

2.4 Data and Econometric Methodology

2.4.1 Data

To empirically analyze the link between inflation uncertainty and output growth, we use monthly consumer price index (CPI) and monthly seasonally adjusted industrial production index (IPI) for the U.S. economy. Data are obtained from the International Financial Statistics of the International Monetary Fund and spans the period 1960:01–2009:12. In the second part of the investigation we check for the robustness of our results using quarterly real GDP and CPI series that cover the period 1960:QI–2009:QIV.

We measure output growth (y_t) by the first difference of the logarithm of the industrial production index $\left[y_t = log\left(\frac{IPI_t}{IPI_{t-1}}\right)\right]$. Similarly, we compute the inflation rate (π_t) as the first difference of the logarithm of the consumer price index

$\left[\pi_t = log\left(\frac{CPI_t}{CPI_{t-1}}\right)\right]$. We check for the presence of GARCH effects in the inflation series by applying Lagrange multiplier test. This test reveals significant GARCH effects in the inflation series. We then estimate a simple GARCH(1,1) model for inflation where the conditional variance follows $h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$. As the sum of the coefficients of ARCH and GARCH terms $(\alpha_1 + \alpha_2)$ from this model is very close to one, we suspect that the effects of past shocks on current variance is very strong; i.e. the persistence of volatility shocks is strong. In this context, Lamoureux and Lastrapes (1990) and Gray (1996) point out that the high volatility persistence may be due to the regime shifts in the conditional variance. In such circumstances, the use of a single regime model where there are regime shifts in the data is likely to yield parameters that show high volatility persistence.

To test for the presence of regime shifts in both inflation and output growth series, we implement a number of tests. Standard likelihood ratio test cannot be used to check for the null of linearity against the alternative of Markov switching model. The reason is that under the null of linearity the parameters of the transition probabilities are unidentified as the scores with respect to the parameters of interest are equal to zero and the information matrix is singular. We implement tests proposed by Hansen (1992, 1996) which overcome this problem. In addition, Psaradakis and Spagnolo (2003) suggest selecting the number of regimes using the Akaike information criteria (AIC), Bayesian information criterion (BIC) and three-pattern method (TPM).[10] In their study, using Monte Carlo analysis, Psaradakis and Spagnolo (2003) find that selection procedures based on the TPM and the AIC are generally successful in choosing the correct number of regimes, provided that the sample size and parameter changes are not too small.

[10] Granger et al. (1996) and Sin and White (1996) argue that such methods are more appropriate for model selection than hypothesis testing procedures. The use of complexity-penalized criteria in model selection has been studied by Leroux (1992), Poskitt and Chung (1996) and Zhang and Stine (2001) among others. More concretely, Zhang and Stine (2001) show that any weakly stationary process generated by a Markov regime switching model has a linear autoregressive ARMA representation. Psaradakis and Spagnolo (2003) using Monte-Carlo experiments investigate the properties of complexity-penalized criteria in determining the number of states.

Insert Table 1 about here.

The results of the Hansen test are presented in Table 1. The results show that the Hansen test rejects the null of linearity both for monthly and quarterly inflation and industrial production growth series.[11] Exception to this is the quarterly GDP growth series where the null of linearity is not rejected. This rejection may be due to the availability of smaller number of observations. In addition, we use AIC as suggested by Psaradakis and Spagnolo (2003), which provides evidence that both series contain two regimes. As a result of this investigation, we implement models that accommodate the presence of regime shifts in the inflation and output growth series as we investigate the linkages between inflation uncertainty and output growth.

2.4.2 Generating Inflation Uncertainty: Markov Switching GARCH Approach

To compute a measure of inflation uncertainty we apply the Markov switching GARCH methodology as proposed by Gray (1996). So that we can properly capture the regime shifts in the inflation series. We do so because; the generalized regime switching (GRS) model suggested by Gray (1996) is independent of the entire history of the unobserved state variable $S\{t\}$. More concretely, Cai (1994) and Hamilton and Susmel (1994) argue that it is not possible to estimate a regime switching GARCH model due to the dependence of the model on the entire history of the data. This is so because, a regime switching GARCH model at time t depends directly on the unobserved state $S\{t\}$ and indirectly on the history of $S\{t\}$ (i.e., $\{S_{t-1}, S_{t-2,...,}S_1\}$). Gray (1996) solves the problem of path dependence as described in equation (3) below.

We use Markov switching GARCH(1,1) approach to model the conditional

[11] The Hansen test treats the transition probabilities as nuisance parameters and maximize the likelihood ratio test for the null hypothesis of one state over all admissible values of the nuisance parameters.

mean and the conditional volatility of the inflation process while we allow the series to switch between high- and low-inflation regimes. This model is superior to standard ARCH models as its GARCH term can capture the persistence parsimoniously as it takes into account the regime shifts in the series. In this set up, conditional mean of inflation follows an AR(p) process:

$$\pi_{it} = \theta_{0i} + \sum_{j=1}^{p} \theta_{ji}\pi_{t-j} + \varepsilon_t, \tag{1}$$

where $i = 1, 2$ and

$$\pi_{it} \mid \Omega_{t-1} \sim \begin{cases} N\left(\theta_{01} + \sum_{j=1}^{p} \theta_{j1}\pi_{t-j}, h_{1t}\right) & \text{w.p. } p_{1t}, \\ \\ N\left(\theta_{02} + \sum_{j=1}^{p} \theta_{j2}\pi_{t-j}, h_{2t}\right) & \text{w.p. } 1 - p_{1t} \end{cases}$$

and

$$\varepsilon_t \mid \Omega_{t-1} \sim N\left(0, h_{it}\right), \text{i=1,2.}$$

In equation (1) i indicates the regime, π_t represents the inflation process and h_t denotes the conditional variance of inflation. Here, $p_{1t} = Pr\left(S_t = 1 \mid \Omega_{t-1}\right)$ is the probability that the unobserved state variable S_t is in regime 1 conditional on the information set available at time $t-1$ (Ω_{t-1}).[12]

Following Hamilton (1989) regime switches are assumed to be directed by a

[12]The t^{th} observation is classified in the i^{th} state if the smoothed probability of the occurrence of state i is greater than 0.5 for this observation.

first-order Markov process with fixed transition probabilities:[13]

$$\begin{aligned}
&Pr\left[S_t = 1 \mid S_{t-1} = 1\right] = P_{11},\\
&Pr\left[S_t = 2 \mid S_{t-1} = 1\right] = 1 - P_{11},\\
&Pr\left[S_t = 2 \mid S_{t-1} = 2\right] = P_{22},\\
&Pr\left[S_t = 1 \mid S_{t-1} = 2\right] = 1 - P_{22}.
\end{aligned} \tag{2}$$

In his regime-switching GARCH model, Gray (1996) aggregates the conditional variances from the two regimes based on the regime probabilities at each step. In doing so, the aggregate conditional variance is not path dependent but it is still regime dependent. Then it can be used to calculate the conditional variance of the next time period. In this framework, the conditional variance, which follows a GARCH(1,1) process, can be expressed as:

$$h_{it} = \alpha_{0i} + \alpha_{1i}\varepsilon_{t-1}^2 + \alpha_{2i}h_{t-1} \tag{3}$$

where

$$\varepsilon_{t-1} = \pi_{t-1} - \left[p_{1t-1}\mu_{1t-1} + \left(1 - p_{1t-1}\right)\mu_{2t-1}\right],$$

$$\mu_{it-1} = \theta_{0i} + \sum_{j=1}^{p} \theta_{ji}\pi_{t-j-1}$$

and

$$\begin{aligned}
h_{t-1} = {} & p_{1t-1}\left(\mu_{1t-1}^2 + h_{1t-1}\right) + \left(1 - p_{1t-1}\right)\left(\mu_{2t-1}^2 + h_{2t-1}\right) - \\
& \left[p_{1t-1}\mu_{1t-1} + \left(1 - p_{1t-1}\right)\mu_{2t-1}\right]^2.
\end{aligned}$$

The non-negativity of h_t for all t, is ensured by assuming $\alpha_{0i} \geq 0$, $\alpha_{1i} \geq 0$ and $\alpha_{2i} \geq 0$. The necessary condition for stationarity is $\alpha_{1i} + \alpha_{2i} < 1$ as in a single-regime GARCH(1,1) model. Here, note that all parameters of the conditional variance of inflation are state-dependent.

[13] For instance, if the economy is in the first state in the previous period ($S_{t-1} = 1$), P_{11} is the probability of switching to the first state in the present period ($S_t = 1$).

We use the maximum likelihood methodology to estimate the model. The likelihood function for this generalized regime switching model is derived by Gray (1996) and takes the form:

$$L = \sum_{t=1}^{T} log \left[p_{1t} \frac{1}{\sqrt{2\Pi h_{1t}}} exp \left\{ - \frac{(\pi_t - \mu_{1t})^2}{2h_{1t}} \right\} + (1 - p_{1t}) \frac{1}{\sqrt{2\Pi h_{2t}}} exp \left\{ - \frac{(\pi_t - \mu_{2t})^2}{2h_{2t}} \right\} \right],$$

where the regime probability p_{1t} follows a simple nonlinear recursive system:

$$\begin{aligned} p_{1t} = P_{11} & \left[\frac{f_{1t-1} p_{1t-1}}{f_{1t-1} p_{1t-1} + f_{2t-1} (1 - p_{1t-1})} \right] + \\ (1 - P_{22}) & \left[\frac{f_{2t-1} (1 - p_{1t-1})}{f_{1t-1} p_{1t-1} + f_{2t-1} (1 - p_{1t-1})} \right]. \end{aligned} \tag{4}$$

Assuming conditional normality, the conditional distribution of inflation, f_{it} where $i = 1, 2$, can be written as:

$$f_{it} = f(\pi_t \mid S_t = i, \Omega_{t-1}) = \frac{1}{\sqrt{2\Pi h_{it}}} exp \left\{ - \frac{(\pi_t - \mu_{it})^2}{2h_{it}} \right\}.$$

The conditional variance of the inflation process obtained from the above procedure, is next used as a proxy for inflation uncertainty. It should be noted that the measure of inflation uncertainty that we use in the second stage regression is a generated regressor by the nature of its construction. Pagan (1984) and Pagan and Ullah (1988) argue that the generated regressor measures the true but unobserved regressor with error, hence biasing the coefficient estimates or the standard errors in the second step.[14] As a solution to the errors in variables problem connected to the use of a generated regressor, Pagan and Ullah (1988) suggest an instrumental variable estimation procedure. However, in our case where the generated regressor is the conditional variance of inflation estimated from a Markov Switching GARCH model, it is not possible to use the standard instrumental

[14]It could be more efficient to use an approach which allows the researcher to examine the relation between inflation, inflation uncertainty and growth simultaneously as in a GARCH-in-mean model but to my knowledge Markov switching GARCH-in-mean models have not been established completely yet.

variable estimation approach where the lags of the variable are used as instruments. The reason is that the conditional variance of inflation is a function of all previous history and hence there are no available instruments which can be used instead. In this case, Pagan and Ullah (1988) propose using specification tests to see whether the GARCH-type model is correctly specified.[15] In section 2.5.4, we run diagnostic tests to that end.

2.4.3 Modeling Output Growth Series: Markov Switching Approach

Prior to estimating the impact of inflation uncertainty on output growth, we must scrutinize the behavior of the output growth series. In particular we must determine if the behavior of the output growth series exhibit linear or non-linear characteristics. Given the above evidence in Table 1 we construct an autoregressive Markov switching model for output growth rate to identify the low and high growth periods for the U.S. economy. The model takes the following form:

$$y_t = \phi_{0i} + \sum_{j=1}^{m} \beta_{ji} y_{t-j} + \xi_t, \tag{5}$$

$$\xi_t \mid \Omega_{t-1} \sim N\left(0, \sigma_{0i}^2\right), \text{i=1,2 regimes}$$

where y_t is the growth rate of output at time t. The error term, ξ_t, is assumed to be conditionally normal with a zero mean and a variance, σ_{0i}^2, which is subject to regime shifts. We set the number of lags (m) for the lagged dependent variable to 3 based on the SIC.

Table 2 provides the parameter estimates of the benchmark model in equation (5). These results suggest that during State 1, the U.S. economy experiences a steady-state output growth rate of around 0.24 per cent and that during State 2, output growth declines at a steady-state rate of around 0.13 per cent.[16] Given

[15] See Ruge-Murcia (2003) who follows this approach to assess whether the GARCH(1,1) model in his study adequately captures the conditional heteroscedasticity in the U.S. unemployment data.

[16] The steady state growth rate is $\frac{\phi_{01}}{1-(\beta_{11}+\beta_{21}+\beta_{31})}$ in State 1 and $\frac{\phi_{02}}{1-(\beta_{12}+\beta_{22}+\beta_{32})}$ in State 2.

these figures, we therefore classify State 1 as the high growth regime and State 2 as the low growth regime.[17]

Insert Table 2 about here

Now that we identified the low and high growth periods for the U.S. economy, we can implement a full blown Markov regime switching framework which incorporates the impact of inflation and inflation uncertainty. Using this framework, our aim is to capture the regime dependent impact of inflation uncertainty on the output growth as we control for periods of expansion and contraction in the economy.[18] The specification for our baseline model takes the following form:

$$y_t = \phi_{0i} + \sum_{j=1}^{m} \beta_{ji} y_{t-j} + \sum_{j=1}^{k} \varphi_{ji} \pi_{t-j} + \delta_{0i} \sigma_{\pi_{t-1}} + \xi_t, \tag{6}$$

$$\xi_t \mid \Omega_{t-1} \sim N\left(0, \sigma_{0i}^2\right), \text{i=1,2 regimes,}$$

where y_t is the growth rate of output at time t and $\sigma_{\pi_{t-1}}$ is the first lag of inflation uncertainty. The model includes a lagged rather than a contemporaneous measure of uncertainty as we aim to examine the impact of inflation uncertainty on output growth without being subject to the endogeneity problem.[19] The model also includes lagged inflation rate to control for the level effects of inflation on output growth. Last but not least, the lagged dependent variable allows us to control for the persistence of output growth.

[17]According to the estimated smoothed probabilities, 1960:02-1960:03, 1960:11-1961:05, 1961:09-1962:02, 1964:10-1964:12, 1967:02-1967:08, 1969:11-1970:01, 1970:09-1971:02, 1971:08-1971:09, 1974:11-1974:12, 1976:11-1977:02, 1978:01-1978:04, 1980:04-1981:02, 1981:09-1982:04, 1996:01-1996:02, 1998:06-1998:08, 2005:09-2005:11, 2008:08-2009:01, 2009:07-2009:08 are identified as low growth periods. The remaining periods are recognized as high growth periods.

[18]Despite the fact that the Markov regime switching model displays the volatility clustering characteristics in the output growth series and allows the variance to change over the sample period (see, Timmermann (2000)), for the monthly output growth series a Markov switching GARCH model can also be used.

[19]The inflation uncertainty measure could capture an endogenous response to an exogenous shock to either inflation or output growth where causation from inflation uncertainty to economic growth is not clear. This is so because a negative demand or supply shock will increase uncertainty. But the level of inflation depends on the nature of the shock; i.e supply or demand shock. So an unobservable shock can lead to an increase in the correlation between output growth and inflation uncertainty.

Given the above evidence, we allow all coefficients of equation (6), which are indexed by i, to vary over the high and low growth regimes. The error term ξ_t in equation (6), is assumed to be conditionally normal with a zero mean and a variance, σ_{0i}^2, which is also subject to regime shifts. The variance of the error term, σ_{0i}^2, is also allowed to change across the two regimes since the variability of output in recessions is generally different from the variability of output in expansions. In this model, the key coefficients of interest are those associated with lagged conditional variance of inflation (δ_{01} and δ_{02}) which we use to test the Friedman hypothesis.

2.5 Empirical Results

2.5.1 Markov Switching GARCH model for Inflation

Table 3 reports the maximum likelihood estimates of the Markov Switching GARCH(1,1) model for inflation. The mean inflation rate is modeled as an AR(1) process as determined by the minimum SIC. Results show that coefficients in the mean equation for inflation are highly significant for both regimes. In State 1, the implied monthly inflation rate is around 0.21 per cent and in State 2, that rate is around 0.55 per cent.[20] Thus, State 1 is identified as the low inflation regime and State 2 is recognized as the high inflation regime.

Insert Table 3 about here

When we inspect the conditional variance of inflation over the two regimes we observe that all parameters are highly significant. Within each regime the GARCH processes are stationary as ($\alpha_{1i} + \alpha_{2i} < 1$). In addition, high inflation regime is more sensitive to recent shocks (i.e. $\alpha_{12} > \alpha_{11}$). Moreover, high inflation regime is more persistent to shocks than low inflation regime (i.e. $\alpha_{22} > \alpha_{21}$). This means that the effect of individual shocks do not die quickly in the high inflation regime. It is worth noting that a single regime GARCH model could not

[20] The implied monthly inflation rate is equal to $\frac{\theta_{01}}{1-\theta_{11}} = 0.21\%$ in State 1 and $\frac{\theta_{02}}{1-\theta_{12}} = 0.55\%$ in State 2.

capture this difference.

We plot the conditional variances of inflation in high inflation and low inflation regimes in Figure 1. In line with the Friedman hypothesis, both series of inflation uncertainty increase in the high inflation periods which are shaded in Figure 1. However, inflation uncertainty in the high inflation regime (H2) is higher than the inflation uncertainty in the low inflation regime (H1).

Insert Figure 1 about here

The estimates of the transition probabilities P_{11} and P_{22} are 0.988 and 0.987, respectively, which implies the presence of strong persistence of both regimes. Similar to Gray's findings, within-regime persistence of conditional variance is lower than the persistence of a single-regime GARCH model. To be more specific, the sum of the coefficients of ARCH and GARCH terms $(\alpha_{1i} + \alpha_{2i})$ are 0.572 in State 1 and 0.755 in State 2 constituting an advantage of the regime switching model over the single-regime GARCH model.

Insert Figure 2 about here

For comparison purposes in Figure 2 we plot the implied conditional variances of inflation generated from a single-regime GARCH(1,1) model and that from the Markov switching GARCH(1,1) model. This figure shows us that inflation uncertainty obtained from the single-regime GARCH(1,1) model generally underestimates uncertainty at high inflation periods which are shaded. The reason is that the simple GARCH(1,1) model does not account for the structural changes in the inflation process.

2.5.2 Effects of Inflation Uncertainty on Output Growth

Having identified the low and high growth periods for the U.S. economy as in Section 2.4.3, we estimate equation (6) to understand the impact of inflation uncertainty on output growth. The results of the estimation are presented in

Table 4 and the estimated smoothed probabilities for State 1 are plotted in Figure 3. As depicted in Figure 3, State 1 coincides with high growth periods and State 2 coincides with low growth periods which are observed in Section 2.4.3.

Insert Figure 3 about here

Insert Table 4 about here

In Table 4, we observe that the impact of inflation uncertainty over both regimes is significant and negative. The effect of inflation uncertainty in regime one (δ_{01}), the high growth regime, is -0.048 and significant at the 10% level. Alternatively, the impact of inflation uncertainty on output in regime two (δ_{02}), the low growth regime, is -0.090 and significant at the 10% level. That is, under the same conditions when the inflation uncertainty increases by 1 percentage point, the monthly output growth rate decreases by -0.048 percentage points in a high growth regime, while in a low growth regime the figure can reach -0.090 percentage points. In other words, the magnitude of the adverse impact of inflation uncertainty on monthly output growth in the low growth regime is about 2 times greater than that in the high growth regime. Moreover, it can be said that the adverse impact of inflation uncertainty is quite big as 1 percentage point increase in annual inflation uncertainty leads to a reduction in annual output growth rate by 0.576 percentage points in a high growth regime and 1.080 percentage points in a low growth regime. This is an interesting finding and has not been shown in the existing empirical literature: the impact of inflation uncertainty on output growth is negative and this negative effect varies depending on the growth phase of the economy. In particular, the negative impact of inflation uncertainty on real economic activity is more profound during periods of low growth. These findings support the Friedman hypothesis which claims that inflation uncertainty exerts a negative impact on output growth. Another finding that arises from Table 4 is the direct impact of inflation on the growth rate of output. The effect of inflation on economic performance is negative and but it is not significantly different from zero in both regimes.

2.5.3 Robustness Analysis

To investigate the robustness of our results, we estimate the model in equation (6) using quarterly real GDP series. The data cover the period between 1960:QI–2009:QIV. We measure the growth rate of real GDP in period t, Y_t, as the first difference of the logarithm of real GDP (RGDP) $\left[Y_t = log\left(\frac{RGDP_t}{RGDP_{t-1}}\right)\right]$. An interesting advantage of working with quarterly data is that we can compare the estimated dates for low- and high-growth phases of the economy with the dates provided by the NBER.[21] A match between the implied dates for contraction that we infer from the Markov switching model with that announced by the NBER would indicate a success. As a result, this will provide more conviction to the results regarding the impact of inflation uncertainty on output growth.

Insert Table 5 about here

Table 5 provides the NBER dates covering the period under investigation in this study. We see that between 1960-2009, the U.S. economy experienced eight recessionary episodes. In this empirical investigation, we use the first difference of the logarithm of the quarterly consumer price index to analyze the direct effects of inflation on economic growth and to match the frequency of output growth series. However, we continue to use inflation uncertainty proxy obtained from the monthly data after we aggregate it to quarterly frequency.[22] Based on the SIC, we select the number of lags for the lagged dependent variable as 3 and the number of lags for inflation and inflation uncertainty as 1. Table 6 presents the results for our model in equation (6).

Insert Table 6 about here

[21] Recession is generally defined as a period when GDP falls for at least two consecutive quarters. However NBER defines an economic recession as: “a significant decline in economic activity spread across the country, lasting more than a few months, normally visible in real GDP growth, real personal income, employment (non-farm payrolls), industrial production, and wholesale-retail sales.”

[22] It is well established in the time series literature, ARCH/GARCH models tend to yield more efficient estimates in case of the data with high frequency. Thus, in the robustness check we use the monthly conditional variance of inflation series by aggregating to quarterly frequency.

The smoothed probabilities for this model are shown in Figure 4. When we examine the smoothed probabilities of the occurrence of State 1 we observe that our model captures the economic contractions provided by the NBER which we report in Table 5 over 1960, 1980, 1981/1982, 1990/1991, 2000/2001, 2008/2009. It also picks up some additional turning points in the data as periods of contraction. However, following the censoring rule of Harding and Pagan (2002), we assume that a completed cycle (peak to peak or through to through) last at least five quarters.[23] Thus, we cannot classify these additional episodes as periods of recession. Additionally, inspecting the data closely, we can observe that the additional dates which the model suggests as periods of contraction are due to rapid changes in output growth series and do not necessarily imply that the model is improperly specified. Overall, we think that the model succeeds in capturing the business cycle peaks and troughs in the U.S. economy over the period of our investigation as dated by NBER.

