Essays in Markov switching causality

Essays in Markov Switching Causality

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This dissertation is submitted for the degree of
Doctor of Philosophy

Birkbeck College January 2024

I would like to dedicate this thesis to my loving wife, Cinthia, and my incredible sister, Ruth.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this thesis are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this or any other university. This thesis is my own work, with the first chapter adapted from a paper written jointly with my supervisors, Professor Zacharias Psaradakis and Professor Yunus Aksoy. Similarly, the second chapter is a variant of a paper co-written with Dr Pedro Gomes and Ozde Kurter. This dissertation contains fewer than 65,000 words, including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

Rubens Morita
January 2024

Acknowledgements

I would like to express my sincere gratitude to my supervisors, Professors Zacharias Psaradakis, Yunus Aksoy and Pedro Gomes, for their guidance, encouragement, and support throughout my research. Their insightful comments and feedback helped me improve the quality of my work. I hope one day I can re-tribute their generosity.

I am privileged to have been supervised by Haris. His expertise and insights have been instrumental in shaping my ideas and helping me achieve my goals. Your constructive feedback, constant encouragement, and willingness to provide assistance whenever needed have driven my success. His dedication to helping me develop my skills and knowledge has been truly inspiring and has contributed significantly to my personal and professional growth.

I also feel very fortunate to have met Yunus. I am sincerely grateful for Yunus' unwavering support and guidance during my thesis. I am extremely grateful for the invaluable mentorship Yunus has provided me during this challenging but rewarding journey. The time and energy Yunus has dedicated to helping me achieve my goals is enormous. His support has been an integral part of my success, and I feel privileged to have had the opportunity to work with him.

Finally, I wanted to express my deep appreciation for Pedro's support and guidance throughout my thesis. Pedro's mentorship has been an essential part of my journey, and I am incredibly grateful for his insights, feedback, and encouragement.

I would also like to take a moment to express my deepest gratitude to all faculty members, in special professors Martin Solá (From Universidad Torcuato Di Tella), Ron Smith, Stephen Wright and Sandeep Kapur; Doctors Walter Beckert, David Schroeder and Daniel Kaliski, and the head of school Dr Ken Hori for their guidance and support throughout my PhD. Also, Professor Rodrigo DL Bueno from the University of Sao Paulo and Professor Marcelle Chauvet from the University of California - Riverside for helping me at the beginning of my academic journey.

I am also thankful to all the professional and support staff members of Birkbeck EMS for their assistance during my PhD. Without their help, going through the necessary administrative issues during my research would have been very difficult. You all are amazing! Finally, a special thanks to my friend Awuku Danso for his IT support.

I would like to thank my family, represented by my mother-in-law, Dona Ima and my sister-in-law, Aline, for their support. Their love and care kept me motivated and helped me stay focused. And, my friends, Jose Maria, Federico, Charisios, Konstantinos, Issan, Paul, Xiaghong, Veronika, Kim and Zeynep, for their persistent support and encouragement during my academic journey. Your friendship has inspired on me and will keep inspiring me.

Finally, I would like to acknowledge the academic and financial support provided by Birkbeck College and ESRC. Their funding enabled me to conduct my research and present my findings at international conferences. Birkbeck is an incredible place, and I will miss going there enormously.

I am grateful to all those who contributed to my thesis, and I acknowledge their invaluable help and support.

Abstract

This thesis extends the framework developed by Psaradakis et al. (2005) for the analysis of Markov switching Granger causality in three different ways. In the first chapter, the bivariate VAR setting is extended to a trivariate one to provide a comprehensive account of the evolution of macroeconomic causal relationships of the monetary rules and map the direction of causality associated with Federal Reserve chairs' tenures since 1965. While the Federal Funds rate (FFR) or Domestic Money (DM) have causal predictive content to explain variations in real output and inflation in most periods, this chapter demonstrates that these are often substitutes in their role as lead or feedback variables. Estimated shifts in smoothed regime probabilities align remarkably well with monetary policy shock dates as identified by Romer and Romer (1989, 1994, 2004). In the second chapter, flexible likelihood functions suitable in the analysis of financial time series are considered. The chapter contributes to the analysis of the causal relationship between sovereign bond and stock markets in three ways. First, the exact dates when there are shifts in the causality are found. Second, although the markets are very integrated, the chapter provides evidence that a global (or regional) crisis affects the countries non-identically. Finally, the results indicate that economic events, whether they are global or country-specific, can trigger reversals in the causality between these two variables. The third chapter incorporates time-varying volatility into the analysis of Markov switching causality. The extended model is applied to a monetary aggregate and Federal Funds rate, in the search of the so called Liquidity Effect. The impulse responses functions are computed and conditional on a particular regime. Based on these impulse responses, it is possible to conclude that the Liquidity Effect is present in domestic money but not in the currency component of M1, even if the vector autoregression is conditioned on inflation.

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Chapter 1

Introduction

Time series data are essential for the analysis of macroeconomic or financial phenomena, mainly through empirical macroeconomic or financial models and tools. The occurrences of events such as economic crises or sudden regime changes in government policies can engender breaks in economic time series data dynamics. In the fields of macroeconomics and finance, sophisticated models have emerged to handle these potential nonstationarities and nonlinearities. One such model is the regime-switching regression, initially developed by Quandt (1958) and later refined by Goldfeld and Quandt (1973). In this particular version, usually referred to as a Markov-switching model, regime shifts are governed by a serially dependent latent regime (state) variable that follows a Markov-chain process. In a widely cited article, Hamilton (1989) popularizes the Markov-switching model, extending it to the case of time-series dependent data. Empirical applications of Markov-switching models have corroborated stylized facts and offered new explanations for economic policy impacts. As a result, this method has been used extensively by academics, policy institutes, and think tanks. This method has been applied in many fields, particularly to model and explain business cycles and monetary economics.

Another important statistical concept developed for time-series data is Granger Causality. Clive Granger introduced the concept in the 1960s, and ever since, it has been widely used in econometrics and other fields. Essentially the concept determines if one or more time series are useful in predicting another time series. Therefore it is natural to incorporate this concept into the vector autoregression (VAR) framework. Many strategies have been used to test for Granger causality; nonetheless, the classical Granger Causality test is sensitive to two factors: the number of lags and the sample period.

In the vector autoregression framework, the number of lags can be determined by many approaches, for instance, by using Information Criteria. The number of lags is important because the Granger causality test is a joint test among the lags of a particular variable that the researcher believes has some power to predict a variable of interest. Nonetheless, the main issue on the Granger

Causality is its sensitivity to the sample period. The article from Psaradakis et al. (2005) address the problem by considering Granger Causality within the vector autoregression Markov-Swithcing model (see figure (1.1)), ultimately called Markov Switching Granger causality.

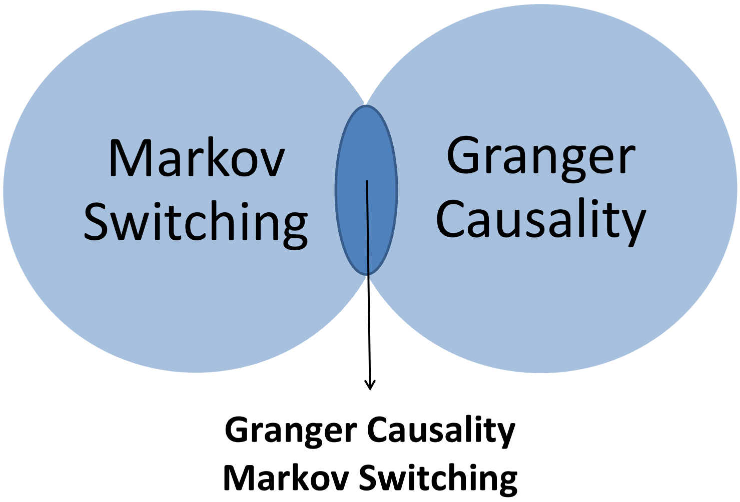


Figure 1.1 Markov-Switching Granger Causality

The model's novelty is that instead of defining regime shifts in terms of recessions and expansions, as Hamilton (1989) and the subsequent approaches do, the model associates regime changes with shifts in Granger causality patterns. Figure (1.2) below describes the mechanism behind Markov-Swithicng Granger Causality for the case of bivariate $VAR(n)$. Notice that the arrows define the direction of the causalities and the regimes. Regime 1 is nothing but unrestricted VAR. In regime 2, the variable x_t causes y_t; however, not the opposite. Regime 3, the variable y_t causes x_t; however, not the opposite. Finally, in regime 4, there is no Granger causality, ultimately in regime 4, the variables follow an autoregressive process.

Psaradakis et al. (2005)'s model is a vector autoregression, conditioned on a particular variable, in their case, inflation. Nonetheless, treating a particular variable as exogenous may lead to missing the Granger causality of all variables of interest; hence, treating all variables as endogenous is preferable. Therefore, the generalization of this concept to a more general model is necessary. The first chapter of this thesis expands Markov Switching Granger causality to a tri-variate vector autoregression. Most importantly, the results of the monetary policy rule are encouraging, particularly during the zero lower bound period from 2008 onward.

The first chapter aims to shed some light on the historical Granger causality regimes of the U.S. monetary policy and the role of the seven U.S. Fed chairpersons throughout the sample period from 1965 to 2016. Most existing literature, for instance, Clarida et al. (2000), estimates policy rules based on the structural break premise around the early 1980s, when U.S. Federal Reserve,

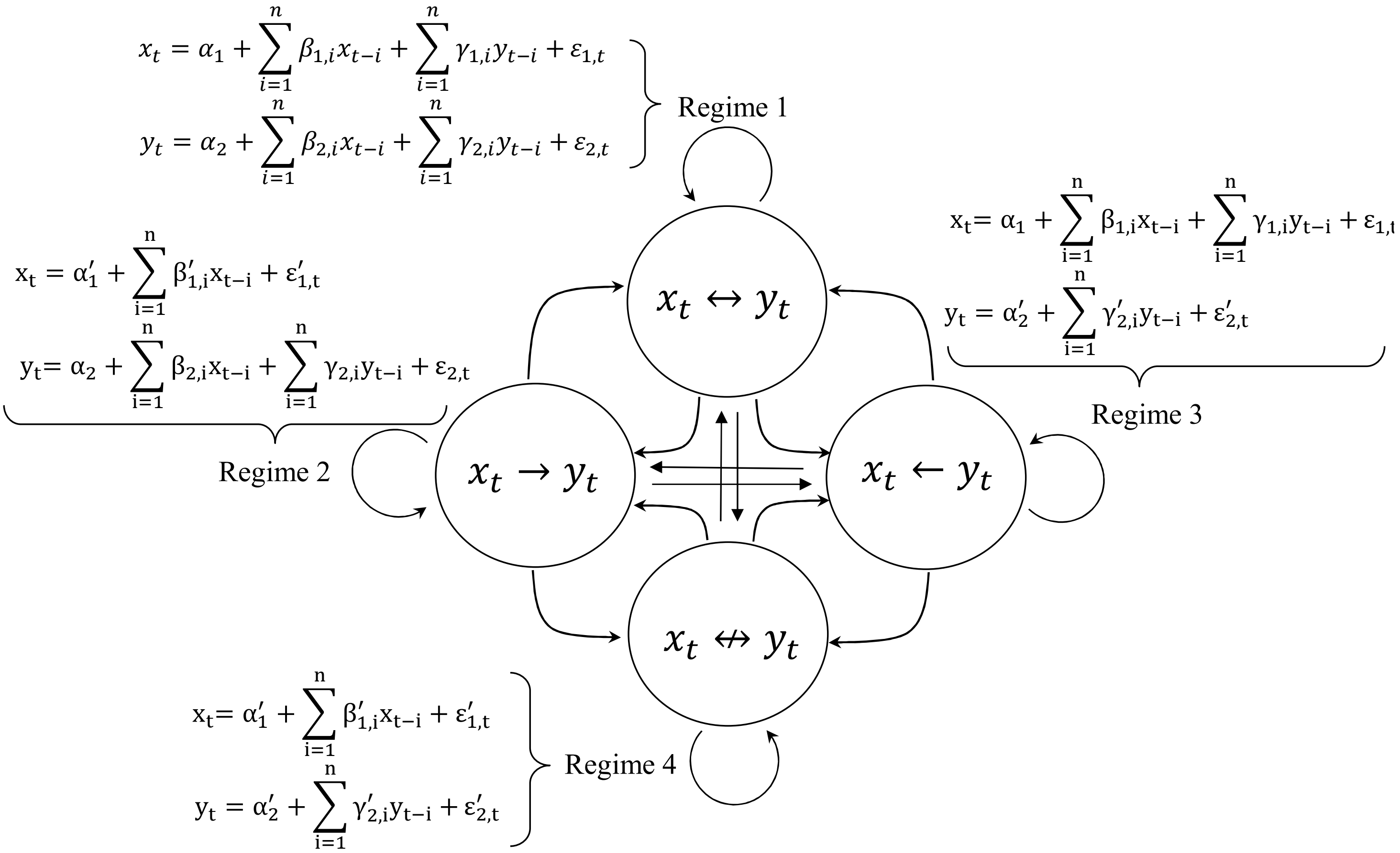


Figure 1.2 Markov-Switching Granger Causality - VAR(2)

under the chairmanship of Volcker, implemented contractionary monetary policies. In this chapter, regimes are identified endogenously, and any assumptions on the dates of causal regime change are imposed. The U.S. monetary policy is investigated using a multivariate causal relationship. Regime Dependent Granger Causality between real output, inflation and a series of monetary indicators, in addition to the Federal Funds Rates (FFR), is examined using a particular type of Markov switching vector autoregressive model that endogenously determines the causal regimes. In particular, the analysis focuses on U.S. Domestic Money (DM) and FFR, the key variables for controlling liquidity developments.

The model identifies episodes of causation from (i) FFR and DM to real output and/or inflation; (ii) from the real output and/or inflation to FFR and DM; and also identifies episodes of no such causal relationships. Second, this thesis maps these identified nonlinear causality regimes with the corresponding U.S. Fed's Chairperson's tenure. The mapping allows for the evaluation of changes in possible policy instrument preferences (FFR or DM) associated with the policymaker in charge of the U.S. monetary policy at the time. The aim of this chapter is to explicitly focus on the time-varying nonlinear causal information content in two potential monetary policy instruments, FFR and DM, to explain variations in U.S. real output and inflation and vice versa; hence the use of the notion of regime-dependent Granger causality.

Nonetheless, as discussed by Pesaran and Smith (1995), it is important to note that the presence or absence of a statistically significant causal relationship does not necessarily indicate shifts in the objectives of the U.S. Federal Reserve. Therefore, any analysis of whether the monetary policy-making became more or less effective, or in the case of causal feedback rules, and whether policy instruments successfully accommodate macroeconomic variations must be conducted cautiously. The results also indicate that well-known shocks generate the shift mechanism from one pattern of Granger causality to another, particularly the shocks identified by Romer and Romer (1989). And most importantly, there is a clear shift in terms of the monetary instrument after 2008, in the event of the zero lower bound. These findings are aligned with Bernanke and Reinhart (2004) discussion on alternative instruments for monetary policy during events of very low short-term interest rates.

Another extension of the model useful for applications that involve financial times series allows the use of likelihood functions more flexible than the Gaussian likelihood of Psaradakis et al. (2005). The second chapter of this thesis considers this extension and applies Psaradakis et al. (2005)'s model to financial data, particularly bond yields and stock returns for eight European countries. It is well known that financial data have moments that differ from the standard normal distribution, particularly regarding skewness and Kurtosis. This extension uses the GED (Generalized Error distribution) because the Kurtosis of this distribution is reflected by a parameter that can be incorporated and estimated in the model. The application of this extension shows two main results: First, there is a clear co-movement in the Granger causality direction among the eight European countries, and most importantly, the co-movement is directly related to the stylized facts, for instance, the Financial Crisis. Second, these results, to some extent, can be considered evidence of contagion.

This chapter contributes to the empirical finance literature in three ways. First, the exact dates when there are shifts in the causality are found. Second, although the markets are very integrated, the chapter provides evidence that a global (or regional) crisis affects the countries heterogeneously. Third, in terms of price discovery, the evidence indicates that the direction of the causality is mostly from the stock returns to the first difference in sovereign bond yield (changes in sovereign bond yields. The results indicates that economic events, whether they are global or country-specific, can trigger reversals in the causality between these two variables. For instance, we find there is a shift in causality in most of the countries, coinciding with the global financial crisis. Additionally, these results contradict the common knowledge that the stock markets always lead the bond markets. The results suggest that the direction of the causality depends on the period, country and nature of the crisis. For instance, changes in sovereign bond yields cause stock returns in some periods in all countries except Germany. The actual duration of the causality regimes also varies across countries.

Finally, the third chapter of this thesis extends the original Psaradakis et al. (2005)'s model by incorporating time-varying volatility in the model. The model may be viewed as a multivariate version of a so-called GARCH-in-mean. By introducing the observed features of conditional heteroskedasticity in the estimation of the conditional mean, more efficient estimates of the conditional mean can be obtained. For this extension, the third chapter estimates a bivariate vector autoregression, using federal funds rate, particularly the shadow rates, to overcome flatness during the zero lower bounds, and a monetary aggregate, in particular, a narrow definition of monetary aggregates, such as currency component of M1 and the currency component of M1 adjusted by U.S. Dollars' foreign holdings, already mentioned, called Domestic Money.

By estimating this bivariate vector autoregression, the chapter aims to show the Friedman-Cagan Effect empirically, and more specifically the Liquidity Effect. In the economic literature, the Friedman-Cagan Effect refers to the relationship between changes in money supply and changes in the interest rates. Liquidity Effect occurs when an increase in money supply leads to a decrease in the interest rates. Notice that this relationship reflects the impact of changes in the money supply on the economy's ability to borrow and lend, hence, the resulting impact on borrowing costs and spending decisions. The Liquidity Effect has played an essential role in the Keynesian analysis. In the celebrated book of Keynes, "The General Theory of Employment, Interest and Money", the interest rate is the price of equilibrium that determines the wiliness to hold cash. This theoretical outcome is commonly used by central banks to control inflation and to achieve other macroeconomics objectives.

The empirical evidence of the Liquidity Effect is difficult to be captured by empirical analysis due to its sensitivity to the sample period, as pointed out by Pagan and Robertson (1998), and the attractiveness of the method developed in this chapter lies in making the sample choice endogenously determined. Therefore, the main findings of the empirical analysis are: Friedman-Cagan Effect is triggered by recessions, and the results are robust either to the currency component of M1 or the domestic money. During recessions, the central banks may use monetary policy to stimulate the economy by increasing the rate of change of the money supply, ultimately reducing the downturn and preventing a more severe contraction.

The impulse responses function can also be computed and conditioned on a particular regime. Considering the impulse responses function, it is also possible to conclude that the Liquidity Effect is present in domestic money but not in the currency component of M1, even if the vector autoregression is conditioned by inflation. One possible explanation that may be given for why the Liquidity Effect is not observed by the currency component of M1, is because this monetary aggregate contains U.S. Dollars' foreign holdings, which are removed by domestic money.

Finally, the results for a broad definition of money, such as M1 and M2, are ambiguous, and as was documented by Bryant (1983) and Gordon and Leeper (1994), and also by many authors such as Meltzer (1963), Cagan (1966) and Cochrane (1989), the central banks do not have full control of M1 and M2; therefore the results by these variables could not represent the Liquidity Effect. The results of this chapter show very short periods of the Friedman-Cagan Effect, for instance, for M2, or no effect for the case of M1.

Chapter 2

Federal Reserve Chairs and U.S. Macroeconomic Causality Regimes

1. Introduction

The Federal Reserve Act mandates the Federal Reserve to conduct monetary policy 'so as to promote effectively the goals of maximum employment, stable prices, and moderate long-term interest rates'. Post World War II period monetary policy consensus and its evolution can be summarized by the U.S. Federal Reserve's decisions to adjust short-term interest rates procyclically in small but persistent steps with the intention of controlling the credit available in the economy and in a way that will offset sustained deviations of output growth from its potential. Each U.S. Federal Reserve chair had more or less the same policy toolkit to achieve the same objectives as described by the mandate.Given this background and in principle, unless there are shifts in policy preferences (objectives and/or instruments) or expectations formation, there are no obvious reasons to expect that the causal relationships regimes (to be defined later) between policy instruments and key macroeconomic variables, such as Output and Inflation coincides with a particular U.S. Fed's chair's tenure. Ultimately, many papers have emphasized the importance of independence of the monetary policy concerning political pressure such as Alesina and Summers (1993) and Dincer and Eichengreen (2014). Nonetheless, most recently Bianchi et al. (2023) found that President Trump's criticism has impacted market monetary policy expectations, and Drechsel (2023) found that President Nixon seeking re-election influenced Fed Chairman Burns to ease monetary policy, which led to economic consequences such as higher and more persistent inflation. Finally, Weise (2012) has also found that the pressure on the Federal Open Market Committee (FOMC) during the 1970s contributed to the rise in inflation during that period.

The assumption that the Federal Funds rate (FFR) approximates well the stance of the U.S. monetary policy, and monetary policy shocks identified through FFR, means that there is relatively little concern for alternative measures of liquidity and credit in the economy. It also means that the direction of causality between these other potential policy variables, such as the causal liquidity effects, is often a side issue. Given the Zero Lower Bound (ZLB) problems since December 2008 and the wide ranging utilization of unconventional monetary policy measures and forward guidance, the appropriateness of the level of FFR as an accurate measure of the U.S. monetary policy stand has been subject to close scrutiny (Kocherlakota (2019)). Moreover, Gürkaynak et al. (2005)'s scepticism on the conventional descriptions of the monetary transmission mechanisms via FFR, the role of forward guidance and their impact on credit costs led to voluminous recent work on the high frequency identification of monetary policy shocks using alternative external instruments such as three months ahead Fed Funds futures starting with the work by Gertler and Karadi (2015).

In this paper we aim to shed some light on the historical causality regimes of the U.S. monetary policy and the role of the seven U.S. Fed chairs throughout the sample period from 1965 to 2016. Ever since the work by Clarida et al. (2000), policy rule estimates are based on the structural break premise around early 1980's, when Volcker implemented contractionary monetary policies. Here, instead of imposing assumptions on the dates of causal regime changes, we use endogenous regime identification methods.

We first assess the U.S. monetary policy conduct and investigate the multivariate causal relationships. *Regime Dependent Granger Causality*, henceforth referred to as simply *causality*, between real output, inflation and a series of monetary indicators, in addition to the FFR, is examined using a particular type of Markov switching vector autoregressive (MS-VAR) model that endogenously determines the causal regimes. In particular, we focus on U.S. Domestic Money (DM) (to be defined later on), along with FFR, to account for controllable liquidity developments that are not subject to ZLB problem. We identify episodes of causation from: (i) FFR and DM to real output and/or inflation; (ii) from real output and/or inflation to FFR and DM; we also identify episodes of no such causal relationships. Second, we map these identified nonlinear causality regimes with the corresponding U.S. Fed's chair's tenure. The mapping allows us to evaluate changes in possible policy instrument preferences (FFR or DM) associated with the policymaker in charge of the U.S. monetary policy at the time. Our aim is to explicitly focus on the time-varying nonlinear causal information content in two potential monetary policy instruments, FFR and DM, to explain variations in U.S. real output and inflation and vice versa; hence the use of the notion of regime-dependent Granger causality. As discussed by Pesaran and Smith (1995) at length, the presence or absence of a statistically significant causal relationship does not necessarily indicate shifts in the objectives of the U.S. Federal Reserve or whether the monetary policymaking became more or less effective, or in the case of causal feedback rules, whether policy instruments successfully accommodate macroeconomic variations.

We compute smoothed regime probabilities for monetary indicators (FFR and DM) upon which the Federal Reserve has direct control. We find that, while both policy indicators have some causal predictive content for real output and inflation during Fed chairmen tenures, they are often substitutes in their role as causal lead or feedback variables when used to analyze real output and inflation suggesting that liquidity effects are quite sparse. That means that, quite often, when the FFR is causally leading inflation and/or output, DM is not a leading variable, and vice versa.

In order to give a macroeconomic policy interpretation to our identified regimes, we map these to the corresponding tenures of U.S. Fed chair (and U.S. Presidents) by defining the dominant regime as the one that prevails at least 50% (or 80%) of the time the relevant chair was in office. We then provide external verification for the shifts in smoothed regime probabilities by comparing these with the monetary shocks identified by the literature benchmark. In particular we show that regime turning points align very well with the monetary policy shock dates suggested by Romer and Romer (1989, 1994, 2004).

We focus on three types of regimes: output regime refers to the case where the monetary indicator causally leads real output, inflation regime to the case where the monetary indicator leads inflation, and finally a Taylor or a McCallum rule regime in which the monetary indicator is a feedback variable.

Monetary Rule regimes: Meltzer (2014) suggested that the Federal Reserve followed successful Taylor rule policies after 1985. We find that the latter half of Volcker and most of Greenspan tenures can be described as Taylor type of feedback regime and is replaced by DM-McCallum type of feedback regimes around 2003 (Greenspan) followed by Bernanke and Yellen's terms suggesting a relatively recent shift towards monetary aggregates as feedback variables. Thus while we confirm Meltzer (2014)'s claims on the relevance of Taylor rules up until the new millennium, policy preferences seem to have shifted from FFR towards controllable monetary aggregates as feedback variables.