Insert Figure 4 about here

We next turn to examine how economic growth is affected by inflation uncertainty and whether this effect would change across periods of contraction and expansion. As we can observe from Table 6, results for the quarterly data are stronger compared to the case of monthly data. This may be due to the fact that industrial production represents only a portion of the output generated in the economy whereas GDP represents total output generated in the country. As a consequence, the use of GDP data allows us to detect the full impact of inflation uncertainty on real output growth in this model.

Table 6 shows that during the recession regime, inflation uncertainty has a negative effect ($\delta_{02} = -0.288$) which is significantly different from zero at the 1%

[23] Harding and Pagan (2002) specify a censoring rule such that phases last at least 2 quarters and the completed cycle last at least 5 quarters. Mitchell and Mouratidis (2004) using alternative measures of business cycles for 12 European Union (EU) countries show that recession and expansion last on average 18 and 60 months respectively.

significance level. That is, ceteris paribus, 1 percentage point increase in the inflation uncertainty, decreases quarterly output growth by -0.288 percentage points in a a low growth regime. From Table 6 we also observe the effect of inflation uncertainty on growth during period of expansion is also negative ($\delta_{01} = -0.086$) but it is insignificant.[24] Comparing the magnitude of inflation uncertainty on output growth, *ceteris paribus*, we see that the adverse impact of inflation uncertainty on economic growth is 3 times more in a period of contraction than that in an expansion. Finally, we observe inflation has a negative and significant effect on economic growth during periods of contraction and during periods of expansion. Furthermore, the direct adverse impact of inflation is also 3 times more in a period of contraction than that in an expansion. Overall, we conclude that inflation uncertainty has a negative impact on output growth supporting the Friedman hypothesis.

2.5.4 Specification Tests

To check if the Markov switching GARCH(1,1) model and the Markov switching output growth model are correctly specified, we apply the ARCH LM test to the squared standardized residuals. As seen in Table 7, for both series we cannot reject the hypothesis of no conditional heteroscedasticity. Thus, we conclude that the Markov switching GARCH(1,1) model for inflation captures the conditional heteroscedasticity of inflation in the U.S. adequately. Furthermore, the Markov switching model for output growth is properly specified and does not contain any ARCH effects. These findings provide support for the specification we use throughout the study.

Insert Table 7 about here

[24]The differences between the estimation results from the monthly and the quarterly data may also be attributed to the few number of observations in the robustness analysis.

2.6 Conclusion

In this chapter, we examine the impact of inflation uncertainty on output growth for the U.S. economy. To carry out our investigation, we use two sets of data. The main investigation is carried out on monthly U.S. inflation and industrial production series covering the period 1960:01–2009:12. We then check the robustness of our findings using quarterly GDP series over 1960:QI–2009:QIV. Prior to estimating any model, we investigate the properties of inflation and output growth series. Detecting that both series can be characterized by regime shifts we implement Markov switching models. In particular, we apply a Markov switching GARCH model to inflation so that we can obtain a measure of uncertainty which allows for shifts in the inflation process. We then construct a Markov switching model for the output series to fully capture the growth dynamics as we investigate the impact of uncertainty on growth.

This approach enables us to examine whether the effects of inflation uncertainty change across different regimes as the economy expands and contracts. Our investigation shows that inflation uncertainty exerts a significant and negative impact on output growth. Furthermore, different from the earlier research, we show that the negative effect of inflation uncertainty is more pronounced during periods of contraction. In particular, the negative impact of inflation uncertainty on output growth in the low growth regime is about 2 times greater than that in the high growth regime. The greater negative real effect of inflation uncertainty can be attributed to the fact that in a recession when firms' cash flows are low, their balance sheets are weak and they are more dependent on external finance, firms are likely to be more sensitive to the changes in the level of uncertainty and tend to delay investment projects or to cut production. However, in an expansion when the level of cash flows is relatively higher compared to the level in an economic downturn and their balance sheets are strong; firms can largely finance themselves with internal sources. Hence, firms are likely to be stronger to the changes in the level of uncertainty during an expansion and they do not tend to cut production.

We examine the robustness of our results by re-estimating the model on quarterly GDP series. We detect that the low and high growth regimes coincide well with the NBER dates of contraction and expansion for the U.S. economy. The results regarding the impact of inflation uncertainty on output growth are similar to those findings reported for monthly industrial production data. We observe that inflation uncertainty exerts a negative and significant impact on economic growth which is almost 3 times higher in the periods of contraction than that in the periods of expansion. Our investigation using quarterly data also provides evidence that inflation has a negative and significant effect on economic growth during the periods of contraction and expansion. Moreover, specification tests provide convincing evidence that the model is properly specified.

Overall our findings verify that both inflation and inflation uncertainty exert a negative impact on output growth through the business cycle. We also observe that inflation and the related uncertainty have stronger negative effects on real economic activity during the periods of bottlenecks in economic growth. These results provide support to the proponents of price stability as a major policy for monetary policy makers. Our results also show that it is important to use a model that captures the proper behavior of the underlying series to capture the interlinkages between the variables accurately.

Appendix to Chapter 2

Table 1: Hansen Test Results

	Inflation (monthly)	IP Growth	Inflation (quarterly)	GDP Growth
	Linearity versus two-states Markov switching model			
Standardized LR test				
LR	2.464	3.471	5.282	1.415
$M = 0$	(0.0340)	(0.0010)	(0.0000)	(0.2745)
$M = 1$	(0.0485)	(0.0005)	(0.0000)	(0.2755)
$M = 2$	(0.0650)	(0.0010)	(0.0000)	(0.2910)
$M = 3$	(0.0695)	(0.0015)	(0.0000)	(0.2885)
$M = 4$	(0.0905)	(0.0025)	(0.0005)	(0.2785)

Notes: 1) IP stands for industrial production. 2) The range $[0.1,\ 1]$ in steps of 0.1 (10 grid points) is used as a grid for the transition probabilities; for the autoregressive coefficient and innovations variance, we use the range $[0.1,\ 0.9]$ and $[0.01,\ 0.17]$, respectively, in steps of 0.1 and 0.01 (9 grid points). The P-value is calculated according to the method described in Hansen (1996), using 2,000 random draws from the relevant limiting Gaussian processes and bandwidth parameter $M = 0, 1, \ldots, 4$, see Hansen (1992a) for further details.

Table 2: Estimation Results of the Output Growth Model in Equation (5)–Monthly Data (1960:01-2009:12)

$$y_t = \phi_{0i} + \sum_{j=1}^{m} \beta_{ji} y_{t-j} + \xi_t,$$

$$\xi_t \mid \Omega_{t-1} \sim N\left(0, \sigma_{0i}^2\right), \text{i=1,2 are regimes.}$$

Parameter	Estimate	Standard Error
ϕ_{01}	0.001***	0.000
β_{11}	0.159***	0.055
β_{21}	0.243***	0.047
β_{31}	0.163***	0.048
ϕ_{02}	0.001	0.001
β_{12}	0.346***	0.104
β_{22}	-0.008	0.126
β_{32}	0.155	0.124
σ_{01}	0.005***	0.000
σ_{02}	0.012***	0.001
P_{11}	0.934***	0.021
P_{22}	0.725***	0.080
Log-likelihood	2181.213	

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.

Table 3: Estimation Results of the Markov Switching GARCH Model

$$\pi_{it} = \theta_{0i} + \sum_{j=1}^{p} \theta_{ji} \pi_{t-j} + \varepsilon_t, \text{where } \varepsilon_t \mid \Omega_{t-1} \sim N\left(0, h_{it}\right),$$

$$h_{it} = \alpha_{0i} + \alpha_{1i} \varepsilon_{t-1}^2 + \alpha_{2i} h_{t-1} \text{ and i=1,2 are regimes.}$$

Parameter	Estimate	Standard Error
θ_{01}	0.002***	0.000
θ_{11}	0.266***	0.055
θ_{02}	0.002***	0.000
θ_{12}	0.624***	0.056
α_{01}	0.000***	0.000
α_{11}	0.327***	0.108
α_{21}	0.245**	0.121
α_{02}	0.000***	0.000
α_{12}	0.480***	0.159
α_{22}	0.275*	0.154
P_{11}	0.988***	0.006
P_{22}	0.987*	0.008
Log-likelihood	2760.376	

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.

Table 4: Estimation Results of the Output Growth Model in Equation (6)–Monthly Data (1960:01-2009:12)

$$y_t = \phi_{0i} + \sum_{j=1}^{m} \beta_{ji} y_{t-j} + \sum_{j=1}^{k} \varphi_{ji} \pi_{t-j} + \delta_{0i} \sigma_{\pi_{t-1}} + \xi_t,$$

$$\xi_t \mid \Omega_{t-1} \sim N\left(0, \sigma_{0i}^2\right), \text{ and i=1,2 are regimes.}$$

Parameter	Estimate	Standard Error
ϕ_{01}	0.002***	0.000
β_{11}	0.164***	0.055
β_{21}	0.238***	0.046
β_{31}	0.150***	0.046
φ_{11}	-0.077	0.071
δ_{01}	-0.048*	0.027
ϕ_{02}	0.002*	0.001
β_{12}	0.313***	0.089
β_{22}	-0.015	0.099
β_{32}	0.162	0.115
φ_{12}	-0.087	0.188
δ_{02}	-0.090*	0.047
σ_{01}	0.005***	0.000
σ_{02}	0.012***	0.001
P_{11}	0.931***	0.020
P_{22}	0.718***	0.080
Log-likelihood	2183.959	

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.

Table 5: NBER Dates of Expansions and Contractions

Business Cycles Reference Dates		Duration in Months	
Peak	Trough	Contraction	Expansion
April 1960(II)	February 1961(I)	10	24
December 1969(IV)	November 1970(IV)	11	106
November 1973(IV)	March1975(I)	16	36
January 1980(I)	July 1980(III)	6	58
July 1981(III)	November 1982(IV)	16	12
July 1990(III)	March 1991(I)	8	92
March 2001(I)	November 2001(IV)	8	120
December 2007(IV)	June 2009(II)	18	73

Source: National Bureau of Economic Research (NBER),
Quarterly dates are in parentheses.

Table 6: Estimation Results of the Output Growth Model in Equation (6)–Quarterly Data (1960:QI-2009:QIV)

$$y_t = \phi_{0i} + \sum_{j=1}^{m} \beta_{ji} y_{t-j} + \sum_{j=1}^{k} \varphi_{ji} \pi_{t-j} + \delta_{0i} \sigma_{\pi_{t-1}} + \xi_t,$$

$\xi_t \mid \Omega_{t-1} \sim N\left(0, \sigma_{0i}^2\right)$, and i=1,2 are regimes.

Parameter	Estimate	Standard Error
ϕ_{01}	0.010***	0.001
β_{11}	0.156***	0.053
β_{21}	0.158**	0.064
β_{31}	-0.098	0.064
φ_{11}	-0.210***	0.074
δ_{01}	-0.086	0.080
ϕ_{02}	0.001	0.001
β_{12}	0.752***	0.043
β_{22}	0.420***	0.038
β_{32}	0.012	0.032
φ_{12}	-0.575***	0.026
δ_{02}	-0.288***	0.030
σ_{01}	0.007***	0.000
σ_{02}	0.001***	0.000
P_{11}	0.927***	0.027
P_{22}	0.251***	0.121
Log-likelihood	691.649	

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.

Table 7: ARCH LM Test for Squared Standardized Residuals

		Output Growth Equation	Inflation Equation
1960:01-2009:12 (monthly data)	ARCH LM test (lag=4)	0.889 [0.926]	1.111 [0.892]
1960:QI-2009:QIV (quarterly data)	ARCH LM test (lag=4)	0.857 [0.930]	

Notes: p values in square brackets.

Figure 1: The Inflation Uncertainties in State 1 and State 2

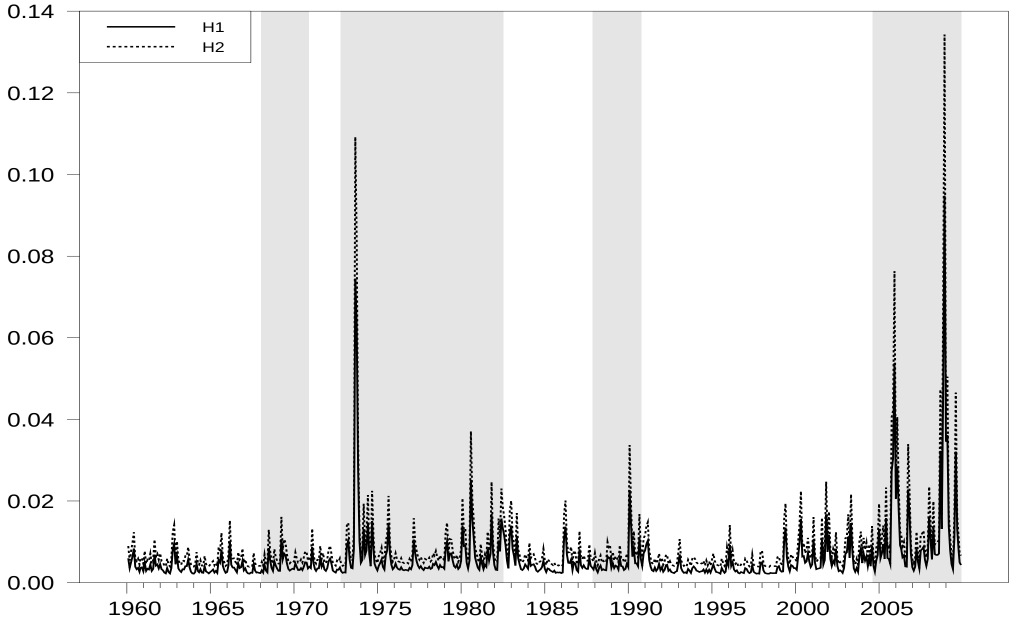


Figure 2: The Inflation Uncertainties Estimated with Single Regime GARCH(1,1) Model and Markov Switching GARCH(1,1) Model

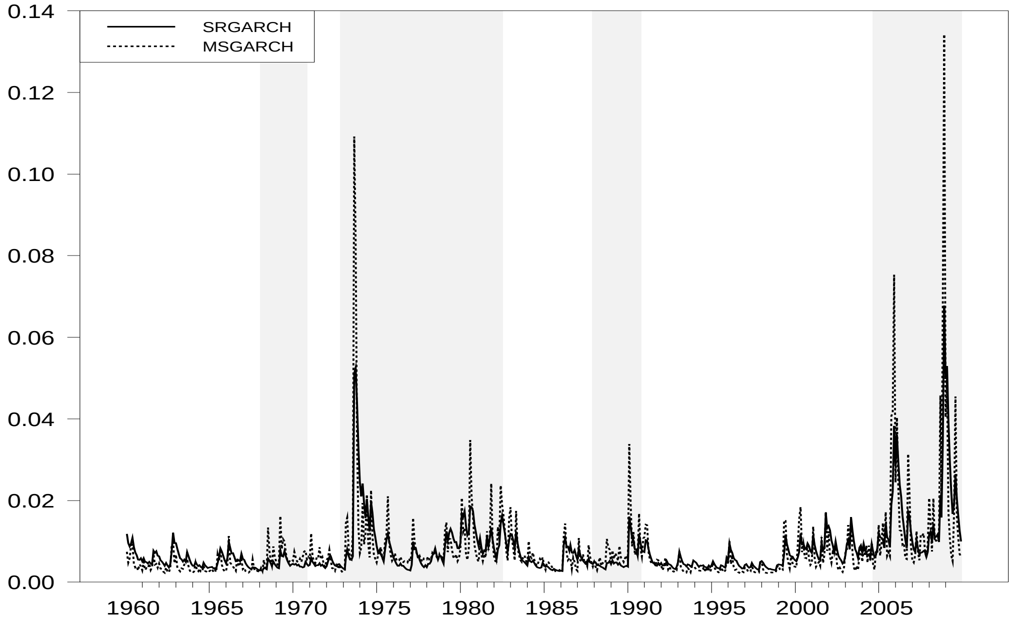


Figure 3: Smoothed Probabilities for State 1 (High Growth Regime)– Monthly Data (1960:01-2009:12)

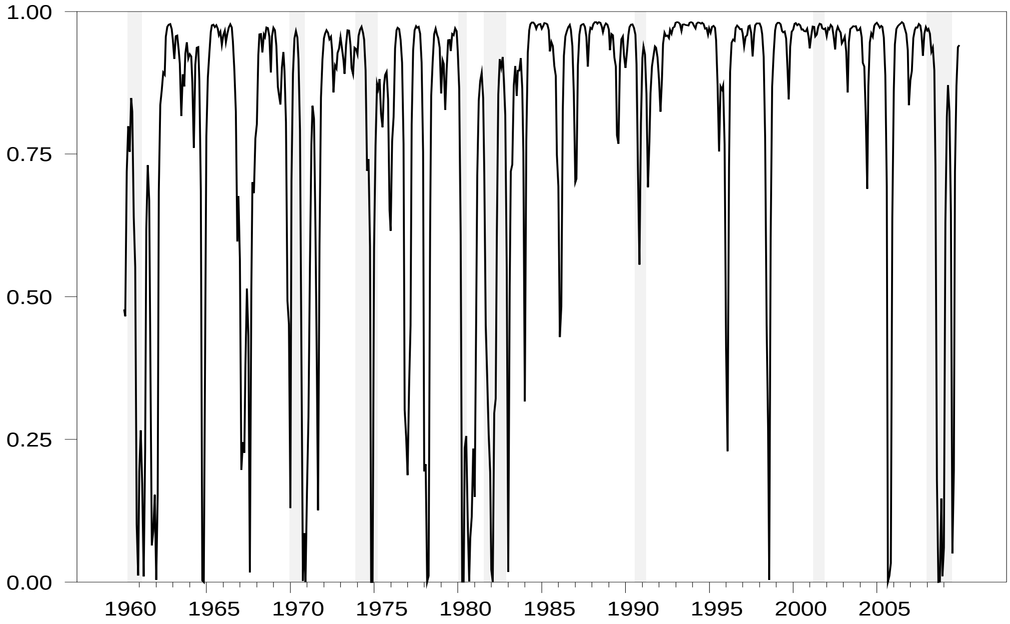
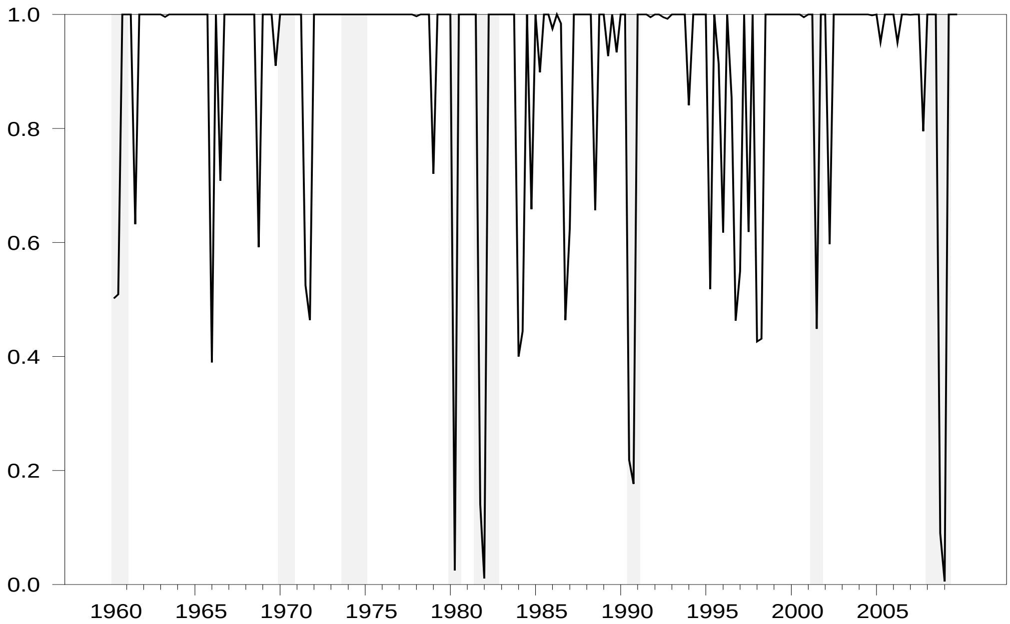


Figure 4: Smoothed Probabilities for State 1 (Expansion Regime)–Quarterly Data (1960:QI-2009:QIV)



Chapter 3

The Asymmetric Effects of Monetary Policy in the U.S.: An Instrumental Variables Estimation in Markov Switching Model

3.1 Key Findings

In this chapter, we investigate whether there are indeed asymmetries in the real effects of monetary policy shocks across business cycle and whether financial depth plays an important role in dampening the effects of monetary policy shocks on output growth using quarterly U.S. data over the period 1981:QI–2009:QII. We apply an instrumental variables estimation in Markov regime switching methodology which accounts for the endogeneity problem between monetary policy and output growth. We document that the impact of monetary policy changes on output growth is stronger during recessions over the period under investigation. We also find that financial development is very prominent in dampening the real effects of monetary policy shocks especially during the periods of recession.

3.2 Introduction

A vast empirical literature examines the effects of monetary policy shocks on the economy. Although most of the evidence on the impact of monetary policy is based on linear models, recent research has shown that the effects of money supply shocks on output are asymmetric. In this chapter, we, too, empirically examine the asymmetric effects of monetary policy on the economy. In our investigation, different from the available research, we consider the role of financial depth as the economy is subjected to monetary policy shocks across the different phases of business cycle. [25]

The related literature presents us several analytical models which suggest that monetary policy may exert an asymmetric impact on the economy. For instance, we can relate to the convexity of the aggregate supply curve to explain the asymmetric effect of monetary policy over the business cycle.[26] Since output is initially low in the flatter part of the supply curve when the economy is in a recession, shifts in the aggregate demand due to the changes in monetary policy would result in a larger impact on output but a smaller impact on price level. In contrast, at the steeper part of the supply curve when the economy is in an expansion state, the changes in monetary policy which induce shifts in the aggregate demand will result in a weaker change in the output while inducing a greater change in the price level.

To study the asymmetric impact of monetary policy, researchers also examine models in which there are agency costs of financial intermediation. Because of asymmetric information problems in the financial markets monetary policy would exert different effects on the economy between expansionary and recessionary periods as financial constraints will be more binding during recessions when the net worth of agents is low. During recessions an increase in interest rates will not only increase the cost of capital but also raise the external finance premium possibly due to informational frictions in the credit market. As a result, a monetary contraction will cause a greater fall in the demand for investment in the periods of recession than in the expansion episodes.[27] Raddatz (2006) stress that in an environment with financial market imperfections a decline in firms' net worth will adversely affect fixed investment decisions rendering a reduction in future output.

[25]Other possible symmetries can arise due to i) the size of the monetary policy shocks and ii) the direction (sign) of the monetary policy shocks (Keynesian asymmetry).

[26]See, for example, Caballero and Engel (1992), Tsiddon (1993), Ball and Mankiw (1994), Senda (2001).

[27]See, for instance Bernanke and Gertler (1989), Bernanke et al. (1996).

However, any decline in future output will lessen the future net worth of the firms amplifying the initial impact of the shock.

At this point it is important to refer to the literature that emphasizes the role of credit market imperfections in propagating the shocks in the economy. Earlier several studies have investigated the link between depth of the financial markets–or financial development in general–and the fluctuations in the growth rates of output, consumption and investment.[28] These studies suggest that the level of financial depth is closely related to the degree of credit market imperfections in an economy. In particular, it is shown that an economy with a higher financial depth is more likely to solve problems that arise due to the information asymmetries. In such environments where financial markets are deeper it would be easier to match a borrower with a lender so that the impact of shocks can be suppressed more effectively.

This study is related to several strands of literature. Our primary goal is to investigate if monetary policy has an asymmetric impact on real output over the business cycle as the economy goes through periods of expansion and contraction. We pursue this goal implementing an instrumental variables Markov regime switching framework and testing whether monetary policy has a stronger impact as the economy goes through a recession. Second, in our investigation we account for the importance of financial depth in the monetary transmission mechanism. We do so because empirical studies have shown that there is a linkage between growth and financial depth. For any country (developed or developing) the extent of financial depth changes over the course of the economy. For instance, even developed nations struggle during the periods of credit crunch. Coupled with asymmetric information, the impact of monetary policy as the economy evolves through the ebbs and tides will be greatly determined by the depth of

[28]See, for instance, Denizer et al. (2002), Easterly et al. (2001), Raddatz (2006), Beck et al. (2006).

the financial markets as well. Here, we use a model which allows financial depth to affect output growth both directly and indirectly through the interaction of monetary policy shocks and financial depth. Hence, in this set up we examine the interrelations between the two factors as we study the asymmetric effects of monetary policy on output growth across expansion and recession regimes.

Our empirical approach as we integrate financial depth and the interaction term serves on two fronts. First, we can determine whether financial depth has a regime dependent impact on output growth (i.e. across expansion and recession regimes). This can be achieved by comparing the direct impact of financial depth variable over the business cycle. Second, we can examine whether financial depth plays any role in dampening the impact of shocks on output growth. This effect can be observed through the interaction between financial depth and monetary policy shocks.

In this context, we aim to shed light on the question whether the effects of monetary policy shocks on output growth vary with the level of financial depth over the business cycle. Put differently, we examine whether the level of financial depth dampen or amplify the impact of monetary policy shocks on the economic growth. Moreover, the use of a Markov regime switching framework enables us to examine whether this interaction between financial depth and output growth is regime-dependent. We expect to see that the scope of the monetary policy shocks on economic activity should be related to the depth of financial markets. This is so because deeper financial markets are subjected to less credit market imperfections which are considered as a propagator of shocks to the economy. That is, given all things equal, we predict that the negative impact of a contraction in monetary policy on economic growth is likely to be less pronounced during a recession should the private sector have easier access to credit. Estimating the regime dependency is important because as stressed by Larrain (2006) the impact of a larger share of credit extended to the private sector is uncertain. If the firms face with tighter financial constraints during contractions, more credit available decreases output volatility as the firms do not have to reduce their production. While if there are tighter financial constrains during expansionary periods, higher access to credit may constrain output growth since firms may undertake new investment projects quickly wasting resources.

To summarize, this study addresses the following issues. First, we search whether monetary policy shocks have asymmetric real effects on output over the business cycle using an instrumental variables Markov regime switching framework. Second, we revisit the literature on the role of financial development in growth and we examine if there is a significant regime-dependent impact of financial development on growth. Last but not least, we contribute to the ongoing debate about the role of capital market imperfections in propagating the influences of the monetary policy shocks on economic activity.

As argued by Garcia and Schaller (2002), an investigation of the asymmetries over business cycles through the use of a Markov regime switching model has various benefits. For instance, a Markov regime switching model allows the output growth rate to depend on a latent state variable that represents an expansion or a recession and thereby allows for asymmetries. Also, these models give larger relative weight to observations which are likely to coincide with recession periods while estimating the recession coefficients. Last but not least, these models endogenously identify the optimal recession dating using the sample data. Despite the advantages of Markov regime switching models, in some cases the use of the standard maximum likelihood estimator for Markov regime switching models may not be suitable. In particular, if the standard maximum likelihood estimator does not take into account the correlation between the explanatory variables and the disturbances when some of the explanatory variables are endogenous, the estimates will be inconsistent and suffer from within-regime orthogonality failures. Hence, in this study we implement an instrumental variables approach as suggested by Spagnolo et al. (2005) to overcome the endogeneity problems. To achieve that we simultaneously estimate an output growth equation and an instrumenting equation for monetary policy measure while we estimate state dependent parameters for both variables in question.

The investigation is carried out for the U.S. economy using quarterly data from over the period 1981:QI–2009:QII. The choice of the period for investigation is related to the recent research findings which point out that the effectiveness of monetary policy have changed by the mid 1980s in the U.S. economy. For instance, Gertler and Lown (1999), Barth and Ramey (2000), Boivin and Giannoni (2002) argue that since the beginning of the 1980s real effects of monetary policy have diminished in the U.S. economy. Boivin and Giannoni (2002) point out that the reason behind the diminishing real effects of monetary policy in the U.S. is the increased emphasis on output and inflation stabilization over time. Their argument is in line with that of Leeper et al. (1996) who show that only a minor part of the variance in output in the U.S. since 1960s can be explained by the changes in monetary policy. Similarly, Uhlig (2005) finds that contractionary monetary policy shocks exert an ambiguous impact upon real GDP and these shocks may be neutral. On the other hand, Barth and Ramey (2000) state that the financial innovations beginning in the 1970s and the deregulation of the early 1980s have increased the available sources of funds for banks and firms and thereby removed the restrictions on the availability of working capital. They argue that the weakening of the real effects of monetary policy in U.S. since 1980s may be explained with these changes in the financial structure. On this account, using a sample period which starts before the 1980s may overestimate the effects of a monetary policy change on output growth.

Results are very clear; the magnitude of the negative impact of a monetary contraction on economic growth in the periods of recession is about 2 times greater than that in the periods of expansion. Higher financial depth fosters output growth when the recession regime persists while it does not exert any impact on economic activity during the expansion regime. Moreover, a deeper financial market dampens the real effects of monetary policy shocks in both regimes but this impact is particularly important in the periods of recession.

In what follows, we first briefly summarize the empirical literature to date in Section 3.3. Then, we present the instrumental variables Markov regime switching methodology, the empirical model and the data in Section 3.4. Empirical results from this model are discussed in Section 3.5. Section 3.6 concludes the chapter. The results are presented in the Appendix.

3.3 Literature Review

There is an extensive empirical literature which has investigated the asymmetric impact of monetary policy changes on real economic activity. Researchers explore different asymmetries concerning the effects of monetary policy actions on economic growth. For example, the asymmetric effects of positive and negative monetary policy changes, asymmetric effects related to the monetary policy changes with different sizes and asymmetric effects of monetary policy changes over different stages of business cycle. Cover (1992), De Long et al. (1988), Morgan (1993), Karras (1996), Thoma (1994) show that output growth reacts more to a contractionary monetary policy than to an expansionary monetary policy. Ravn and Sola (2004) investigate the asymmetric impact of monetary policy related to the size of monetary policy shocks.

Many other studies have analyzed the asymmetric impact of monetary policy shocks on the economy over business cycles using nonlinear empirical models.

For example, using a Markov regime switching model of Hamilton (1989, 1990), Garcia and Schaller (2002) examine whether a monetary policy change has same effect on real economic activity in expansions and in recessions for the U.S. economy over the period 1955-1993. They use the change in the Federal Funds rate and the monetary policy innovations obtained from a structural VAR model respectively as measures of monetary policy. Their findings show that both of the monetary policy measures have larger effects during a recessionary period than during an expansionary period. They confirm that the results are robust to the changes in the period of the sample, the frequency of the data and the specification of the empirical model. Furthermore, they find that an increase in the spread between the commercial paper and t-bill rates decreases the transition probability of going from a recession regime to an expansion regime substantially.

Based on a similar Markov regime switching model, Peersman and Smets (2002) asses whether euro area wide monetary policy shocks which are obtained from VAR models have asymmetric effects across the business cycle in seven euro area countries. Their study shows that these seven countries exhibit the same business cycle and the area wide shocks have more profound effects on output during recessionary periods than during expansionary periods. Similarly, Kaufmann (2002), using data from Austria for the period 1976:QI-1998:QIV, provides evidence that the effects of monetary policy on output growth are significantly negative during the periods of economic downturn while the effect is found to be insignificant during the periods of normal or above average output growth.

Modeling the asymmetries with a logistic smooth transition vector autoregressive (LSTVAR) model, Weise (1999) searches whether the effects of monetary policy shocks vary over the business cycles for the U.S. over the period 1960:QII to 1995:QII. He finds that monetary shocks exert a stronger negative impact on economic activity in recessions. He also reports that the positive and negative shocks are found to have similar effects in both stages of the business cycle. Similar with Weise (1999), Lo and Piger (2005) using an unobserved-component model with regime switching and time varying transition probabilities, argue that the monetary policy changes in the U.S. have stronger real effects during recession periods than during booms.[29] Subsequently, Höppner et al. (2008) applying a time-varying coefficient VAR model for the period from 1962:QI to 2002:QII, confirm the asymmetry of monetary policy over the business cycle for the U.S.. Their empirical results document that the impact of U.S. monetary policy on output has been decreasing systematically since the 1960s.

There is also a large and growing body of empirical work which documents the role that credit market imperfections play in magnifying the fluctuations in output. According to this line of research imperfections in the financial systems act as a propagator of shocks. Thus, countries with highly developed financial systems are expected to have a higher and a more stable output growth. For instance, Beck et al. (2006) address the question whether financial development dampens or amplifies the impacts of real sector shocks and monetary shocks using a panel of 63 countries over the period of 1960-1997. They use the standard deviations of real per capita GDP, standard deviation of terms of trade and standard deviation of inflation to proxy the macroeconomic, real and monetary volatilities, respectively. They measure the financial development as the ratio of the claims on the private sector by financial intermediaries to GDP. Their results show that financial development may reduce the impact of terms of trade volatility on growth volatility. In addition, they find that financial development amplifies the effect of inflation volatility on output volatility in countries which have less developed stock exchanges while they are unable to find any robust evidence for countries with highly developed stock exchanges.

[29] Their empirical results do not provide support for the asymmetries that result from the direction or the magnitude of the monetary policy changes.

Using fixed effects estimation technique on a panel of 70 countries over the years between 1956 and 1998, Denizer et al. (2002) confirm that countries with well-developed financial markets have less volatility in real per capita output, consumption and investment growth. They use different indicators of financial development but they show that the relative importance of private sector banks in the whole banking system is prominent in reducing output, consumption and investment volatility. Besides, the level of credit supplied to the private sector rather than public sector is more powerful in lowering the volatility of consumption and output growth. Easterly et al. (2001) also suggest that better access to credit in a deeper financial system leads to less output volatility in the economy.

Several other researchers provide empirical evidence at the micro level. Raddatz (2006) using industry level data for a sample of countries finds that higher financial depth significantly reduces output volatility especially in sectors which need high liquidity to function properly. He argues that the results provide strong evidence for the importance of financial development in reducing the output fluctuations. This so because, according to his findings higher financial depth in an economy improves the ability of the financial system to provide liquidity to firms during the periods of economic downturn. Larrain (2006) using both industry-level and firm-level data of a set of countries also concludes that industrial output is less volatile the greater the size of bank credit in a country is. His results further show that a well-developed banking system absorbs the shocks to the economy particularly providing liquidity through short-term debt.

Another area of debate concerns the impact of financial development on the volatility and length of business cycles. For instance Ferreira da Silva (2002) using a generalized method of moments methodology on a set of 40 countries over the period 1960-1997 finds that countries with deeper financial markets experience smoother business cycles. Tharavanij (2007) fails to provide any significant evidence that the frequency of the recessions is affected by the development of the capital markets using a sample of 35 countries for the period 1975-2004. Yet, he documents that countries with well-developed capital markets are likely to have shorter periods of recession.

To capture and scrutinize the nonlinear dynamics in the data some researchers use nonlinear time series analysis. For instance, using a threshold vector autoregression model, Balke (2000) provides evidence for the presence of switching credit regimes in the U.S. economy covering the period 1960:M1-1997:M3. He finds that shocks to the economy during a tight credit regime exert a greater impact on economic activity than in a normal credit regime. He also shows that contractionary monetary policy shocks have a more pronounced effect on growth than do expansionary monetary policy changes. Following Balke (2000)'s methodology and using the United Kingdom data over the period 1984:M1-2002:M4, Atanasova (2003) documents that contractionary monetary policy shocks have a larger impact on economic activity in the credit constrained regime.

In this study, we connect these three lines of literature. To be specific, we implement an instrumental variables estimation in Markov regime switching framework to examine the asymmetric effects of monetary policy shocks while considering the role of financial markets on output growth. The use of instrumental variable approach as suggested by Spagnolo et al. (2005) is relevant in our study for the endogeneity problem may affect our results given the potential correlation between the monetary policy shocks and the disturbance term. In section 3.4.2 we provide the details of this methodology.

3.4 Data and Econometric Methodology

3.4.1 Data

To carry out our investigation, we use the first difference of the logarithm of Federal Funds rate to measure of monetary policy shocks (mp_t), a proxy which is commonly used in the empirical literature.[30] We measure output growth (y_t) in period t, by the first difference of the logarithm of the real GDP series. To measure financial depth, (fd_t), we use the ratio of the claims on the nonfinancial private sector to total domestic credit (excluding credit to money banks).[31] The credit to private sector is a critical key variable which reflects the "depth" of the financial system and thus is chosen as the measure of financial development in this study. The financial depth proxy in our study provides information on the percentage of credit allocated to private firms in the economy. Thus, it measures the extent to which credit is allocated to the private rather than public sector. Data are obtained from the International Financial Statistics (IFS) of the International Monetary Fund (IMF).[32] The empirical model is estimated over the period from the first quarter of 1981 to the second quarter of 2009.

3.4.2 Econometric Methodology

To examine whether the real effects of monetary policy are different over business cycle we use short-term interest rate to measure the monetary policy shock. The complication that may arise from this approach is the potential endogeneity of the short-term interest rate which we use an explanatory variable in the output growth equation.[33] As noted by Spagnolo et al. (2005) a standard maximum

[30]See, for instance, McCallum (1983), Bernanke and Blinder (1992), Sims (1992), Christiano et al. (1996), Bernanke and Mihov (1998), Clarida et al. (2000), Mihov (2001).

[31]Total domestic credit (excluding credit to money banks) is composed of claims on central government, claims on state and local governments, claims on public nonfinancial corporations and claims on the nonfinancial private sector.

[32]Claims on the nonfinancial private sector is IFS line 32d and domestic credit (excluding credit to money banks) is IFS lines 32a through 32f excluding 32e.

[33]A standard "Taylor rule" argues that the short term interest rates react to contemporaneous values of inflation and output-gap. Thus, estimating a growth equation where one of the regressors is the current value of short term interest rate is subject to endogeneity problem. This is so because the short term interest rate will be correlated with the error term of output

likelihood estimator within the framework of a regime switching model yields inconsistent parameter estimates due to the within-regime correlation between the regressors and the disturbance term. To overcome this problem, we employ an instrumental variables approach proposed by Spagnolo et al. (2005) where the instrumenting equations for the endogenous regressors also have state-dependent parameters. In particular, we estimate the following system of equations including the output growth equation and the instrumenting equation for monetary policy change:

$$\begin{aligned}
y_t &= \left[\alpha_0\left(1-s_t\right)+\alpha_1 s_t\right]+\left[\gamma_0^{(1)}\left(1-s_t\right)+\gamma_1^{(1)} s_t\right] y_{t-1} \\
&+\left[\gamma_0^{(2)}\left(1-s_t\right)+\gamma_1^{(2)} s_t\right] y_{t-2}+\ldots+\left[\gamma_0^{(j)}\left(1-s_t\right)+\gamma_1^{(j)} s_t\right] y_{t-j} \\
&+\left[\beta_0\left(1-s_t\right)+\beta_1 s_t\right] \widehat{mp}_{t-1}+\left[\varphi_0\left(1-s_t\right)+\varphi_1 s_t\right] fd_t+\left[\eta_0\left(1-s_t\right)+\eta_1 s_t\right] \widehat{mp}_{t-1} fd_t \\
&+\left[\sigma_0\left(1-s_t\right)+\sigma_1 s_t\right] \varepsilon_t
\end{aligned} \tag{7}$$

$$\begin{aligned}
mp_{t-1} &= \left[\kappa_0\left(1-s_t\right)+\kappa_1 s_t\right]+\left[\delta_0^{(1)}\left(1-s_t\right)+\delta_1^{(1)} s_t\right] y_{t-1} \\
&+\left[\delta_0^{(2)}\left(1-s_t\right)+\delta_1^{(2)} s_t\right] y_{t-2}+\ldots+\left[\delta_0^{(k)}\left(1-s_t\right)+\delta_1^{(k)} s_t\right] y_{t-k} \\
&+\left[\phi_0^{(1)}\left(1-s_t\right)+\phi_1^{(1)} s_t\right] mp_{t-2}+\left[\phi_0^{(2)}\left(1-s_t\right)+\phi_1^{(2)} s_t\right] mp_{t-3}+\ldots \\
&+\left[\phi_0^{(l)}\left(1-s_t\right)+\phi_1^{(l)} s_t\right] mp_{t-l-1}+\left[\theta_0\left(1-s_t\right)+\theta_1 s_t\right] \xi_t
\end{aligned} \tag{8}$$

where y_t is the growth rate of output, mp_t is the monetary policy shock (change in the logarithm of the short term interest rate) and fd_t is a measure of financial depth in period t. $\widehat{mp}_{t-1} fd_t$ is the interaction term between financial depth and the fitted value of monetary policy term $\widehat{mp}_t = E\left[mp_t \mid s_t, \Omega_t\right]$ where s_t is state variable and Ω_t is the information set available at time t. We include the first lag of the mp_t in equation (7) as output growth reacts to monetary policy changes with a lag. Equation (8) is the reduced-form equation for the endogenous regressor, mp_{t-1}. In this framework, mp_{t-1} responds to changes in lagged output and changes in lagged short term interest rate.

growth.

The state variable, s_t, is a homogenous first order Markov chain on $\{0,1\}$ with the following transition probabilities:

$$\begin{aligned} q &= P\left[s_t = 0 \mid s_{t-1} = 0\right], \\ p &= P\left[s_t = 1 \mid s_{t-1} = 1\right]. \end{aligned} \tag{9}$$

Within this framework, our main hypothesis is that the impact of a contractionary monetary policy shock, $\beta_{s_t} + \eta_{s_t} fd_t$, is more negative at low levels of financial depth.

In the model shown by equations (7) and (8) neither the error terms (ε_t, ξ_t) nor the Markov regimes, s_t, are observed. To estimate this model, Spagnolo et al. (2005) suggest using a form of recursive algorithm explained in Hamilton (1994). This process yields a likelihood function which can be maximized with respect to:

$$\begin{aligned} \nu =&(\alpha_0, \alpha_1, \gamma_0^{(1)}, \gamma_1^{(1)}, \gamma_0^{(2)}, \gamma_1^{(2)}, ..., \gamma_0^{(j)}, \gamma_1^{(j)}, \delta_0^{(1)}, \delta_1^{(1)}, \delta_0^{(2)}, \delta_1^{(2)}, ..., \delta_0^{(j)}, \delta_1^{(j)}, \phi_0^{(1)}, \phi_1^{(1)}, \phi_0^{(2)}, \\ &\phi_1^{(2)}, ..., \phi_0^{(j)}, \phi_1^{(j)}, \beta_0, \beta_1, \eta_0, \eta_1, \sigma_0, \sigma_1, \varphi_0, \varphi_1, \kappa_0, \kappa_1, \theta_0, \theta_1). \end{aligned}$$

We can therefore write the conditional probability density function of the data w_t =(y_t,mp_t) given the state s_t and the history of the system as follows:

$$\begin{aligned} pdf(w_t \mid w_{t-1}, ..., w_1; \nu) = &\frac{1}{\sqrt{2\pi}\sigma_{s_t}} exp \\ &\left[-\frac{1}{2}\left(\frac{y_t - \alpha_{s_t} - \sum_{j=1}^{J} \gamma_{s_t}^{(j)} y_{t-j} - \beta_{s_t}\widetilde{mp}_{t-1} - \varphi_{s_t} fd_t - \eta_{s_t}\widetilde{mp}_{t-1} fd_t}{\sigma_{s_t}}\right)^2\right] \\ &\times \frac{1}{\sqrt{2\pi}\theta_{s_t}} exp \\ &\left[-\frac{1}{2}\left(\frac{mp_{t-1} - \kappa_{s_t} - \sum_{k=1}^{K} \delta_{s_t}^{(k)} y_{t-k} - \sum_{l=1}^{L} \phi_{s_t}^{(l)} mp_{t-l-1}}{\theta_{s_t}}\right)^2\right] \end{aligned} \tag{10}$$

Here $\widetilde{mp}_{t-1} = \kappa_{s_t} + \sum_{k=1}^{K} \delta_{s_t}^{(k)} y_{t-k} + \sum_{l=1}^{L} \phi_{s_t}^{(l)} mp_{t-l-1}$ is the state-dependent instrumenting equation for mp_{t-1}.

3.5 Empirical Results

3.5.1 Asymmetric Real Effects of Monetary Policy Shocks

We initially focus on the asymmetric real effects of monetary policy changes and estimate the instrumental variables Markov regime switching model described above without the financial depth variable and the interaction term. The estimated output growth equation includes four lags of output growth to control for the persistence of growth and the measure of the monetary policy shock to examine the presence of the asymmetry. In equation (8) which is the instrumenting equation for monetary policy shock we also include four lags of output growth rate and we incorporate two lags of monetary policy shock variable as instruments. Our findings are summarized in Table 8.