Output regimes: Burns/Greenspan/Bernanke tenures can be characterized as output regimes where the FFR causally leads real output, whereas Greenspan tenures are characterized as output regimes where the DM leads real output. That the DM and FFR were leading output overlaps with the Greenspan era also suggests that liquidity effects, that is the inverse relationship between the monetary aggregate and FFR, were more likely present during that time.

Inflation regimes: We confirm widely reported failure of FFR to explain variations in inflation post Volcker era (see, for instance, Stock and Watson (2007), Stock and Watson (2010) and Faust and Wright (2013), who report strong forecasting performance of univariate models of inflation against economic model based alternatives). FFR was a causal lead indicator during Martin/Burns/Miller tenures and, briefly, during the Global Financial Crisis (GFC) under Bernanke leadership. In contrast, we find that the DM causally leads U.S. inflation throughout Burns/Volcker/Greespan tenures almost uninterrupted suggesting that relevant liquidity effects influencing inflation were only present during Burns tenure in 70's.

We also compute causal regime durations associated with monetary indicators and macroeconomic variables. Our calculations strongly favour DM over FFR and alternative monetary indicators, meaning that regimes in which DM is identified as a causal variable in explaining variations in real output and/or inflation tend to be significantly longer than regimes associated with other monetary indicators.

Finally, we conduct empirical and computational robustness tests of our results. We repeat the exercise for two alternative and potentially useful monetary indicators upon which the Federal Reserve has no direct control: M2 and Divisia M4, a certain measure of the synthetic Divisia index[1]. We find for these monetary indicators that the Volcker era is crucial in the direction of causality. While there is some causal lead from either M2 or Divisia to inflation and real output up until the Volcker disinflations, the causal relation reverses with Volcker and continued to be the case during Greenspan-Bernanke-Yellen periods. We also carry out Monte Carlo simulations to verify the accuracy of our causal regime identification strategy and confirm that identified regimes are not spurious.

Related Literature

Our work is related to the extensive empirical literature concerned with the *linear* relationships between monetary aggregates, real output and/or inflation. In their seminal work, Friedman and Schwartz (1963) argued that long leads and lags determine the association between monetary aggregates, real output and inflation. However, Friedman and Kuttner (1992) reported that the information content of U.S. monetary aggregates for real output and inflation has mostly disappeared after Volcker disinflation policies, whereas short-term rates and credit spreads remained as useful information variables in explaining variations in real output, undermining the confidence in the use of monetary aggregates as intermediate targets. In contrast, Leeper and Roush (2003) show that money contains significant information to identify monetary policy that is not available in FFR. Aksoy and Piskorski (2006, 2005) argued that U.S. monetary aggregates are subject to major measurement problems since money supply data includes substantial and unstable foreign holdings of the U.S. dollars. They showed that, when corrected for foreign holdings of U.S. Dollars, DM has significant and stable information content for the variations in the U.S. real output and inflation both in and out of sample. Similarly, Belongia and Ireland (2016) showed that Friedman-Schwartz stylized facts can be replicated when the synthetic money supply measure, Divisia, is used.

There is a good deal of econometric research that investigates the evolution of U.S. monetary policy by focusing on the FFR. For instance, Meltzer (2014) suggests that the Federal Reserve followed Taylor rule policies after 1985. Sims and Zha (2006) argue that while there are no changes in the parameters of the Taylor rule, there are significant shifts in the volatility of structural disturbances such as the Volcker reserves-targeting period. Davig and Doh (2014) find that a more aggressive FFR regime was in place after the Volcker disinflation and before 1970 than during the Great Inflation episode of the 1970s. They suggest that the timing of the different regimes is associated with variations in the inflation persistence.

Our work is directly related to the literature that evaluates the causal patterns between money supply measures and macroeconomic variables at recessions/recoveries and expansions. Ever since

[1] This index is a discrete-time approximation of a monetary aggregate as a function of the weighted average of the growth rates of the component quantities and so called Divisia weights that take into account the opportunity cost of holding a dollar's worth of an asset against the yield of a benchmark asset, held only to carry wealth between different time periods. See Barnett (1980) and Barnett and Su (2020) for details.

the work of Neftci (1984), it is recognized that business cycles are asymmetric around recessions and expansions, suggesting that the monetary policy effectiveness should be different given the state of the business cycle. Psaradakis et al. (2005) directly address the changing causal relationships by introducing the concept of *temporary* causality, where nonlinear causal relationships between money supply measures and real output can be evaluated within the context of Markov regime switching models. Droumaguet et al. (2017b) provide a formal, nevertheless alternative definition of temporary causality. They develop a Bayesian framework and extend the approach of Krolzig (1997) and Warne (2000a). They consider a benchmark unrestricted MS-VAR where regimes are associated with expansions and recessions (as in Hamilton (1989)), and assess causality on the basis of the estimated switching parameters.The main difference between Droumaguet et al. (2017b) and our approach is that the regimes in our MS-VAR are directly associated with different causality relationships (rather than with expansions and recessions). These regimes encompass all possible directions of causality within the model and transitions between them are governed by exogenous unobservable Markov processes.

The paper is organized as follows. Section 2 describes the nonlinear MS-VAR econometric framework with potential monetary instruments, real output and inflation as endogenous variables and with eight possible causality regimes in the macroeconomic environment. Section 3. presents and discusses the results of our causal regimes, duration of regimes and dominant regimes corresponding to tenures of Fed chairs, and compares our results with monetary policy shocks suggested by the literature. Section 4. presents some robustness results using alternative monetary indictors and Monte Carlo simulations. Finally, Section 5. concludes.

2. A Model of Temporary Granger Causality

Our analysis is based on a regime switching multivariate model for real output growth (y), price inflation (π), and a monetary indicator or interest rate (m). Our modelling approach is consistent with the notion of temporary Granger causality, that is causality which may hold during some time periods but not in others. Changes in the causal relationships among the three endogenous variables of interest are viewed as unobservable random events governed by an exogenous finite-state Markov process whose state space represents all possible alternative causal states of nature in a trivariate model. In this respect, the approach to causality that is considered here is similar to that of Psaradakis et al. (2005), but differs from those of Krolzig (1997) and Droumaguet et al. (2017b). The latter make use of regime switching models in which different regimes are not identified as being associated with different causality links and whose state-dependent parameters are not necessarily consistent with the notion of temporary causality that is the focus of our analysis here. We note that it is well known that the empirical support for such causal relationships is highly sensitive to the data and model specification(e.g. Psaradakis et al. (2005)).

Formally, we consider a MS-VAR model of order $h \geq 1$ of the form

$$X_t = D_t + \sum_{k=1}^{h} A_t^{(k)} X_{t-k} + \Omega_t^{1/2} U_t, \quad t = 1, 2, \ldots, T, \tag{2.1}$$

where $X_t' = [y_t, \pi_t, m_t]$, D_t and $A_t^{(k)}$ are state-dependent parameter matrices given by

$$D_t = \begin{bmatrix} \mu_{10} + \mu_{11} s_{y,t} \\ \mu_{20} + \mu_{21} s_{\pi,t} \\ \mu_{30} + \mu_{31} s_{m,t} \end{bmatrix}, \quad A_t^{(k)} = \begin{bmatrix} \phi_{10}^{(k)} + \phi_{11}^{(k)} s_{y,t} & \psi_1^{(k)} s_{y,t} & \psi_2^{(k)} s_{y,t} \\ \psi_3^{(k)} s_{\pi,t} & \phi_{20}^{(k)} + \phi_{21}^{(k)} s_{\pi,t} & \psi_4^{(k)} s_{\pi,t} \\ \psi_5^{(k)} s_{m,t} & \psi_6^{(k)} s_{m,t} & \phi_{30}^{(k)} + \phi_{31}^{(k)} s_{m,t} \end{bmatrix}, \tag{2.2}$$

$\{U_t' = [u_{y,t}, u_{\pi,t}, u_{m,t}]\}$ are uncorrelated Gaussian random vectors with mean zero and identity covariance matrix, and $\Omega_t^{1/2}$ denotes the lower triangular Cholesky factor of a symmetric positive definite 3×3 matrix Ω_t the elements of which depend on $(s_{y,t}, s_{\pi,t}, s_{m,t})$ in a way to be made more precise later. The variables $s_{y,t}$, $s_{\pi,t}$ and $s_{m,t}$ are latent binary random variables with values in $\{0,1\}$ which characterize the regime (state) that prevails at each time period t. The initial values $X_{1-h}, \ldots, X_0$ are taken as given.

The model allows for eight causality regimes, which may be indexed by the random variable

$$S_t = \begin{cases} 1, \text{ if } (s_{y,t}, s_{\pi,t}, s_{m,t}) = (1,1,1), \\ 2, \text{ if } (s_{y,t}, s_{\pi,t}, s_{m,t}) = (1,1,0), \\ 3, \text{ if } (s_{y,t}, s_{\pi,t}, s_{m,t}) = (1,0,1), \\ 4, \text{ if } (s_{y,t}, s_{\pi,t}, s_{m,t}) = (0,1,1), \\ 5, \text{ if } (s_{y,t}, s_{\pi,t}, s_{m,t}) = (1,0,0), \\ 6, \text{ if } (s_{y,t}, s_{\pi,t}, s_{m,t}) = (0,1,0), \\ 7, \text{ if } (s_{y,t}, s_{\pi,t}, s_{m,t}) = (0,0,1), \\ 8, \text{ if } (s_{y,t}, s_{\pi,t}, s_{m,t}) = (0,0,0). \end{cases} \tag{2.3}$$

The state-dependent covariance matrices Ω_t of the noise may be specified accordingly as

$$\Omega_t = \sum_{\ell=1}^{8} \Omega_\ell I(S_t = \ell), \tag{2.4}$$

where $\Omega_1, \ldots, \Omega_8$ are symmetric positive definite non-random matrices and $I(\cdot)$ is an indicator function whose value is 1 when its argument is true and 0 otherwise.

The specification of the model is completed by assuming that the random sequences $\{s_{y,t}\}$, $\{s_{\pi,t}\}$ and $\{s_{m,t}\}$ are homogeneous first-order Markov chains, independent of the noise $\{U_t\}$, with corresponding transition matrices $P^{(r)} = [p^{(r)}_{i,j}]$, $r = y, \pi, m$, where

$$p^{(r)}_{i,j} = \mathscr{P}(s_{r,t+1} = j | s_{r,t} = i), \quad i, j = 0, 1; \; r = y, \pi, m. \tag{2.5}$$

It is further assumed that $\{s_{y,t}\}$, $\{s_{\pi,t}\}$ and $\{s_{m,t}\}$ are independent of each other. In consequence, the regime indicators $\{S_t\}$ form a homogeneous first-order Markov chain on the state space $\{1, 2, \ldots, 8\}$ with transition matrix $P_S = [P_{i,j}]$, $P_{i,j} = \mathscr{P}(S_{t+1} = j | S_t = i)$, $i, j = 1, \ldots 8$, such that

$$P_S = P^{(y)} \otimes P^{(\pi)} \otimes P^{(m)}, \tag{2.6}$$

where $\otimes$ denotes Kronecker product. The independence assumption implies that regime switching in each of the equations of the model is driven by a Markov process which is independent of the Markov process that controls regime changes in another equation. The assumption can be relaxed but only at the cost of a substantial increase in the number of free parameters in what is already a high-dimensional multiple equation model.

Aggregating (Classifying) Regimes: The causal patterns in our trivariate model are directly associated with the binary variables $(s_{y,t}, s_{\pi,t}, s_{m,t})$.If $s_{r,t} = 0$ $(r = y, \pi, m)$, then the r-th element of X_t is not Granger caused by either of the other two elements. Since the focus of the analysis are the temporary causal relationships among the three variables in X_t, defining the states of nature directly in terms of these causal relationships is arguably a natural way of classifying regimes. To this end, and in order to have a parsimonious presentation of the identified regimes in our discussion, we will aggregate regimes according to a three-way classification: (i) Output regime $(s_{y,t} = 1)$ is characterized by $S_t = 1$, $S_t = 2$, $S_t = 3$ and $S_t = 5$; (ii) Inflation regime $(s_{\pi,t} = 1)$ is characterized by $S_t = 1$, $S_t = 2$, $S_t = 4$ and $S_t = 6$; (iii) Monetary Rule regime $(s_{m,t} = 1)$ is characterized by $S_t = 1$, $S_t = 3$, $S_t = 4$ and $S_t = 7$. This aggregation scheme, which is summarized in Table 2.1 below, is helpful for interpreting the stylized facts.

$$(s_{y,t}, s_{\pi,t}, s_{m,t}) \begin{cases} s_{y,t} = \begin{cases} 1, \text{ then } \pi \text{ and } \Delta m_t \rightarrow \Delta y_t \text{ (Output Regime)} \\ 0, \text{ then } \pi \text{ and } \Delta m_t \nrightarrow \Delta y_t \end{cases} \\ s_{\pi,t} = \begin{cases} 1, \text{ then } \Delta y_t \text{ and } \Delta m_t \rightarrow \pi \text{ (Inflation Regime)} \\ 0, \text{ then } \Delta y_t \text{ and } \Delta m_t \nrightarrow \pi \end{cases} \\ s_{m,t} = \begin{cases} 1, \text{ then } \pi \text{ and } \Delta y_t \rightarrow \Delta m_t \text{ (Monetary Rule Regime)} \\ 0, \text{ then } \pi \text{ and } \Delta y_t \nrightarrow \Delta m_t \end{cases} \end{cases} \tag{2.7}$$

The regime associated with $S_t = 1$ is a *mutual causation regime* in which all three endogenous variables are causally linked to each other and hence monetary policy indicators are feedback

When	Granger Causality	$\overbrace{1}^{P(S_t=j\vert X_t;\Phi)}$	2	3	4	5	6	7	8
$s_{y,t} = 1$	π_t and $\Delta m_t \rightarrow \Delta y_t$ (Output Regime)	$\oplus$	$\oplus$	$\oplus$		$\oplus$			
$s_{\pi,t} = 1$	ΔY_t and $\Delta m_t \rightarrow \pi_t$ (Inflation Regime)	$\oplus$	$\oplus$		$\oplus$		$\oplus$		
$s_{m,t} = 1$	π_t and $\Delta y_t \rightarrow \Delta m_t$ (Monetary Rule Regime)	$\oplus$		$\oplus$	$\oplus$			$\oplus$	
$s_{y,t} = 0$ $s_{\pi,t} = 0$ $s_{m,t} = 0$	$\pi_t \not\leftrightarrow \Delta y_t \not\leftrightarrow \Delta m_t$ $\pi_t \not\leftrightarrow \Delta m_t$ (No Causality)								$\oplus$

Note: $P(S_t = j|X_t;\Phi)$ is the smoothed and Φ is the vector of parameters probability

Table 2.1 Summary of regime aggregation

variables; fundamentally it is the unrestricted reduced form VAR where all variables impact each other. The regime associated with $S_t = 2$, $S_t = 3$ and $S_t = 4$ are the regimes where one of the variables follows an autoregressive process (AR) without being caused by any of the other two. For instance, $S_t = 2$ is the regime where the monetary indicator causes both inflation and GDP growth, however the monetary indicator itself follows an AR process. $S_t = 5$, $S_t = 6$ and $S_t = 7$ are regimes where two of the variables have autoregressive dynamics but cause the third one. In particular, the regime associated with $S_t = 7$ may be considered a policy rule regime (McCallum or Taylor) where the policy indicator is a feedback variable and thus responds to changes in macroeconomic conditions but with a lag. The regime associated with $S_t = 8$ is a *no-causation regime* in which none of the endogenous variables are causally linked to each other.

The parameters of the model defined by equations (2.1) to (2.6) can be estimated by the method of maximum likelihood (ML), using a recursive algorithm analogous to that discussed in Hamilton (1994, Sec. 22.4) to evaluate the sample log-likelihood. The Broyden–Fletcher–Goldfarb–Shano (BFGS) quasi-Newton optimization algorithm, with numerically computed derivatives, is used here to find the ML estimates of the parameters.Standard errors for estimated parameters are then obtained from the outer-product-of-the-gradient estimate of the information matrix. We use a second-order model ($h = 2$) in all cases, a lag structure which is rich enough to produce residuals which exhibit no signs of significant autocorrelation on the basis of conventional Ljung–Box portmanteau tests.

3. Empirical Analysis and Simulations

3.1. Data

Our data set consists of annualized quarterly growth rates (log-differences) in real GDP (y_t) and in the GDP deflator/inflation (π_t), as well as quarterly observations on a variety of monetary indicators (m_t). One such indicator is the change (in first-difference) in the FFR (ΔFFR). Specifically, we use the shadow rates, as defined by Wu and Xia (2016), in order to overcome the difficulties associated with the ZLB period.[2] When assessing the relevance of monetary indicators, we take a nuanced stance by distinguishing those that the Federal Reserve can directly control from those it cannot. Therefore as an alternative monetary instrument, we use annualized quarterly changes (log-differences) in DM (ΔDM). We include DM as the monetary aggregate as this monetary instrument (currency component of monetary aggregate corrected for foreign holdings of U.S. Dollars) has at least two important properties: first, it is the monetary aggregate that comes closest to a monetary aggregate as a policy instrument – the Federal Reserve knows exactly how much money is printed and tracks closely U.S. Dollar shipments abroad (Porter and Judson (1996)); second, it has predictive content for U.S. inflation and real output (Aksoy and Piskorski (2006, 2005)). While FFR and DM can be considered as potential policy instruments upon which the Federal Reserve can exert direct control, the monetary aggregate M2 and the Divisia indices are monetary/financial variables reflecting variations in U.S. wide financial activities and state of the credit upon which the Federal Reserve has only indirect influence. The underlying reason for using Divisia relies on its construction. The standard Monetary aggregates (or Index) attribute the same weights for each of the components of the Monetary aggregate, which ultimately assumes that these components are perfect substitutes. The main drawback of assuming that the components are perfect substitutes is that the elasticity substitution is very likely to vary over time. By looking at the Demand side, it has been assumed that a valid Monetary Aggregate is the one where the demand for those assets is independent of its quantities. Therefore, to build such aggregate it is necessary to consider a time-varying elasticities of substitutions between each of the components. Another way to look at the demand and therefore the extent of substitutability is to examine their relative rate of return. Therefore, to reflect the demand for Monetary aggregates, it is necessary to construct weights (or indexes) that consider the price (rate of return) and the quantities of components. One of the methods that explore these features is the Divisia. In addition to that, we include Divisia measures in our monetary indicators as these are shown to be useful in forecasting changes in key U.S. macroeconomic aggregates (Belongia and Ireland (2016)). In Section 4.1. we will compare our FFR and DM results with M2 ($\Delta M2$), and in a synthetic Divisia measure,namely Divisia M4

[2] The use of rates which are almost zero for long periods presented a serious challenge for the numerical optimisation routines used to estimate the parameters of the model.

(ΔDivisia$M4$). The data cover the period 1965:1 to 2015:4, except for Divisia M4 for which data is only available from 1967:1 onwards.[3,4]

Our sample overlaps with seven chairs who served at the Federal Reserve: William M. Martin (April 2, 1951 to February 1, 1970) appointed by Harry Truman, Arthur F. Burns (February 1, 1970 to January 31, 1978) appointed by Richard Nixon, G. William Miller (March 8, 1978 to August 6, 1979) and Paul Volcker (August 6, 1979 to August 11, 1987) both appointed by Jimmy Carter, Alan Greenspan (August 11, 1987 to January 31, 2006) appointed by Ronald Reagan, Ben Bernanke (February 1, 2006 to January 31, 2014) appointed by George W. Bush, and Janet Yellen (February 3, 2014 to February 3, 2018) appointed by Barack Obama.

3.2. Parameter Estimates

We begin by reporting in Table 2.2 full-sample estimates of the parameters that are directly related to the causal link, that is, $\psi_1^{(k)},\dots,\psi_6^{(k)}$, $k=1,2$. Estimates of the remaining parameters of the various models and the value of the maximized log-likelihood function can be found in Tables A.1 and A.2 in Appendix 0.2.. We note that estimates of the transition probabilities $(p_{i,j}^{(r)})$ and of the intercepts in D_t are highly significant. In addition, the estimates reveal significant persistence in real output in models with ΔFFR but no persistence in the model with ΔDM. Inflation is persistent in both FFR and DM models.

Money-output causal parameters ($\psi_2^{(k)}$) are significant for both ΔFFR and ΔDM for the first lag and thus these have in-sample predictive content for output. Similarly, money-inflation causality parameters ($\psi_4^{(k)}$) are significant and variations in both FFR and DM temporarily cause price inflation. The parameters $\psi_5^{(k)}$ and $\psi_6^{(k)}$ are associated with the monetary indicator feedback, as in variants of the McCallum (ΔDM) or Taylor rule (ΔFFR) for real output and inflation, respectively. We find that the estimated output-money feedback parameter ($\psi_5^{(1)}$) is significant for both FFR and DM. Inflation-money feedback parameters ($\psi_6^{(k)}$) are significant only for ΔDM. It is interesting to note that there is little evidence for Taylor Regimes: ΔFFR responses to past inflation are not significant.

[3]For more details on the data see Appendix 0.1.

[4]We note that the hypothesis of a unit root can be rejected by a breakpoint unit root test with innovative outlier, at the 5% significance level, for all variables under consideration; see Appendix 0.2. for descriptive statistics and unit root tests.

Causal Effect		FFR	ΔDM
$\pi_t \to y_t$	$\psi_1^{(1)}$	-0.4013	-0.0184
		(0.3990)	(0.3624)
	$\psi_1^{(2)}$	0.1562	0.2976
		(0.3707)	(0.3924)
$m_t \to y_t$	$\psi_2^{(1)}$	0.4896**	0.2263**
		(0.2450)	(0.1029)
	$\psi_2^{(2)}$	-0.2205	-0.1534*
		(0.2518)	(0.1165)
$y_t \to \pi_t$	$\psi_3^{(1)}$	-0.0518	-0.0041
		(0.0622)	(0.0275)
	$\psi_3^{(2)}$	-0.0081	0.0078
		(0.0525)	(0.0226)
$m_t \to \pi_t$	$\psi_4^{(1)}$	0.1089*	0.0256
		(0.0804)	(0.0286)
	$\psi_4^{(2)}$	0.0530	0.1161***
		(0.0670)	(0.0381)
$y_t \to m_t$	$\psi_5^{(1)}$	0.1603***	-0.4685***
		(0.0589)	(0.1710)
	$\psi_5^{(2)}$	0.0456	-0.2665**
		(0.0634)	(0.1646)
$\pi_t \to m_t$	$\psi_6^{(1)}$	0.2689**	-0.1625
		(0.1370)	(0.5324)
	$\psi_6^{(2)}$	-0.1906	0.1708
		(0.1345)	(0.4166)

Note: * , **, *** are respectively 10%,5% and 1% significance
Standard errors in the brackets

Table 2.2 Results for Causality Parameters

3.3. Federal Reserve Chairs and US Presidents Regime Probabilities

Estimates reported in Table 2.2 provide only partial evidence of causal relationships. In this section we compute smoothed probabilities (based on the full sample information) of being in the output, inflation, monetary rule or non-causality regimes described in Section 2. For the sake of direct comparison we present in Figure 2.1 and 2.3 estimated probabilities for FFR and DM models together where we mark associated Fed chairs. We reproduce same figure in Figure 2.2 and 2.4 to show the elected presidents and corresponding smoothed probabilities.[5]

[5] Specifically these are the sums of estimated smoothed probabilities associated with the relevant states in the ΔFFR model (Figure A.1 in the Appendix), the ΔDM model (Figure A.2 in the Appendix). We also report in Figure 2.8 smooth probabilities for those variables where Federal Reserve has only indirect control ($\Delta M2$ and $\Delta DivisiaM4$)

Federal Reserve Chairs and Monetary Rules Regime

The most striking result in our model is the overlapping between the Federal Reserve chairperson's tenure and the monetary rule. According to our estimates, the smoothed probabilities indicate for the monetary rule associated with FFR that there were some episodes where FFR responded to inflation and output, for instance, in Martin's tenure and Burn's tenure. Nonetheless, the most outstanding period started after Paul Volcker took place. As can be observed in the first plot of the figure 2.1 FFR responded to inflation and output from October 1979 to April 2003, except for a period after the beginning of the 80's recession. In the second plot of the figure 2.1, it is possible to observe from October 1988 that DM also responded to inflation and output during Greenspan's tenure. However, starting at the end of Greenspan's term (from July 2003) towards our sample's end, DM responded to inflation and output, whereas FFR did not, thereby confirming Meltzer (2014)'s claims.

This result is interesting because, except if there are shifts in policy preferences (objectives and/or instruments) or expectations formation, there are no straightforward reasons to expect an overlap in shifts in the causal relationships between alternative policy instruments and key macroeconomic variables (causality regimes) corresponding to a particular U.S. Fed's chair's tenure.

In a famous article, Bernanke and Reinhart (2004) shed light on how central banks could effectively conduct monetary policy during episodes of low-interest rates; in this particular case, during the Zero Lower bound episode. Our result suggests that causality has changed from July of 2003, coinciding with the lowest value of FFR before the ZLB, indicating that policymaking focusing on monetary aggregates may have been the hallmark of the millennium.

In their article, Bernanke and Reinhart (2004) pointed out that altering the composition of the Central Bank's balance sheet, ultimately expanding the size of the Central Bank's balance sheet, despite being controversial, can be effective. In this context, quantitative easing may influence economic activity over distinct alternative channels. Particularly, considering that money is an imperfect substitute for other financial assets; therefore considerable increases in the money supply will lead economic agents to rebalance their portfolio positions, consequently raising prices and reducing yields on non-money assets. Finally, lower yields on long-term assets will stimulate the economy.

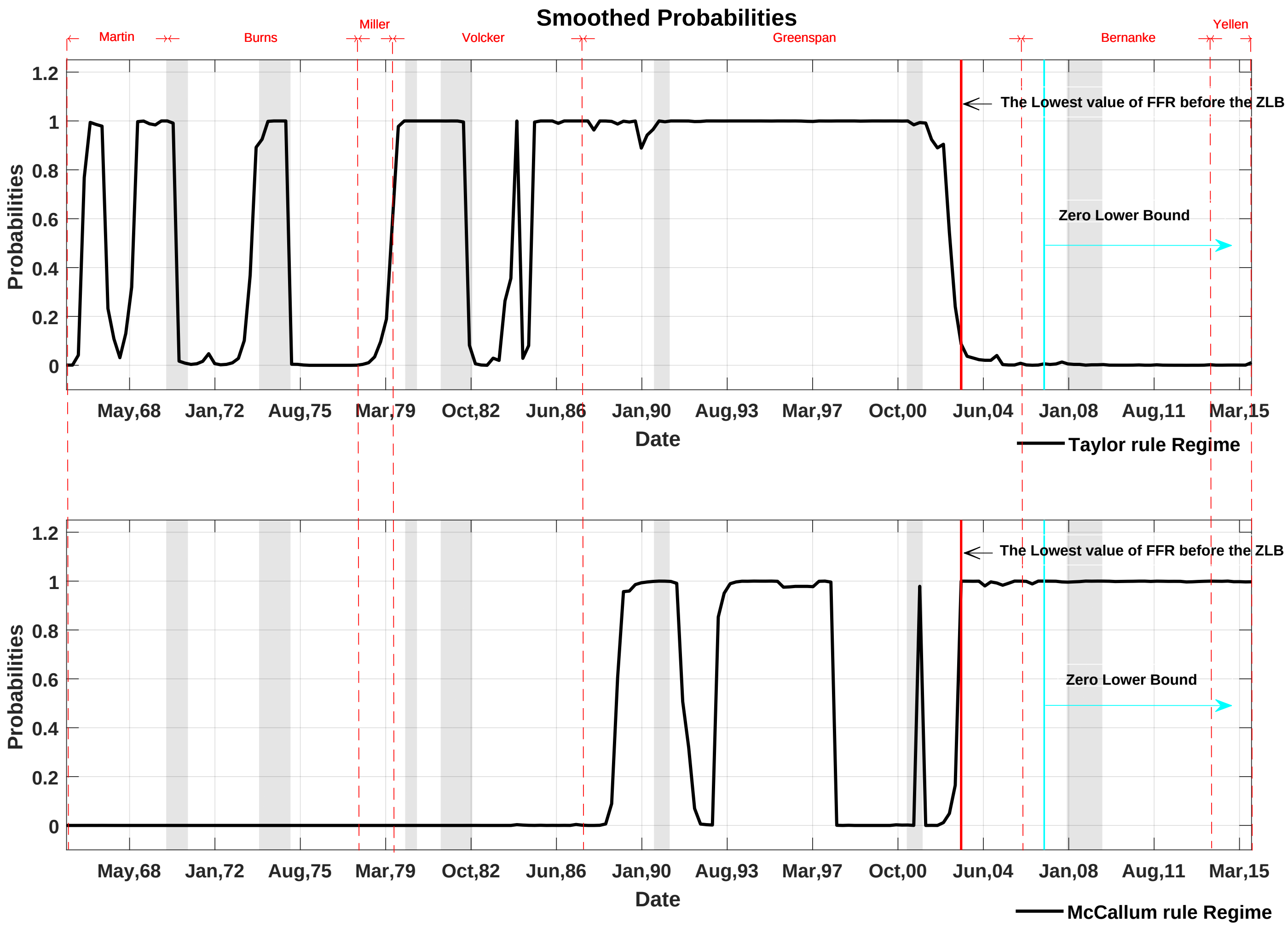


Figure 2.1 Smoothed Probabilities for Policy Instruments: 'Monetary Rule Regime' ($S_t = 1,3,4,7$), where U.S. real output and/or price inflation lead the monetary policy indicator.

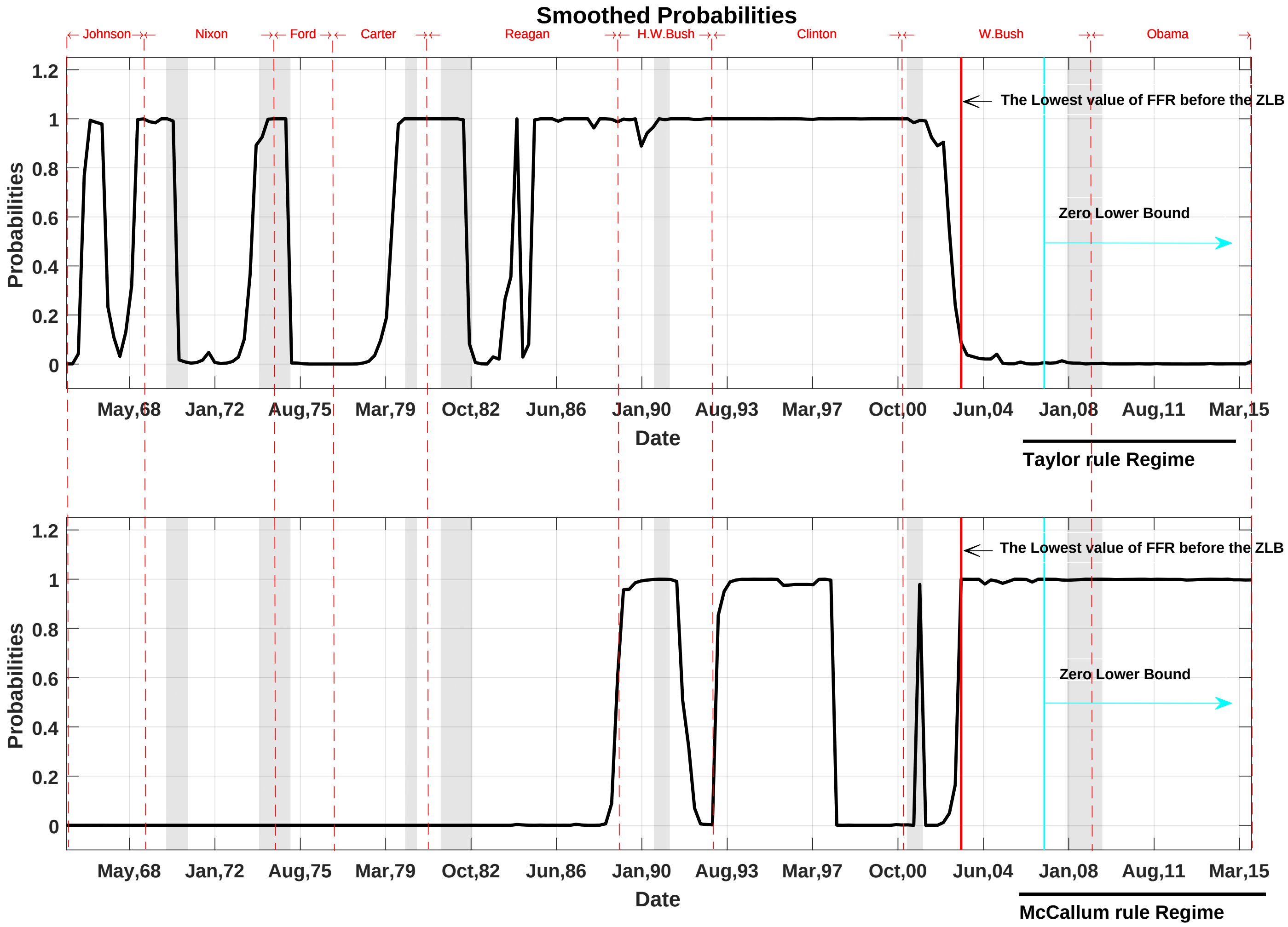


Figure 2.2 Smoothed Probabilities for Policy Instruments: 'Monetary Rule Regime' ($S_t = 1,3,4,7$), where U.S. real output and/or price inflation lead the monetary policy indicator.

In figure 2.2, instead of looking at the Federal Reserve chairman, the smoothed probabilities are plotted, considering the presidencies. The plots do not indicate an apparent relationship between the Monetary instrument rule and the presidencies. However, it is not easy to draw any conclusion about the Federal Reserve's political independence.

Federal Reserve Chairs and Other Regimes

We can **also** sketch some broad contours for smoothed probabilities for the **other** regimes. We first comment on Figures 2.3 and 2.4. Then, we map the smoothed probabilities to tenures of Fed Reserve chairs and compute the dominant regime (50% or 80% of the tenure duration) for both policy indicators we consider. That way we provide political economy interpretation of the computed regimes and monetary policy preferences.

We first note that estimated regime probabilities for the monetary indicators FFR and DM causally affect output or inflation or serve as a feedback variable. We do not find any meaningful evidence of absence of such causal relationships throughout the sample period we study. Second, business cycle causal regimes often switch as lead indictors, meaning, for instance, that when FFR leads real output, DM, in general, does not and vice versa. This suggests the liquidity effects are not always present.

Output regimes: Figures 2.3 and 2.4 top panels show causal patterns from FFR and DM to real output. We observe that there are several episodes where either DM, FFR or both lead real output movements. Broadly speaking from 1965 up until the end of the Volcker tenure, DM or FFR were causal in most periods. Note that these causal leads do not overlap, suggesting that the effects of monetary expansions/contractions or changes in the FFR rate did not transmit to the alternative monetary indicator (liquidity effect). This is followed by almost the entire Greenspan tenure up until the transition of the U.S. presidency from Clinton to G.W. Bush, where both indicators were causally leading real output indicating liquidity effects which in turn influencing real output movements. In contrast, Bernanke/Yellen tenures suggest a reversal of policymaking not unlike the pre-Greenspan era both in terms of the FFR causal lead and the absence of relevant liquidity effects for real output.

Inflation regimes: Figures 2.3 and 2.4 second rows display causality regimes from FFR and DM to U.S. inflation. First, it is well established that the FFR fails to explain variations in U.S. inflation (see, for instance, Stock and Watson (2007, 2010) and Faust and Wright (2013)) whereas DM contains some information in explaining inflation variations (Aksoy and Piskorski (2006)). Our analysis complements this by posing the question in terms of causality. FFR causal lead to explain the U.S. inflation started around the Martin tenure and lasted up until the in the end of the Volcker tenure. This also suggests that the Greenspan era marks a breakdown in the causal relationship between inflation and FFR. Second, DM was uninterruptedly causal for inflation from the early Burns era up to the Greenspan tenure and until the first half of Bill Clinton's first term. Third, the Bernanke era started with a return to the causal relationship between FFR and inflation that has lasted up until the GFC. Given that both FFR and DM were mostly causal for inflation from Burns onwards until the end of the Volcker episodes, liquidity effects were relevant for the U.S. inflation up until the end of the Volcker tenure; otherwise we do not find any liquidity channels in inflation determination. Finally, post GFC is marked by the absence of any causal relationship between FFR or DM and U.S. inflation.

No Causation Figures 2.3 and 2.4 bottom panels show regimes without any causal relationships. It is sufficient to say that we do not find any meaningful presence of such regimes in the sample period we consider.

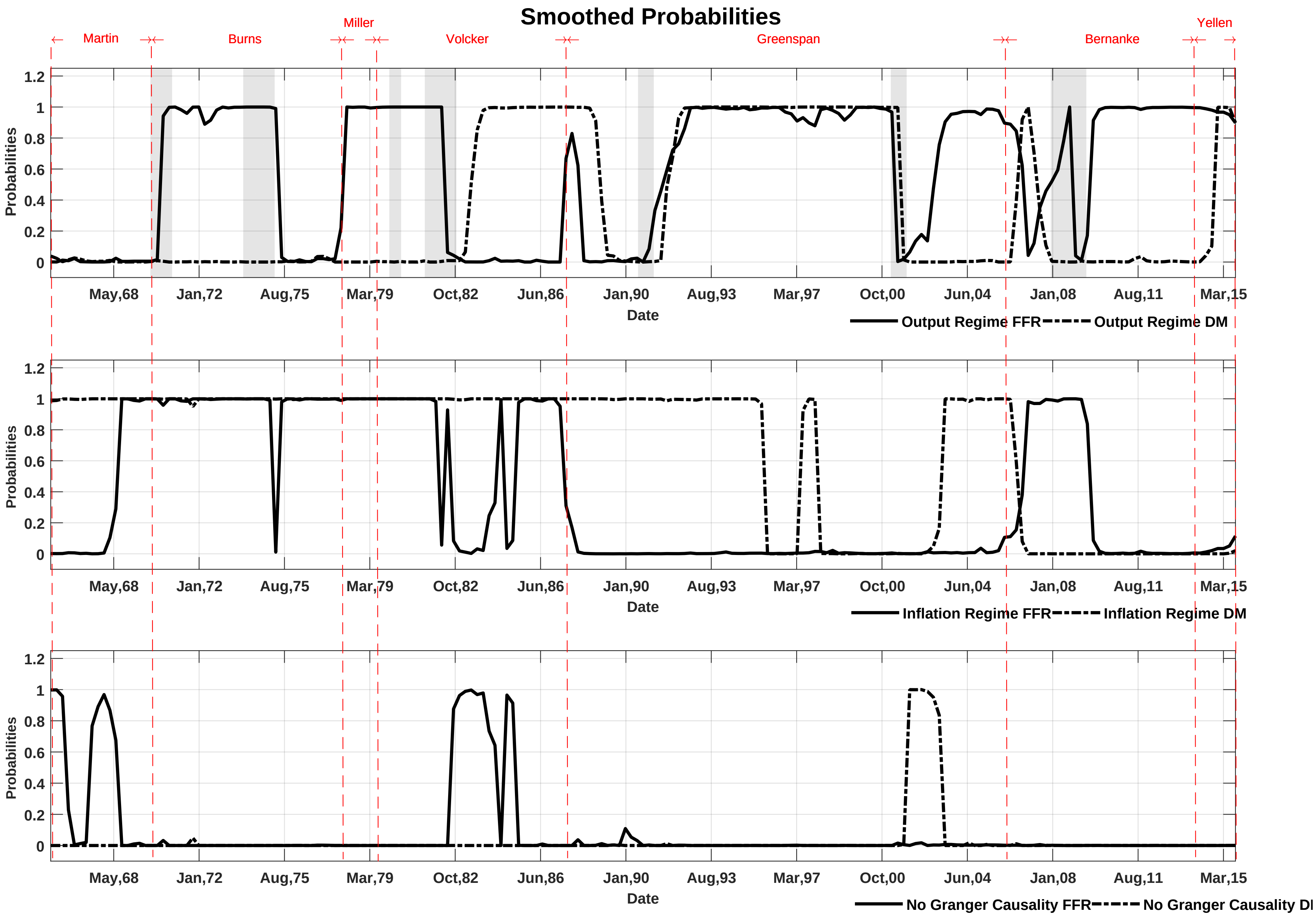


Figure 2.3 Smoothed Probabilities for Policy Instruments: ‘Output Regime’ ($S_t = 1,2,3,5$), where the relevant monetary policy indicator causally leads U.S. real output, a ‘Inflation Regime’ ($S_t = 1,2,4,6$), where the relevant monetary policy indicator causally leads price inflation, and finally the ‘Non-Causality Regime’ ($S_t = 8$) where none of the variables are causally linked to each other.

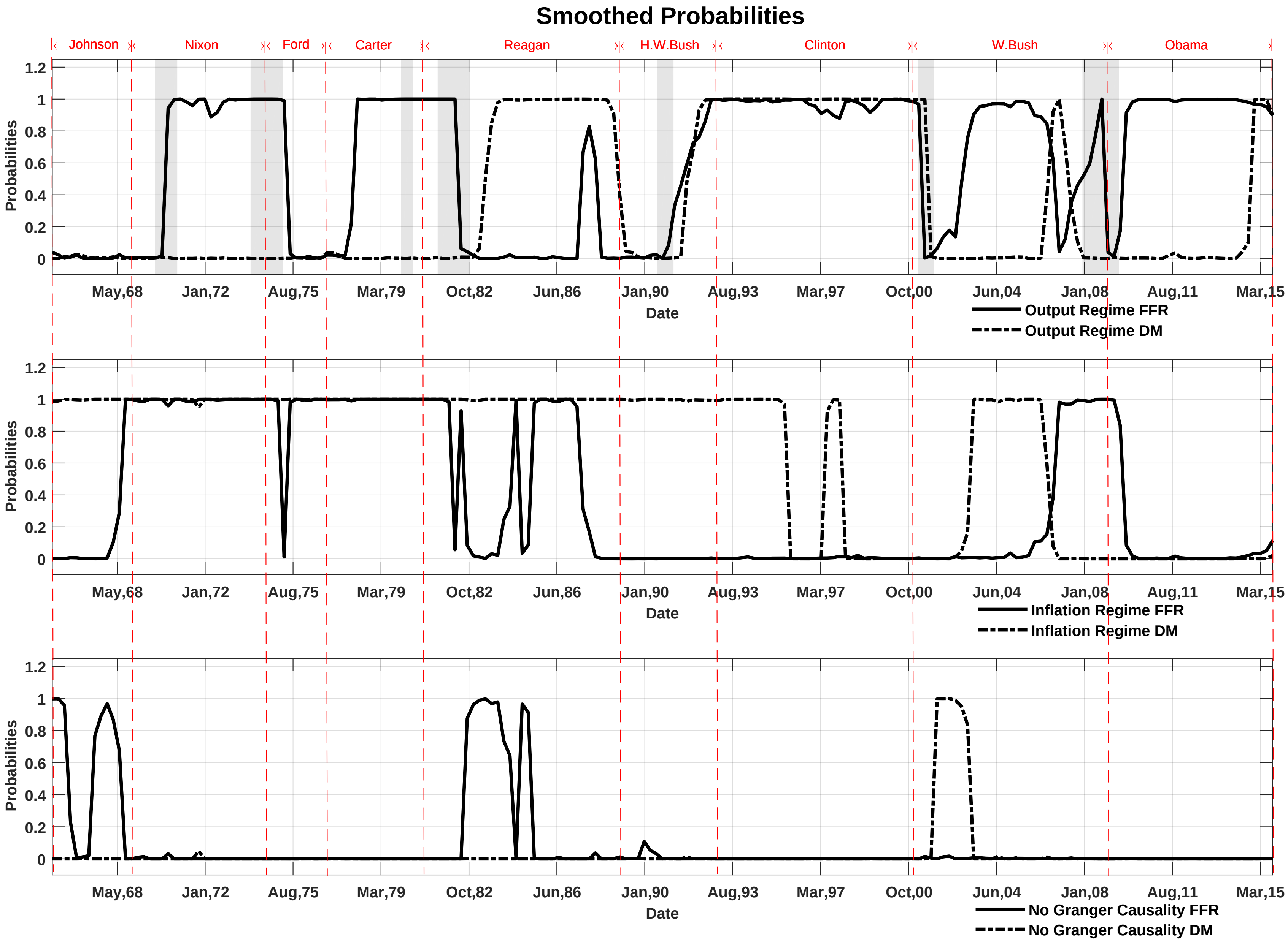


Figure 2.4 Smoothed Probabilities for Policy Instruments: ‘Output Regime’ ($S_t = 1,2,3,5$), where the relevant monetary policy indicator causally leads U.S. real output, a ‘Inflation Regime’ ($S_t = 1,2,4,6$), where the relevant monetary policy indicator causally leads price inflation, and finally the ‘Non-Causality Regime’ ($S_t = 8$) where none of the variables are causally linked to each other.

Dominant Regimes: Following Hamilton (1989), we consider the regime associated with $S_t = \ell$, $\ell = 1,\ldots,8$, to be the prevailing regime at time t if the smoothed regime probability $\mathscr{P}(S_t = \ell | X_{1-h},...,X_T;\hat{\theta})$, based on the ML estimate $\hat{\theta}$ of the model's parameters, exceeds $1/2$. Using this rule, we report in Table 2.3 the total number of quarters in which each of the four composite regimes described in Section 3.3. (namely, output, price, monetary rule, and non-causality) prevailed.

	FFR	ΔDM
Output Regime	123	68
Inflation Regime	74	137
Monetary Rule Regime	102	83
Non-Causality Regime	18	6

Table 2.3 Number of Quarters Associated with Each Regime

It can be seen that the number of quarters associated with the non-causality regime is lower than that associated with any of the other three aggregate regimes. The price regime (output regime) appears to be the most prevalent one in models that involve DM (FFR).

We also compute the estimated expected duration of each of these four regimes. Letting $\hat{P}_S = [\hat{P}_{i,j}]$, $i,j = 1,\ldots 8$, denote the ML estimate of the transition matrix of $\{S_t\}$, the expected durations of the output, price, monetary rule, and non-causality regimes are estimated as:

$$\begin{aligned}
\text{Output} &: (1-\hat{P}_{1,1})^{-1} + (1-\hat{P}_{2,2})^{-1} + (1-\hat{P}_{3,3})^{-1} + (1-\hat{P}_{5,5})^{-1}, \\
\text{Price} &: (1-\hat{P}_{1,1})^{-1} + (1-\hat{P}_{2,2})^{-1} + (1-\hat{P}_{4,4})^{-1} + (1-\hat{P}_{6,6})^{-1}, \\
\text{Monetary Rule} &: (1-\hat{P}_{1,1})^{-1} + (1-\hat{P}_{3,3})^{-1} + (1-\hat{P}_{4,4})^{-1} + (1-\hat{P}_{7,7})^{-1}, \\
\text{Non-causality} &: (1-\hat{P}_{8,8})^{-1}.
\end{aligned}$$

	FFR	ΔDM
Output Regime	30.48	54.92
Inflation Regime	28.07	57.80
Monetary Rule Regime	30.53	50.42
Non-Causality Regime	7.07	14.48

Table 2.4 Conditional Expected Duration (Quarters)

Similarly to the results in Table 2.3, the estimated expected durations shown in Table 2.4 also indicate that the non-causality regime is expected to last the shortest. The expected duration varies from 18 (non-causality regime) to 123 quarters (output regime) in the FFR model, and from 6 (non-causality regime) to 137 quarters (inflation regime) in the DM model.

Alternatively, we can evaluate causality regimes by focusing on the regime dominance during a chair's mandate. More specifically, using the notion of a *Dominant Regime*, we can compute the proportion of quarters that a specific regime has dominated a mandate. For instance, during Greenspan's mandate, which lasted for 74 quarters, the output regime prevailed for 19 quarters in the case of FFR, which is approximately 25.6% of that mandate. The entire period from Martin's up until the end of Greenspan mandates was dominated by the Inflation Regime in the case of DM.[6]

Tables 2.5 and 2.6 display dominant regimes that we match with tenures of each Federal Reserve chair, where the black and grey bars indicate a dominant regime for more than 80% and 50% of chair's tenure time, respectively confirming our findings. The tables 2.5 and 2.6 are separated in a similar way (Monetary Rules and Other Rules) to the smoothed probabilities.

In sum, our results for models with controllable monetary indicators (FFR and ΔDM models) suggest that these two controllable monetary indicators regularly switch in terms of their causal usefulness in explaining variations of inflation and real output: an indication of regular absence of liquidity effects. We find that while the DM variations contain causal lead information to explain variations in real output and inflation up until the turn of the century, it became a feedback variable (McCallum rule) post GFC. Throughout our sample period, from 1965 up until end of 2015 DM serves, without any interruption, as a dominant causal or feedback variable. We note that the Greenspan tenure marks the relevance of the Taylor rule, where FFR is the feedback variable with respect to variations in U.S. inflation and real output.

[6]Table A.3 in Appendix (0.2.) shows all the results.