Insert Table 8 about here

We find that the mean growth rate in U.S. economy during State 0, α_0, is negative, -0.027, but statistically insignificant. While, in State 1 U.S. economy experiences a positive and significant mean growth rate, α_1, which is equal to 0.004. Given these estimates, we therefore classify State 0 as the recession regime and State 1 as the expansion regime. Table 5 presents the contraction and expansion dates provided by NBER covering the period under investigation in this study. We see that between 1981-2009, the U.S. economy experienced 5 recessionary episodes between: 1981:QIII-1982:QIV, 1990:QIII-1991:QI, 2001:QI-2001:QIV, 2007:QIV-2009:QII.

Insert Table 5 about here

We can compare the estimated dates for expansion and recession periods of the U.S. economy with the dates provided by the NBER. In Figure 5 we plot the estimated smoothed probabilities for State 1 and shade the NBER recession dates.

When we investigate the smoothed probabilities of the occurrence of State 1 (expansion regime) in Figure 5, we observe that our model captures the economic contractions provided by the NBER around 1981/1982, 2001 and 2007/2009. The reason why the model fails to classify the economic downturn in 1990 could be due to the fact that this recessionary episode was relatively moderate and lasted only two quarters. A match between the dates for expansion and recession that we estimate from the instrumental variables Markov regime switching model with those announced by the NBER shows that the model is able to capture the business cycles successfully.

Insert Figure 5 about here

Next, we analyze whether the monetary policy affects real economic activity and there is any asymmetry in the real effects of monetary policy over business cycles. In Table 8, β_0 shows the contemporaneous impact of a monetary policy shock on output growth when the economy is in a downturn. In a similar manner, β_1 can be interpreted as the impact of a nominal shock on output growth if the economy is in an expansion.

The findings in Table 8 show that the impact of an increase in monetary policy measure on output growth in a recession regime, β_0, is positive but it is insignificant at any reasonable level. In contrast, the real effect of a change in monetary policy measure with same magnitude and direction in an expansion regime, β_1, is negative and statistically insignificant. Given these results, we cannot claim that monetary policy has any significant (asymmetric or symmetric) impact on economic growth in the U.S. over the period under study.

3.5.2 The Financial Depth and Monetary Policy

In this section, we investigate the importance of financial depth in determining the impact of monetary policy on output in the U.S. as given in the system of equations (7) and (8). Here, the financial depth enters the equation on its own and in interaction with monetary policy shock. In doing so, we examine whether higher financial depth leads to greater growth and whether the presence of deeper financial market dampens or enhances the real regime-dependent impact of the monetary policy shock. The instrumenting equation for monetary policy measure still includes four lags of output growth rate and two lags of monetary policy shock variable. Table 9 presents the estimation results of this model.

Insert Table 9 about here

The first question we ask is whether there is a business-cycle dependent impact of monetary policy shocks on output growth in the U.S. economy. When we scrutinize the estimation results reported in Table 9, we observe that β_0 and β_1 are both negative and significantly different from zero at the 5% significance level. The significant and negative values for β suggest that a monetary contraction exerts a negative impact on real economic activity in both expansion and recession regimes. Moreover, the results document that the impact of a 1 percentage point increase in the monetary policy measure on output growth in an expansionary regime is -0.348 percentage points while the real effect of a shock with same magnitude and direction in a recessionary regime is -0.650 percentage points. Put differently, the magnitude of the negative impact of a monetary tightening on real economic activity is about 2 times greater in the periods of recession than that in the periods of expansion. These results are in line with the theoretical models which imply asymmetries in the real effects of monetary policy building on the price rigidities, the capital market imperfections or the convexity of aggregate supply curve. The evidence also supports the previous empirical literature which documents that monetary policy shocks have a larger effect on output during the periods of bottleneck.

We next turn to examine whether higher financial depth fosters economic growth and whether this effect would change across different stages of business cycle. As we can observe from Table 9, the impact of financial depth on growth,

φ, is positive and significantly different from zero at the 1% significance level only in the recession regime. That is, higher credit to the private sector leads greater output growth during the recession regime while it has no effect on economic activity during the expansion regime. This finding is consistent with Braun and Larrain (2005) who show that financial frictions in the capital markets amplify the output fluctuations particularly when the firms and industries are highly dependent on external finance in the recession periods.

Next, we examine the coefficient of the interaction term between the monetary policy shock and the financial depth so that we can test whether the real effects monetary policy shocks vary with the level of financial depth. We observe that η is positive and significant in both regimes. Furthermore, this interaction is more pronounced in the recession regime compared to expansion regime as η_0 (0.801) is about 2 times greater than η_1 (0.413). The implication is that financial market depth dampens the real effects of monetary policy shocks in both regimes but this impact is especially important in the periods of economic downturn. This finding suggests that the adverse impact of monetary policy shocks weakens as the depth in the financial markets improves. Given that the direct impact of monetary policy is insignificant (in the case we do not control the financial depth and the related interaction); our findings imply that monetary policy shocks affect economic activity mainly through capital market imperfections.

The smoothed probabilities of State 1 (expansion regime) estimated for the model with financial depth and the interaction term are given in Figure 6. We find that the estimates of the model with financial depth and the interaction term yield a recession dating which is quite similar to the one provided by NBER. When we look at the smoothed probabilities of the occurrence of State 1, similar to the earlier case that our model captures the economic contractions over 1981/1982, 2001, 2007/2009.

Insert Figure 6 about here

To scrutinize the total effects of monetary policy shocks on output growth in expansion and recession regimes, we select different percentiles of the financial depth and we plot the total effects of a nominal shock on output growth at these percentiles. That is, we compute and plot $\partial y/\partial mp$ as fd takes on different values. The point estimates of the derivatives and their standard errors are presented in Table 10. Besides, these point estimates of the derivatives and the 95% confidence interval for each derivative in each regime are depicted in Figure 7. An inspection of these derivatives shows that as financial depth increases the impact of monetary policy shock on economic activity becomes insignificant in both regimes. That is, at higher percentiles of financial depth, the impact of monetary policy shock on growth is weakening. In particular, one can see that the role of the financial depth in dampening the negative effects of a monetary contraction is very prominent in State 0, the recession regime. In fact, the total impact of an adverse monetary shock on economic growth becomes zero more quickly in the recession regime, State 0, compared to the expansion regime, State 1. In this context, it is clear that there is also an asymmetry in the total real effects of monetary policy shocks across stages of the business cycle.

Insert Table 10 about here

Insert Figure 7 about here

Next, we turn to analyze the total effects of financial depth, $\partial y/\partial fd$, as monetary policy shocks attain different magnitudes. The point estimates of the derivatives and their standard errors are shown in Table 11. In addition, the estimates and 95% confidence interval for each estimate in each regime are plotted in Figure 8.

Insert Table 11 about here

Insert Figure 8 about here

Figure 8 illustrates that financial depth fosters economic growth in State 0, during the recession regime. That is, a deeper financial system has a large and positive effect in fostering economic growth in the periods of economic downturn. This may be due to the fact that the role of financial markets in liquidity provision to firms suffering working capital problems is comparatively more prominent in these periods. In contrast, it exerts a negative but insignificant impact on economic activity in the expansion regime, State 1. This finding supports Larrain (2006) who points out that more credit increases output volatility when the firms are financially constrained during expansions but on average financial depth softens the impact of the shocks on output.

3.6 Conclusion

This study empirically addresses several interrelated questions. First, we examine if monetary policy shocks have an asymmetric impact on output growth over business cycle. Second, we examine the impact of financial depth on growth and whether this effect changes over recessions or expansions. Last but not least, we investigate the role of financial depth in dampening the impact of monetary policy shocks to the economy. The analysis is carried out for the U.S. economy covering the period 1981:QI–2009:QII.

To test our hypotheses we apply a Markov regime switching model which allows state dependent coefficients on the explanatory variables and variances. This approach allows us to examine whether monetary policy shocks, financial depth and the interaction between financial depth and monetary policy shocks exerts regime dependent effects on economic activity. To overcome the estimation problems that arise due to the endogeneity of the monetary policy measure variable, we apply instrumental variables estimation in Markov regime switching model as proposed by Spagnolo et al. (2005). In this approach, we simultaneously estimate the output growth equation and the reduced form-equation for the endogenous regressor which both have state-dependent parameters.

Our model is able to detect the expansion and recession dates for the U.S. economy as announced by NBER. The findings provide convincing evidence to confirm the asymmetry in the real effects of monetary policy shocks over the business cycle when the level of financial depth is controlled for. The empirical results document that a change in monetary policy exerts a negative and statistically significant impact on output growth in both recession and expansion regimes in the U.S. economy. However, the impact of monetary policy shocks is stronger during recessions. This finding provides strong support for the theoretical models based on the credit channel and the convex supply curves and also it is in line with the previous empirical research which has documented the regime dependent impact of monetary policy shocks.

Besides, the empirical findings show that financial depth significantly increases output growth during the periods of economic downturns. Moreover, the development of financial markets seems to play a prominent role in reducing the extent of the impact of monetary policy shocks particularly in recession regimes. In other words, our findings verify that the impact of a monetary policy shock is likely to be more pronounced when an economy with a low level of financial depth has a recession.

Appendix to Chapter 3

Table 8: Estimates of Parameters of the Model for Monetary Policy Shock and Output Growth

$$y_t = [\alpha_0 (1 - s_t) + \alpha_1 s_t] + \left[\gamma_0^{(1)} (1 - s_t) + \gamma_1^{(1)} s_t\right] y_{t-1} + \left[\gamma_0^{(2)} (1 - s_t) + \gamma_1^{(2)} s_t\right] y_{t-2}$$
$$+ ... + \left[\gamma_0^{(4)} (1 - s_t) + \gamma_1^{(4)} s_t\right] y_{t-4} + [\beta_0 (1 - s_t) + \beta_1 s_t] \widehat{mp}_{t-1}$$
$$+ [\sigma_0 (1 - s_t) + \sigma_1 s_t] \varepsilon_t$$

Parameter	Estimate	Standard Error
α_0	-0.027	0.397
$\gamma_0^{(1)}$	0.379	0.322
$\gamma_0^{(2)}$	-0.655*	0.339
$\gamma_0^{(3)}$	0.199	0.415
$\gamma_0^{(4)}$	0.168	0.304
β_0	0.022	0.014
σ_0	0.007***	0.001
α_1	0.004***	0.001
$\gamma_1^{(1)}$	0.258**	0.100
$\gamma_1^{(2)}$	0.519***	0.094
$\gamma_1^{(3)}$	-0.197**	0.098
$\gamma_1^{(4)}$	-0.119	0.093
β_1	-0.005	0.005
σ_1	0.005***	0.000
q	0.550***	0.136
p	0.895***	0.040
Log-likelihood	556.870	

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.

Table 9: Estimates of Parameters of the Model for Monetary Policy Shock, Output Growth, Financial Depth and Interaction Term

$$
\begin{aligned}
y_t = & \left[\alpha_0 (1 - s_t) + \alpha_1 s_t\right] + \left[\gamma_0^{(1)} (1 - s_t) + \gamma_1^{(1)} s_t\right] y_{t-1} \\
& + \left[\gamma_0^{(2)} (1 - s_t) + \gamma_1^{(2)} s_t\right] y_{t-2} + ... + \left[\gamma_0^{(4)} (1 - s_t) + \gamma_1^{(4)} s_t\right] y_{t-4} \\
& + \left[\beta_0 (1 - s_t) + \beta_1 s_t\right] \widehat{mp}_{t-1} + \left[\varphi_0 (1 - s_t) + \varphi_1 s_t\right] fd_t + \left[\eta_0 (1 - s_t) + \eta_1 s_t\right] \widehat{mp}_{t-1} fd_t \\
& + \left[\sigma_0 (1 - s_t) + \sigma_1 s_t\right] \varepsilon_t
\end{aligned}
$$

Parameter	Estimate	Standard Error
α_0	-0.299***	0.102
$\gamma_0^{(1)}$	-0.585	0.390
$\gamma_0^{(2)}$	-0.121	0.410
$\gamma_0^{(3)}$	0.136	0.160
$\gamma_0^{(4)}$	-0.324	0.343
β_0	-0.650**	0.249
φ_0	0.371***	0.130
η_0	0.801**	0.307
σ_0	0.004***	0.001
α_1	0.181	0.178
$\gamma_1^{(1)}$	0.235**	0.096
$\gamma_1^{(2)}$	0.216**	0.106
$\gamma_1^{(3)}$	-0.185*	0.094
$\gamma_1^{(4)}$	-0.049	0.098
β_1	-0.348**	0.135
φ_1	-0.209	0.216
η_1	0.413**	0.164
σ_1	0.005***	0.000
q	0.691***	0.118
p	0.943***	0.026
Log-likelihood	532.950	

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.

Table 10: **Total Effects of Monetary Policy Shock**

	State 0	State 1
10th percentile of	-0.031	-0.028
financial development	(0.018)	(0.017)
25th percentile of	-0.021	-0.023
financial development	(0.016)	(0.016)
50th percentile of	-0.007	-0.016
financial development	(0.014)	(0.015)
75th percentile of	0.011	-0.007
financial development	(0.015)	(0.015)
90th percentile of	0.029	0.003
financial development	(0.018)	(0.016)

Notes: Standard errors in brackets.

Table 11: **Total Effects of Financial Depth**

Monetary Policy Shock (percentage)	State 0	State 1
0.05	0.375 (0.131)	-0.207 (0.214)
0.10	0.379 (0.133)	-0.205 (0.211)
0.15	0.383 (0.134)	-0.203 (0.209)
0.20	0.387 (0.135)	-0.201 (0.207)
0.25	0.391 (0.136)	-0.199 (0.204)
0.30	0.395 (0.137)	-0.197 (0.202)
0.35	0.399 (0.138)	-0.195 (0.200)
0.40	0.403 (0.139)	-0.193 (0.197)
0.45	0.407 (0.141)	-0.191 (0.195)
0.50	0.411 (0.142)	-0.189 (0.192)

Notes: Standard errors in brackets.

Figure 5: Smoothed Probabilities for State 1 (Expansion Regime)– Monetary Policy Shock, Output Growth

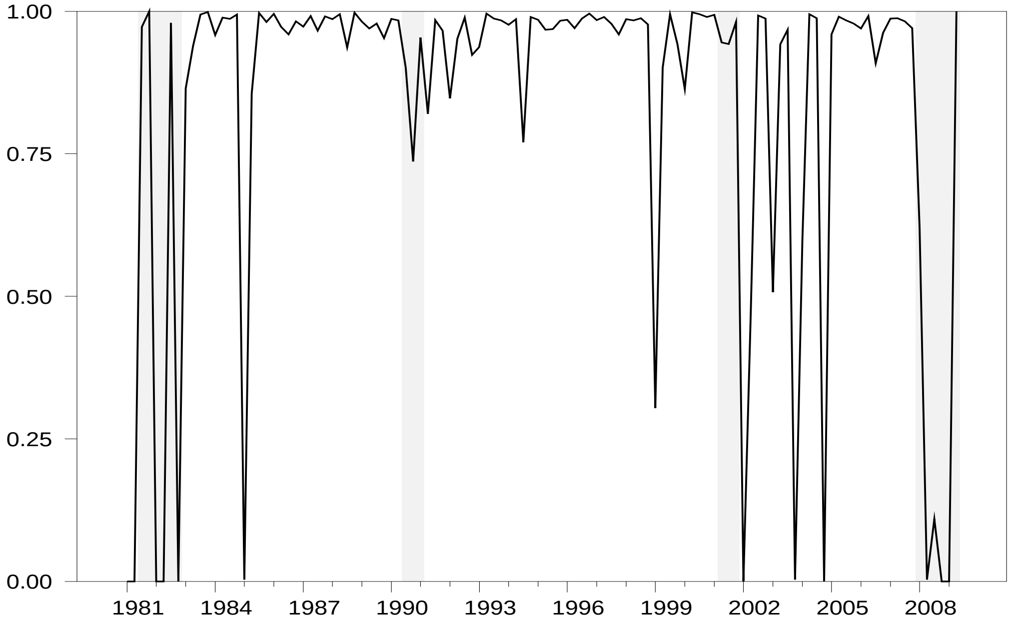


Figure 6: Smoothed Probabilities for State 1 (Expansion Regime)– Monetary Policy Shock, Output Growth, Financial Depth and Interaction Term

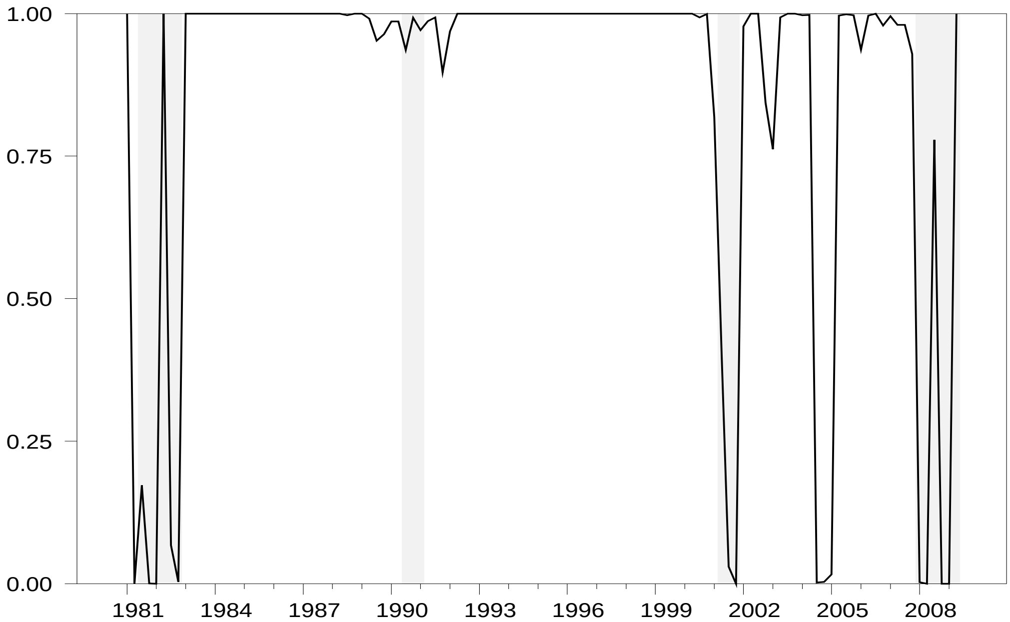
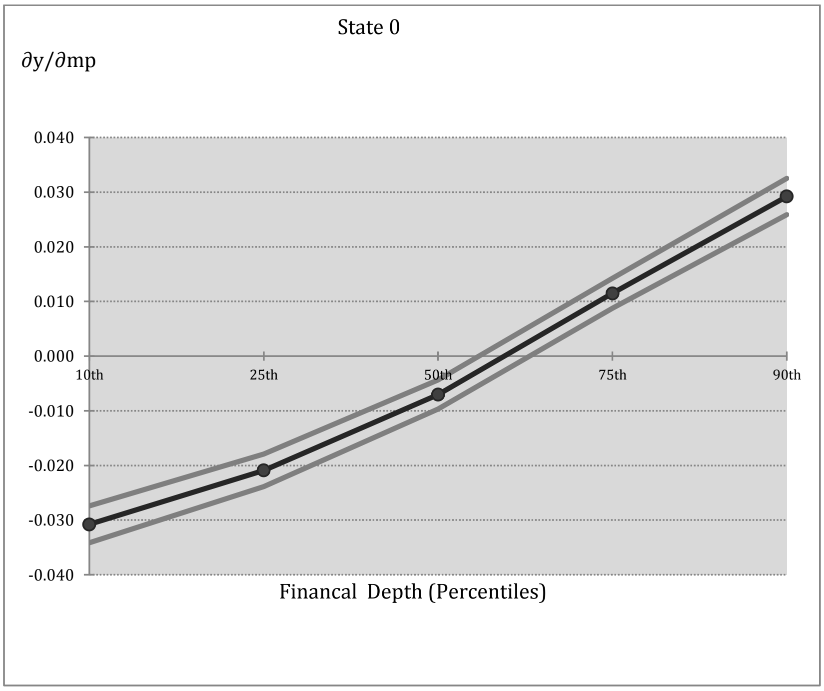