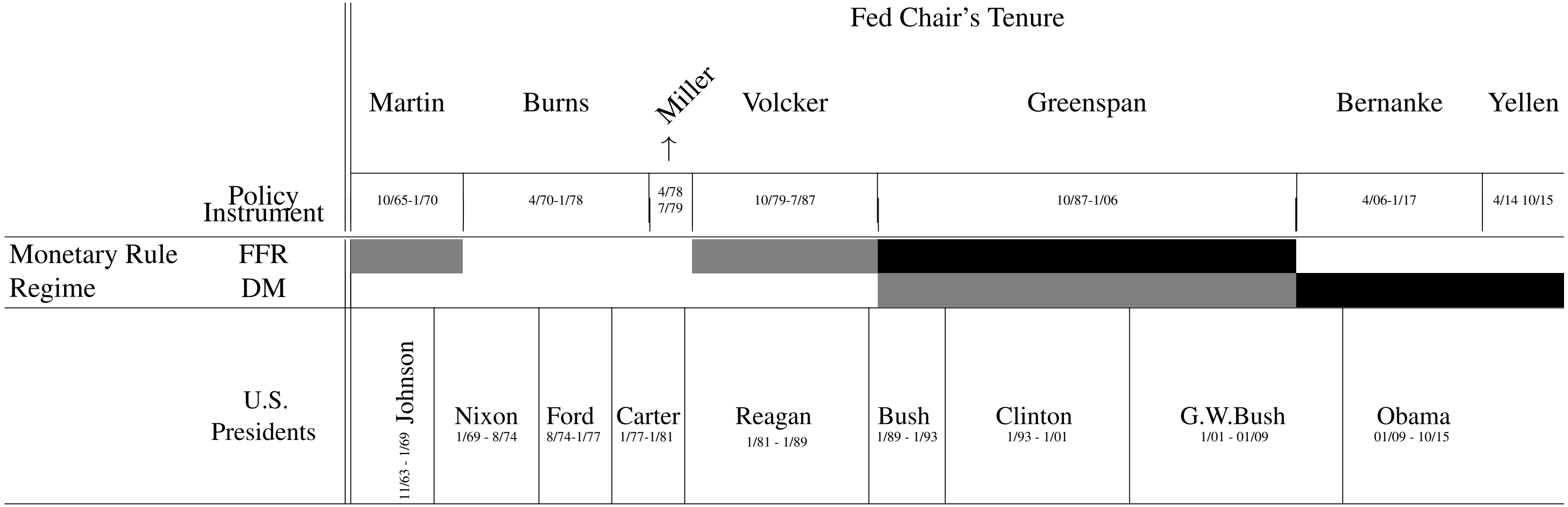


Table 2.5 Dominant Regime for Monetary Policy Rule

In the diagram, the black and the grey bars indicate that the regime dominates more than 80% and 50% respectively.

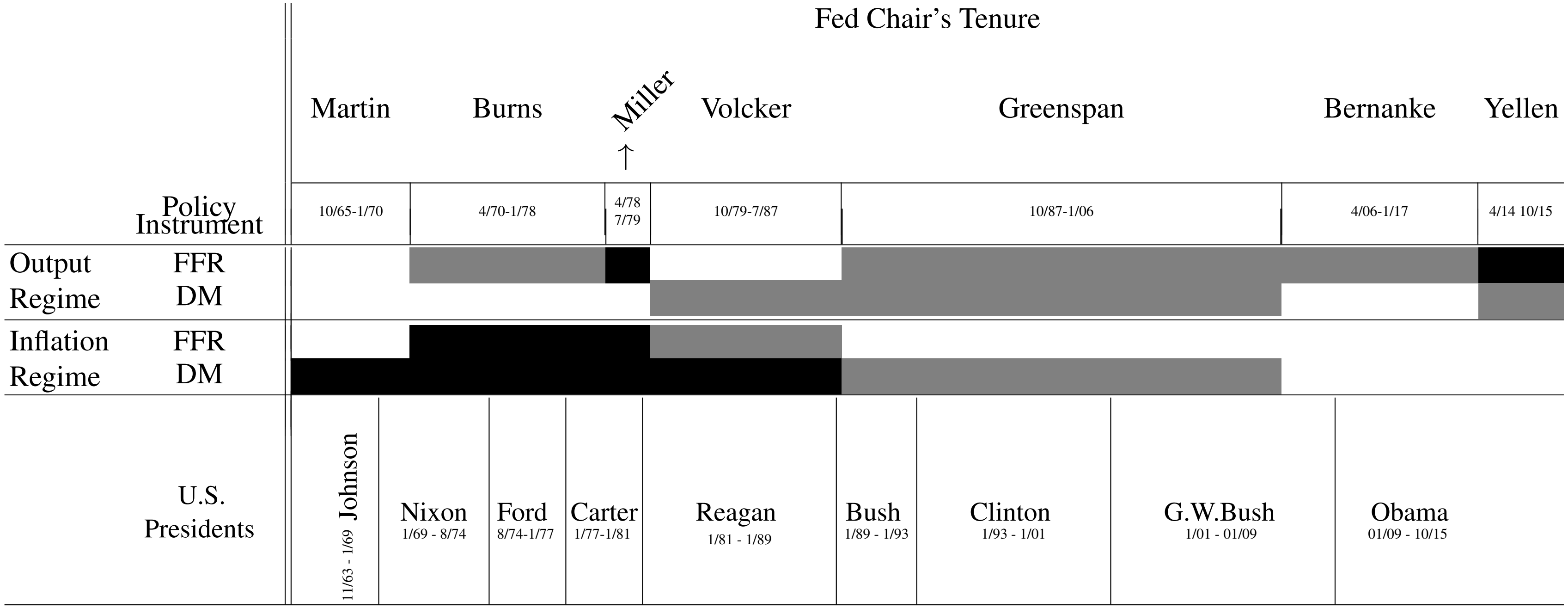


Table 2.6 Dominant Regime for the Other Regimes

3.4. Granger-Causality Shifting Mechanism

One important issue that is addressed in this section is the shifting mechanism. The shifting mechanism in the Markov-Switching literature plays an important role in defining the regimes, and in the Makov-Switching Causality is not different. In fact, the mechanism is the same. As you will observe later on, the shocks play an important role. In our model, the shocks define the causality patterns, which ultimately require external validation. For this purpose, we will rely on Romer and Romer (1989), Bernanke and Reinhart (2004) papers and some historical events that we believe have trigged the shifting in the causality.

Compatibility with Narrative Approach of Monetary Shock Identification

As a further check of whether results reached by means of our analysis of temporary causality patterns are sensible, we provide further external verification by comparing with monetary policy shocks identified by the narrative approach based on the FOMC's reports (Romer and Romer (1989, 1994)) and by regressing the FFR to Greenbook forecasts (Romer and Romer (2004)). In Figures 2.6 and 2.7, we first plot Romer and Romer (2004) series of shock clusters for 1969, 1973-1974, and 1979-1982(indicated by ellipses at the bottom panel)[7] second with the Romer & Romer individual narrative shocks (indicated by vertical blue lines) dated at December 1968, April 1974, August 1978, October 1979 and October 1988 together with our estimated smoothed regime probabilities. We also add red lines that bookend the period starting with the Plaza Accord (September 1985) aiming to reduce U.S. trade deficits by orderly appreciation of the non-dollar currencies up until the date when the FFR reached its lowest value before hitting the zero lower bound.

Monetary Rule Regimes and Narrative Approach

Figure 2.6 compares estimated smooth probabilities when the FFR is the policy indicator with the Romer & Romer narrative and clustered monetary policy shocks. We first note that the identification of shifts in regime probabilities align very well with the timing of the Romer & Romer narrative shocks. Our results suggest that the start of the inflation regime around late 1968, output regime around late 1978 ,and Taylor rule regime around late 1979, exactly aligning with the Romer & Romer narrative shocks. Second, shock clusters as suggested by Romer and Romer (2004) align well with the duration of Taylor regimes identified by our switching models. Third, we stress that the estimated long-lasting Taylor rule regime characterizing the period of mid 1980's up until 2003 overlaps with the period starting with the Plaza Accord and up until the transition towards the ZLB episode when mostly Greenspan was at the helm of the Federal Reserve. We repeat the same exercise when we consider DM as the policy indicator (Figure 2.7). In addition to the above, we

[7]We utilise Breitenlechner (2018) updates for the Romer and Romer (2004) monetary shock series.

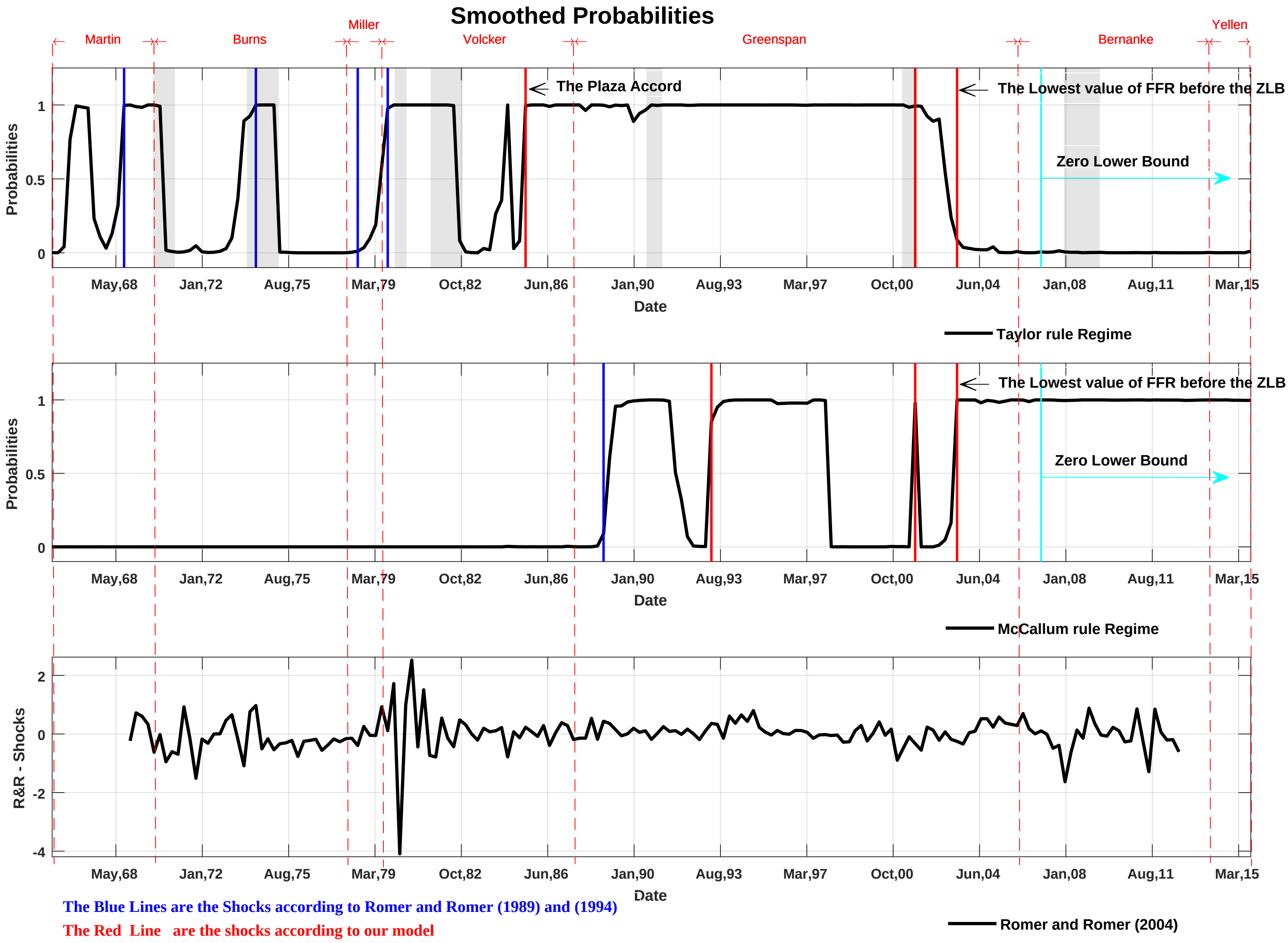


Figure 2.5 Smoothed Probabilities for Policy Instruments: 'Monetary Rule Regime' ($S_t = 1,3,4,7$), where U.S. real output and/or price inflation lead the monetary policy instrument.

find that the narrative shock identified in 1988 aligns very well with the end of our estimated output regime and the start of the McCallum regime.

Overall, we conclude that our estimated smooth probabilities agree with the policy shocks as identified by Romer & Romer.

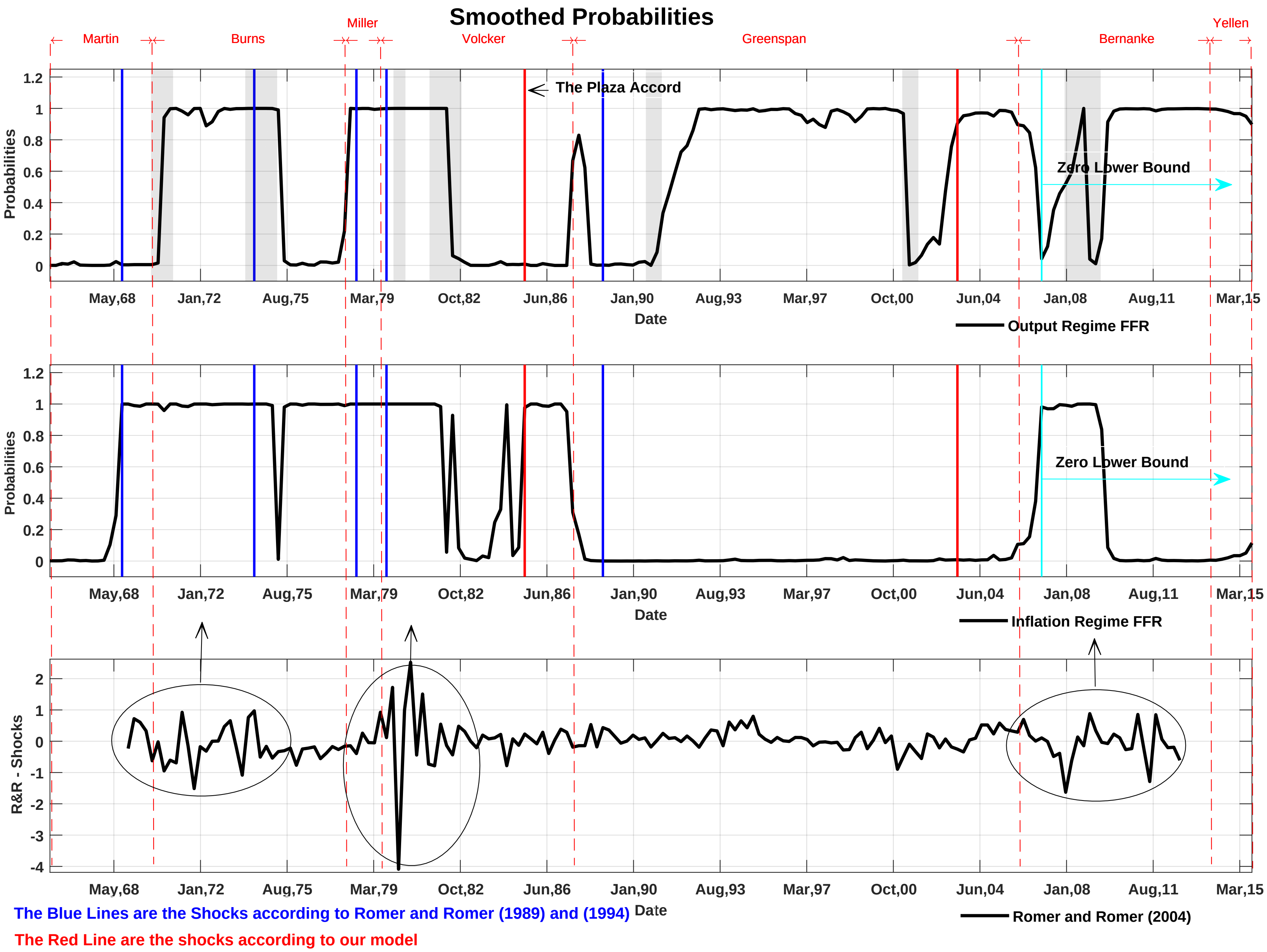


Figure 2.6 Smoothed Probabilities for Policy Instruments: 'Output Regime' ($S_t = 1,2,3,5$), where the relevant monetary policy instrument causally leads U.S. real output, and a 'Inflation Regime' ($S_t = 1,2,4,6$), where the relevant monetary policy instrument causally leads price inflation.

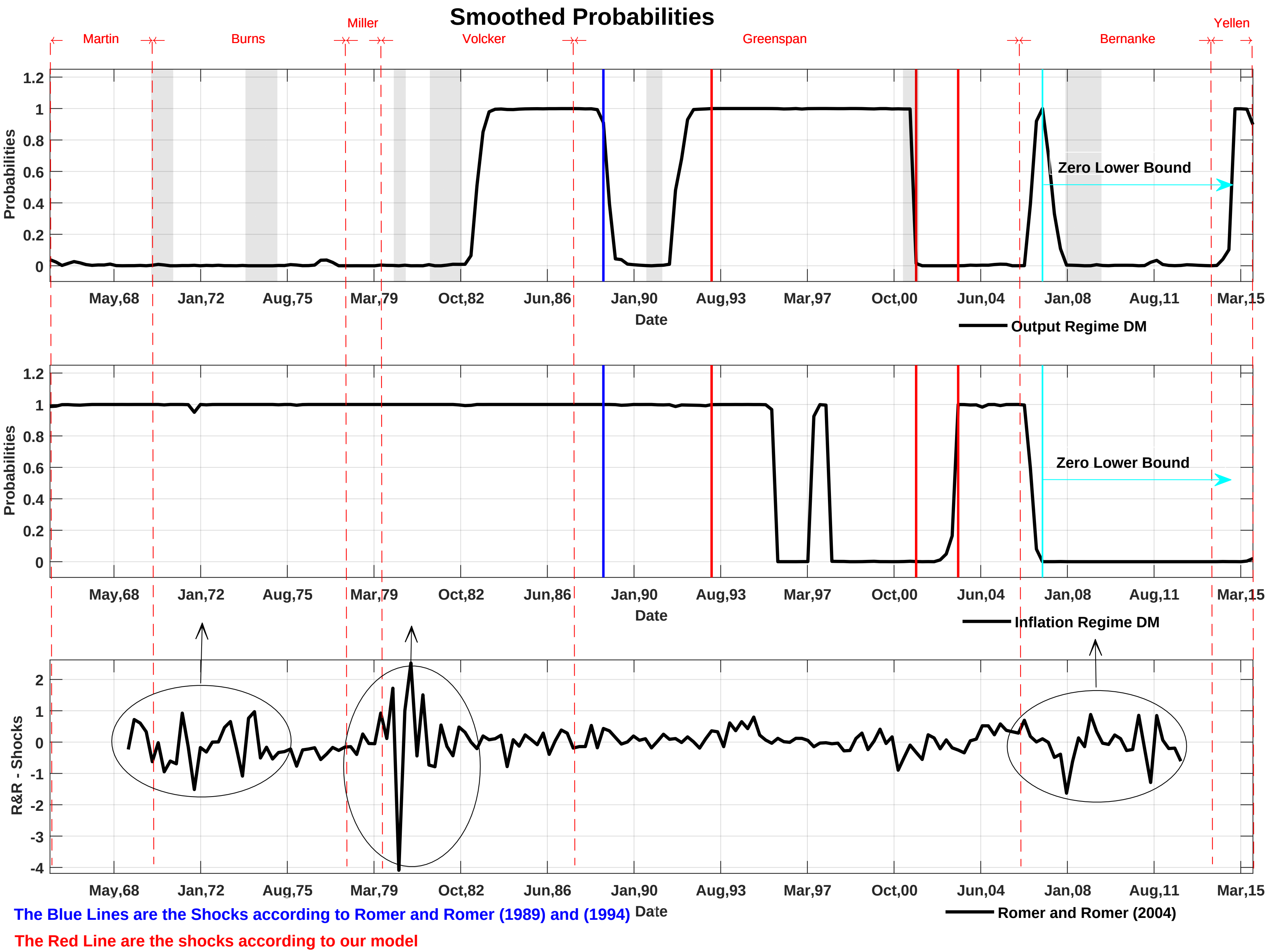


Figure 2.7 Smoothed Probabilities for Policy Instruments: 'Output Regime' ($S_t = 1,2,3,5$), where the relevant monetary policy instrument causally leads U.S. real output, and a 'Inflation Regime' ($S_t = 1,2,4,6$), where the relevant monetary policy instrument causally leads price inflation.

4. Robustness

In this section we first compare our results with alternative monetary indicators and second provide statistical evidence based on Monte Carlo simulations that our findings are not spurious.

4.1. Alternative Monetary Indicators

In this section we replicate the analysis for models with $M2$ and $DivisiaM4$ upon which the monetary authority has no direct control. Figure 2.8 displays smoothed probabilities for these two indicators. As can be observed, we obtain only scant evidence of causal lead to explain variations in U.S. inflation or real output for either $M2$ or $DivisaM4$. At the same time, we find overwhelming evidence of their usefulness as feedback variables (McCallum regimes). In both $M2$ and $DivisaM4$ models, there are two distinct episodes, before and after the Volcker disinflationary period starting around 1982. Our calculations suggest that, before 1982, monetary policy can be characterized by both output and inflation causality regimes and after 1982 by McCallum feedback regimes supporting the findings of Belongia and Ireland (2015).

Causal Effect		$\Delta M2$	$\Delta DivisiaM4$
$\pi_t \rightarrow y_t$	$\psi_1^{(1)}$	-0.4125	0.0254
		(0.4712)	(0.4542)
	$\psi_1^{(2)}$	-0.6047*	0.3191
		(0.4525)	(0.5104)
$m_t \rightarrow y_t$	$\psi_2^{(1)}$	0.3431***	0.7545**
		(0.1305)	(0.4136)
	$\psi_2^{(2)}$	0.2975**	0.2193
		(0.1816)	(0.3861)
$y_t \rightarrow \pi_t$	$\psi_3^{(1)}$	-0.0036	-0.0487
		(0.0652)	(0.1124)
	$\psi_3^{(2)}$	0.0406	0.0868
		(0.0626)	(0.0957)
$m_t \rightarrow \pi_t$	$\psi_4^{(1)}$	0.0489	0.1199*
		(0.0903)	(0.0759)
	$\psi_4^{(2)}$	-0.0027	-0.0698
		(0.0853)	(0.0992)
$y_t \rightarrow m_t$	$\psi_5^{(1)}$	-0.3083***	-0.3183**
		(0.1102)	(0.1790)
	$\psi_5^{(2)}$	0.3328***	0.2479*
		(0.1009)	(0.1550)
$\pi_t \rightarrow m_t$	$\psi_6^{(1)}$	-0.5460**	-0.4585*
		(0.2741)	(0.3518)
	$\psi_6^{(2)}$	0.4823**	-0.1412
		(0.2361)	(0.3924)

Note: * , **, *** are respectively 10%,5% and 1% significance

Standard errors in the brackets

Table 2.7 Results for Causality Parameters

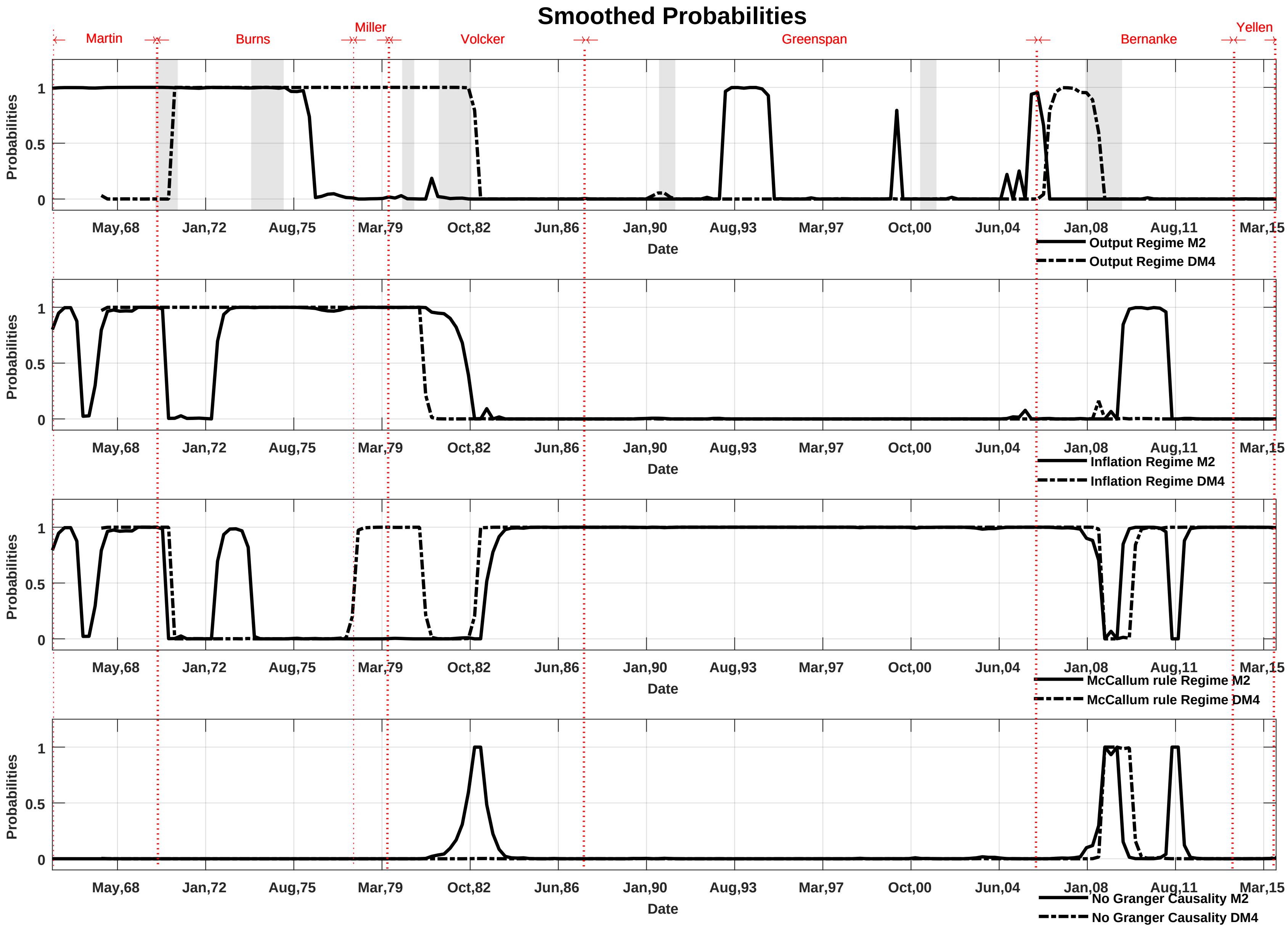


Figure 2.8 Smoothed Probabilities for Monetary Information Variables: ‘Indicator-Output Regime’ ($S_t = 1,2,3,5$), where the relevant monetary policy indicator causally leads U.S. real output, a ‘Indicator-Inflation Regime’ ($S_t = 1,2,4,6$), where the relevant monetary policy indicator causally leads price inflation, a ‘Monetary Rule Regime’ ($S_t = 1,3,4,7$), where U.S. real output and/or price inflation lead the monetary policy indicator and finally the ‘Non-Causality Regime’ ($S_t = 8$) where none of the variables are causally linked to each other.