Figure 7: Total Effects of Monetary Policy Shock



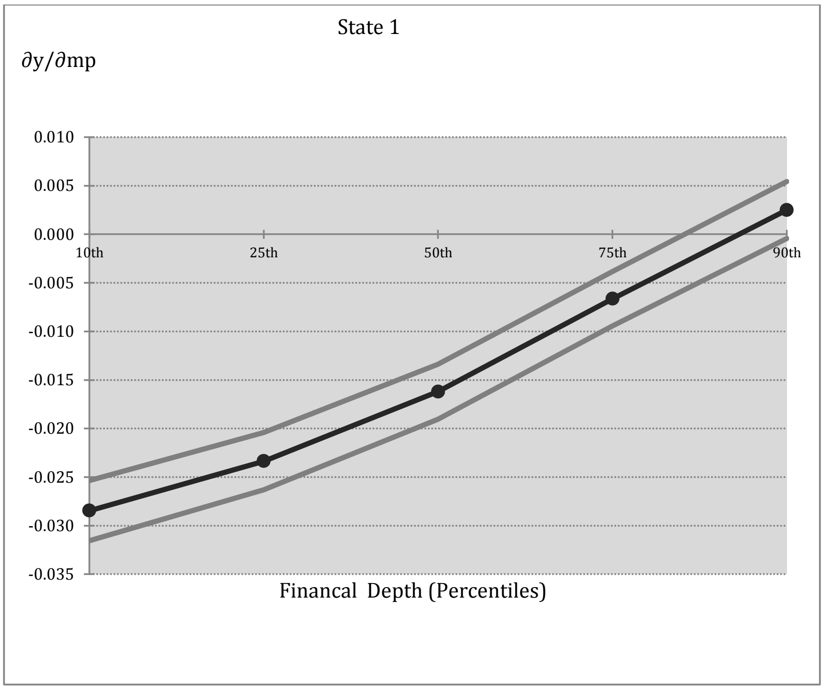
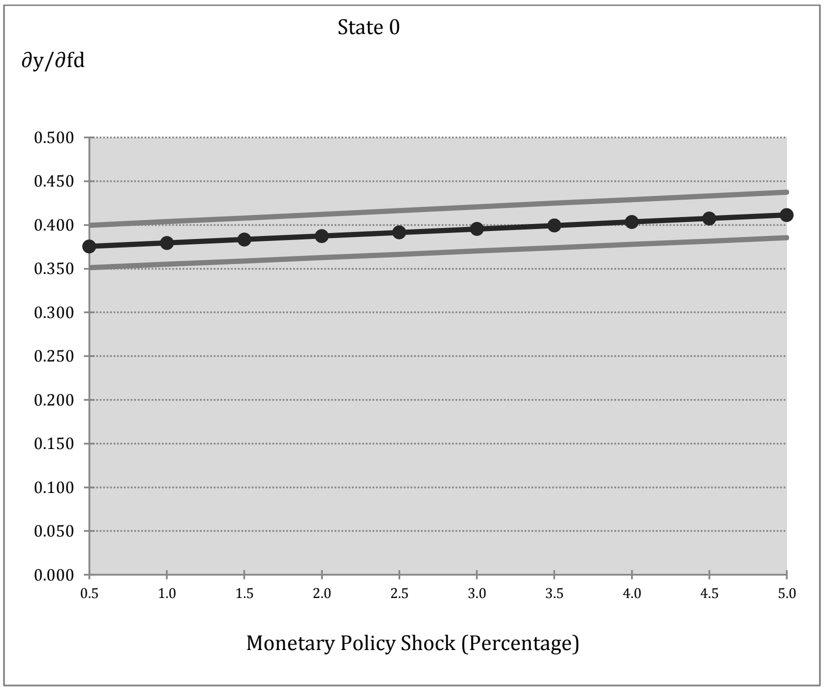
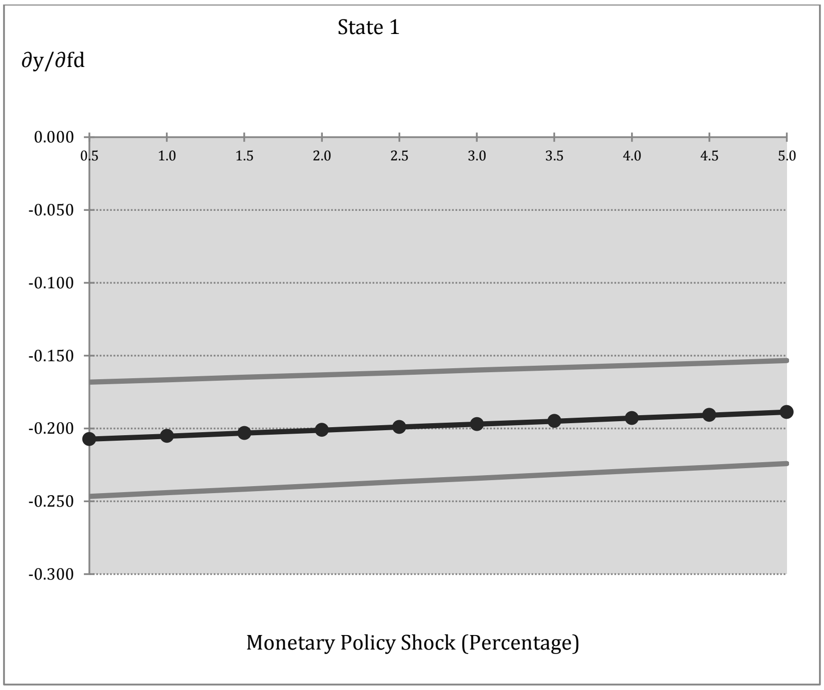


Figure 8: **Total Effects of Financial Depth**





Chapter 4

Markov Switching Causality and the Energy-Output Relation in the U.S.

4.1 Key Findings

In this chapter, we empirically investigate the causal link between energy consumption and economic growth employing a Markov switching Granger causality analysis. We carry out our investigation using quarterly U.S. real GDP and total energy consumption data which cover the period between 1975:QI–2009:QIV. We find that there are significant changes in the causal relation between energy consumption and economic growth over the sample period. Our results show that total energy consumption has predictive content for real economic activity. Furthermore, the causality running from total energy consumption to output growth seems to be strongly apparent only during the periods of economic downturn and energy crisis. We also document that output growth has predictive power in explaining total energy consumption and this power disappears during the periods of recession and evidently arises again during the periods of expansion. In addition, the time span that output growth Granger causes energy consumption is longer than that of the reverse causality.

4.2 Introduction

The relation between energy consumption and economic growth has attracted a great deal of attention in recent years. Several researchers have investigated the causal link between the energy consumption and the output growth using different econometric approaches, countries and sample periods with varying results. Knowledge of this causal direction between energy and output may have important policy implications. For instance, if the direction of the causality is from energy use to real GDP, any energy conservation policy which restricts energy consumption may lead to a decrease in economic growth. However, the causality running from real GDP to energy consumption implies that applying energy conservation policies may not exert any negative impact on real economic activity.

Some researchers provide evidence that the direction of the causality is from energy consumption to growth, others show that the direction of the causality is from economic growth to energy consumption. Researchers even suggest that there is a bidirectional causality or no causal relation. It is obvious that the results are very sensitive to the changes in the sample of countries and econometric methodologies. But even some country-specific studies have provided contradictory results using similar causality tests but different sample periods. For instance for the U.S., Kraft and Kraft (1978) and Abosedra and Baghestani (1989) show that the unidirectional causality runs from real GDP to energy consumption. While Akarca and Long (1980) and Yu and Hwang (1984) using similar type causality tests argue that no causality exists between energy consumption and real GDP in the U.S..

One possible reason behind the little consensus in the empirical studies could be the presence of regime shifts and structural changes in the output and energy series. As many other macroeconomic time series output and energy series may exhibit nonlinear behavior due to different factors like policy changes, economic or energy crises (see for instance, Seifritz and Hodgkin (1991), Fallahi (2011)). Thus, if output and energy data exhibit regime shifts and structural changes then a model assuming constant parameters over the sample period is likely to yield misleading results.

Moreover, the empirical results of the causality tests may significantly depend on the selection of the sample period due to the structural changes in output growth and energy series. The sensitivity of results of the causality tests with respect to the sample period under study seems to be one other reason of the contradictory evidence and the unstable energy-output causality in the existing empirical literature. Therefore, modeling the causal relation between energy and output within a nonlinear framework is more suitable to deal with such instabilities and to model the changing causality patterns over the sample period when the inconstancy of the model parameters is clear to the researcher.

To analyze the causal link between energy consumption and economic growth and to tackle with the issues discussed above, we employ a Markov switching Granger causality analysis which is proposed by Psaradakis et al. (2005). This study is the first attempt in empirically investigating the causal link between energy and output growth using the Markov switching Granger causality methodology. In this methodology the Granger causality is based on a VAR model with time varying parameters. In particular, time variation in the parameters is specifically designed to show the changes in the causality patterns between the variables under study. The number and timing of the changes in the causal relation between energy consumption and economic growth is unknown a priori but this methodology enables the data to capture the time points at which the changes in the causality pattern occur. The changes in the causal link between energy consumption and economic growth are assumed to follow a Markov chain with unknown transition probabilities.

The specification of the model allows for four alternative states in which energy consumption is Granger-causal for output growth, output growth is Granger-causal for energy consumption, both variables are Granger causal for each other and both variables are Granger non-causal for each other, respectively. We carry out our investigation using quarterly U.S. real GDP and total final energy consumption data which cover the period between 1975:QI–2009:QIV. We find that there are indeed four different states and that in each state we observe a different causal relation between energy consumption and economic growth.

Our results can be summarized as follows. According to the standard Granger causality test based on a linear VAR model, total energy consumption does not have any predictive power for output growth. However, our findings from estimation of the Markov switching VAR model provide evidence that it has predictive content for real economic activity. Importantly, the causality running from total energy consumption to output growth appears to exist only during the periods of economic downturns and energy crisis. More specifically, total energy consumption is found to Granger-cause output growth during the economic recessions in 1975, 1980, 1981/1982, 1990/1991, 2000/2001, 2008/2009 and also during the periods of oil crisis including the one started in 1978 caused by the Iranian Revolution, 1980 oil crisis induced by Iran–Iraq War and 1990 oil price shock due to the Gulf War.

Regarding the causality that runs from output growth to energy consumption, we observe that the output growth has predictive power for total energy consumption and this predictive ability clearly disappears during the periods of recession and rises again during the periods of expansion. In contrast to those empirical studies which argue that there is an absence of causality between the related series, overall we find that both series have predictive power for each other during different regimes over the sample period under investigation. Thus the smoothed probability of each series being Granger non-causal for the other one is quite low almost over the whole sample period.

In what follows, we first briefly summarize the existing empirical literature to date in Section 4.3. Next, we describe the data and the Markov switching Granger causality methodology in Section 4.4. Section 4.5 discusses the empirical results and Section 4.6 concludes the chapter. The results are presented in the Appendix.

4.3 Literature Review

Several researchers have investigated the presence of a causal link between energy consumption and real economic activity employing alternative econometric methodologies ever since the pioneering study of Kraft and Kraft (1978). However, the existing empirical literature does not allow one to reach a coherent conclusion as the previous empirical studies have provided contradictory results concerning whether there is a causal relation between energy use and economic growth and what the direction of the causality is. For instance, Kraft and Kraft (1978), show that the causality runs from real GNP to gross energy inputs applying Sims (1972) causality test to the U.S. annual data for the post-war period that covers 1947-1974. Using the same econometric technique, Akarca and Long (1980) re-examine the causal link between energy usage and real GNP for a two years shorter sample period from 1947 to 1972. That is, they exclude the years 1973-1974 which is a period of recession and of rising energy prices due to the oil embargo. Having found that there exists no causality between energy consumption and real GDP by shortening the sample period of Kraft and Kraft (1978), Akarca and Long (1980) argue that the causal order suggested by Kraft and Kraft (1978) is spurious and it is sensitive to the sample period.

In line with Akarca and Long (1980), Yu and Hwang (1984) find no causal link between real GNP and energy usage employing both Sims (1972) and Granger (1969) causality tests for the extended U.S. annual data from 1947 to 1979. Moreover, they show that a significant structural shift occurred around 1973 performing a Chow test. Abosedra and Baghestani (1989) questioned the evidence provided by Akarca and Long (1980) and Yu and Hwang (1984) by utilizing Granger (1969) causality tests for 1947-1974, 1947-1979 and 1947-1987 sample periods and find that there is a unidirectional causality running from real GNP to energy consumption. Murry and Nan (1990) also support Abosedra and Baghestani (1989)'s findings by indicating that there is a causality running from employment to energy consumption based on a Granger (1969) causality test for the monthly U.S. data from 1974 to 1988.

More recently, Thoma (2004) tests the presence of the causal link between electricity usage and industrial production in the U.S. economy using monthly data covering the period 1973:01-2000:01. Using Granger (1969) causality tests he indicates that there is a unidirectional causality running from industrial production to electricity consumption. He also investigates the impulse responses of electricity usage caused by a shock to output and finds a positive and significant response of electricity consumption over the first 26 months after the shock. More importantly, he examines the nature of the cyclical frequency at which the causal link between output and energy consumption occurs based on a spectral frequency bands analysis. His findings reveal that there is a low frequency relation between electricity consumption and output. That is, the fluctuations in output due to business cycles induce the low frequency fluctuations in the energy consumption. Moreover, he shows that the causality that runs from output to electricity usage is stronger at the peak of the cycle and weaker at the trough of the cycles forecasting a model for peak, average and trough energy use for each year in the sample period.

Following the advances in time series econometrics, new techniques have been used to re-examine the causal link between energy and output. Cointegration and error correction models are two of the most frequently used techniques. For instance, based on a four equation VAR model of the U.S. real GDP, energy usage, capital and labor, Stern (2000) shows the presence of a cointegration between energy and real GDP from 1948 to 1994 using Johansen procedure (Johansen (1988), Johansen and Juselius (1990)). His multivariate cointegration analysis indicates that energy significantly explains real GDP. Soytas and Sari (2003) test the causal link between real GDP and energy usage in ten emerging economies and G7 countries performing Johansen and Juselius (1990) cointegration procedure for the period 1950-1992. Having found the presence of cointegration between the series for some of the countries in the sample, they estimate the related vector error correction models to identify the direction of the causality for these countries. They show that there is a long run unidirectional causality running from energy consumption to real GDP for Turkey, France, West Germany and Japan while the reverse causality exists for Italy and Korea. However, they are unable to find a cointegration relation between energy usage and real GDP in the U.S..

Chontanawat et al. (2008) uncover the causality between energy consumption and real GDP for 30 OECD countries and 78 non-OECD countries using the Johansen and Juselius (1990) cointegration procedure. In line with Soytas and Sari (2003) they find no cointegration between energy and real GDP in the U.S. economy from 1960 to 2000. To reduce the omitted variables bias Soytas and Sari (2006) apply a multivariate Johansen and Juselius (1990) cointegration procedure and vector error correction (VEC) models with the inclusion of capital and labor inputs. They use a sample of G7 countries for the period 1960-2004 to search the presence of causality between energy and real GDP. For all G7 countries they find at least one cointegration relation. Having established the presence of cointegration, they next estimate a multivariate VEC model for all the countries in their sample. As far as the U.S. economy is concerned, their results show that there is a unidirectional causality running from energy usage to real GDP in both short and long run in the U.S..

To infer the energy-income relation Toda and Yamamoto (1995) causality test is also applied in the existing empirical literature. Since this methodology does not depend on the cointegration properties of the series under investigation, one does not have to test for cointegration before committing a causality analysis. For example, Soytas et al. (2007) search the long run Granger causality between real GDP, energy usage and carbon emissions including the factors of production based on the Toda and Yamamoto (1995) causality test for the U.S. economy between 1960-2000. In regard to their results, income does not Granger cause carbon dioxide emissions in the long run. Energy consumption is found to be Granger causal for carbon emissions while it is found as Granger non-causal for real output. Their result implies that U.S. may not have to reduce output to solve the existing carbon emissions problem but may reduce energy consumption to decrease the emissions levels.

Some studies point out that, sectoral differences should be taken account before choosing a specific energy policy. For instance, Bowden and Payne (2009) use both aggregate and sectoral U.S. data from 1949 to 2006 to investigate the causality between energy usage and real GDP. They utilize a Toda and Yamamoto (1995) long run causality test within a multivariate framework that also includes the levels of capital formation and employment. Their results indicate that the causality patterns between the related series may differ across different sectors. More specifically, industrial energy consumption is found to Granger cause real GDP while there exists no causality between total energy, transportation energy and real GDP, respectively. Their findings suggest a bidirectional causality between residential energy consumption, commercial energy consumption and real GDP, respectively. Using the same sample period in a different study Payne (2009) applies Toda and Yamamoto (1995) test to search for the long run causality between renewable/non-renewable energy consumption and real GDP with the inclusion of real gross fixed capital formation and employment. His results reveal that neither renewable nor non-renewable energy consumption Granger causes real GDP for the period under investigation. Similarly, there exists no causality running from real GDP to renewable and non-renewable energy consumption, respectively. Lee (2006) also uses the Toda and Yamamoto (1995) test to uncover the long run causality for G11 annual data from 1960 to 2001. With regard to the U.S., his results provide evidence of a bidirectional causality between energy consumption and real GDP.

Recently, some researchers point out that the use of short sample periods in country specific studies lowers the power of cointegration tests. Thus, they choose to apply panel cointegration tests and panel vector error correction models to re-investigate the energy-output relation. For instance, for a sample of 22 OECD countries, Lee et al. (2008) employ the Pedroni (1999) panel cointegration test and panel vector error correction model using the annual data from 1960 to 2001. Their model is based on a multivariate framework of electricity consumption per capita, real GDP per capita and net capital stock per capita. The results of their study show that there is a positive long run relation between the related series. Once having established the presence of cointegration relation, they employ the panel causality test and find a bidirectional causality between electricity consumption, capital stock and income.

Narayan and Smyth (2008) also apply the panel cointegration procedure suggested by Pedroni (1999) to examine the energy-output link using the G7 annual data from 1972 to 2002. Besides, they also utilize the Westerlund (2006) panel cointegration test to take account of the structural breaks that may exist in energy consumption and real GDP series. According to the findings of the Pedroni (1999) test, real GDP per capita, energy use per capita and real gross fixed capital formation per capita do not have a long run cointegration. On the other hand, the results of the Westerlund (2006) procedure show that there exist structural breaks in the related series for the G7 countries. For instance, they find a break in 1988 immediately after the stock market crash and before the Gulf War in the U.S. economy. In contrast to the findings of the Pedroni (1999) panel cointegration test which ignores the presence of possible structural breaks in the data, the results of the Westerlund (2006) panel cointegration test document that there is a long run equilibrium relation between real GDP, energy usage, and capital formation. Having found the presence of structural breaks and cointegration, they estimate panel vector error correction models to examine the direction of the causality between the related series and they find a causality running from energy consumption per capita to real GDP per capita both in the short and long run for the G7 panel.

In line with Narayan and Smyth (2008), Chiou-Wei et al. (2008) provide evidence of nonlinearity in the energy and output series applying the BDS test suggested by Brock et al. (1987) on the residuals of a VAR model of energy and real GDP for a sample of Asian countries and U.S. as well. They argue that there may be nonlinearity in the causal link between the related series as the identically and independently distributed assumption is rejected for the residuals. For that reason, they apply a nonlinear Granger causality test proposed by Baek and Brock (1992) to uncover the presence of causality. However, they find that no causality exists between energy and real GDP in the U.S. economy over the period from 1960 to 2003.

More recently, Fallahi (2011) shows that energy consumption is Granger causal for economic growth using U.S. annual data of real GDP and energy consumption from 1960 to 2005. Based on Krolzig (1997)'s Markov switching VAR model, he finds that the causality running from energy consumption to growth is significant only in one regime which mostly includes the recession periods in the U.S. economy.

As discussed above, the results of the standard causality tests applied to search the causality between energy and output are very sensitive to the changes in the sample period. In particular, due to the structural changes which are common for energy and output series the empirical results of the Granger causality tests for country specific studies may substantially depend on the selection of the sample period. Thus, it is obvious that the direction of the causal link between energy and output may change or the causal link even may not hold during some time intervals over the sample period under study. Furthermore, as argued by Psaradakis et al. (2005) the unstable causality pattern between the related variables may cause significant econometric problems in the application of standard tests for Granger causality.

To tackle with the econometric difficulties arising from non-constant causal patterns one can split the sample period. But in this case the researcher is supposed to know the specific dates at which the causal relation changes. One may have a priori knowledge about the specific dates at which the economy has been subjected to a structural change such as an economic crisis, an energy crisis or a policy change but these events may not be necessarily related to the changes in causality patterns. In this study, observing that the results of the standard causality tests are time dependent we choose to employ a Markov switching Granger causality methodology. In our investigation, we search for the temporal Granger causality relation between energy consumption and output growth.

4.4 Data and Econometric Methodology

4.4.1 Data

The aim of this study is to empirically investigate the causal link between energy consumption and output growth controlling the inflation level in the economy. We carry out our empirical investigation based on the U.S. data for the period from 1975 to 2009. We use quarterly real GDP and quarterly consumer price index (CPI). However, for the total final energy consumption series, data is only available at annual frequency. On that account, we interpolate annual total final energy consumption series to quarterly frequency by employing proportional Denton procedure (see Baum and Hristakeva (2011)). [34]

The quarterly data for real GDP and consumer price index (CPI) are obtained from International Financial Statistics database of the International Monetary Fund covering the period 1975:Q1–2009:QIV. The annual series of total final energy consumption is obtained from the International Energy Agency (IEA) database for the period 1975–2009. According to IEA's documentation total final energy consumption is equal to the sum of the consumption in the end-use sectors. Energy used for transformation processes and for own use of the energy producing industries is not included. The unit value is kilo tonnes of oil equivalent (ktoe).[35] We measure output growth (y_t) by the first difference of the logarithm of real GDP and energy consumption growth (tec_t) by the first difference of the logarithm of total final energy consumption. Similarly, we calculate the inflation rate (π_t) as the first difference of the logarithm of the consumer price index.

4.4.2 Econometric Methodology

Ever since the pioneering study of Hamilton (1989), Markov regime switching models have been utilized by numerous researchers to investigate the asymmetries and nonlinearities which are embedded in many macroeconomic time series (see, among the others, Goodwin (1993), Filardo (1994), Gray (1996), Artis et al. (2004)). Recently, some researchers have proposed Markov regime switching VAR models (see Krolzig (1997), Warne (2000), Ehrmann et al. (2003)). In these models the intercept, autoregressive coefficients and/or the error variance may be regime dependent. However, as pointed out by Psaradakis et al. (2005) by allowing only regime dependent parameters, these models are not competent enough to

[34] As stated by Baum and Hristakeva (2011) this method is suggested in IMF publications as it is "relatively simple, robust, and well-suited". The objective of the Denton proportional method is to keep the ratio of the estimated quarterly series to the indicator series as constant as possible under the annual constraints.

[35] Different forms and sources of energy have been converted to a single unit by IEA using specific conversion factors.

search the changes in the causality patterns over the sample period. First of all, in these models one regime may be composed of periods in which the underlying variables have different causal links. To overcome this difficulty, we employ the Markov regime switching causality methodology suggested by Psaradakis et al. (2005) in analyzing the presence and the direction of the causality in the energy-output relation. Within this framework, the parameters of the Markov switching VAR model change with respect to the presence and direction of the Granger causality. By this way, the model enables the researcher to identify not only the time periods in which the Granger causality exists but also the direction of the causal link provided that any evidence of causality is found.