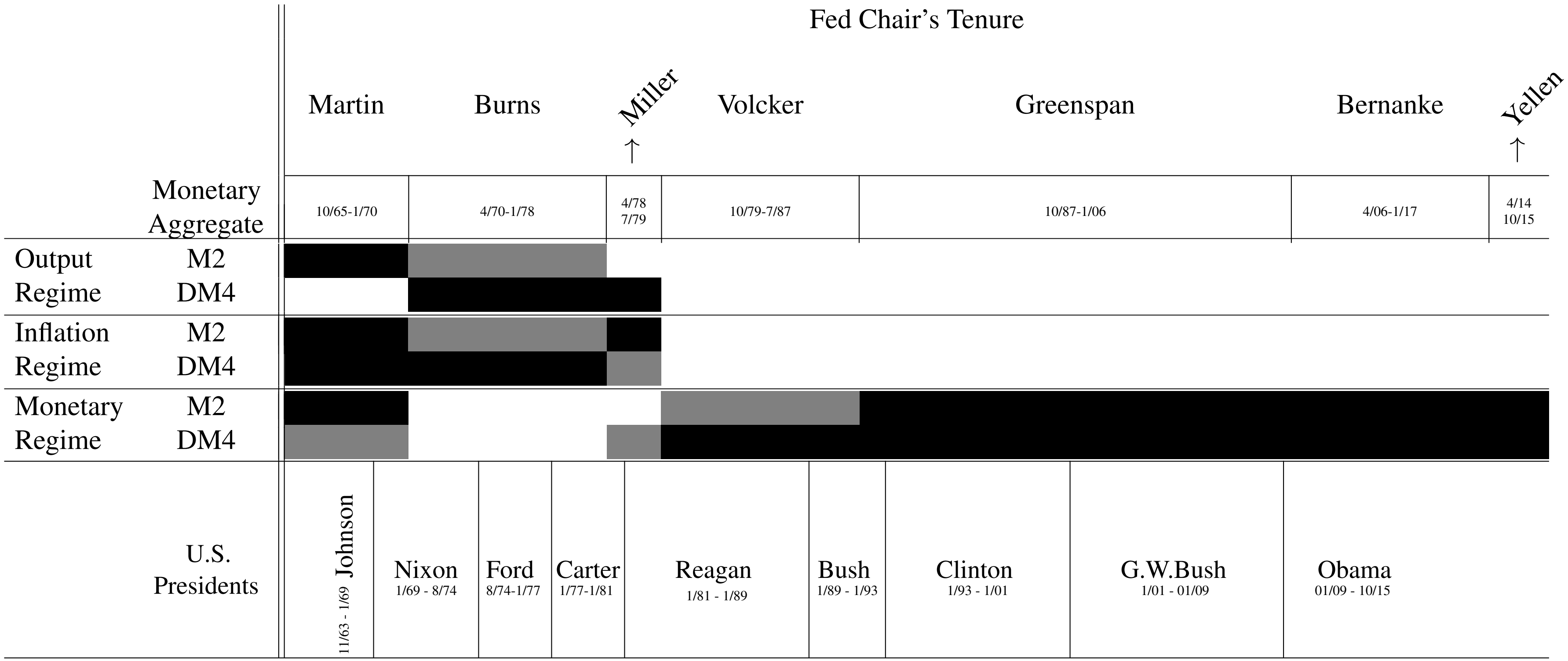


Table 2.8 Dominant Regime

In Table 2.8, the black and the grey bars indicate that the regime dominates more than 80% and 50% respectively.

	$\Delta M2$	$\Delta DivisiaM4$
Output Regime	55	59
Inflation Regime	65	53
Monetary Rule Regime	147	149
Non-Causality Regime	8	5

Table 2.9 Number of Quarters Associated with Each Regime

	$\Delta M2$	$\Delta DivisiaM4$
Output Regime	32.08	74.62
Inflation Regime	26.66	62.57
Monetary Rule Regime	32.48	90.33
Non-Causality Regime	10.05	20.91

Table 2.10 Conditional Expected Duration (Quarters)

4.2. Monte Carlo Experiments

It is informative to consider the results of Monte Carlo experiments designed to evaluate the accuracy of regime classification associated with the trivariate model presented in Section 2. To ensure that the simulations are empirically relevant, the parameter values used to generate pseudo-data are the estimates obtained from trivariate models in which the monetary indicator variable is either DM (ΔDM) or M2 ($\Delta M2$). In each case, we generate 500 independent samples of size 255, but only the last $T = 205$ pseudo-data points in each sample are used for estimation in order to minimize the effects of initial values.

As a measure of the accuracy of regime classification we use the quantity

$$C_\ell = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{\mathscr{P}}(S_t = \ell) - I(S_t = \ell)\right|, \quad \ell = 1,2,\ldots,8,$$

where $\hat{\mathscr{P}}(S_t = \ell)$ is either the filtered probability $\mathscr{P}(S_t = \ell | X_{1-h},...,X_t;\hat{\theta})$ or the smoothed probability $\mathscr{P}(S_t = \ell | X_{1-h},...,X_T;\hat{\theta})$. Note that $0 \le C_\ell \le 1$ and that low values of C_ℓ imply accurate classification of regimes while high values imply inaccurate classification. The average values of C_ℓ over the 500 Monte Carlo replications, when the estimated model is correctly specified, are reported in Table 2.11. The regime classification measure C_ℓ has very low values for all regimes, suggesting that our modelling approach is effective in identifying temporary causality links.

In an additional set of simulation experiments, we assess the performance of the model with three endogenous variables (our model) relative to two somewhat similar models, one with two endogenous and one conditioning variable (the model considered in Psaradakis et al. (2005)) and

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	
FFR Model	0.15	0.16	0.17	0.12	0.31	0.19	0.28	0.19	Filtered
DM Model	0.19	0.25	0.14	0.14	0.19	0.20	0.12	0.15	
M2 Model	0.12	0.11	0.14	0.11	0.18	0.10	0.23	0.13	
Divisia M4 Model	0.12	0.15	0.17	0.23	0.15	0.16	0.21	0.20	
FFR Model	0.15	0.16	0.16	0.12	0.31	0.18	0.27	0.18	Smoothed
DM Model	0.18	0.23	0.14	0.14	0.18	0.19	0.11	0.14	
M2 Model	0.11	0.11	0.13	0.10	0.17	0.09	0.21	0.12	
Divisia M4 Model	0.12	0.15	0.16	0.22	0.14	0.16	0.20	0.19	

Table 2.11 Regime Classification

a model with two endogenous variables and no conditioning variable. The aim is to investigate whether the reduction in the dimension of the model achieved by essentially omitting one of its equations and treating one variable as exogenous, or omitting the third variable entirely, has adverse effects on the identification of causality regimes. As before, pseudo-data are generated according to the estimated three-equation eight-regime models.In view of the fact that a two-equation model (with or without a conditioning variable) has only four causality regimes, and in order to make the comparison between bivariate and trivariate models meaningful, we focus only on the four regimes associated with $S_t = 3$, $S_t = 5$, $S_t = 7$ and $S_t = 8$, since these correspond to the four causality regimes of Psaradakis et al. (2005). The simulation results are displayed in Table 2.12.

	$C_3 = C_1^*$	$C_5 = C_2^*$	$C_7 = C_3^*$	$C_8 = C_4^*$	
	$m_t, \pi_t^E \to y_t$ $y_t, \pi_t^E \to m_t$	$m_t, \pi_t^E \to y_t$	$y_t, \pi_t^E \to m_t$	No Granger Causality	
FFR Model	0.24	0.36	0.42	0.33	Filtered
DM Model	0.27	0.29	0.32	0.29	
M2 Model	0.30	0.39	0.26	0.33	
Divisia M4 Model	0.20	0.31	0.34	0.30	
FFR Model	0.23	0.36	0.43	0.33	Smoothed
DM Model	0.27	0.29	0.32	0.29	
M2 Model	0.30	0.38	0.25	0.33	
Divisia M4 Model	0.18	0.31	0.35	0.28	

C^* indicates the regimes of Psaradakis et al. (2005). π_t^E is exogenous

Table 2.12 Monte Carlo Results

The two-equation model identifies state 1 successfully, but is outperformed by the three-equation model in the case of all other states. This confirms that treating a variable such as inflation as endogenous is important for accurately identifying causality regimes.

The results presented in Table 2.13 for the bivariate model (with no conditioning/exogenous variable) suggest that the omitted variable does not affect the identification of causality regimes adversely when compared to a bivariate model conditioned on the same variable. It can be seen that

	$C_3 = C_1^*$	$C_5 = C_2^*$	$C_7 = C_3^*$	$C_8 = C_4^*$	
	$m_t \to y_t$ $y_t \to m_t$	$m_t \to y_t$	$y_t \to m_t$	No Granger Causality	
FFR Model	0.27	0.37	0.42	0.31	Filtered
DM Model	0.26	0.28	0.31	0.30	
M2 Model	0.30	0.39	0.26	0.32	
Divisia M4 Model	0.19	0.32	0.32	0.31	
FFR Model	0.26	0.37	0.42	0.31	Smoothed
DM Model	0.26	0.28	0.31	0.30	
M2 Model	0.30	0.38	0.25	0.32	
Divisia M4 Model	0.17	0.32	0.33	0.29	

C^* indicates the regimes of Psaradakis et al. (2005). The Exogenous variables is omitted

Table 2.13 Monte Carlo Results

the average number of times that the states are identified correctly is very similar to the averages presented in the Table 2.12. In terms of identifying causality patterns, it would seem, therefore, that omitting the inflation equation is not significantly worse than including inflation as a conditioning variable in a bivariate model, although both approaches are inferior to using a trivariate model.

5. Conclusions

In this chapter, we have studied the relationship between the policy variables and the two other pillars of macroeconomics, Output and inflation. By overcoming a well-known problem in Granger Causality, called sample period bias, our findings suggest that significant shifts in causal relationships between key macroeconomic variables and potential policy instruments are often associated with tenures of the seven Federal Reserve chairs appointed since 1965. Contrary to expected, these findings suggest that Central Banks might be susceptible to the preferences of the Chairman, intimately not immune from political pressure as also has been suggested by Drechsel (2023) and Weise (2012).

The estimated regime probabilities also suggest that monetary indicators such as the Federal Funds rate and Domestic Money have significant causal content for output or inflation or serve as feedback variables. These two variables often switch as lead indicators for U.S. output and inflation, which suggests that liquidity effects are not always present. These findings also indicate that new Keynesian theoretical models that use Federal Funds rates in their policy rule might be neglecting the importance of Money, as observed during the Zero Lower bound. Ever since the Zero Lower bound, policymakers have been suggesting many other types of unconventional monetary policies, for instance, Forward Guidance. Along the lines of any other unconventional Monetary policy, our findings also recommend the use of Monetary rules with Money, such as the McCallum Rule, as there is no guarantee that the so-called Liquidity Effect is effective overall sample periods.

Although Divisia and M2 are common variables used in empirical works, due to their adherence to money demand, as suggested by Barnett (1980), we found little evidence for Divisia M4 and M2 as causal lead variables for either inflation or real output; however, these are relevant feedback variables to changes in inflation and real output starting with the Volcker tenure.

Finally, our estimated regime probabilities align remarkably well with monetary policy shock dates identified by Romer and Romer (1989), Romer and Romer (1994), and Romer and Romer (2004). This corroborates the importance of dating monetary policy shock, as Romer and Romer (1989), Romer and Romer (1994), and Romer and Romer (2004) dated, and the importance of regime-switching models to corroborate these shocks systematically.

Chapter 3

European Sovereign Bond and Stock Market Granger Causality Dynamics

1. Introduction

The financial crisis of 2008-2009 had adverse consequences for the real economy around the globe and in Europe. Several European countries faced recessions and falling stock indexes and market value of equities, later exacerbated by unsustainable fiscal policies, consequence of large budget deficits and high government debt levels. Euro area bond markets faced intense pressure from May 2010, reflecting the sovereign debt crisis. On the one hand, investors demanded higher yields on European sovereign bonds in order to compensate their risk. On the other hand, high debt and deficits led investors to lose their confidence about the future returns of equities in a higher bond yield environment.

Stocks and sovereign bonds, two major components of capital markets, played an essential role in the country risk assessment during the recent crisis. The first represents market risk. The second, once generally viewed as safe assets for equity investors to diversify their portfolios, during the crisis they reflected, or were a proxy for, sovereign risk. Both markets are strong indicators of investor's portfolio choice and were affected by the fragility of the financial sectors and the length and depth of the global recession. In full information conditions, both markets should assimilate new information simultaneously and prices should be contemporaneously discovered. Nonetheless, when the public and private information are asymmetrically absorbed by one of the markets, it is possible to observe a lead-lag relationship between the prices of sovereign bonds and stocks. In these situations, it is important to understand which market leads the other, whether for governments and researchers to anticipate specific country risk, or for investors or financial institutions to adapt their financial strategies.

Taking the limited transmission of information with the markets into account, we study the country-specific lead-lag relation between changes of 10-year sovereign (government) bond yields and stock (market) returns. We examine the Granger causality, henceforth *causality*, between the changes in sovereign bond prices and stock market returns, at a weekly frequency, for a set of eight European countries during the period between 2008 and 2022. The usual causality test has a critical shortcoming. It is susceptible to the sample period, which can reverse the estimates of the causality test statistics and lead to inaccurate conclusions. Our main contribution is to overcome this shortcoming by using a methodology that measures the causality and defines the sample period endogenously.

Our methodology based on Markov-Switching Causality, proposed by Psaradakis et al. (2005), consist on a vector autoregressive model with time-varying parameters, and consequently a time-varying pattern of causality. The parameter time-variation is modelled through a hidden Markov chain that reflects changes in causality between the variables of interest, over the sample, endogenously. In the literature, the results of the Vector Autoregressive (VAR) causality tests for a particular country often depend on the selection of the sample period, which generates instability in the causality patterns. To illustrate this problem, we estimate a (VAR) and conduct the Granger Causality tests by splitting the whole sample into three sub-samples to show the instabilities in the causality patterns. Then, we estimate the Markov-switching Causality VAR method that finds endogenously the periods in which the data suggests the presence of causality[1]. The method also enables us to calculate the *expected duration* and *actual duration* of the regimes for each country. Knowing the dates of regime switches, we can look at the global or country-specific events that overlap with changes in the direction of causality.

We contribute to the empirical finance literature in three dimensions. First, we find the exact dates when there are shifts in the causality. Second, although the markets are very integrated, we provide some evidence that a global (or regional) crisis affects the countries heterogeneously. Third, in terms of price discovery, we add to the evidence that the direction of the causality is mostly from the stock returns to the first difference in sovereign bond yield.[2] Nevertheless, we find that there are several episodes where causality runs from the changes in sovereign bond yields to stock market return.

Our paper is also related to the literature on Markov-Switching VAR, for instance, Taamouti (2012), Droumaguet et al. (2017a) and Warne (2000b). Taamouti (2012) generalizes the methodology by Timmermann (2000) to find the conditional and unconditional moments of a Markov-Switching VAR and verifies the relevance of conditional information to asset allocation between a stock index and 10-year government bond. Droumaguet et al. (2017a) and Warne (2000b) test the Granger causality parameters in the Markov-Switching VAR setting, using a Bayesian and frequentist approach respectively. Our method differs from those because we do not test the Granger Causality parameters; instead, we constraint the regimes in a VAR model to obtain all possible Granger causality patterns and allow the data to select them.

[1]Nonlinear Granger Causality has been also studied by Song and Taamouti (2018) in a non-parametric setting.

[2]As pointed out by Gyntelberg et al. (2018), this conclusion demands a discretionary interpretation due to the weekly data frequency we are using in the paper.

Most of the previous studies that investigate the causality between sovereign risk and stock markets focussed on credit default swap spreads (CDS). Examples include Silva (2014), Coronado et al. (2012) and Corzo-Santamaria et al. (2012)[3]. In particular, the later two papers performed VAR-Granger causality tests on the lead-lag relation between CDS and stock market indexes and find that the direction of the Granger Causality depends on the sample period that was defined ad-hoc. However, mostly the stock markets react faster to new information than CDS market. Instead of CDS's, we use sovereign bond yields as a measure of sovereign risk, for four reasons. First, sovereign bonds yields are issued by governments to investors and their creditworthiness depend on governments perceived ability to repay debts. Second, according to Phillips and Shi (2019) the long-term sovereign bond yields are proxies for the sovereign risk. Thirdly, the sovereign bond markets were not subject to any kind of selling restriction as it happened in 2011 to the CDS markets (Sambalaibat, 2014). The CDS ban led to reducing liquidity in the sovereign CDS market, in particular for Greece, Ireland, Italy, Portugal, and Spain, which rendered this market ineffective for hedging (IMF, 2013). Also, it is difficult to examine the sovereign CDS market in Greece after the International Swaps and Derivatives Association, declared the Greek sovereign default in March 2012. Finally, the literature has offered several papers that measures the lead-lag relationship between sovereign bond yields and CDS, which include Fontana and Scheicher (2016) and Gyntelberg et al. (2018). In general, they conclude the CDS reacts to new information faster than sovereign bond yields. As we have pointed out, the stock market reacts faster to new information than CDS market and the literature suggests that the CDS Market responds faster than sovereign bond yields. Therefore, the transmission mechanism of price discovering seems to be from stock returns to CDS and then to sovereign bond yields.

Our sample period captures several global events. It starts at the onset of the financial crisis. It then encompasses the European sovereign debt crisis, when sovereign bonds became central to investors concerned with the ability of some European countries to repay their debts, increasing the bond yields. Later, in 2015, the European Central Bank (ECB) launched the Quantitative Easing (QE) program, known as a bond-buying program, to keep bond yields low. As pointed by Flavin and Lagoa-Varela (2019), the whole context drove stock market investors to use long-term sovereign bonds as a hedge for their financial decisions during the stock market turbulence, depending on the countries and market conditions. As a result of this of the asymmetric flight-to-safety tendencies, domestic sovereign bond became the most important element of heterogeneity across the countries. Finally, the sample also captures many country-specific events, such as the Brexit Referendum, the Spanish Bank Bailout, the Greek International Bailout or the Portuguese Financial crisis.

We find that economic events, whether they are global or country-specific, can trigger reversals in the causality between these two variables. For instance, we find there is a shift in causality in

[3]Other papers have focused on the credit risk and stock market at the corporate level, for instance Longstaff et al. (2005), Norden and Weber (2009), Bystrom (2005), Fung et al. (2008), Forte and Pena (2009), Marsch and Wagner (2012) and Hilscher et al. (2015). Additionally, by focussing on the lead-lag relation between corporate bonds and stock returns Tolikas (2018) finds that the daily stock returns lead the daily bond returns.

most of the countries, coinciding with the global financial crisis. Additionally, our results contradict the common knowledge that the stock markets always lead the bond markets. The results suggest that the direction of the causality depends on the period, country and nature of the crisis. For instance, we find that the changes in sovereign bond yields cause stock returns in some periods in seven countries, except Germany. The actual duration of the causality regimes also varies across countries.

The remainder of the paper is organized as follows. Section 2. motivates our analysis. First, it provides a description of economics events during the sample period, together with the description of the data. Second, it reports the estimation of a VAR to highlight how the results on causality depend on the sample choice. Section 2. describes the Markov Switching Causality methodology. Section 3. shows the results and Section 5. concludes.

2. Motivation

2.1. Narrative of the crisis

We start with brief overview of economic events that happened in Europe since 2008. Our methodology identifies endogenously dates in which the direction of causality changed and we will relate these to the events associated with the global and European financial crisis, which peaked between 2009 and 2012.

The European sovereign debt crisis began when the government of Greece reported errors in past budgetary data, which was higher than the country had let on. As a consequence, their 10-year bond spreads increased significantly. Compounded by the global financial crisis, Greek deficit and debt reached high levels soon after which caused distress about its ability to pay its debts and, in late 2008, fears of a deep recession escalated in the Eurozone. Borrowing costs in Greece, Portugal, Ireland and Spain reached prohibitive levels. Unable to roll over their debts, they had to receive bailouts from the European Stability Mechanism (ESM), International Monetary Fund (IMF), or both.

Despite the IMF and the EU's bailouts, the concerns about the financial crisis led the European Union members, in a meeting on the 22nd of June in 2012, to support a second bailout program for Greece, together with the IMF, to prevent the crisis spreading across Europe. Although Greece and its creditors agreed to a debt restructuring for the bailout funds in 2012, growing risk that Greece will default and the possibility of contagion led to a fall in investors confidence.[4]

The period from 2009 to 2014 was the hardest period for Portuguese economy, which was affected by both the global financial crises and the sovereign debt crisis. On January 2010, fears over the liquidity and stability of Eurozone bonds spread to Portugal, leading bond yields to accelerate to unsustainable levels. This caused the Portugal government to pursue emergency austerity measures.

[4]For instance, Afonso et al. (2012) documented contagion in stock returns and bond yields across different European countries following downgrades in sovereign credit ratings.

In 2014, the fears of a recession spreading to the Eurozone's core and breaking up the single currency returned. In macroeconomic terms, inflation was low and even negative in Spain, Portugal and Greece, increasing their debt burdens. These concerns led European stocks to temporarily crash. This last period led the ECB to announce the Quantitative Easing (QE) program in February 2015 in order to stabilise the inflation, stimulate the economy, and maintain low bond yields.

The Coronavirus pandemic has had a huge impact on the global economy. The coronavirus spread led to widespread lockdowns and disruptions to supply chains, resulting in a sharp decline in economic activity. The world economy is estimated to have contracted by 4.3% in 2020, the sharpest contraction since the Great Depression of the 1930s.

Many countries, including European countries, have implemented large fiscal stimulus packages to mitigate the economic impact of the pandemic, including direct transfers to individuals, loans and grants to larger and small businesses, and increased spending on health care and social safety net programs. Although the actions taken by governments and central banks have helped to limit the economic damage, many businesses have gone bankrupt, and millions of people have lost their jobs.

The economic recovery from the pandemic has been unequal, with some countries and industries recovering faster than others. The COVID-19 pandemic has also highlighted pre-existing inequalities and imbalances in the world economy, emphasizing the need for more coordinated and sustained global action to support economic recovery.

2.2. Data

For the empirical analysis, we use weekly observations on changes of 10-year sovereign bond yields, denoted by ΔYLD for eight European countries: Germany, France, Spain, Portugal, Italy, Greece, Ireland and the United Kingdom. For the stock market returns, denoted by ΔR, the sample consists of the changes in weekly closing price for DAX (Germany), CAC 40 (France), IBEX 35 (Spain), FTSEMIB (Italy), FTSE 100 (UK) and ISEQ (Ireland), PSI 20 (Portugal) and ASE (Greece). The data is provided by DataStream. Our sample comprises the period from January of 2008 to March of 2022, which gives us the total of 745 observations. A few considerations about our key choices are in order.

One possible alternative was to rely on daily data but, in our case, it would introduce three main difficulties. First, at daily frequency, the data is very noisy, imposing a large computational burden. Secondly, we are not interested in measuring time-varying volatility, where the information content in daily basis could be more important, Instead, we focus on the mean equation and a VAR-type estimator. Finally, although more observations is preferable for econometric precision, using higher frequency data raises the number of outliers that can impose some bias in our estimates, as we are using Markov-Switching methods. An outlier might trigger a switch that has not occurred. Additionally, the studies on inter-market linkages that use daily data have been criticized due to the differences at the end of the day markets which could lead an upward-bias of stock prices (Vijh, 1988). For these reasons, we believe the information contained in weekly data is preferable for our exercise (Goodhart and O'Hara, 1997).