The following Markov switching VAR model is estimated to analyze the causality between $Y_{1,t}$ and $Y_{2,t}$ conditionally on the the series X_t:

$$\begin{aligned}\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix} &= \begin{bmatrix} \mu_{10}\left(1-S_{1,t}\right)+\mu_{11}S_{1,t} \\ \mu_{20}\left(1-S_{2,t}\right)+\mu_{21}S_{2,t} \end{bmatrix} \\ &+\sum_{k=1}^{h_1}\begin{bmatrix} \phi_{10}^{(k)}\left(1-S_{1,t}\right)+\phi_{11}^{(k)}S_{1,t} & \gamma_1^{(k)}S_{1,t} \\ \gamma_2^{(k)}S_{2,t} & \phi_{20}^{(k)}\left(1-S_{2,t}\right)+\phi_{21}^{(k)}S_{2,t} \end{bmatrix}\begin{bmatrix} Y_{1,t-k} \\ Y_{2,t-k} \end{bmatrix} \\ &+\sum_{k=1}^{h_2}\begin{bmatrix} \theta_{10}^{(k)}\left(1-S_{1,t}\right)+\theta_{11}^{(k)}S_{1,t} \\ \theta_{20}^{(k)}\left(1-S_{2,t}\right)+\theta_{21}^{(k)}S_{2,t} \end{bmatrix} X_{t-k}+\begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, t=1,2,...,T \end{aligned} \tag{11}$$

Within this model we investigate the Granger causality between the elements of the bivariate time series $Y_t' = [y_t : tec_t]$ conditionally on the time series $X_t = \pi_t$. We choose inflation as the conditioning variable since an increase in the energy prices would increase the overall price level in the economy. $S_{1,t}$ and $S_{2,t}$ are latent state variables which take values of 0 or 1 at time t depending on the prevailing regime. $\varepsilon_t' = [\varepsilon_{1,t} : \varepsilon_{2,t}]$ is a white noise process independent of $S_{1,t}$ and $S_{2,t}$ with mean zero and covariance matrix which depends on $S_{1,t}$ and $S_{2,t}$. Within this specification, we have four different states which are indexed by S_t:

$$S_t = \begin{cases} 1 \text{ if } S_{1,t} = 1 \text{ and } S_{2,t} = 1 \\ 2 \text{ if } S_{1,t} = 0 \text{ and } S_{2,t} = 1 \\ 3 \text{ if } S_{1,t} = 1 \text{ and } S_{2,t} = 0 \\ 4 \text{ if } S_{1,t} = 0 \text{ and } S_{2,t} = 0 \end{cases} \tag{12}$$

Thus, in that way the model in equation (11) suggests that:

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix} = \begin{bmatrix} \mu_{11} \\ \mu_{21} \end{bmatrix} + \sum_{k=1}^{h_1} \begin{bmatrix} \phi_{11}^{(k)} & \gamma_1^{(k)} \\ \gamma_2^{(k)} & \phi_{21}^{(k)} \end{bmatrix} \begin{bmatrix} Y_{1,t-k} \\ Y_{2,t-k} \end{bmatrix} + \sum_{k=1}^{h_2} \begin{bmatrix} \theta_{11}^{(k)} \\ \theta_{21}^{(k)} \end{bmatrix} X_{t-k} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \quad \text{if } S_t = 1$$

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix} = \begin{bmatrix} \mu_{10} \\ \mu_{21} \end{bmatrix} + \sum_{k=1}^{h_1} \begin{bmatrix} \phi_{10}^{(k)} & 0 \\ \gamma_2^{(k)} & \phi_{21}^{(k)} \end{bmatrix} \begin{bmatrix} Y_{1,t-k} \\ Y_{2,t-k} \end{bmatrix} + \sum_{k=1}^{h_2} \begin{bmatrix} \theta_{10}^{(k)} \\ \theta_{21}^{(k)} \end{bmatrix} X_{t-k} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \quad \text{if } S_t = 2$$

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix} = \begin{bmatrix} \mu_{11} \\ \mu_{20} \end{bmatrix} + \sum_{k=1}^{h_1} \begin{bmatrix} \phi_{11}^{(k)} & \gamma_1^{(k)} \\ 0 & \phi_{20}^{(k)} \end{bmatrix} \begin{bmatrix} Y_{1,t-k} \\ Y_{2,t-k} \end{bmatrix} + \sum_{k=1}^{h_2} \begin{bmatrix} \theta_{11}^{(k)} \\ \theta_{20}^{(k)} \end{bmatrix} X_{t-k} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \quad \text{if } S_t = 3$$

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix} = \begin{bmatrix} \mu_{10} \\ \mu_{20} \end{bmatrix} + \sum_{k=1}^{h_1} \begin{bmatrix} \phi_{10}^{(k)} & 0 \\ 0 & \phi_{20}^{(k)} \end{bmatrix} \begin{bmatrix} Y_{1,t-k} \\ Y_{2,t-k} \end{bmatrix} + \sum_{k=1}^{h_2} \begin{bmatrix} \theta_{10}^{(k)} \\ \theta_{20}^{(k)} \end{bmatrix} X_{t-k} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \quad \text{if } S_t = 4$$

As it is observed, the state variables $S_{1,t}$ and $S_{2,t}$ reflect the causality patterns within this model. More specifically, $S_{1,t}$ shows whether $Y_{2,t}$ Granger causes $Y_{1,t}$ and $S_{2,t}$ shows whether $Y_{1,t}$ Granger causes $Y_{2,t}$. Provided that at least one of the $\gamma_1^{(1)}, ..., \gamma_1^{(h1)}$ is not equal to zero, $Y_{2,t}$ is Granger causal for $Y_{1,t}$ when $S_{1,t} = 1$ (if $S_t = 1$ or $S_t = 3$) and is not Granger causal for $Y_{1,t}$ when $S_{1,t} = 0$ (if $S_t = 2$ or $S_t = 4$). In a similar manner, given that at least one of the $\gamma_2^{(1)}, ..., \gamma_2^{(h1)}$ is not equal to zero $Y_{1,t}$ is Granger causal for $Y_{2,t}$ when $S_{2,t} = 1$ (if $S_t = 1$ or $S_t = 2$) and is not Granger causal for $Y_{2,t}$ when $S_{2,t} = 0$ (if $S_t = 3$ or $S_t = 4$). The covariance matrix of the disturbances of the VAR model in equation (11) is specified as follows:

$$\mathbb{E} = (\varepsilon_t \varepsilon_t' \mid S_t = l) = [\sigma_{ij,l}], \qquad i, j = 1, 2; l = 1, ..., 4$$

It is worth noting that the model assumes that data selects the prevailing state at time t with a probability which depends on the state persisting at time *t-1*. Building on this assumption, Psaradakis et al. (2005) indicate that regime or state switches are assumed to be directed by a first-order Markov process with the following transition probabilities:

$$p_{ij}^{l} = \mathbb{P}(S_{l,t+1} = j \mid S_{l,t} = i), \qquad i, j = 0, 1; l = 1, 2$$

The model is completed by assuming that the random unobservable processes $S_{1,t}$ and $S_{2,t}$ are independent and time homogenous. In this respect, the random process S_t is defined as time-homogenous and it has first order Markov chain with the following transition matrix where **P** refers the stochastic matrix whose (i,j) component is the probability $\mathbb{P}(S_{t+1} = i \mid S_t = j)$, for i,j=1,...,4.

$$\mathbf{P} = \begin{bmatrix} p_{11}^{(1)} p_{11}^{(2)} & p_{11}^{(2)}\left(1-p_{00}^{(1)}\right) & p_{11}^{(1)}\left(1-p_{00}^{(2)}\right) & \left(1-p_{00}^{(1)}\right)\left(1-p_{00}^{(2)}\right) \\ p_{11}^{(2)}\left(1-p_{11}^{(1)}\right) & p_{00}^{(1)} p_{11}^{(2)} & \left(1-p_{11}^{(1)}\right)\left(1-p_{00}^{(2)}\right) & p_{00}^{(1)}\left(1-p_{00}^{(2)}\right) \\ p_{11}^{(1)}\left(1-p_{11}^{(2)}\right) & \left(1-p_{00}^{(1)}\right)\left(1-p_{11}^{(2)}\right) & p_{11}^{(1)} p_{00}^{(2)} & p_{00}^{(2)}\left(1-p_{00}^{(1)}\right) \\ \left(1-p_{11}^{(1)}\right)\left(1-p_{11}^{(2)}\right) & p_{00}^{(1)}\left(1-p_{11}^{(2)}\right) & p_{00}^{(2)}\left(1-p_{11}^{(1)}\right) & p_{00}^{(1)} p_{00}^{(2)} \end{bmatrix} \tag{13}$$

A causality analysis building on the Markov switching VAR model in equation (11) performs well since the states in the model directly reflect the patterns of the causal link between the variables being analyzed. Furthermore, the model enables the researcher to identify the unknown possible turning points in the causality over the sample period and to make inferences about them. All these are of vital importance within the framework of our study for it is observed that the existing empirical results are considerably sensitive to the changes in the sample period.

In spite of the fact that the state variables are unobservable, they can be recognized at each time point in the sample period based upon the estimated conditional probabilities $\mathbb{P}\left(S_t = l \mid \mathbf{W_1}, ..., \mathbf{W_t}; \hat{\theta}\right)$, $l = 1, ..., 4$ where $\mathbf{W_t'} = [\mathbf{Y_t'} : \mathbf{X_{t-1}}]$ and $\hat{\theta}$ is the estimator of the parameters in the model constructed in equation (11).

4.5 Empirical Results

4.5.1 Results from Linear VAR Model

Prior to analyzing the causal link between energy consumption and output growth by the Markov switching VAR model in equation (11), we first focus on the Granger causality between underlying series based on the following linear VAR model:

$$\boldsymbol{Y_t} = \boldsymbol{\mu} + \sum_{k=1}^{n_1} \boldsymbol{\Phi_k} Y_{t-k} + \sum_{k=1}^{n_2} \boldsymbol{\Theta_k} \pi_{t-k} + \boldsymbol{\xi_t} \tag{14}$$

Here, $Y_t' = [y_t : tec_t]$ and π_t is the inflation rate at time t, and $\boldsymbol{\xi_t}$ is a vector of disturbances. We add the lagged inflation rate to the model as a conditioning variable while testing the Granger causality between the related series.[36]

We apply a standard Granger causality test looking at whether there is any causal relation between total energy consumption and output growth in the system. The p-value for a standard Granger causality test from total energy consumption to output growth is 0.215, and from output growth to total energy consumption the corresponding p-value is 0.000. Given these p-values we can say that the total energy consumption does not help to predict output growth while output growth has a significant predictive power for total energy consumption.

[36] n_1 and n_2 are determined as 2 based on the Akaike information criteria.

At the next step, based on the estimation of the linear VAR model in equation (14) we investigate whether the estimated causal link is stable over the sample period. For this purpose, we test the constancy of parameters of the VAR model utilizing the tests proposed by Hansen (1992b), Andrews (1993), Andrews and Ploberger (1994) and Brock et al. (1987). For Hansen (1992b), Andrews (1993), Andrews and Ploberger (1994) tests, the null hypothesis is that parameters are stable while the alternative is that there is an evidence of one-time change at the break point. The test statistic constructed by Brock et al. (1987) is used to test the null hypothesis that the residuals from the VAR model are independently and identically distributed (i.i.d.) against an unspecified alternative. The rejection of the i.i.d. assumption implies that there is an evidence of nonlinearity in the series. In that case, a nonlinear approach is arguably more appropriate to search the causal link between the underlying series instead of a linear model which ignores the presence of the embedded nonlinearity in the series. Table 12 shows the results of the tests which are performed for the output equation.

Insert Table 12 about here

The results in Panel A in Table 12 show that, only the Hansen (1992b) test confirms the evidence of parameter instability in the output equation. As a further check, we investigate whether the residuals from the output growth-total energy consumption VAR model are independently and identically distributed based on the Brock et al. (1987) test. The results of the test are presented in Panel B in Table 12. Under different embedding dimensions (m=2,3,.., 5) and lengths in standard deviation (ϵ=0.5,1,...,2) i.i.d. assumption can be strongly rejected for the residual series from the output equation.

Overall, the rejection of the parameter stability over the sample period indicates that a linear VAR model is unlikely to capture the main features of the underlying data generating process. Although these parameter stability tests presented here do not cover regime switching models, their results arguably show that a nonlinear model might be more well suited to analyze the underlying link between the related variables.

4.5.2 Results from Markov Switching VAR Model

We now focus on the empirical evidence from the maximum likelihood estimation of the parameters of the Markov switching VAR model described in equation (11) with $Y_t' = [y_t : tec_t]$ and the conditioning variable $X_t = \pi_t$.[37] The maximization of the likelihood function is carried out by applying a form of iterative algorithm explained in Hamilton (1994, chap. 22). Table 13 reports the maximum likelihood estimates of the parameters of the model and the related standard errors. The estimated parameters of the output equation are shown in the first column of Table 13.

Insert Table 13 about here

Turning to our estimation results from the Markov switching VAR model, first of all, we observe that the parameters which show the changes in causality between the total energy consumption and economic growth are significantly different from zero except $\gamma_1^{(2)}$. More specifically, $\gamma_1^{(1)}$ in the output equation is positive and highly significant. Thus, total energy consumption Granger causes output growth when the economy is in $S_t = 1$ or $S_t = 3$. It is worth noting that the statement that total energy consumption Granger causes output growth does not imply that output growth is the result of total energy consumption nor does it imply that total energy consumption is responsible for the changes in output growth. Hamilton (1994, chap. 11) shows that there is not any direct link between causality in an economic sense and causality in an econometric sense. In this context, Granger causality is in econometric sense and shows the presence of the power of one variable in predicting the other one. That is, according to the empirical results total energy consumption has predictive ability for output

[37] We choose h_1 and h_2 as 2 based on the Akaike information criteria

growth rate if $S_t = 1$ or $S_t = 3$ prevails in the economy.

Furthermore, $\gamma_2^{(1)}$ and $\gamma_2^{(2)}$ in the total energy consumption equation are negatively and positively significant at the 1% level, respectively. Put differently, output growth has predictive power for total energy consumption while the economy is in $S_t = 1$ or $S_t = 2$. These results imply that there are indeed regime shifts in the causality patterns between the variables under study.

In an effort to get a better understanding of the extent and timing of the changes in the causality relation over the sample period, we first plot the estimated smoothed probability of total energy consumption Granger causing output growth in Figure 9. Specifically, this probability is the sum of $P\left(S_t = 1 \mid W_1, ..., W_t; \hat{\theta}\right)$ and $P\left(S_t = 3 \mid W_1, ..., W_t; \hat{\theta}\right)$. The shaded areas in Figure 9 represent the recession periods announced by NBER reported in Table 5.

Insert Table 5 about here

It is evident from Figure 9 that the predictive power of total energy consumption is high almost only during recession periods. In particular, the causality running from total energy consumption to output growth is strong purely during the economic downturns in 1975, 1980, 1981/1982, 1990/1991, 2000/2001, 2008/2009 in the U.S. economy. Some of these turning points overlap with the oil crisis started in 1978 caused by the Iranian Revolution, 1980 oil crisis induced by Iran–Iraq War and 1990 oil price shock due to the Gulf War. These findings partially support the results of Fallahi (2011) which show that the causality running from energy consumption to output growth is significant in recession periods in the U.S. economy. However, unlike Fallahi (2011) the results from our model point out that there are also different significant causality patterns between the related series across different regimes.

Insert Figure 9 about here

So far, the findings we presented here are quite interesting. To begin with, although the standard Granger causality test based on a linear VAR model does not provide any significant evidence to confirm that total energy consumption is Granger causal for real economic activity, the results from the Markov switching VAR model provide evidence that total energy consumption has predictive content for output growth. Last but not least, the causality running from total energy consumption to output growth seems to be solely and strongly evident during the periods of economic downturn and energy crisis.

These results are also somewhat in line with the arguments of Hamilton (2003) who suggests that the recession periods in the U.S. economy are closely related to the price of oil and the increases in oil price rather than the decreases in oil price are able to predict GDP. More clearly, he argues that the great bottlenecks in the supply of energy and the following higher energy prices are one of the reasons behind most of the post-war recessions in the U.S.. Besides, he points out that the military conflicts seem to drive energy supply into bottleneck and lead to a rise in the energy prices.

In summary, from Hamilton (2003)'s point of view conflicts are more prominent in driving the economy into contraction as compared to the particular fluctuations in the energy prices as there will be higher uncertainty about future level of energy prices and decreasing private spending in such an unsettled environment. On that account, it is reasonable to expect a causal link between energy and output around the periods of energy crisis as is in our findings. Besides, if there is not a linear relation between energy prices and real output as argued by Hamilton (2003)[38] there is no reason to expect a linear relation between energy consumption and real GDP as well. It would not be surprising that a linear modeling of a relation which is nonlinear in nature suffers from parameter instability

[38] Mork (1989), Lee et al. (1995), Hamilton (1996), Davis and Haltiwanger (2001) also have shown that the relation between energy prices and real economic activity is nonlinear.

over time.

Channeling the attention to the estimation results, we now examine the reverse causality from economic growth to total energy consumption. The plot of the estimated smoothed probability of output growth Granger causing total energy consumption is shown in Figure 10. Here, this probability is the sum of $P\left(S_t = 1 \mid W_1, ..., W_t; \hat{\theta}\right)$ and $P\left(S_t = 2 \mid W_1, ..., W_t; \hat{\theta}\right)$. Again, the shaded areas in Figure 10 represent the recession periods according to NBER dating.

Insert Figure 10 about here

We can observe that the predictive content of output growth in determining total energy consumption is generally high over the sample period. In addition, the period that output growth is Granger causal for energy consumption is longer than the period of the reverse causality. As a further investigation, in Figure 11 we plot the smoothed probability of $P\left(S_t = 2 \mid W_1, ..., W_t; \hat{\theta}\right)$. This probability represents only the probability of the unidirectional causality running from output growth to total energy consumption excluding the probability of the bidirectional causality between total energy consumption and output growth which equals to $P\left(S_t = 1 \mid W_1, ..., W_t; \hat{\theta}\right)$.

Insert Figure 11 about here

Now, observing Figure 11 one can clearly see that the predictive content of output growth for total energy consumption vanishes during the periods of recessions and goes up again during the periods of expansions. Thoma (2004) finds a similar result which indicates that the causality running from output growth to energy usage is stronger at the peak of the cycles and weaker at the trough of the cycles.

We also examine the smoothed probability of being in a regime where each series does not have a causal effect on the other one. This is the smoothed probability of being in $S_t = 4$, $\mathbb{P}\left(S_t = 4 \mid W_1, ..., W_t; \hat{\theta}\right)$, and it is plotted in Figure 12. As shown in Figure 12, the smoothed probability of non-causality is quite low almost over the whole sample period implying that there is not any persistence in $S_t = 4$ where $S_{1,t} = 0$ and $S_{2,t} = 0$. Thus, unlike the empirical studies which yield a lack of causality between the energy and output, we show that both series have predictive power for each other during different regimes over the sample period under study.

Insert Figure 12 about here

Finally, regarding the coefficients of the conditioning variable, we observe that the coefficients of inflation are statistically insignificant for both lags in the output growth equation while they are all significantly different from zero in the total energy consumption equation. That is, inflation has predictive ability for total energy consumption, but not for output growth in the U.S. economy in the sample period being analyzed.

4.6 Conclusion

In this chapter, we empirically examine the causal relation between total energy consumption and output growth in the U.S. economy. The empirical investigation is carried out by using real GDP, total final energy consumption and consumer price index series for the period 1975:QI–2009:QIV. Having observed that the results of the standard causality tests in the existing empirical literature are quite sensitive to the sample period under study, our empirical investigation specifically aims to search whether there are changing causality patterns over time.

Based upon the evidence of parameter instability from the estimation of the linear VAR model, we conjecture that a nonlinear modeling is well suited to analyze the changing causality patterns between energy consumption and economic activity. For this purpose we utilize the methodology suggested by Psaradakis et al. (2005) which is based on a Markov switching VAR model with time varying parameters. Within this study, the parameters of the Markov switching VAR model of total energy consumption and output growth vary with respect to the presence and the direction of the Granger causality. In that sense, this econometric methodology allows us to examine the presence of a temporal Granger causal link between the underlying variables. We also consider the impact of inflation by adding the lags of inflation as a third right-hand side variable in the Markov switching VAR model.

Our investigation provides evidence that there are four different states and in each state a different causal link between energy consumption and economic growth prevails. Interestingly, despite the standard Granger causality test based on a linear VAR model does not provide any evidence of causality running from total energy consumption to output growth, Markov switching VAR model suggests that energy consumption has predictive power for real economic activity. In particular, the causality running from total energy consumption to output growth appears to be strong only during the periods of downswings and energy crisis in the U.S. economy. More precisely, the causality running from total energy consumption to output growth is likely to be substantial during the downturns in the U.S. in 1975, 1980, 1981/1982, 1990/1991, 2000/2001, 2008/2009 and also during the periods of energy crisis including the one started in 1978 leaded by the Iranian Revolution, 1980 oil crisis triggered by Iran–Iraq War and 1990 oil price shock because of the Gulf War.

When we consider the reverse causality, we show that output growth has predictive ability for total energy consumption as well. Besides, we reveal that the predictive ability of output growth clearly rises during the periods of economic boom and then falls during the periods of economic downturn. Overall, we observe that total energy consumption and output growth Granger cause each other during different states. Hence, the smoothed probability of Granger non-causality between the underlying series is rather low nearly over the entire sample period implying this state is not highly persistent.

Although there is not a direct link between Granger causality and causation in economic sense, from the policy perspective our study points out the possibility that energy conservation policies aiming to curtail energy consumption may exert a negative impact on economic growth during recession periods. In particular, this sort of policies may deepen the extent of the bottlenecks in economic growth. In that sense, our study is unique in the light of the existing empirical literature on energy–output nexus. This is so because to our knowledge, the previous empirical studies have not explored the presence of temporal causal links between energy and output and the asymmetry in these causal links depending on the state of the business cycle.

Appendix to Chapter 4

Table 12: Stability Tests for Output Growth Equation

Panel A:				
Hansen (1992)				2.055
				(0.030)
Andrews (1993)				16.519
				(0.153)
Andrews, Ploberger (1994)				5.366
				(0.163)
Panel B: Brock, Dechert, and Scheinkman(1987)				
	$m = 2$	$m = 3$	$m = 4$	$m = 5$
$\epsilon = 0.5$	3.624	3.931	3.888	4.623
	(0.000)	(0.000)	(0.000)	(0.000)
$\epsilon = 1$	5.083	6.238	6.598	7.033
	(0.000)	(0.000)	(0.000)	(0.000)
$\epsilon = 1.5$	4.560	5.955	6.488	7.071
	(0.000)	(0.000)	(0.000)	(0.000)
$\epsilon = 2$	3.000	4.389	4.902	5.474
	(0.003)	(0.000)	(0.000)	(0.000)

Notes: p values in brackets.