We opted to use the (difference in) yields in levels rather than in spreads because the spreads are usually calculated, taking into account the bonds yield level of Germany. In our set of countries, we are using Germany, which would be left out otherwise. Besides, the findings of Phillips and Shi (2019) suggest that after 2008 there are not many differences between the bond yields and bond yield spreads to detect financial collapses, which is the primary mechanism of our method to trigger the shifts from one regime to another.

We chose these eight countries to represent the variety of cases within the European Union. Germany and France are the most robust economies of the Eurozone. The U.K. did not belong to the Eurozone and started the process of leaving the European Union, which we believe it works as an interesting counterfactual. Italy has robust economy, but with economic and political turmoil. The remaining four countries were rescued due to their financial fragility during the analysed period.

Table 3.1 provides the descriptive statistics for each country's weekly changes in sovereign bond yields and stock returns. The graphs for the two variables are shown in Appendix. The maximum change in sovereign bond yields in Greece, Portugal, Spain, Ireland and Italy are significantly higher than Germany, France and the UK for the entire period. The mean of stock returns is positive in Germany, Ireland, the UK and France while it is negative in the remaining countries. Regarding the kurtosis of the stock returns, Greece has the lowest kurtosis while Ireland and Germany has the

Table 3.1 Descriptive Statistics

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis
ΔYLD						
Germany	-0.006	0.36	-0.37	0.10	0.13	3.58
France	-0.006	0.41	-0.49	0.10	0.16	5.31
Spain	-0.004	0.72	-1.26	0.18	-1.16	12.61
Italy	-0.02	0.60	-1.13	0.15	-0.83	10.49
United Kingdom	-0.006	0.39	-0.56	0.11	0.02	4.16
Ireland	-0.006	1.46	-2.27	0.24	-0.96	23.13
Portugal	-0.004	2.14	-1.69	0.34	0.12	12.06
Greece	-0.0009	8.16	-20.69	1.26	-7.73	139.89
$\frac{\Delta R}{R}$						
Germany	0.11	14.94	-24.34	3.19	-1.01	11.07
France	0.02	12.43	-25.05	3.13	-1.21	11.40
Spain	-0.05	11.10	-23.82	3.48	-0.89	7.58
Italy	-0.09	10.24	-25.11	3.61	-1.16	8.26
United Kingdom	0.05	12.58	-23.63	2.60	-1.40	17.80
Ireland	0.03	14.47	-32.90	3.51	-1.97	19.57
Portugal	-0.12	8.50	-20.56	3.04	-1.04	7.52
Greece	-0.32	17.56	-22.54	4.81	-0.44	4.71

Note: Weekly observations on changes of 10-year sovereign bond yields (ΔYLD) and stock market returns ($\frac{\Delta R}{R}$). Sample from January of 2008 to March of 2022, with 745 observations.

highest. In contrast, changes in sovereign bond yields have kurtosis greater than 3, with Greece having the highest and Germany the lowest.

2.3. VAR Model: Causality between the Changes in Sovereign Bonds and Stock Returns

We motivate our methodology by analysing the dynamic co-movement of weekly changes in sovereign bonds and stock returns using a standard VAR conditional on an exogenous variable. In line with Norden and Weber (2004), we estimate the following two-dimensional VAR model:

$$\begin{bmatrix} \Delta YLD_t \\ \Delta R_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \sum_{k=1}^{h} \begin{bmatrix} \phi_1^{(k)} & \psi_1^{(k)} \\ \psi_2^{(k)} & \phi_2^{(k)} \end{bmatrix} \times \begin{bmatrix} \Delta YLD_{t,t-k} \\ \Delta R_{t,t-k} \end{bmatrix} + \begin{bmatrix} \varphi_{1,1} \\ \varphi_{1,2} \end{bmatrix} \times \begin{bmatrix} VIX_t \\ VIX_t \end{bmatrix} + \begin{bmatrix} \varphi_{2,1} \\ \varphi_{2,2} \end{bmatrix} \times \begin{bmatrix} Euribor_t \\ Euribor_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{3.1}$$

where ΔR_t is the stock index return at t, ΔYLD_t is the first differences of sovereign bond yield at t, h is the lag order index, ε_t is the disturbance term at t. In addition to the endogenous variables, we conditioned the model to variables that reflects a global risk and regional risk, respectively. Other articles have used several variables to indicate global risk (factor); for instance, Gomes and Taamouti (2016) uses risk factors based on Google search data. Instead, we conditioned our model to CBOE Volatility Index[5], VIX_t[6] and similarly to Caporin et al. (2018) we use $Euribor_t$ from Euro Interbank. One advantage of using this variable is that it reflects the expected volatility based on past values. Therefore, our model does not suffer from endogeneity problems, as VIX_t is contemporaneous to the endogenous variables.

We use the Augmented Dickey-Fuller test with optimal lag length selection based on Akaike's information criterion to check the stationary for all series. Both stock returns and government bond yields changes are stationary for all countries. We found the optimal lag of ther VAR to be 2, by computing information criteria: the likelihood ratio (LR), final prediction error (FPE), Akaike's information criteria (AIC), Hannan-Quinn information criteria (HQIC) and Schwarz's Bayesian information criteria (SBIC). The presence of the VIX controls for the volatility that varied substantially in the financial markets during the sample period. We follow other authors, such as Corzo-Santamaria et al. (2012), in performing the Granger causality test for each country. This implies testing the parameters ($\psi_1^{(k)}$) and ($\psi_2^{(k)}$).

We first estimate the VAR for the whole sample and conduct the Granger causality test. We then repeat the estimation and the test in three sub-samples of equal length. The results are reported in Table 3.2. According to the causality test for the full sample, stock returns cause the changes in sovereign bond yields in only three countries: Germany, France and the United Kingdom. Using the full sample, there is no causality from the changes in sovereign bond yields to stock markets in any country. However, the conclusion of causality is dependent on the choice of the sample

[5]Rapach et al. (2013) conditioned a VARX with Lagged U.S. returns and found that this variable is a good predictor for other non-US returns. We use VIX_t because it represent a shock in the mean equation, therefore we avoid use a VAR-in-Mean type of of approach, which would increase the complexity of the problem.

[6]The original VIX_t is divided by $\sqrt{52}$ to reflect the weekly frequency.

period. In Germany, Greece and in the UK, there is at least one sub-period where stock returns cause the changes in sovereign bond yields, for the other countries there is no causality. Also, in one sub-sample in the United Kingdom (from 10/12 to 07/17), Germany (from 07/17 to 03/22), France (from 10/12 to 07/17 and from 07/17 to 03/22) and in Portugal (07/17 to 03/22) changes in sovereign bond yields cause stock returns.

The choice of sub-period is arbitrary and clearly affects the results. Our main contribution is to employ the Markov-Switching Causality methodology to verify how the causality pattern changes throughout the sample and determine endogenously the timing of the switches.

3. Markov Switching Causality

3.1. Setting

The Markov-Switching Causality was first proposed by Psaradakis et al. (2005), is a vector autoregression where some parameters are constrained to allow different patterns of Granger causality and the switching between each pattern follows a hidden Markov process.
The model is as follows:

$$\begin{bmatrix} \Delta YLD_t \\ \Delta R_t \end{bmatrix} = D_t + \sum_{k=1}^{h} A_t^{(k)} \begin{bmatrix} \Delta YLD_{t,t-k} \\ \Delta R_{t,t-k} \end{bmatrix} + Z_{1,t} \begin{bmatrix} VIX_t \\ VIX_t \end{bmatrix} + Z_{2,t} \begin{bmatrix} Euribor_t \\ Euribor_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}, \quad t = 1, 2, \ldots, T.$$

Table 3.2 Granger Causality Test

	Stocks cause Yields ($\Delta R_t \to \Delta YLD_t$)				*Yields cause Stocks* ($\Delta YLD_t \to \Delta R_t$)			
	Full sample	2/08 to 10/12	10/12 to 7/17	7/17 to 3/22	Full sample	2/08 to 10/12	10/12 to 7/17	7/17 to 3/22
Germany	0.004*	0.05*	0.02*	0.40	0.440	0.31	0.32	0.02*
France	0.013*	0.16	0.23	0.29	0.936	0.71	0.08*	0.08*
Spain	0.596	0.82	0.58	0.14	0.899	0.88	0.36	0.77
Italy	0.155	0.32	0.77	0.31	0.608	0.94	0.44	0.16
United Kingdom	0.002*	0.01*	0.06*	0.69	0.192	0.53	0.02*	0.55
Ireland	0.638	0.83	0.54	0.37	0.431	0.66	0.80	0.76
Portugal	0.930	0.90	0.32	0.23	0.646	0.89	0.41	0.00*
Greece	0.841	0.71	0.30	0.08*	0.219	0.23	0.98	0.98

Note: The null hypothesis of the Granger Causality test is that there is no causality. We report the p-values of the test. The $*$ signals Granger causality. The VAR in equation 3.1 included the VIX_t and $Euribor_t$ as an exogenous variable was estimated with two-lags with 745 observations (full sample).

Where [ΔYLD_t , ΔR_t] are the change in sovereign bond yields and stock market returns, ε_{1t} and ε_{2t} are the reduced form disturbance of the two equations, and D_t, $A_t^{(k)}$ and Z_t are state-dependent parameter matrices given by

$$D_t = \begin{bmatrix} \mu_{10} + \mu_{11}s_{1,t} \\ \mu_{20} + \mu_{21}s_{2,t} \end{bmatrix}, \quad A_t^{(k)} = \begin{bmatrix} \phi_{10}^{(k)} + \phi_{11}^{(k)}s_{1,t} & \psi_1^{(k)}s_{1,t} \\ \psi_2^{(k)}s_{2,t} & \phi_{20}^{(k)} + \phi_{21}^{(k)}s_{2,t} \end{bmatrix}, \quad Z_{i,t} = \begin{bmatrix} \varphi_{i,10} + \varphi_{i,11}s_{1,t} \\ \varphi_{i,20} + \varphi_{i,21}s_{2,t} \end{bmatrix}, \quad i = 1,2$$

Additionally, the model is conditioned to two exogenous variable, VIX_t and $Euribor_t$. The four regimes can be summarized as[7]:

$$S_t = \begin{cases} 1 \text{ if } s_{1,t} = 1 \text{ and } s_{2,t} = 1 & \text{bidirectional causality } (\Delta R_t \leftrightarrow \Delta YLD_t) \\ 2 \text{ if } s_{1,t} = 0 \text{ and } s_{2,t} = 1 & \text{changes in sovereign bonds cause stock returns } (\Delta YLD_t \rightarrow \Delta R_t) \\ 3 \text{ if } s_{1,t} = 1 \text{ and } s_{2,t} = 0 & \text{stock returns cause changes in sovereign bonds } (\Delta R_t \rightarrow \Delta YLD_t) \\ 4 \text{ if } s_{1,t} = 0 \text{ and } s_{2,t} = 0 & \text{no causality } (\Delta R_t \nleftrightarrow \Delta YLD_t) \end{cases}$$

or explicitly:

For $S_t = 1$:

$$\begin{bmatrix} \Delta YLD_t \\ \Delta R_t \end{bmatrix} = \begin{bmatrix} \mu_{10} + \mu_{11} \\ \mu_{20} + \mu_{21} \end{bmatrix} + \sum_{k=1}^{h} \begin{bmatrix} \phi_{10}^{(k)} + \phi_{11}^{(k)} & \psi_1^{(k)} \\ \psi_2^{(k)} & \phi_{20}^{(k)} + \phi_{21}^{(k)} \end{bmatrix} \begin{bmatrix} \Delta YLD_{t,t-k} \\ \Delta R_{t,t-k} \end{bmatrix} + \sum_{i=1}^{2} \begin{bmatrix} \varphi_{i,10} + \varphi_{i,11} \\ \varphi_{i,20} + \varphi_{i,21} \end{bmatrix} \begin{bmatrix} X_{i,t} \\ X_{i,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

For $S_t = 2$:

$$\begin{bmatrix} \Delta YLD_t \\ \Delta R_t \end{bmatrix} = \begin{bmatrix} \mu_{10} \\ \mu_{20} + \mu_{21} \end{bmatrix} + \sum_{k=1}^{h} \begin{bmatrix} \phi_{10}^{(k)} & 0 \\ \psi_2^{(k)} & \phi_{20}^{(k)} + \phi_{21}^{(k)} \end{bmatrix} \begin{bmatrix} \Delta YLD_{t,t-k} \\ \Delta R_{t,t-k} \end{bmatrix} + \sum_{i=1}^{2} \begin{bmatrix} \varphi_{i,10} \\ \varphi_{i,20} + \varphi_{i,21} \end{bmatrix} \begin{bmatrix} X_{i,t} \\ X_{i,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

For $S_t = 3$:

$$\begin{bmatrix} \Delta YLD_t \\ \Delta R_t \end{bmatrix} = \begin{bmatrix} \mu_{10} + \mu_{11} \\ \mu_{20} \end{bmatrix} + \sum_{k=1}^{h} \begin{bmatrix} \phi_{10}^{(k)} + \phi_{11}^{(k)} & \psi_1^{(k)} \\ 0 & \phi_{20}^{(k)} \end{bmatrix} \begin{bmatrix} \Delta YLD_{t,t-k} \\ \Delta R_{t,t-k} \end{bmatrix} + \sum_{i=1}^{2} \begin{bmatrix} \varphi_{i,10} + \varphi_{i,11} \\ \varphi_{i,20} \end{bmatrix} \begin{bmatrix} X_{i,t} \\ X_{i,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

For $S_t = 4$:

$$\begin{bmatrix} \Delta YLD_t \\ \Delta R_t \end{bmatrix} = \begin{bmatrix} \mu_{10} \\ \mu_{20} \end{bmatrix} + \sum_{k=1}^{h} \begin{bmatrix} \phi_{10}^{(k)} & 0 \\ 0 & \phi_{20}^{(k)} \end{bmatrix} \begin{bmatrix} \Delta YLD_{t,t-k} \\ \Delta R_{t,t-k} \end{bmatrix} + \sum_{i=1}^{2} \begin{bmatrix} \varphi_{i,10} \\ \varphi_{i,20} \end{bmatrix} \begin{bmatrix} X_{i,t} \\ X_{i,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

Where:

$$X_{i,t} = \begin{cases} VIX_t & \rightarrow \text{If } i = 1 \\ Euribor_t & \rightarrow \text{If } i = 2 \end{cases}$$

Notice that, the parameters $\psi_1^{(k)}$ and $\psi_2^{(k)}$ are the parameters that give the *temporary* Granger causality, henceforth *temporary* causality: $S_t = 2$ is the regime where the changes in sovereign bonds

[7] Matrices D_t, $Z_{i,t}$, and the main diagonal of $A_t^{(k)}$ could be restricted to not switch over time; nevertheless, these restricted cases are nested by our model, for instance, when μ_{11} and μ_{21} are statistically not significant. Hence the model would not lose generality by allowing other terms, different than Granger Causality terms, to switch.

temporarily cause stock returns and $S_t = 3$ is the case when the stock returns *temporarily* cause the changes in sovereign bonds. The state $S_t = 1$ is the state where there is a dual *temporary* causality and $S_t = 4$ is the state where there is no-*temporary* causality. Beside the imposed differences in the *temporary* causality patterns in the four regimes, the regimes differ on other parameters, namely μ_{11}, μ_{21}, $\varphi_{i,11}$, $\varphi_{i,21}$, ϕ_{11}, ϕ_{21} and the regime-dependent variance-covariance matrix of the structural error term, that we define later. It is important to point out that this is not a classical MS-VAR in which the different regimes may be associated with recessions or expansions, or periods with different volatility. In our approach, each regime correspond by construction to different Granger Causality patterns.

To complete the specification of the model, as defined by Psaradakis et al. (2005), the Markov process that defines the behaviour of the regimes can be described as:

$$p_{i,j}^{(l)} = \mathscr{P}(s_{l,t+1} = j | s_{l,t} = i), \text{ where } i,j = 0,1 \text{ and } l = 1,2$$

Notice that $p_{i,j}^{(l)}$ probability of being at the regime at time $t+1$ conditioned to the regime at t and the regimes $s_{1,t}$ and $s_{2,t}$ are independent. The assumption of independence between the regimes is important for two reasons: Firstly, while $s_{1,t}$ represents the Granger causality from the changes in sovereign Bonds *temporary* to stock returns, $s_{2,t}$ accounts for the opposite. This means that periods of Granger Causality in one direction do not necessarily depend on the periods of Granger causality in the other. Therefore changes in the Granger causality direction is likely occurs independently. In another context; however similarly to us, Assenmacher-Wesche (2006) and McConnell and Perez-Quiros (2000a) also use independent process based on the stylized facts, and in the same framework Psaradakis et al. (2005) uses the independent process for $s_{1,t}$ and $s_{1,t}$.. Therefore, the transition matrix is:

$$P = \begin{bmatrix} p_{11}^{(1)} \times p_{11}^{(2)} & (1-p_{00}^{(1)}) \times p_{11}^{(2)} & p_{11}^{(1)} \times (1-p_{00}^{(2)}) & (1-p_{00}^{(1)}) \times (1-p_{00}^{(2)}) \\ (1-p_{11}^{(1)}) \times p_{11}^{(2)} & p_{00}^{(1)} \times p_{11}^{(2)} & (1-p_{11}^{(1)}) \times (1-p_{00}^{(2)}) & p_{00}^{(1)} \times (1-p_{00}^{(2)}) \\ p_{11}^{(1)} \times (1-p_{11}^{(2)}) & (1-p_{00}^{(1)}) \times (1-p_{11}^{(2)}) & p_{11}^{(1)} \times p_{00}^{(2)} & (1-p_{00}^{(1)}) \times p_{00}^{(2)} \\ (1-p_{11}^{(1)}) \times (1-p_{11}^{(2)}) & p_{00}^{(1)} \times (1-p_{11}^{(2)}) & (1-p_{11}^{(1)}) \times p_{00}^{(2)} & p_{00}^{(1)} \times p_{00}^{(2)} \end{bmatrix} \tag{3.2}$$

3.2. Expected Duration

As a by-product of the transition matrix, we can provide a theoretical metric that summarizes in how long each regime is expected to last, in the absence shocks. The expected duration is calculated directly from the estimates of the transition matrix as suggested by Hamilton, 1989:

$$ED_m = \sum_{i=1}^{\infty} i \times \left[\pi_{m,m}\right]^{i-1} \times \left[1 - \pi_{m,m}\right] = (1 - \pi_{m,m})^{-1} \tag{3.3}$$

where $\pi_{m,m}$ are the main diagonal elements of the transition matrix P. In our case, we are interested in how long the states where the changes in sovereign bonds *temporarily* cause stock returns and stock returns *temporarily* cause the changes in sovereign bonds last. These are given by:

$$\begin{aligned} ED_{Y\to R} &= (1-\pi_{1,1})^{-1} + (1-\pi_{2,2})^{-1} \\ ED_{R\to Y} &= (1-\pi_{1,1})^{-1} + (1-\pi_{3,3})^{-1} \\ \sum ED &= ED_{Y\to R} + ED_{R\to Y} - (1-\pi_{1,1})^{-1} \\ ED_{Y\nleftrightarrow R} &= (1-\pi_{4,4})^{-1} \end{aligned}$$

Where $\sum ED$ is the expected duration of at least one of the variables causes each other.

This metric is important because it shows the degree of persistence. The closer the probability $\pi_{m,m}$ is to one, the longer it takes to switch to another regime. Also, unlike the probability, the expected duration provides a measurement unit as it is measured in weeks.

3.3. Distribution

To estimate the model using maximum likelihood we need to assume a particular distribution for the error. In the original article, Psaradakis et al. (2005), the error term is assumed to be normally distributed. However, as illustrated in Table 3.2, high-frequency financial time-series data are more leptokurtic than macroeconomic quarterly data. Taking this feature into consideration, we assume that the error follow a Generalized Error Distributed (GED). The bivariate cumulative density function of the GED is described by Giller (2005) as:

$$F(x|\Phi_m,\Sigma_m,\kappa_m) = \frac{x}{\sqrt{\pi^2|\Sigma_m|}}\frac{\Gamma(2)}{\Gamma(1+2\kappa_m)}\left\{\frac{\Gamma(3\kappa_m)}{\Gamma(\kappa_m)}\right\}\exp - \left\{\frac{\Gamma(3\kappa_m)}{\Gamma(\kappa_m)}(\varepsilon_t)'\Sigma_m^{-1}(\varepsilon_t)\right\}^{\frac{1}{2\kappa_m}}$$

where Σ_m is the covariance matrix , Φ_m is the parameter vector and κ_m is the distributional parameter reflecting the kurtosis. We allow both the covariance matrix and the distributional parameter to vary across the four regimes $m = 1,2,3,4$.

3.4. Estimation Method

The parameters of this Markov-Switching Granger Causality model are estimated by maximum likelihood (*MLE*), assuming that the conditional distribution of $[\Delta YLD_t, \Delta R_t]$ with respect of all past values of variables and states is *GED*[8]. There is large evidence that Markov Switching models are strongly dependent on the initial values, and sometimes the results depend on their choice. Taking this into account, we construct a grid search of the initial values for some crucial parameters, namely the ones related to the distribution (κ) and the transition probability matrix (P). To obtain initial values of the parameters, we estimate a set of unconstrained and constrained linear regression of the variables and combine these estimates. Two grid methods were used, one that varies the values of the transition probabilities (from 0.500 to 0.999 in steps of 0.001) and the distributional

[8] The optimization algorithm for *ML* is the secant update of the Hessian matrix, also known by Broyden-Fletcher-Goldfarb-Shano.

parameter (from 0.25 to 2 in steps of 0.20) and another one that just varies the values of the transition probabilities (from 0.500 to 0.999 in steps of 0.001) with the distributional parameter fix to the value of 0.5 which corresponds to the assumption of the error term being normally distributed. In total, about four thousands initial values points are evaluated, and the point that returns the highest likelihood is picked to calculate the final estimates of the parameters. The standard error of the estimates are obtained by the outer product of the scores as an estimator for the information matrix (see Davidson and MacKinnon (1993)).

4. Markov Switching Granger Causality - Results

4.1. Estimation Results

We set the lags of the Markov-Switching VAR to $h = 2$, the same as the unrestricted VAR in Section 2.3.. This was further supported by the Box-Pierce Q-test and by the literature, in particular Kapetanios (2001). The key estimated parameters are presented in Table 4.5 and the remaining estimates are reported in Appendix.

The parameters that dictate the *temporary* causality from stock market to sovereign bonds are ($\psi_1^{(k)}$) and from sovereign bonds to stock markets are ($\psi_2^{(k)}$). We find that ($\psi_1^{(k)}$) are significant for most of countries, except Ireland, whereas ($\psi_2^{(k)}$) is significant most of countries except Germany. Therefore, except to Ireland in all other countries stock returns cause the changes in sovereign bonds at some point in the sample and the changes in sovereign bonds cause stock returns at some point in France, Greece, UK, Italy, Ireland, Portugal and Spain. In Spain and Greece, the regime without a lead-lag relationship between stock returns and bond yields is expected to be very persistent. The expected duration of state with no-*temporary* causality, is around 21 weeks for both countries, around 17 weeks for Portugal and Ireland, and between 9 and 15 weeks for the remaining countries.[9] In all countries, the estimates related to $Euribor_t$ are significant for some states; nonetheless, the estimates related to VIX_t are not significant for Germany, Italy and the UK. This means that a regional factor tends to play an important role in the model, whereas a global factor a role for some counties. $Euribor_t$ affected contemporaneously the two variables during the no-*temporary* causality periods.

The table 3.4 shows the actual duration and its calculated by considering all smoothed regime probabilities, $\mathscr{P}(S_t = \ell | X_{1-h}, ..., X_T; \hat{\Phi})$, that exceeds 0.85 (higher than the 0.5 threshold used by Hamilton (1989)). Then:

$$AD_n = \sum_{i=1}^{n} I(\mathscr{P}(S_t = \ell | X_{1-h}, ..., X_T; \hat{\Phi}) > 0.85) \tag{3.4}$$

[9]Notice, this is a theoretical outcome from the transition matrix, and it is different than the actual causality.