Table 13: Estimates of Parameters of the Model for Total Energy Consumption and Output Growth

$$\begin{bmatrix} y_t \\ tec_t \end{bmatrix} = \begin{bmatrix} \mu_{10}\left(1-S_{1,t}\right)+\mu_{11}S_{1,t} \\ \mu_{20}\left(1-S_{2,t}\right)+\mu_{21}S_{2,t} \end{bmatrix}$$
$$+\sum_{k=1}^{2}\begin{bmatrix} \phi_{10}^{(k)}\left(1-S_{1,t}\right)+\phi_{11}^{(k)}S_{1,t} & \gamma_1^{(k)}S_{1,t} \\ \gamma_2^{(k)}S_{2,t} & \phi_{20}^{(k)}\left(1-S_{2,t}\right)+\phi_{21}^{(k)}S_{2,t} \end{bmatrix}\begin{bmatrix} y_{t-k} \\ tec_{t-k} \end{bmatrix}$$
$$+\sum_{k=1}^{2}\begin{bmatrix} \theta_{10}^{(k)}\left(1-S_{1,t}\right)+\theta_{11}^{(k)}S_{1,t} \\ \theta_{20}^{(k)}\left(1-S_{2,t}\right)+\theta_{21}^{(k)}S_{2,t} \end{bmatrix}\pi_{t-k}+\begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, t=1,2,...,T$$

Parameter	Estimate	Std. error	Parameter	Estimate	Std. error
$p_{11}^{(1)}$	0.677***	0.127	$p_{11}^{(2)}$	0.900***	0.041
$p_{00}^{(1)}$	0.853***	0.056	$p_{00}^{(2)}$	0.417**	0.203
μ_{10}	0.007***	0.001	μ_{20}	0.010***	0.001
μ_{11}	0.007	0.004	μ_{21}	0.008***	0.001
$\phi_{10}^{(1)}$	0.136*	0.069	$\phi_{20}^{(1)}$	0.158***	0.024
$\phi_{10}^{(2)}$	0.056	0.072	$\phi_{20}^{(2)}$	0.317***	0.022
$\phi_{11}^{(1)}$	-0.975**	0.490	$\phi_{21}^{(1)}$	0.910***	0.081
$\phi_{11}^{(2)}$	0.450	0.397	$\phi_{21}^{(2)}$	-0.123*	0.072
$\gamma_1^{(1)}$	0.941***	0.342	$\gamma_2^{(1)}$	-1.660***	0.125
$\gamma_1^{(2)}$	0.161	0.272	$\gamma_2^{(2)}$	0.969***	0.136
$\theta_{10}^{(1)}$	-0.078	0.067	$\theta_{20}^{(1)}$	-0.380***	0.062
$\theta_{10}^{(2)}$	-0.031	0.070	$\theta_{20}^{(2)}$	0.077*	0.045
$\theta_{11}^{(1)}$	0.084	0.236	$\theta_{21}^{(1)}$	-0.162**	0.081
$\theta_{11}^{(2)}$	0.047	0.302	$\theta_{21}^{(2)}$	-0.178**	0.080
$\sigma_{11}^{(1)}$	0.009***	0.002	$\sigma_{22}^{(1)}$	0.014***	0.003
$\sigma_{11}^{(2)}$	0.003***	0.000	$\sigma_{22}^{(2)}$	0.004***	0.000
$\sigma_{11}^{(3)}$	0.016***	0.006	$\sigma_{22}^{(3)}$	0.020***	0.007
$\sigma_{11}^{(4)}$	0.007***	0.002	$\sigma_{22}^{(4)}$	0.001***	0.000
Log likelihood =	1018.600				

Notes: *, **, *** denote significance at the 10%, 5% and 1% levels.

Figure 9: $\mathbb{P}\left(S_t = 1 \mid W_1, ..., W_t; \hat{\theta}\right) + \mathbb{P}\left(S_t = 3 \mid W_1, ..., W_t; \hat{\theta}\right)$: **Smoothed Probability of Total Energy Consumption Granger-causing Output Growth**

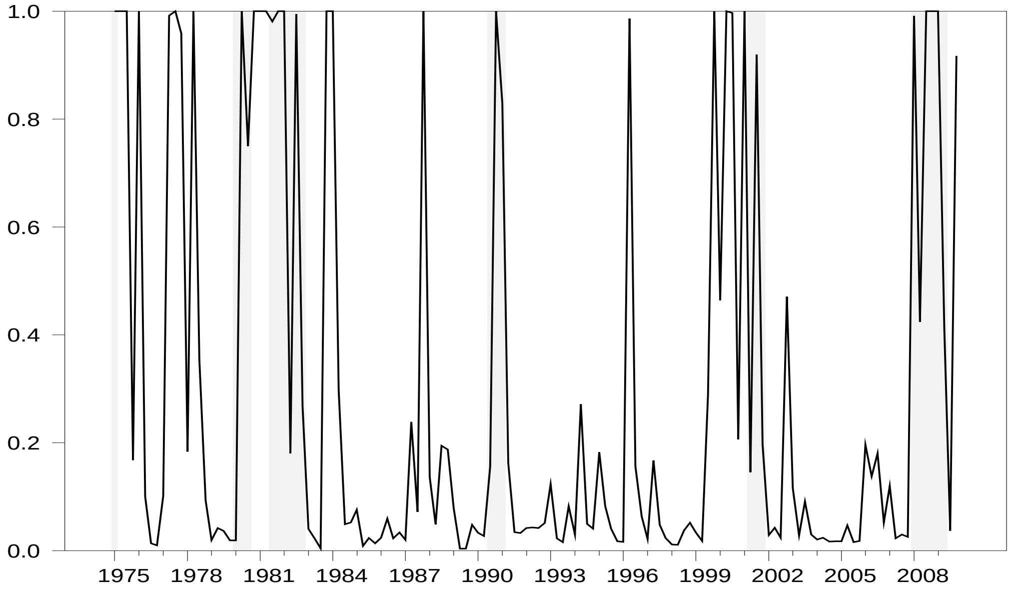


Figure 10: $\mathbb{P}\left(S_t = 1 \mid W_1, ..., W_t; \hat{\theta}\right) + \mathbb{P}\left(S_t = 2 \mid W_1, ..., W_t; \hat{\theta}\right)$: **Smoothed Probability of Output Growth Granger-causing Total Energy Consumption**

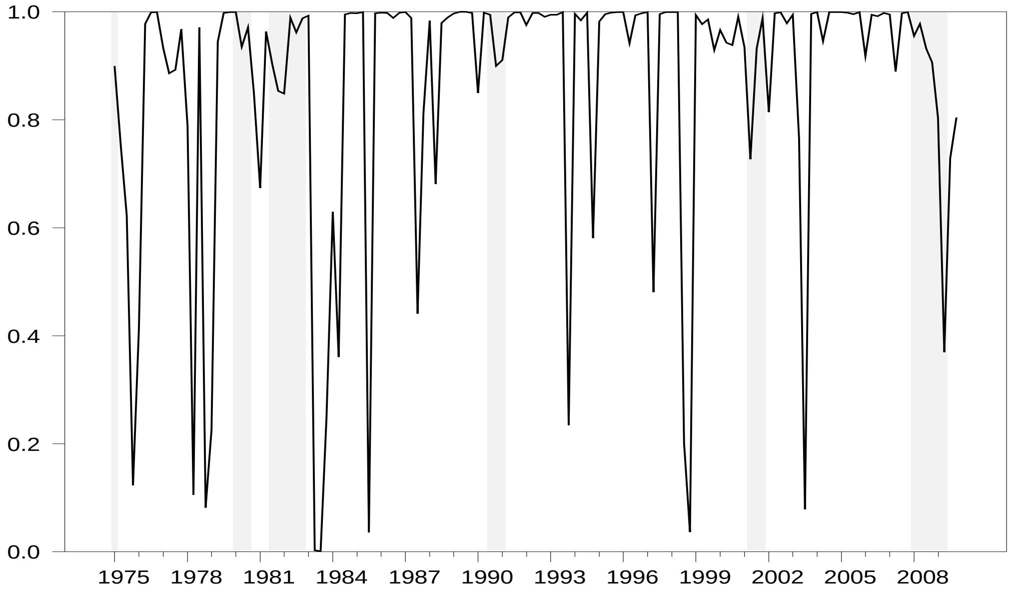


Figure 11: $\mathbb{P}\left(S_t = 2 \mid W_1, ..., W_t; \hat{\theta}\right)$: **Smoothed Probability of Unidirectional Granger Causality from Output Growth to Total Energy Consumption**

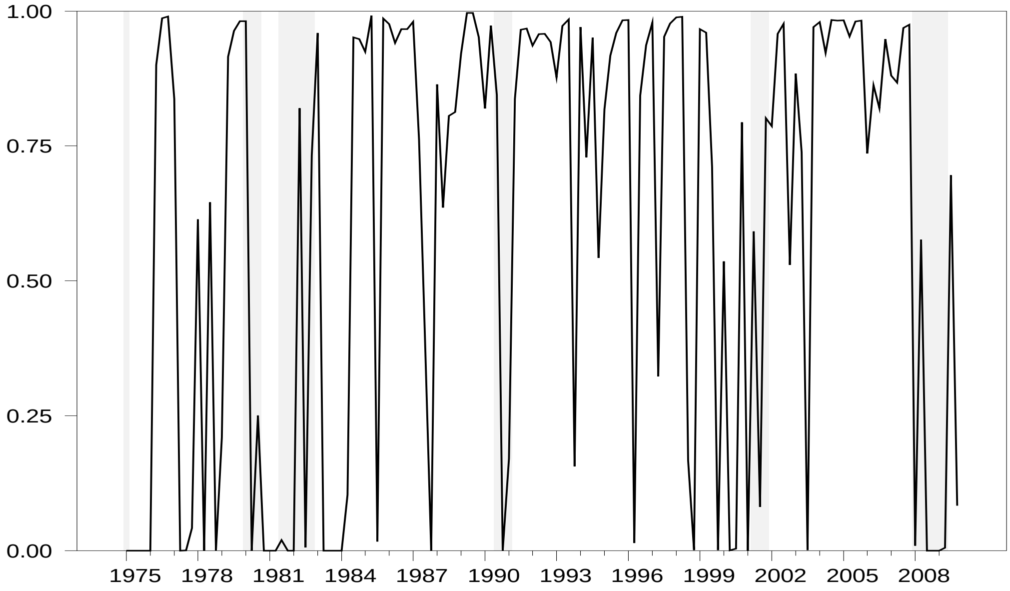
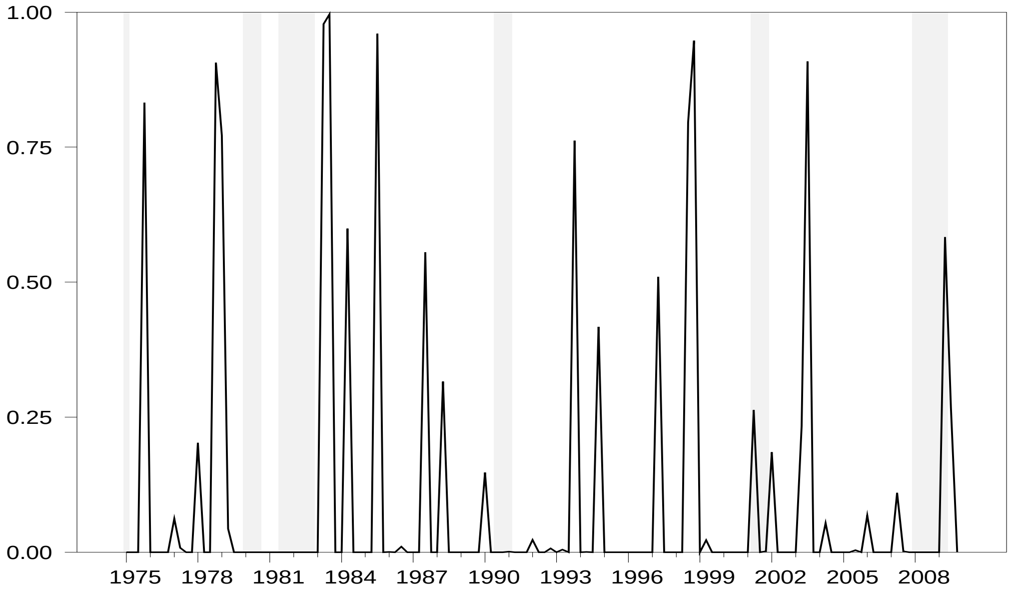


Figure 12: $\mathbb{P}\left(S_t = 4 \mid W_1, ..., W_t; \hat{\theta}\right)$: **Smoothed Probability of Granger Non-causality**



Chapter 5

Conclusion

This thesis is composed of three separate yet related empirical studies which have thoroughly assessed the relation between separate macroeconomic variables and economic growth. In the first study presented in Chapter 2, we explore the effects of inflation uncertainty on output growth for the U.S. economy. We carry out the empirical investigation using both monthly and quarterly data. The data used in the main investigation are monthly U.S. inflation and industrial production series range from 1960:01 to 2009:12. We then proceed to check the robustness of our findings using quarterly U.S. GDP series covering the period 1960:QI–2009:QIV.

Since no a priori assumption of nonlinearity is made, we first scrutinize regime switching behavior of the inflation and output growth series. If there were nonlinearities in the series of concern, then a linear modeling would probably over or understate the relation between inflation and output growth. Once the existence of regime shifts in inflation and output growth series has been established, we implement Markov switching models. The choice of the model was motivated by the fact that single regime GARCH models tend to overestimate the persistence in the conditional variance implying that the shocks to the conditional variance which occurred in the distant past continue to exert an impact on the current value of the conditional variance. Researchers show that these high levels of volatility persistence are related to the structural breaks or regime shifts in the volatility (see, Lamoureux and Lastrapes (1990); Gray (1996)). Thus, we apply a Markov switching GARCH model allowing for regime shifts in the inflation process to obtain a measure of inflation uncertainty. Our results show that the use of Markov switching GARCH approach to model conditional variance of inflation leads to a substantial decrease in the degree of volatility persistence, compared to that implied by the single regime GARCH model. Further, it is observed that inflation uncertainty obtained from single-regime GARCH model tends to underestimate the level of uncertainty at high inflation periods. The results also provide supporting evidence for the Friedman hypothesis since the conditional variances of inflation in the high inflation and low inflation regimes are found to increase in the high inflation periods. Moreover, inflation uncertainty in the high inflation regime is higher than the inflation uncertainty in the low inflation regime.

We next employ a Markov regime switching model to analyze the impact of uncertainty on growth. Indeed, one particular novelty of applying such a model is that it allows us to examine whether the effects of inflation uncertainty on real economic activity change across different regimes as the economy moves through the business cycle. Our findings point out that inflation uncertainty exerts a significant and negative impact on output growth in both low growth and high growth periods. Importantly, our results further indicate that the negative effects of inflation uncertainty are crucially more pronounced during the periods of low growth. In particular, the negative impact of inflation uncertainty on output growth in a low growth regime is about 2 times greater than that in a high growth regime. This finding might be attributable to the fact that in a recession when cash flows are low and firms are more dependent on external finance they tend to be more sensitive to the changes in the level of uncertainty. Yet, in an economic boom when the level of cash flows are relatively higher compared to the level in an economic downturn and their balance sheets are strong; firms can largely finance themselves with internal sources and thereby they are likely to be much more stronger to the changes in the level of uncertainty.

To check the robustness of our results we re-estimate the model using quarterly GDP series. It is clearly observed that the estimated low and high growth regimes for the U.S. economy coincide well with the NBER dates of contraction and expansion. That is, the model is able to detect the business cycle dates as announced by NBER successfully. With regards to the impact of inflation uncertainty on output growth, our investigation provides robust results which are in line with those obtained for monthly industrial production data. Once again, we show that inflation uncertainty has a negative and significant impact on economic growth which is almost 3 times higher in the periods of contraction than that in the periods of expansion. Finally, it is observed that inflation has a negative and significant effect on economic growth in both regimes.

In sum, our findings reveal that inflation uncertainty has a negative impact on output growth through the business cycle but its negative effect on real economic activity is stronger in the periods of downswings. Based upon our results, we point out that it is important to use an appropriate model that account for the behavior of the underlying series to capture the interlinkages between the variables precisely. In regards to the policy implications, the results indicate that policy makers should avoid adopting unstable monetary policies which may arise the public doubts about their future preferences regarding the conduct of the monetary policy. This is so, because the loss of public's confidence in future monetary policy inducing increase in inflation uncertainty may cause a dramatic fall in output growth in an economy in recession. Overall our findings provide strong support to the advocates of price stability as a fundamental objective for monetary policy makers.

The primary focus of the first empirical study is to examine the effects of inflation and inflation uncertainty on output growth. However there are some other interactions between inflation, output growth and their respective uncertainties.[39] For instance, there are some economic theories explaining the impact of output uncertainty on macroeconomic performance (see, Black (1987), Black-

[39] For a detailed discussion see Conrad and Karanasos (2010)

burn (1999)). Hence, it would be worthwhile to examine the effects of output uncertainty on output growth in a Markov Switching framework by obtaining the proxy of output uncertainty with the use of Markov switching GARCH methodology.

It is also worth to note that in the Markov switching GARCH model of Gray (1996), we can only use the information set available at time *t-1*. That is, we are not able to use all available information. As pointed out by some researchers if all information available were used, the model would enable more accurate forecasting analysis (see, Klaassen (2002)). However, in our context that does not constitute a prominent deficiency as we do not perform forecasting in our first empirical study.

The second study presented in Chapter 3 tries to answer several interrelated questions. Firstly, we assess if monetary policy shocks have an asymmetric impact on output growth across expansion and recession periods. Secondly, we search whether financial depth has a significant impact on growth and whether this effect changes over stages of the business cycle. Our final goal is to explore the role of financial depth in dampening the impact of monetary policy shocks to the economy. We carry out the empirical investigation for the U.S. economy covering the period 1981:QI–2009:QII.

To provide answers to these questions, we employ a Markov regime switching model which allows for state dependent coefficients on the explanatory variables and variances. The choice of the model was motivated by the fact that the methodology enables one to scrutinize if monetary policy shocks, financial depth and the interaction between financial depth and monetary policy shocks exert different effects on output growth over expansions and recessions. We get around the estimation problems that arise due to the endogeneity between monetary policy measure and output growth by applying an instrumental variables method in Markov regime switching model as proposed by Spagnolo et al. (2005). One particular novelty of this approach is that it allows us to simultaneously estimate the output growth equation and the instrumenting equation for the endogenous regressor which both have state-dependent parameters.

The results provide supporting evidence in favor of the asymmetry in the real effects of monetary policy shocks on economic growth over the business cycle. Indeed, our empirical findings suggest that a change in monetary policy exerts negative and statistically significant impact on output growth in both recession and expansion regimes. Yet, the impact of monetary policy shocks is found as noticeably greater in recessions than that in expansions. This finding not only complements the previous empirical literature which has revealed the asymmetries in the effects of monetary policy shocks but also provides strong support for the theoretical models based on the credit channel and the convexity of supply curves.

Based on our findings, financial depth is observed to foster output growth during the periods of recession. Besides, deeper financial markets appear to play a crucial role in reducing the size of the negative impact of monetary policy shocks in the U.S. economy. Put simply, the more the financial markets are developed, the smaller the magnitude of the real effects of monetary policy shocks. However, the dampening role of financial depth on the propagation of monetary policy shocks is found to be noticeably more prominent during the periods of economic downturn. Based on these results, we conclude that the policies that improve the financial markets and increase the depth and efficiency of these markets are likely to exert a positive impact on economic growth.

The second empirical study is based on U.S. data. However, it would be interesting to examine whether financial depth plays an important role in propagating the monetary policy shocks in other economies which have a similar structure of financial markets, such as the United Kingdom (market-oriented economies) or for other countries which have different financial systems as Germany and Japan (bank-oriented economies). Moreover, in the Chapter 3 we focus on the impact of monetary policy changes and the interaction between financial depth and monetary policy shocks. Nevertheless, there are some studies which have pointed out that financial depth also affects the output growth via its impact on real sector shocks (see, Beck et al. (2006)). Thus, our empirical framework in Chapter 3 can be used to find out the other channels through which financial depth affects output growth.

The third study presented in Chapter 4 empirically addresses the issue of whether there is a causal relation between total energy consumption and output growth in the U.S. economy. We implement the empirical investigation by using real GDP, total final energy consumption and consumer price index series for the period covering 1975:QI–2009:QIV. Given that the results of the standard causality tests in the previous empirical work are rather sensitive to the sample period, our empirical investigation mainly aims to complement and improve upon the existing empirical literature by examining whether there are changing causality patterns between the variables of concern over time.

Having found evidence of parameter instability from the estimation of the linear VAR model, we naturally test whether there is a time-dependent causality pattern between energy consumption and economic activity using a nonlinear model. To formally assess the presence of a changing causal link, we apply the methodology suggested by Psaradakis et al. (2005). Their econometric methodology is grounded in a Markov switching VAR model with time varying parameters. More precisely, the parameters of the Markov switching VAR model change according to the presence and the direction of the Granger causality. By doing so, this econometric methodology allows for an examination of the presence of a temporal Granger causal link between the variables of concern.

What we observe, in fact, is that there are four different states which are governed by separate causal links between energy consumption and economic growth. Although the standard Granger causality test based on a linear VAR model does not support the presence of causality running from total energy consumption to output growth, the findings from the Markov switching VAR model indicate that energy consumption has predictive power for real economic activity. It is important to note that the causality running from total energy consumption to output growth tends to be apparent only during the periods of recession and energy crisis in the U.S. economy. More concretely, total energy consumption is found to Granger-cause output growth during the downturns in the U.S. economy in 1975, 1980, 1981/1982, 1990/1991, 2000/2001, 2008/2009 and during the periods of energy crisis as well, including the one started in 1978 leaded by the Iranian Revolution, 1980 oil crisis triggered by Iran–Iraq War and 1990 oil price shock because of the Gulf War.

In regards to the reverse causality, our findings suggest that the output growth has predictive ability for total energy consumption. Further, based on the findings we observe that the predictive ability of output growth clearly increases during the periods of upswing in economic growth and then decreases during the periods of downswing in economic activity. In sum, total energy consumption and output growth are found to Granger cause each other during different states. Thus, the smoothed probability of Granger non-causality between the related series is observed as substantially low nearly over the entire sample period.

Our study differs from the previous empirical work in a crucial way as we search whether there are temporal causal links between energy and output. Our study explains why no clear evidence on the presence and the direction of causality has been found for U.S. economy in the existing empirical literature. This is so because our results point out that there are changing causality patterns between output and energy over time. It suggests that an appropriate analysis considering the possible regime shifts and structural changes should be undertaken to have a proper understanding of the causal links between the variables of concern. Despite the fact that the Granger causality in econometric sense and the causation in economic sense are not directly related, our empirical results attract attention to the possibility that energy conservation policies aiming to curb energy consumption may lead to a fall in the growth of output during recession periods.

It is important to note that the the model in the third empirical study lacks the energy prices as one of the important fundamental variables which affect both the output growth and energy consumption. However, the price of energy is likely to be an endogenous variable in this model. In that case we need to apply a trivariate Markov Switching VAR model to the data instead of the bivariate one that we estimated. But for the trivariate model the likelihood function is too flat for the maximization algorithm to converge statistically and economically meaningful estimates.