Table 3.3 Estimation Results

		Germany	France	Spain	Italy	U.K.	Ireland	Portugal	Greece
Autoregressive Parameters	$\phi_{10}^{(1)}$	-0.0151	0.0287	-0.0531	0.0401	-0.0172	0.0956	0.0024	0.0405
		(0.38)	(0.26)	(0.09)	(0.18)	(0.35)	(0.06)	(0.49)	(0.24)
	$\phi_{10}^{(2)}$	-0.0535	0.0196	-0.0297	0.0035	0.0226	-0.0131	-0.0726	-0.0884
		(0.12)	(0.32)	(0.21)	(0.47)	(0.31)	(0.40)	(0.14)	(0.00)
	$\phi_{11}^{(1)}$	-0.1143	-0.0458	-0.1935	-0.1207	0.0701	-0.1329	-0.0251	-0.0566
		(0.13)	(0.29)	(0.02)	(0.07)*	(0.25)	(0.04)	(0.37)	(0.20)
	$\phi_{11}^{(2)}$	0.0385	-0.1650	0.0775	0.1357	-0.0971	-0.0105	0.1341	0.1031
		(0.32)	(0.02)	(0.22)	(0.07)*	(0.16)	(0.44)	(0.04)	(0.01)
	$\phi_{20}^{(1)}$	-0.0597	-0.0935	-0.1667	-0.3427	-0.1877	-0.0972	-0.1373	-0.0578
		(0.17)	(0.01)	(0.00)	(0.00)*	(0.00)	(0.01)	(0.00)	(0.07)
	$\phi_{20}^{(2)}$	0.0056	-0.1118	-0.1863	-0.3190	-0.1647	0.0217	-0.1828	-0.0926
		(0.46)	(0.00)	(0.00)	(0.00)*	(0.00)	(0.27)	(0.00)	(0.01)
	$\phi_{21}^{(1)}$	-0.0542	-0.4073	0.0825	0.2506	-0.1152	-0.3596	0.0000	0.0903
		(0.25)	(0.00)	(0.12)	(0.00)*	(0.07)	(0.00)	(0.50)	(0.10)
	$\phi_{21}^{(2)}$	-0.1369	-0.2596	0.1226	0.2543	-0.0627	-0.4716	0.1359	0.1153
		(0.02)	(0.00)	(0.04)	(0.00)*	(0.18)	(0.00)	(0.01)	(0.05)
Causal Parameters $\psi_{R\to Y}^{(k)}$	$\psi_1^{(1)}$	-0.3196	-0.2718	-0.5105	0.3513	-0.6401	0.0417	0.2165	-0.3375
		(0.01)*	(0.10)*	(0.06)*	(0.17)	(0.01)*	(0.36)	(0.09)*	(0.04)*
	$\psi_1^{(2)}$	-0.0856	0.3130	0.0741	0.9374	0.1698	0.0713	0.2536	0.0691
		(0.26)	(0.08)*	(0.42)	(0.01)*	(0.27)	(0.27)	(0.06)*	(0.36)
Causal Parameters $\psi_{Y\to R}^{(k)}$	$\psi_2^{(1)}$	-0.0060	-0.0427	0.0055	-0.0247	-0.0077	0.0031	-0.0160	-0.0027
		(0.34)	(0.01)*	(0.38)	(0.01)*	(0.23)	(0.20)	(0.00)*	(0.18)
	$\psi_2^{(2)}$	-0.0062	-0.0087	-0.0237	-0.0139	0.0134	0.0081	0.0017	-0.0121
		(0.33)	(0.30)	(0.06)*	(0.09)*	(0.10)*	(0.03)*	(0.37)	(0.00)*
ED[b]	$ED_{R\to Y}$	15.198	15.762	18.315	14.408	11.578	-	58.094	40.785
	$ED_{Y\to R}$	-	21.484	47.098	16.845	14.476	26.983	46.363	34.264
$E(NSwitches)$[c]		33.478	35.824	23.062	40.683	49.015	26.891	16.651	23.256

[a] The terms in the parenthesis are the p-values.
[b] ED stands for expected duration - How many weeks the state is expected to last.
[c] $E(NSwitches)$ stands for expected number of switches throughout the sample period.

Where $S_t = \ell$, $\ell = 1,\ldots,4$ are the associated regimes, $X_t = [\Delta R_t, \Delta YDL_t]$ and the function $I(.)$ is an indicator function that attributes one when the inputs are greater than 0.85. We divide the sample in three periods: the financial crisis, the European debt crisis and the Quantitative Easing.

Except to Ireland, all other countries, the stock market caused the bond markets during some periods. With the exception of Germany and Spain, the actual duration of this regime was shorter during the financial crisis. The actual duration of the regime where bond markets caused stock markets was longer during the financial crisis for Spain, Italy, Ireland, Portugal and Greece. This finding for Germany, France, the U.K. and Portugal are consistent with those from Andersson et al. (2008) who finds a negative causality between stocks and bond prices during periods of stock market uncertainty, maybe driven by a "flight-to-quality" phenomenon, and they are shown by the

Table 3.4 Actual Duration

	Financial Crisis[a]		European Debt Crisis[b]		Q.E.[c]		Covid[d]	
	$\Delta R_t \downarrow \Delta YDL_t$	$\Delta YDL_t \downarrow \Delta R_t$	$\Delta R_t \downarrow \Delta YDL_t$	$\Delta YDL_t \downarrow \Delta R_t$	$\Delta R_t \downarrow \Delta YDL_t$	$\Delta YDL_t \downarrow \Delta R_t$	$\Delta R_t \downarrow \Delta YDL_t$	$\Delta YDL_t \downarrow \Delta R_t$
Germany	24	0	10	0	28	0	18	0
France	74	2	58	19	6	30	17	2
Spain	27	68	75	46	2	54	15	108
Italy	24	37	65	67	0	52	15	73
UK	64	18	36	7	21	40	20	4
Ireland	0	60	0	47	0	5	0	14
Portugal	76	62	21	82	141	29	99	104
Greece	91	56	22	10	102	18	108	89

Note: The actual duration is measure in weeks. [a] 04/02/2008 to 26/10/2009. [b] 02/11/2009 to 24/09/2012. [c] 09/03/2015 to 13/11/2017. [d] 09/03/2020 to 28/03/2022

signs of the *temporary* causality in the table 4.5, in the "Causal Parameters" rows at either lag one or two, or both $\psi_1^{(k)}$.

4.2. Smoothed Probabilities

We aggregate the smoothed probabilities according to the *temporary* causality to provide a clearer interpretation. The probability of being in the regime where stock markets *temporarily* cause the changes in sovereign bond yields is shown in Figure B.5 and the probability of being in the regime where the changes in sovereign bond yields *temporarily* cause stock market returns is shown in Figure B.6. The criteria we have adopted to defined the direction follows the statistical significance, at 10 percent, of $\psi_1^{(k)}$ and $\psi_2^{(k)}$, which are the estimates that control the *temporary* causality. Note that if $\psi_1^{(k)}$ is not significant, regime 1 nests the regime 2, and regime 3 nests the regime 4.

Our results indicate that the global or idiosyncratic shocks coincide with reversals of *temporary* causality between stocks returns and the changes in sovereign bonds. We can observe in Figure B.5 that the plots are similar for Germany, France, Italy, Spain and the U.K., in particular during the financial crisis. The main difference, in this case, lies in the actual duration of the regime. As we can also see in Table 3.4, the actual duration is shorter for Germany and Spain. However, the trigger of this *temporary* causality occurred at the same time for those countries. Another interesting fact is related to the quantitative easing program conducted by the ECB. The QE program triggers the reverse in the *temporary* causality in the three core countries (the U.K., Spain and France) at the beginning of the program.

The European debt crisis also seems to have triggered the *temporary* causality in the direction towards the changes in sovereign bonds, except for Germany; nonetheless, the the European Debit Crisis Meeting has played an important role in terms of reversing the causality in the core countries (except Italy). This indicates the absence of contagious to the Germany from the stock market

Figure 3.1 Smooth Probabilities for Temporary Granger Causality ($\Delta R_t \rightarrow \Delta YLD_t$)

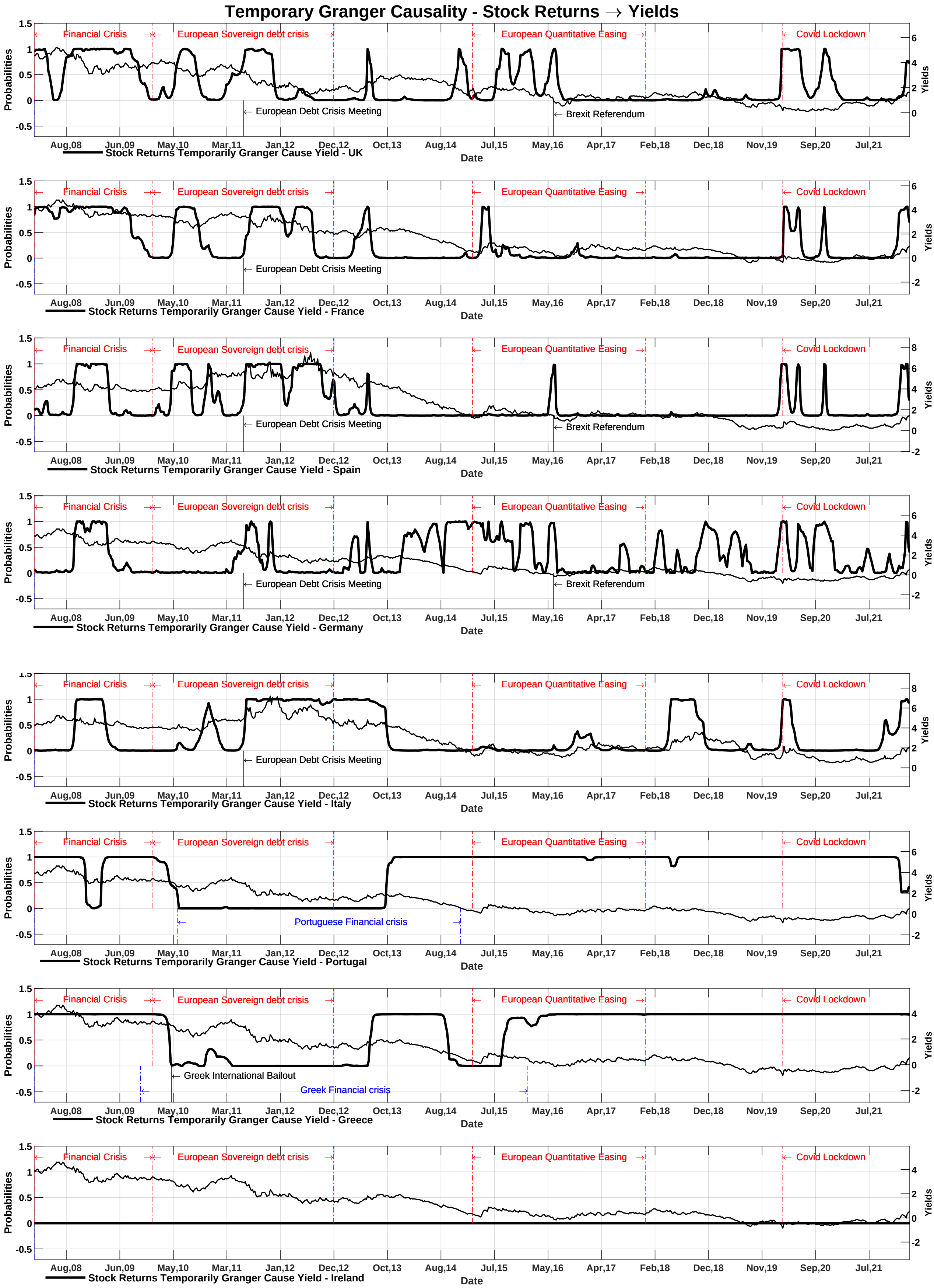
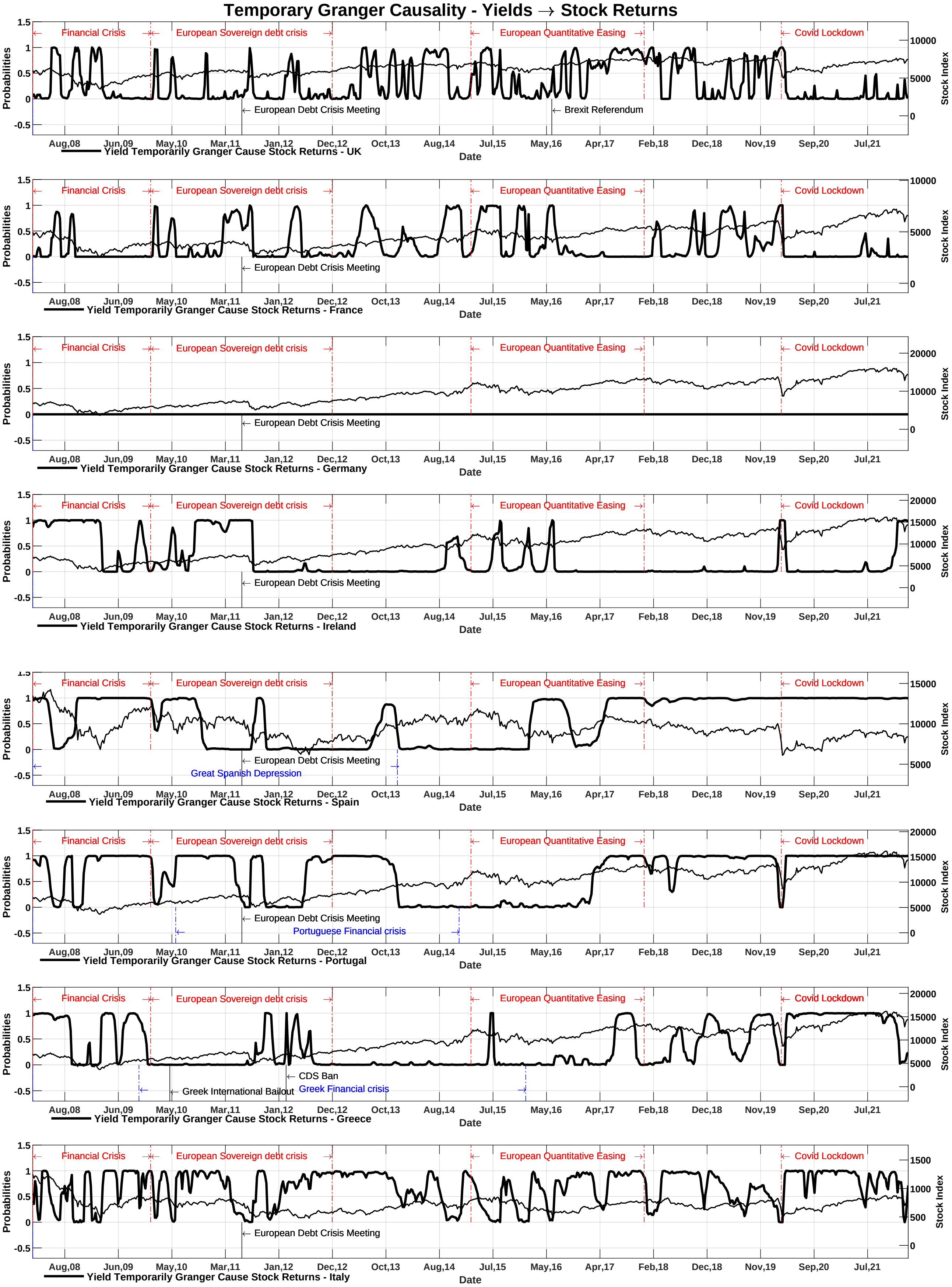


Figure 3.2 Smooth Probabilities for Temporary Granger Causality ($\Delta YLD_t \rightarrow \Delta R_t$)



uncertainty period in the Eurozone at the beginning of the crisis. Some of the remaining shifts appear to be related to idiosyncratic turmoil, for instance the Brexit referendum, that triggered a short lived change of causality in the U.K., but also in the other European countries, such as Germany and Spain. Finally, the Corona virus pandemic triggered the shift in the temporary causality, most evident in the core countries.

Portugal and Greece have very similar patterns, our results link changes in regimes to idiosyncratic events, namely the financial crisis in these countries. These patterns are consistent with other studies that have found that those countries have detached from the "core" countries during this period. Fontana and Scheicher (2016) shows that the CDS-Bond spread in these countries turned negative between 2009 and 2010 and from 2011 onwards.

Turning now to the inverse *temporary* causality, where the changes in sovereign bonds cause stock returns, with exception of Germany[10], it occurs in seven countries. The *temporary* causality pattern is similar during the Financial and European crisis for Portugal, Spain and Greece. Evidently, very similar for Portugal and Greece. The similarity disappear at the beginning of the Quantitative Easing; however returns by the end of the program, with countries diverging in the actual duration. During the Corona virus period the similarities of Portugal, Greece and Italy are also clear. The The *temporary* causality pattern for the U.K. and France are diffuse and difficult to interpret; nevertheless the short living *temporary* causality are also similar. This finding shows the importance of our methodology, as the usual methods applied to the whole sample or different ad-hoc sub-samples do not capture these patterns, as shown in Table 3.2. More importantly, this finding contradicts the previous literature that measures the causality between the country's credit and market risks, that mainly found the causality from market risk to sovereign risk. One exception is Coronado et al. (2012) that found that in 2010, the CDS took the lead over the stock returns. Nonetheless, with sovereign bond yields, our results indicate that had happened in seven countries. For Germany the probability of having *temporary* causal relationship is zero because $\psi_2^{(k)}$ is not significant all lags.

4.3. Synchronization

Our results also reveal some insights on contagion based on the smoothed probabilities' Synchronization. Nonetheless, there is the need to interpret these conclusions cautiously because the market iterations[11] are not estimated directly from the whole system of equations from all countries; instead we use a variable as a proxy for market iterations, namely Euribor. The main argument for avoiding using the whole system, considering all countries and extracting a global factor for contagion, is simplicity. Considering the eight countries we are using would increase the complexity of the

[10]There is no rationality in this case on why the smoothed probability of Germany is zero. The results are counter intuitive as Germany's closer economies present positive smoothed probabilities for this Granger Causality pattern. Nonetheless, the estimation method is very sensitive to initial values. New versions of the paper, that explore more in depth the likelihood surface has changed the smoothed probability for all countries, and all countries have positive probabilities. These new results will be included in Appendix B - Subsection 0.4. of this thesis.

[11]For instance, from Stock Return of Market 1 to Stock return of Market 2, or Stock Return from Market 1 to Sovereign of Market 2

problem and make the problem's solution unfeasible. Therefore, our paper is not about networking causality. Nevertheless, it is possible to use the definition of Forbes and Rigobon (2002) for contagion to infer about countries' synchronization. Forbes and Rigobon (2002) define contagion as the increase in the economic co-movements(synchronization) during crisis periods. We adopt a similar approach to Ge (2020), interpreting the rise of the synchronization in the smoothed probability during an economic crisis as contagion. From the plots in Figures B.5 and B.6, we can identify when the synchronization started and which countries have first risen its smoothed probability into a specific regime, as pointed out in Figure B.3 for *temporary* causality from Stock Return to Yields and Figure B.4 *temporary* causality from Yield to Stock Returns in the appendix (0.3.).

Take the regime where stock markets *temporarily* cause the changes in sovereign bond yields, during the Financial Crisis, the U.K., France Portugal and Greece have entered this regime first, followed by the Germany, Italy and Spain that had entered in the same week. The co-movements of all countries have happened within seven months of the beginning of our sample. During the European Debt Crisis, the U.K., France, and Spain have entered into this regime simultaneously. However, the regime lasted longer for France and Spain, as we observe in table (3.4). Notably, the European Debit Crisis Meeting played an important role in changing the causality patter, as it it possible to observe it had triggered the reversion in the *temporary* causality for all core countries.

In the regime where the changes in sovereign bonds *temporary* cause stock returns, at the onset of the Financial Crisis, Spain, Ireland, Portugal and Greece have entered in this regime first and then was followed by Italy, France and the U.K.. For most the second half of the Financial Crisis, Portugal and Spain were in the same regime. During the European Debt Crisis, the co-movement stated simultaneously after the second week of May of 2010 and lasted for a couple of months for Spain, lasting until the third week of august of 2011 for Portugal. And recurred again on the first week of November of 2011 weeks later of the European Debit Crisis Meeting. Finally, it is clear that for the U.K. and France, the shocks that had triggered the *temporary* causality coincides in the dates of occurrence; nonetheless it did not last longer comparing with the other countries.

Finally, the covid pandemic has also increased the synchronization for the *temporary* causality from Stock Return to Yields and for *temporary* causality from Yields to Stock Return. For the UK, France, Spain, Germany and Italy, the pandemic has shifted for the *temporary* from Stock Return to Yields for a short period. For *temporary* causality from Yields to Stock Return, the synchronization is clear from Portugal, Greece and Italy, as well as for France and the UK.

5. Conclusions

We have studied the causality between stock returns and the changes in sovereign bond, using the weekly data from 2008 and 2022 from eight European countries. We employ a standard methodology based on a VAR model to analyse the country-specific lead-lag relationship for the whole sample, and an approach based on Markov-switching causality to determine the dates of reversals of the causality endogenously. We consider the stock returns as reflecting the economic environment of a country (or market risk indicator) and the changes in sovereign bonds a market current perception of country default risk (sovereign risk indicator). To this end, the *temporary* causality can be interpreted as a propagation mechanism from one market to another.

We draw two main conclusions from our analysis. First, by finding the exact dates when there are shifts in the temporary causality direction, we find the actual duration of the regimes is country-specific, a sign of asymmetry of how shocks are absorbed by the two markets. Second, not surprisingly, an idiosyncratic crisis from a peripheral country has limited strength to define the temporary causality elsewhere, which suggests that the main channel for the spillover effect goes from large economies to Peripheral countries. Idiosyncratic crisis drives changes in the peripheral country's (Greece, and Portugal) actual temporary causality patterns, but does not seem to affect core countries, Germany, France, Spain, U.K., and Italy. These are affected by a global (or regional)-Systemic crisis, which reflects their economic stability. By focusing on the smoothed probabilities, we find that the main difference in temporary causality patterns of the core countries is the actual durations. Still, the starting points are often the same and coincide with a global (or regional) crisis.

The evidence of causality from the changes in sovereign bond yields to stock market returns contradict the literature except for Germany where no *temporary* causality patter is found in this direction. From the perspective of price discovery, we infer that during a systemic crisis, such as the Financial and European debt crisis, stock returns appear to be more informative, but the importance of the sovereign bond yields can not be neglected. In some periods of more idiosyncratic crisis, sovereign risk might lead.

Chapter 4

The Liquidity Effect Shift

1. Introduction

The negative interest rate response to an increase in the money supply is known in the economic literature as the Liquidity Effect. In essence, the traditional Keynesian theory predicts that when the Federal Reserve, henceforth FED, buy treasury bills on the open market, the immediate short-run effect is the fall of the interest rate. This subject is fascinating nowadays because of the periods of Zero Lower Bound and the so-called Quantitative Easing policies.

The Liquidity Effect has played an essential role in Keynesian analysis. In the celebrated book of Keynes, "The General Theory of Employment, Interest and Money", the interest rate is the price of equilibrium that determines the willingness of holding cash. Thus the analysis of the Liquidity Effect reflects shocks to the money demand rather than to the supply.

Many researchers have tried to quantify the liquidity effect theoretically and empirically. From the seminal article of Cagan and Gandolfi (1969), other papers have attempted to explore this theoretical outcome. Despite the efforts to establish the Liquidity Effect empirically, such as the papers from Mishkin (1982), Melvin (1983), Thorntonl (1988), Reichenstein (1987) and Leeper and Gordon (1992), the empirical literature has demonstrated the difficulties to capture this outcome. An empirical approach that has been used to analyse this effect is the Structural Vector Autoregression (SVAR), for instance, Bernanke and Blinder (1992), Gordon and Leeper (1994), Christiano et al. (1996), Bernanke and Mihov (1998). Rudebusch (1998) and Pagan and Robertson (1998). Each of them has an identification strategy, which binds their conclusion to their assumptions. Although there is no embroil against the different identification assumptions, Hamilton (1997) has pointed out that the earlier approaches' vital characteristic is the assump-tion that the innovation of Fed Policy could not be anticipated based on earlier available information. Finally, in Federal Reserve article written by Pagan and Robertson (1995) pointed out that the Liquidity Effect is sensitive to the sample period.

In this chapter, we measure the relationship between a monetary aggregate and Federal Funds Rate by estimating an MGARCH-*in-Mean* - MSVAR-GC (Markov-Switching Granger Causality with GARCH-in-mean). The developed model deals with the sample period sensitivity by endogenizing the Granger Causality pattern in a Vector Autoregression, and similarly to Elder and Serletis (2010), this model also takes into account a policy surprise by considering the MGARCH-*in-Mean* structure. In addition, to the economic reasoning, two are the main theoretical reasons to consider an MGARCH-*in-Mean*: firstly, the inference on the mean equation in a model in which the second moment is misspecified will be invalid. Finally, more efficient estimates of the conditional mean can be obtained by introducing the observed features of the heteroskedasticity inside the estimation of the conditional mean (*-in-Mean*). From the Empirical point of view, as pointed out by McConnell and Perez-Quiros (2000a), the structural change in the volatility imposes misspecification in Markov-Switching Models leading to a reduction in the business cycle. Finally, it is necessary to point out that the paper is not developing a new approach for a Multivariate GARCH model, nonetheless, the paper uses the MGARCH model as an instrument to obtain more efficient estimates as pointed out as well by Hamilton (2008). Nevertheless, one of the novelties of the paper is to introduce a Markov-Switching model with GARCH-*in-Mean*.

We conclude: (1) The so-called Friedman-Cagan regime (to be defined later on) weakens during the recessions. (2) By constructing the impulse responses that are conditional to a particular regime, the currency component of M1 adjusted by U.S. Dollars' foreign holdings presents the Liquidity Effect. (3) Expansionary or Contractionary monetary policy that could lead to economic instability did not last longer, alighting to collapsing bubbles literature.