In the third empirical study we use aggregate data rather than sectoral data. Thus, future work might take account the sectoral differences and use sector level data to search whether there are changing causality patterns between sectoral output growth and energy consumption in different sub-sectors. In a similar econometric framework, the causal link between different sources of energy such as oil, electricity or coal and output growth may also be analyzed.

All the three empirical studies in this thesis together represent a detailed analysis of possible nonlinearities in the behavior of macroeconomic variables and provide fresh evidence regarding the asymmetries in the relation between economic growth and other target variables. Given the well-recognized success of Markov regime switching models in capturing the different characteristics associated with separate phases of the business cycle, this study also shows the ability of these models in detecting the asymmetries that are present in the relation between the underlying variables over the U.S. business cycle phases. The empirical models implemented in this thesis constitute a solid foundation for trying to explain the asymmetries in the behaviors of different macroeconomic variables and for getting a better understanding of the dynamic nature of various economic time series.

References

Abosedra, S. and H. Baghestani (1989). New evidence on the causal relationship between United States energy consumption and Gross National Product. *Journal of Energy and Development 14*(2), 285–292.

Akarca, A. and T. Long (1980). On the relationship between energy and GNP: A reexamination. *Journal of Energy and Development 5*(2), 326–331.

Andrews, D. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica: Journal of the Econometric Society 61*(4), 821–856.

Andrews, D. and W. Ploberger (1994). Optimal tests when a nuisance parameter is present only under the alternative. *Econometrica: Journal of the Econometric Society 62*, 1383–1414.

Arestis, P. and K. Mouratidis (2005). Credibility of monetary policy in four accession countries: A Markov regime-switching approach. *International Journal of Finance & Economics 10*(1), 81–89.

Artis, M., H. Krolzig, and J. Toro (2004). The European business cycle. *Oxford Economic Papers 56*(1), 1–44.

Atanasova, C. (2003). Credit market imperfections and business cycle dynamics: A nonlinear approach. *Studies in Nonlinear Dynamics & Econometrics 7*(4), 5.

Baek, E. and W. Brock (1992). A general test for nonlinear Granger causality: Bivariate model. Working paper, Iowa State University and University of Wisconsin, Madison.

Balke, N. (2000). Credit and economic activity: Credit regimes and nonlinear propagation of shocks. *Review of Economics and Statistics 82*(2), 344–349.

Ball, L. (1992). Why does high inflation raise inflation uncertainty? *Journal of Monetary Economics 29*(3), 371–388.

Ball, L. and N. Mankiw (1994). Asymmetric price adjustment and economic fluctuations. *Economic Journal 104*(423), 247–61.

Barro, R. (1996). Inflation and growth. *Review-Federal Reserve Bank of Saint Louis 78*, 153–169.

Barth, M. and V. Ramey (2000). The cost channel of monetary transmission. *NBER Working Papers* (7675).

Baum, C. F. and S. Hristakeva (2011). Denton: Stata module to interpolate a flow or stock series from low-frequency totals via proportional Denton method. http://EconPapers.repec.org/RePEc:boc:bocode:s422501, [Accessed: 01/11/2011].

Beaudry, P., M. Caglayan, and F. Schiantarelli (2001). Monetary instability, the predictability of prices, and the allocation of investment: An empirical investigation using UK panel data. *The American Economic Review 91*(3), 648–662.

Beck, T., M. Lundberg, and G. Majnoni (2006). Financial intermediary development and growth volatility: Do intermediaries dampen or magnify shocks? *Journal of International Money and Finance 25*(7), 1146–1167.

Bernanke, B. and A. Blinder (1992). The Federal funds rate and the channels of monetary transmission. *The American Economic Review 82*(4), 901–921.

Bernanke, B. and M. Gertler (1989). Agency costs, net worth, and business fluctuations. *The American Economic Review 79*(1), 14–31.

Bernanke, B., M. Gertler, and S. Gilchrist (1996). The financial accelerator and the flight to quality. *The Review of Economics and Statistics 78*(1), 1–15.

Bernanke, B. and I. Mihov (1998). Measuring monetary policy. *The Quarterly Journal of Economics 113*(3), 869–902.

Black, F. (1987). *Business cycles and equilibrium.* New York: B. Blackwell.

Blackburn, K. (1999). Can stabilisation policy reduce long-run growth? *The Economic Journal 109*(452), 67–77.

Bohara, A. and C. Sauer (1994). The role of inflation uncertainty in Germany: Friedman's hypothesis revisited. *Empirical Economics 19*(4), 611–627.

Boivin, J. and M. Giannoni (2002). Assessing changes in the monetary transmission mechanism: A VAR approach. *Federal Reserve Bank of New York Economic Policy Review 8*(1), 97–111.

Bowden, N. and J. Payne (2009). The causal relationship between US energy consumption and real output: A disaggregated analysis. *Journal of Policy Modeling 31*(2), 180–188.

Braun, M. and B. Larrain (2005). Finance and the business cycle: International, inter-industry evidence. *The Journal of Finance 60*(3), 1097–1128.

Brock, W., W. Dechert, and J. Scheinkman (1987). A test for independence based on the correlation dimension. Working Paper, Department of Economics, University of Wisconsin, Madison.

Brunner, A. and G. Hess (1993). Are higher levels of inflation less predictable? A state-dependent conditional heteroscedasticity approach. *Journal of Business & Economic Statistics 11*(2), 187–197.

Caballero, R. and E. Engel (1992). Price rigidities, asymmetries, and output fluctuations. Technical report, National Bureau of Economic Research.

Cai, J. (1994). A Markov model of switching-regime ARCH. *Journal of Business & Economic Statistics 12*(3), 309–316.

Chiou-Wei, S., C. Chen, and Z. Zhu (2008). Economic growth and energy consumption revisited–Evidence from linear and nonlinear Granger causality. *Energy Economics 30*(6), 3063–3076.

Chontanawat, J., L. Hunt, and R. Pierse (2008). Does energy consumption cause economic growth?: Evidence from a systematic study of over 100 countries. *Journal of Policy Modeling 30*(2), 209–220.

Christiano, L., M. Eichenbaum, and C. Evans (1996). The effects of monetary policy shocks: Evidence from the flow of funds. *The Review of Economics and Statistics 78*(1), 16–34.

Chua, C., D. Kim, and S. Suardi (2011). Are empirical measures of macroeconomic uncertainty alike? *Journal of Economic Surveys 25*(4), 801–827.

Clarida, R., J. Gali, and M. Gertler (2000). Monetary policy rules and macroeconomic stability: Evidence and some theory. *Quarterly Journal of Economics 115*(1), 147–180.

Clark, T. (1997). Cross-country evidence on long-run growth and inflation. *Economic Inquiry 35*(1), 70–81.

Conrad, C. and M. Karanasos (2010). Modeling the link between US inflation and output: The importance of the uncertainty channel. *University of Heidelberg, Department of Economics Working Papers*.

Conrad, C., M. Karanasos, and N. Zeng (2010). The link between macroeconomic performance and variability in the UK. *Economics Letters 106*(3), 154–157.

Cover, J. (1992). Asymmetric effects of positive and negative money-supply shocks. *The Quarterly Journal of Economics 107*(4), 1261.

Cukierman, A. (1983, January). Relative price variability and inflation: A survey and further results. *Carnegie-Rochester Conference Series on Public Policy 19*(1), 103–157.

Cukierman, A. and A. Meltzer (1986). A theory of ambiguity, credibility, and inflation under discretion and asymmetric information. *Econometrica: Journal of the Econometric Society 54*(5), 1099–1128.

Cukierman, A. and P. Wachtel (1979). Differential inflationary expectations and the variability of the rate of inflation: Theory and evidence. *The American Economic Review 69*(4), 595–609.

Darrat, A. and F. Lopez (1989). Has inflation uncertainty hampered economic growth in Latin America? *International Economic Journal 3*(2), 1–15.

Davis, G. and B. Kanago (1996). On measuring the effect of inflation uncertainty on real GNP growth. *Oxford Economic Papers 48*(1), 163.

Davis, S. and J. Haltiwanger (2001). Sectoral job creation and destruction responses to oil price changes. *Journal of Monetary Economics 48*(3), 465–512.

De Long, J., L. Summers, N. Mankiw, and C. Romer (1988). How does macroeconomic policy affect output? *Brookings Papers on Economic Activity 1988*(2), 433–494.

Denizer, C., M. Iyigun, and A. Owen (2002). Finance and macroeconomic volatility. *The BE Journal of Macroeconomics 2*(1).

Easterly, W., R. Islam, and J. Stiglitz (2001). Shaken and stirred: Explaining growth volatility. In B. Pleskovic and N. Stern (Eds.), *Annual World Bank Conference on Development Economics*, pp. 191–211. Washington, D.C.: The World Bank.

Ehrmann, M., M. Ellison, and N. Valla (2003). Regime-dependent impulse response functions in a Markov-switching vector autoregression model. *Economics Letters 78*(3), 295–299.

Elder, J. (2004). Another perspective on the effects of inflation uncertainty. *Journal of Money, Credit and Banking 36*(5), 911–928.

Evans, M. and P. Wachtel (1993). Inflation regimes and the sources of inflation uncertainty. *Journal of Money, Credit and Banking 25*(3), 475–511.

Fallahi, F. (2011). Causal relationship between energy consumption (EC) and GDP: A Markov-switching (MS) causality. *Energy 36*(7), 4165–4170.

Ferreira da Silva, G. (2002). The impact of financial system development on business cycles volatility: Cross-country evidence. *Journal of Macroeconomics 24*(2), 233–253.

Filardo, A. (1994). Business-cycle phases and their transitional dynamics. *Journal of Business & Economic Statistics 12*(3), 299–308.

Fountas, S., A. Ioannidis, and M. Karanasos (2004). Inflation, inflation uncertainty and a common European monetary policy. *The Manchester School 72*(2), 221–242.

Fountas, S., M. Karanasos, and J. Kim (2002). Inflation and output growth uncertainty and their relationship with inflation and output growth. *Economics Letters 75*(3), 293–301.

Fountas, S., M. Karanasos, and J. Kim (2006). Inflation uncertainty, output growth uncertainty and macroeconomic performance. *Oxford Bulletin of Economics and Statistics 68*(3), 319–343.

Friedman, M. (1977). Nobel lecture: Inflation and unemployment. *The Journal of Political Economy 85*(3), 451–472.

Garcia, R. and H. Schaller (2002). Are the effects of monetary policy asymmetric? *Economic Inquiry 40*(1), 102–119.

Gertler, M. and C. Lown (1999). The information in the high-yield bond spread for the business cycle: Evidence and some implications. *Oxford Review of Economic Policy 15*(3), 132–150.

Giordani, P. and P. Soderlind (2003). Inflation forecast uncertainty. *European Economic Review 47*(6), 1037–1059.

Goldfeld, S. and R. Quandt (1973). A Markov model for switching regressions. *Journal of Econometrics 1*(1), 3–15.

Goodwin, T. (1993). Business-cycle analysis with a Markov-switching model. *Journal of Business & Economic Statistics 11*(3), 331–339.

Granger, C. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society 37*(3), 424–438.

Gray, S. (1996). Modeling the conditional distribution of interest rates as a regime-switching process. *Journal of Financial Economics 42*(1), 27–62.

Grier, K., Ó. Henry, N. Olekalns, and K. Shields (2004). The asymmetric effects of uncertainty on inflation and output growth. *Journal of Applied Econometrics 19*(5), 551–565.

Grier, K. and M. Perry (2000). The effects of real and nominal uncertainty on inflation and output growth: Some GARCH-M evidence. *Journal of Applied Econometrics 15*(1), 45–58.

Grier, R. and K. Grier (2006). On the real effects of inflation and inflation uncertainty in Mexico. *Journal of Development Economics 80*(2), 478–500.

Hafer, R. (1986). Inflation uncertainty and a test of the Friedman hypothesis. *Journal of Macroeconomics 8*(3), 365–372.

Hamilton, J. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the Econometric Society 57*(2), 357–384.

Hamilton, J. (1990). Analysis of time series subject to changes in regime. *Journal of Econometrics 45*(1-2), 39–70.

Hamilton, J. (1994). *Time series analysis.* Princeton, NJ: Princeton University Press.

Hamilton, J. (1996). This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics 38*(2), 215–220.

Hamilton, J. (2003). What is an oil shock? *Journal of Econometrics 113*(2), 363–398.

Hamilton, J. and R. Susmel (1994). Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics 64*(1-2), 307–333.

Hansen, B. (1992a). The likelihood ratio test under nonstandard conditions: Testing the Markov switching model of GNP. *Journal of Applied Econometrics 7*(S1), 61–82.

Hansen, B. (1992b). Testing for parameter instability in linear models. *Journal of Policy Modeling 14*(4), 517–533.

Hansen, B. (1996). Erratum: The likelihood ratio test under nonstandard conditions: Testing the Markov switching model of GNP. *Journal of Applied econometrics 11*(2), 195–198.

Harding, D. and A. Pagan (2002). Dissecting the cycle: A methodological investigation. *Journal of Monetary Economics 49*(2), 365–381.

Harvey, A., E. Ruiz, and N. Shephard (1994). Multivariate stochastic variance models. *The Review of Economic Studies 61*(2), 247.

Hayford, M. (2000). Inflation uncertainty, unemployment uncertainty and economic activity. *Journal of Macroeconomics 22*(2), 315–329.

Holland, A. (1988). Indexation and the effect of inflation uncertainty on real GNP. *Journal of Business 61*(4), 473–484.

Höppner, F., C. Melzer, and T. Neumann (2008). Changing effects of monetary policy in the US–Evidence from a time-varying coefficient VAR. *Applied Economics 40*(18), 2353–2360.

Jansen, D. (1989). Does inflation uncertainty affect output growth? Further evidence. *Review* (July), 43–54.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control 12*(2-3), 231–254.

Johansen, S. and K. Juselius (1990). Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxford Bulletin of Economics and Statistics 52*(2), 169–210.

Judson, R. and A. Orphanides (1999). Inflation, volatility and growth. *International Finance 2*(1), 117–138.

Karras, G. (1996). Why are the effects of money-supply shocks asymmetric? Convex aggregate supply or "pushing on a string? *Journal of Macroeconomics 18*(4), 605–619.

Kaufmann, S. (2002). Is there an asymmetric effect of monetary policy over time? A Bayesian analysis using Austrian data. *Empirical Economics 27*(2), 277–297.

Klaassen, F. (2002). Improving garch volatility forecasts with regime-switching garch. *Empirical Economics 27*(2), 363–394.

Kraft, J. and A. Kraft (1978). On the relationship between energy and GNP. *Journal of Energy and Development 3*(2), 401–403.

Krolzig, H. (1997). *Markov-switching vector autoregressions : Modelling, statistical inference, and application to business cycle analysis.* Springer, Berlin.

Lamoureux, C. and W. Lastrapes (1990). Persistence in variance, structural change, and the GARCH model. *Journal of Business & Economic Statistics 8*(2), 225–234.

Larrain, B. (2006). Do banks affect the level and composition of industrial volatility? *The Journal of Finance 61*(4), 1897–1925.

Lee, C. (2006). The causality relationship between energy consumption and GDP in G-11 countries revisited. *Energy Policy 34*(9), 1086–1093.

Lee, C., C. Chang, and P. Chen (2008). Energy-income causality in OECD countries revisited: The key role of capital stock. *Energy Economics 30*(5), 2359–2373.

Lee, K. and S. Ni (1995). Inflation uncertainty and real economic activities. *Applied Economics Letters 2*(11), 460–462.

Lee, K., S. Ni, and R. Ratti (1995). Oil shocks and the macroeconomy: The role of price variability. *The Energy Journal 16*(4), 39–56.

Leeper, E., C. Sims, T. Zha, R. Hall, and B. Bernanke (1996). What does monetary policy do? *Brookings Papers on Economic Activity 1996*(2), 1–78.

Leroux, B. (1992). Consistent estimation of a mixing distribution. *The Annals of Statistics 20*(3), 1350–1360.

Lo, M. and J. Piger (2005). Is the response of output to monetary policy asymmetric? Evidence from a regime-switching coefficients model. *Journal of Money, Credit and Banking 37*(5), 865–886.

Ma, H. (1998). Inflation, uncertainty, and growth in Colombia. *IMF Working Paper* (98/161), 1–30.

McCallum, B. (1983). On non-uniqueness in rational expectations models: An attempt at perspective. *Journal of Monetary Economics 11*(2), 139–168.

Mihov, I. (2001). Monetary policy implementation and transmission in the European Monetary Union. *Economic Policy 16*(33), 369–406.

Mitchell, J. and K. Mouratidis (2004). Is there a common Euro-zone business cycle? In G. Mazzi and G. Savio (Eds.), *Monographs of official statistics: Papers and proceedings of the third Eurostat colloquium on modern tools for business cycle analysis.* European Commission.

Morgan, D. (1993). Asymmetric effects of monetary policy. *Economic Review-Federal Reserve Bank of Kansas City 78*, 21–33.

Mork, K. (1989). Oil and the macroeconomy when prices go up and down: An extension of Hamilton's results. *The Journal of Political Economy 97*(3), 740–744.

Murry, D. and G. Nan (1990). The energy consumption and employment relationship: A clarification. *Journal of Energy and Development 16*(1), 121–131.

Narayan, P. and R. Smyth (2008). Energy consumption and real GDP in G7 countries: New evidence from panel cointegration with structural breaks. *Energy Economics 30*(5), 2331–2341.

Okun, A. (1971). The mirage of steady inflation. *Brookings Papers on Economic Activity 1971*(2), 485–498.

Pagan, A. (1984). Econometric issues in the analysis of regressions with generated regressors. *International Economic Review 25*(1), 221–247.

Pagan, A. and A. Ullah (1988). The econometric analysis of models with risk terms. *Journal of Applied Econometrics 3*(2), 87–105.

Payne, J. (2009). On the dynamics of energy consumption and output in the US. *Applied Energy 86*(4), 575–577.

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics 61*(S1), 653–670.

Peersman, G. and F. Smets (2002). Are the effects of monetary policy in the euro area greater in recessions than in booms? In L. Mahadeva and P. Sinclair (Eds.), *Monetary transmission in diverse economies*, pp. 28–48. Cambridge: Cambridge University Press.

Poskitt, D. and S. Chung (1996). Markov chain models, time series analysis and extreme value theory. *Advances in Applied Probability 28*(2), 405–425.

Psaradakis, Z., M. Ravn, and M. Sola (2005). Markov switching causality and the money–output relationship. *Journal of Applied Econometrics 20*(5), 665–683.

Psaradakis, Z. and N. Spagnolo (2003). On the determination of the number of regimes in Markov-switching autoregressive models. *Journal of Time Series Analysis 24*(2), 237–252.

Raddatz, C. (2006). Liquidity needs and vulnerability to financial underdevelopment. *Journal of Financial Economics 80*(3), 677–722.

Ravn, M. and M. Sola (2004). Asymmetric effects of monetary policy in the United States. *Review-Federal Reserve Bank of Saint Louis 86*, 41–58.

Ruge-Murcia, F. (2003). Does the Barro-Gordon model explain the behavior of US inflation? A reexamination of the empirical evidence. *Journal of Monetary Economics 50*(6), 1375–1390.

Seifritz, W. and J. Hodgkin (1991). Nonlinear dynamics of the per capita energy consumption. *Energy 16*(3), 615–620.

Senda, T. (2001). Asymmetric effects of money supply shocks and trend inflation. *Journal of Money, Credit and Banking 33*(1), 65–89.

Silvennoinen, A. and T. Teräsvirta (2009). Modeling multivariate autoregressive conditional heteroskedasticity with the double smooth transition conditional correlation GARCH model. *Journal of Financial Econometrics 7*(4), 373–411.

Sims, C. (1972). Money, income, and causality. *The American Economic Review 62*(4), 540–552.

Sims, C. (1992). Interpreting the macroeconomic time series facts: The effects of monetary policy. *European Economic Review 36*(5), 975–1000.

Soytas, U. and R. Sari (2003). Energy consumption and GDP: causality relationship in G-7 countries and emerging markets. *Energy Economics 25*(1), 33–37.

Soytas, U. and R. Sari (2006). Energy consumption and income in G-7 countries. *Journal of Policy Modeling 28*(7), 739–750.

Soytas, U., R. Sari, and B. Ewing (2007). Energy consumption, income, and carbon emissions in the United States. *Ecological Economics 62*(3-4), 482–489.

Spagnolo, F., Z. Psaradakis, and M. Sola (2005). Testing the unbiased forward exchange rate hypothesis using a Markov switching model and instrumental variables. *Journal of Applied Econometrics 20*(3), 423–437.

Tharavanij, P. (2007). Capital market, frequency of recession, and fraction of time the economy in recession. http://mpra.ub.uni-muenchen.de/5190/.

Thoma, M. (1994). Subsample instability and asymmetries in money-income causality. *Journal of Econometrics 64*(1-2), 279–306.

Thoma, M. (2004). Electrical energy usage over the business cycle. *Energy Economics 26*(3), 463–485.

Timmermann, A. (2000). Moments of Markov switching models. *Journal of Econometrics 96*(1), 75–111.

Toda, H. and T. Yamamoto (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics 66*(1-2), 225–250.

Tsiddon, D. (1993). The (mis) behaviour of the aggregate price level. *The Review of Economic Studies 60*(4), 889–902.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics 52*(2), 381–419.

Warne, A. (2000). Causality and regime inference in a Markov switching VAR. Working Paper Series 118, Sveriges Riksbank (Central Bank of Sweden).

Weise, C. (1999). The asymmetric effects of monetary policy: A nonlinear vector autoregression approach. *Journal of Money, Credit and Banking 31*(1), 85–108.

Westerlund, J. (2006). Testing for panel cointegration with multiple structural breaks. *Oxford Bulletin of Economics and Statistics 68*(1), 101–132.

Wilson, B. (2006). The links between inflation, inflation uncertainty and output growth: New time series evidence from Japan. *Journal of Macroeconomics 28*(3), 609–620.

Wu, J., S. Chen, and H. Lee (2003). Sources of inflation uncertainty and real economic activity. *Journal of Macroeconomics 25*(3), 397–409.

Yu, E. and B. Hwang (1984). The relationship between energy and GNP: Further results. *Energy Economics 6*(3), 186–190.

Zhang, J. and R. Stine (2001). Autocovariance structure of Markov regime switching models and model selection. *Journal of Time Series Analysis 22*(1), 107–124.