2. Markov Switching Causality

2.1. Setting

The model structure for Markov-Switching Causality proposed by Psaradakis et al. (2005) is a vector autoregression where some parameters are constrained to allow different patterns of Granger causality and the switching between each pattern driven by a hidden Markov process. Nonetheless, I modify the original model to incorporate two features. Firstly, in Psaradakis et al. (2005), the standard deviation of errors are state-dependent and constant in each state[1]. Similarly to Caporale et al. (2016), and Elder and Serletis (2010), I incorporate an MGARCH-Type of structure to allow the variance of the errors to vary over time. Secondly, I also incorporate the *in-mean* into the model to take into account an *"unexpected"* policy shock.

The model is defined as:

$$BX_t = \Omega_t + \sum_{k_1=1}^{h_1} \Phi_t^{(k_1)} X_{t-k_1} + \Xi_t diag(H_t) + \sum_{k_2=1}^{h_2} \left\{ \Theta_{t,1}^{(k_2)} y_{t-k_2} + \Theta_{t,2}^{(k_2)} \pi_{t-k_2} \right\} + U_t, \tag{4.1}$$

[1]Distributional parameter

For $t = 1, 2, \ldots, T$

Where $Y_t = [\Delta R_t \ , \left(\frac{\Delta M}{M}\right)_t]$ are the annualized growth rates of a monetary aggregate and first difference of the federal funds rates; or respectively. And y_t and π_t are the annualized growth rates of real GDP and inflation, respectively; D_t, $A_t^{(k)}$,Z_t are state-dependent parameter matrices. Finally, the specification of the matrices in reduce form are given by:

$$B^{-1}\Omega_t = \begin{bmatrix} \omega_{10} + \omega_{11}s_{1,t} \\ \omega_{20} + \omega_{21}s_{2,t} \end{bmatrix}, \quad B^{-1}\Phi_t = \begin{bmatrix} \phi_{10}^{(k_1)} + \phi_{11}^{(k_1)}s_{1,t} & \psi_1^{(k_1)}s_{1,t} \\ \psi_2^{(k_1)}s_{2,t} & \phi_{20}^{(k_1)} + \phi_{21}^{(k_1)}s_{2,t} \end{bmatrix}, \tag{4.2}$$

$$B^{-1}\Xi_t = \begin{bmatrix} \xi_{101} + \xi_{111}s_{1,t} & \xi_{102} + \xi_{112}s_{1,t} \\ \xi_{201} + \xi_{211}s_{2,t} & \xi_{202} + \xi_{212}s_{2,t} \end{bmatrix}, \quad B^{-1}\Theta_{t,\iota}^{(k_2)} = \begin{bmatrix} \theta_{10,\iota}^{(k_2)} + \theta_{11,\iota}^{(k_2)}s_{1,t} \\ \theta_{20,\iota}^{(k_2)} + \theta_{21,\iota}^{(k_2)}s_{2,t} \end{bmatrix}$$

$$B^{-1}U_t = \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}$$

Where $dim(B) = dim(U_t) = (NN)$ and $B^{-1}U_t' \sim N(0, H_t)$ are the Normally distributed "structural disturbances". These "structural disturbances" or "primitive shocks" are assumed to be contemporaneously uncorrelated. Additionally, H_t is diagonal and $\mathscr{F}_{t-1}$ is the information set up to $t-1$.

Routinely, the model is identified by constraining the contemporary relationship of the vector Y_t, the variables of interest. In our case, the model is just-identified by imposing $\frac{N\times(N-1)}{2}$ exclusion restriction on B and imposing diagonality on the covariance matrix. Typically, most of the *VAR* applications assume B to be lower triangular for the given ordering of the variables of interest. Many scholars pointed out that the imposition of these exclusion restrictions must come with an economic interpretation.

By assuming that the above model is corrected specified, the equation i^{th} represents the monetary policy reaction function.

The structural residual u_{it} express the innovation in the policy variable that is not predictable, regardless of the past or any additional information provided by the variable or other contemporaneous innovations. Hence, it can be interpreted as the monetary policy unexpected shock at t or *policy surprise*.

Observe that in the model (4.1), the conditional standard error of the *policy surprise* is allowed to vary over time, *i.e.*, therefore it measures the movements of the policy uncertainty over time.

For the conditional heteroscedasticity structural form of the elements of H_t, I am going to assume CCC-GARCH(1,1)[2].

Finally, the model is conditioned on two exogenous variable, Δy_t and π_t, real GDP and inflation respectively; and by $\sigma_{1,t}$ and $\sigma_{2,t}$, the conditional standard errors. Notice by conditioning the mean equation on the conditional variances, the model becomes an *in-mean VAR*. Therefore, this specification allows us to take into account the "surprise" effect in the *"mean"* equation. Specifically, the conditional variances of the policy "surprise" that considers the contemporary information set

[2]Constant Conditional Correlation (CCC-) GARCH model by Bollerslev (1990), therefore the correlation of the residual terms will be constant over time.

vary over time and measurement uncertainty for the current monetary policy. A similar approach was used by Elder and Serletis (2010) to investigate the relationship between the price of oil and investment, focusing on the role of uncertainty on the oil prices. In addition, to the economic basis, there are two main reasons for considering the conditional standard errors (second moment) even if this paper focuses on the conditional mean (first moment). Firstly, the inference on the mean equation in a model in which the second moment is misspecified will be invalid. Secondly, by introducing the observed features of the heteroskedasticity inside the estimation of the conditional mean, more efficient estimates of the conditional mean can be obtained[3].

In terms of Causality regimes, observe that the matrices (4.2) provide all Granger causality patterns, and the hidden random variables $s_{1,t}$ and $s_{2,t}$ are latent binary random variables with values in $0,1$ which characterize the regime (state) that prevails at each time period t. Therefore, there are four regimes S_t, and they can be summarized as:

$$S_t = \begin{cases} 1 \text{ if } s_{1,t} = 1 \text{ and } s_{2,t} = 1 & \text{bidirectional causality } (\Delta M_t \leftrightarrow \Delta R_t) \\ 2 \text{ if } s_{1,t} = 0 \text{ and } s_{2,t} = 1 & \text{interest rates cause money } (\Delta R_t \rightarrow \Delta M_t) \\ 3 \text{ if } s_{1,t} = 1 \text{ and } s_{2,t} = 0 & \text{money cause interest rates } (\Delta M_t \rightarrow \Delta R_t) \\ 4 \text{ if } s_{1,t} = 0 \text{ and } s_{2,t} = 0 & \text{no causality } (\Delta M_t \not\leftrightarrow \Delta R_t) \end{cases}$$

It is important to point out that the number of regimes in this model is defined by construction, as each regime represents one particular causality pattern.

For simplicity, the model reduced form can be described explicitly:

For $S_t = 1$:

$$\begin{aligned} \begin{bmatrix} \Delta R_t \\ \left(\frac{\Delta M}{M}\right)_t \end{bmatrix} = \begin{bmatrix} \omega_{10}+\omega_{11} \\ \omega_{20}+\omega_{21} \end{bmatrix} &+ \sum_{k_1=1}^{h_1} \begin{bmatrix} \phi_{10}^{(k_1)}+\phi_{11}^{(k_1)} & \psi_1^{(k_1)} \\ \psi_2^{(k_1)} & \phi_{20}^{(k_1)}+\phi_{21}^{(k_1)} \end{bmatrix} \begin{bmatrix} \Delta R_{t-k_1} \\ \left(\frac{\Delta M}{M}\right)_{t-k_1} \end{bmatrix} + \begin{bmatrix} \xi_{101}+\xi_{111} & \xi_{102}+\xi_{112} \\ \xi_{201}+\xi_{211} & \xi_{202}+\xi_{212} \end{bmatrix} \begin{bmatrix} \sigma_{1,t} \\ \sigma_{2,t} \end{bmatrix} \\ &+ \sum_{k_2=1}^{h_2} \left\{ \begin{bmatrix} \theta_{10,1}^{(k_2)}+\theta_{11,1}^{(k_2)} \\ \theta_{20,1}^{(k_2)}+\theta_{21,1}^{(k_2)} \end{bmatrix} y_{t-k_2} + \begin{bmatrix} \theta_{10,2}^{(k_2)}+\theta_{11,2}^{(k_2)} \\ \theta_{20,2}^{(k_2)}+\theta_{21,2}^{(k_2)} \end{bmatrix} \pi_{t-k_2} \right\} + B^{-1}U_t \end{aligned}$$

For $S_t = 2$:

$$\begin{aligned} \begin{bmatrix} \Delta R_t \\ \left(\frac{\Delta M}{M}\right)_t \end{bmatrix} = \begin{bmatrix} \omega_{10} \\ \omega_{20}+\omega_{21} \end{bmatrix} &+ \sum_{k_1=1}^{h_1} \begin{bmatrix} \phi_{10}^{(k_1)} & 0 \\ \psi_2^{(k_1)} & \phi_{20}^{(k_1)}+\phi_{21}^{(k_1)} \end{bmatrix} \begin{bmatrix} \Delta R_{t-k_1} \\ \left(\frac{\Delta M}{M}\right)_{t-k_1} \end{bmatrix} + \begin{bmatrix} \xi_{101} & \xi_{102} \\ \xi_{201}+\xi_{211} & \xi_{202}+\xi_{212} \end{bmatrix} \begin{bmatrix} \sigma_{1,t} \\ \sigma_{2,t} \end{bmatrix} \\ &+ \sum_{k_2=1}^{h_2} \left\{ \begin{bmatrix} \theta_{10,1}^{(k_2)} \\ \theta_{20,1}^{(k_2)}+\theta_{21,1}^{(k_2)} \end{bmatrix} y_{t-k_2} + \begin{bmatrix} \theta_{10,2}^{(k_2)} \\ \theta_{20,2}^{(k_2)}+\theta_{21,2}^{(k_2)} \end{bmatrix} \pi_{t-k_2} \right\} + B^{-1}U_t \end{aligned}$$

For $S_t = 3$:

[3] See: Hamilton (2008)

$$\begin{bmatrix} \Delta R_t \\ \left(\frac{\Delta M}{M}\right)_t \end{bmatrix} = \begin{bmatrix} \omega_{10}+\omega_{11} \\ \omega_{20} \end{bmatrix} + \sum_{k_1=1}^{h_1} \begin{bmatrix} \phi_{10}^{(k_1)}+\phi_{11}^{(k_1)} & \psi_1^{(k_1)} \\ 0 & \phi_{20}^{(k_1)} \end{bmatrix} \begin{bmatrix} \Delta R_{t-k_1} \\ \left(\frac{\Delta M}{M}\right)_{t-k_1} \end{bmatrix} + \begin{bmatrix} \xi_{101}+\xi_{111} & \xi_{102}+\xi_{112} \\ \xi_{201} & \xi_{202} \end{bmatrix} \begin{bmatrix} \sigma_{1,t} \\ \sigma_{2,t} \end{bmatrix}$$
$$+ \sum_{k_2=1}^{h_2} \left\{ \begin{bmatrix} \theta_{10,1}^{(k_2)}+\theta_{11,1}^{(k_2)} \\ \theta_{20,1}^{(k_2)} \end{bmatrix} y_{t-k_2} + \begin{bmatrix} \theta_{10,2}^{(k_2)}+\theta_{11,2}^{(k_2)} \\ \theta_{20,2}^{(k_2)} \end{bmatrix} \pi_{t-k_2} \right\} + B^{-1}U_t$$

For $S_t = 4$:

$$\begin{bmatrix} \Delta R_t \\ \left(\frac{\Delta M}{M}\right)_t \end{bmatrix} = \begin{bmatrix} \omega_{10} \\ \omega_{20} \end{bmatrix} + \sum_{k_1=1}^{h_1} \begin{bmatrix} \phi_{10}^{(k_1)} & 0 \\ 0 & \phi_{20}^{(k_1)} \end{bmatrix} \begin{bmatrix} \Delta R_{t-k_1} \\ \left(\frac{\Delta M}{M}\right)_{t-k_1} \end{bmatrix} + \begin{bmatrix} \xi_{101} & \xi_{102} \\ \xi_{201} & \xi_{202} \end{bmatrix} \begin{bmatrix} \sigma_{1,t} \\ \sigma_{2,t} \end{bmatrix}$$
$$+ \sum_{k_2=1}^{h_2} \left\{ \begin{bmatrix} \theta_{10,1}^{(k_2)} \\ \theta_{20,1}^{(k_2)} \end{bmatrix} y_{t-k_2} + \begin{bmatrix} \theta_{10,2}^{(k_2)} \\ \theta_{20,2}^{(k_2)} \end{bmatrix} \pi_{t-k_2} \right\} + B^{-1}U_t$$

The conditional variance H_t is modelled as bivariate GARCH as follows:

$$\begin{aligned} h_t &= \Gamma + \sum_{i=1}^{g} F_i diag(U_{t-i}U'_{t-i}) + \sum_{j=1}^{n} G_j h_{t-j} \\ h_t &= diag(H_t) = \begin{bmatrix} \sigma_{1,t} \\ \sigma_{2,t} \end{bmatrix} \\ U_t &= H_t^{1/2} z_t \\ z_t &\sim iidN(0,I) \end{aligned}$$

where

$$\Gamma = \begin{bmatrix} \gamma_y \\ \gamma_x \end{bmatrix}, \quad F_i = \begin{bmatrix} f_{i,y} & 0 \\ 0 & f_{i,x} \end{bmatrix}, \quad G_i = \begin{bmatrix} g_{i,y} & 0 \\ 0 & g_{i,x} \end{bmatrix}$$

Observe that the conditional volatility in this case is independent for each variable and does not vary over time. An alternative approach adopted by Elder and Serletis (2010) is to consider the *vech*-GARCH, as:

$$\Gamma = \begin{bmatrix} \gamma_y \\ \gamma_x \end{bmatrix}, \quad F_i = \begin{bmatrix} f_{i,yy} & f_{i,yx} \\ f_{i,xy} & f_{i,xx} \end{bmatrix}, \quad G_i = \begin{bmatrix} g_{i,yy} & g_{i,yx} \\ g_{i,xy} & g_{i,xx} \end{bmatrix},$$

Nonetheless, there are two reasons for considering the first characterization. Firstly, I want to consider just the time-varying unexpected shocks; therefore, if the unconstrained (multivariate) case for the conditional standard errors is considered, the contemporaneous shock might be predicted by the past values of the other variable's shocks. The second and most important reason is parsimony.

Finally, notice that, the parameters $\psi_1^{(k_1)}$ and $\psi_2^{(k_1)}$ are the parameters that give the *temporary* Granger causality, henceforth *temporary* causality: $S_t = 2$ is the regime where interest rates temporarily cause money and $S_t = 3$ is the case when the money temporarily causes interest rates. The state $S_t = 1$ is the state where there is a dual causality and $S_t = 4$ is the state where there is no causality. Beside the imposed differences in the causality patterns in the four regimes, the regimes differ on other parameters, namely μ_{11}, μ_{21}, φ_{11}, φ_{21}, ϕ_{11}, ϕ_{21}.

To complete the specification of the model, the Markov process that defines the behaviour of the regimes can be described as:

$$p_{i,j}^{(l)} = \mathscr{P}(s_{l,t+1} = j | s_{l,t} = i), \text{ where } i, j = 0, 1 \text{ and } l = 1, 2$$

Notice that $p_{i,j}^{(l)}$ probability of being in the regime j at time $t+1$ conditional as being in regime i at t and it is assumed that $s_{1,t}$ and $s_{2,t}$ are independent. Therefore, the transition matrix of S_t is defined as:

$$P = \begin{bmatrix} p_{11}^{(1)} p_{11}^{(2)} & (1-p_{00}^{(1)}) p_{11}^{(2)} & p_{11}^{(1)}(1-p_{00}^{(2)}) & (1-p_{00}^{(1)})(1-p_{00}^{(2)}) \\ (1-p_{11}^{(1)}) p_{11}^{(2)} & p_{00}^{(1)} p_{11}^{(2)} & (1-p_{11}^{(1)})(1-p_{00}^{(2)}) & p_{00}^{(1)}(1-p_{00}^{(2)}) \\ p_{11}^{(1)}(1-p_{11}^{(2)}) & (1-p_{00}^{(1)})(1-p_{11}^{(2)}) & p_{11}^{(1)} p_{00}^{(2)} & (1-p_{00}^{(1)}) p_{00}^{(2)} \\ (1-p_{11}^{(1)})(1-p_{11}^{(2)}) & p_{00}^{(1)}(1-p_{11}^{(2)}) & (1-p_{11}^{(1)}) p_{00}^{(2)} & p_{00}^{(1)} p_{00}^{(2)} \end{bmatrix}$$

2.2. Expected Duration

The expected duration of the regime m is calculated directly from an estimate of the transition matrix as follow:

$$ED_m = \sum_{i=1}^{\infty} i \left[\hat{p}_{m,m}\right]^{i-1} \left[1 - \hat{p}_{m,m}\right] = (1 - \hat{p}_{m,m})^{-1} \quad for \quad m = 1, .., 4 \tag{4.3}$$

where $\hat{p}_{m,m}$ are the estimates of the main diagonal elements of the transition matrix P. In our case, we are interested in how long the states of *temporary* causality are expected to last, particularly, the states where the interest rates *temporarily* cause money and money *temporarily* cause the interest rates, given by:

$$ED_{Y \leftrightarrow R} = (1 - \hat{p}_{1,1})^{-1}$$
$$ED_{M \to R} = (1 - \hat{p}_{2,2})^{-1}$$
$$ED_{R \to M} = (1 - \hat{p}_{3,3})^{-1}$$

2.3. Estimation Method

The Markov-Switching Granger Causality model parameters are estimated by maximum likelihood (MLE), assuming that the conditional distribution of $[M_t, R_t]$ given of all past values of variables and states is Normally Distributed[4].

There is sizeable theoretical evidence that Markov Switching models are strongly dependent on the initial values, which means instability in the results might occur due to the choice of the initial value. Thus a grid search of the initial values is constructed for some crucial parameters, particularly for the parameters related to the transition probability matrix (P).

[4]The optimization algorithm for ML is the secant update of the Hessian matrix, also known by Broyden-Fletcher-Goldfarb-Shano.

Additionally, to obtain initial values of the parameters, a set of unconstrained and constrained linear regressions of the variables are estimated and then the combination of these estimates are used for the initial values of the parameters of the model. The grid methods used vary the values of the transition probabilities (from 0.500 to 0.999 in steps of 0.0001). The initial values for the conditional variance are obtained in a preliminary considering an $GARCH(1,1)-M$ process conditioned on p_t and y_t. The standard errors of the estimates are obtained by the outer product of the scores as an estimator for the information matrix (see Davidson and MacKinnon (1993)).

3. Markov Switching Granger Causality - Results

3.1. Data

The traditional estimates of liquidity effect usually consider M1 and M2 as monetary aggregates, (M_t), and three-month Treasury bills or six-month commercial rates as interest rates (R_t).

In this paper, the quarterly annualised growth rate series of Currency Component of M1, and the Domestic Money[5], henceforth MC and DM respectively, will be used[6]. Notice that the currency component of M1 is closely related to Open Market Operations, which encompass the liquidity effect. For interest rates, this paper will consider the first difference of federal fund rates, henceforth FFR. Specifically for FFR, we use the shadow rates, as defined by Wu and Xia (2016), to overcome the difficulties associated with the ZLB period[7]. Moreover, FFR is the natural choice in this paper because it is very short term. This feature of FFR might help distinguish the liquidity effect from the expected inflation effect without relying upon any theoretical approach, specifically, the term structure of interest rates and expected inflation theories.

Additionally, this paper will consider the MC and DM because the FED has control of these variables via open market operations. In contrast, the other components of the other variables are out of the control of the FED[8]. Besides, this paper will consider FFR because it is very short-term, allowing the analysis to be disentangled from the expected inflation. With larger term rates, it will be necessary to include both theories on expected inflation and the term structure of interest rates. The other data that will be considered are the annualized quarterly growth rates (log-differences) in real GDP (Δy_t) and the GDP deflator/inflation (π_t).

[5]We include DM as a monetary instrument (currency component of monetary aggregate corrected for foreign holdings of US Dollars) because it has two important properties. First, the Federal Reserve knows precisely how much it prints money and tracks US Dollar shipments abroad (Porter and Judson (1996)). Second, it has a desirable information content to predict US inflation and real output (Aksoy and Piskorski (2006, 2005)). Therefore, it is a monetary aggregate that comes closest to a monetary aggregate as a policy instrument.

[6]A Broader definition of money, such as M1 and M2 will be considered in section (4.)

[7]The use of rates which are almost zero for long periods presented a serious challenge for the numerical optimisation routines used to estimate the parameters of the model.

[8]Lepper and Gordon consider monetary base, which also is not totally controllable by the FED, especially in recent year due to late adoption of the Floor System.

The data cover the period 1965:1 to 2015:4, except for Divisia M4 for which data is only available from 1967:1 onwards.[9,10].

Lastly, our sample overlaps with seven chairs who served at the Federal Reserve: William M. Martin (April 2, 1951, to February 1, 1970) appointed by Harry Truman, Arthur F. Burns (February 1, 1970, to January 31, 1978) appointed by Richard Nixon, G. William Miller (March 8, 1978, to August 6, 1979) and Paul Volcker (August 6, 1979, to August 11, 1987) both appointed by Jimmy Carter, Alan Greenspan (August 11, 1987, to January 31, 2006) appointed by Ronald Reagan, Ben Bernanke (February 1, 2006, to January 31, 2014) selected by George W. Bush, and Janet Yellen (February 3, 2014, to February 3, 2018) appointed by Barack Obama.

3.2. Estimation Results

Baseline Model

The analysis start with a baseline model. The baseline model is the model (4.4) that is not conditioned on either an exogenous variable or volatility. Nonetheless, everything else is similar to the model (4.1)

$$B\begin{bmatrix}\Delta R_t\\ \Delta M_t\end{bmatrix} = \Omega_t + \sum_{k_1=1}^{h_1} \Phi_t^{(k_1)} \begin{bmatrix}\Delta R_{t-k_1}\\ \Delta M_{t-k_1}\end{bmatrix} + U_t, \quad t = 1, 2, \ldots, T, \tag{4.4}$$

In this case, $h_1 = 4$, which correspond to a year lagged period; also, the choice is corroborated by the Ljung-Box test.

The Results for this model are presented below:

[9]For more details on the data see the appendix 0.1.

[10]We note that the hypothesis of a unit root can be rejected by a breakpoint unit root test with innovative outlier, at the 5% significance level, for all variables under consideration.

Table 4.1 Estimation Results

				MC	DM
Causal Parameters	Friedman-Cagan Effect	$\psi^{(k_1)}_{M\to R}$	$\psi_1^{(1)}$	-0.455	0.438**
				(0.42)	(0.23)
			$\psi_1^{(2)}$	1.238**	1.368***
				(0.44)	(0.31)
			$\psi_1^{(3)}$	1.018**	-0.198
				(0.38)	(0.25)
			$\psi_1^{(4)}$	-1.443***	0.516
				(0.40)	(0.35)
		$\psi^{(k_1)}_{R\to M}$	$\psi_2^{(1)}$	1.928	-1.057**
				(1.80)	(0.36)
			$\psi_2^{(2)}$	0.836	-0.431
				(1.61)	(0.45)
			$\psi_2^{(3)}$	0.784	-1.274**
				(1.52)	(0.44)
			$\psi_2^{(4)}$	-6.350***	0.741
				(1.57)	(0.52)

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Table 4.2 Duration Results

		MC		DM	
		ED[b]	RD[c]	ED[b]	RD[c]
GC[a]	$M \leftrightarrow R$	4.16	0	20.94	0
	$R \to M$	5.53	22	28.94	98
	$M \to R$	9.24	19	21.40	14
	$R \not\leftrightarrow M$	25.93	158	29.84	87

[a] GC stands for Granger Causality .
[b] ED stands for Expected Duration - How many quarters the regime is expected to last.
[c] RD stands for Realized Duration - How many quarters the regime lasted.

In table (4.1), the Friedman-Cagan Effect is the case where money causes FFR, regardless of the sign of the coefficient. In the same table, it is possible to observe for the MC case that $\psi_1^{(k_1)}$ is significant in at least 5% in almost all lags except for lag 1, but $\psi_2^{(k_1)}$ is only significant for lag 4. Therefore, MC does have predictive content for FFR and vice-versa. Nevertheless, the positive sign of $\psi_1^{(2)}$ and $\psi_1^{(3)}$ indicates that the liquidity effect might not be present. Similarly for DM, $\psi_1^{(k_1)}$ and $\psi_2^{(k_1)}$ are significant for lags 1 and 2, and for lags 1 and 3 respectively. Nonetheless, the sign of $\psi_1^{(k_1)}$ is also positive for the Friedman-Cagan Effect.

Despite the positive sign of $\psi_1^{(k_1)}$, we can not discard the possibility of having the liquidity effect without considering the nature of the changes in the money growth. The anticipation or otherwise of the changes in money growth impact the results since an anticipated monetary expansion primarily lead to higher the expected inflation. However, an unanticipated monetary expansion should produce a liquidity effect. For this reason, it is necessary to build a model that takes in to account the nature of changes in money growth. The complete model, as presented by the model (4.1), encompasses the uncertainty of the monetary shock by considering the contemporary standard error of the shock in the mean equation.

Additionally, this method allow us to calculate the expected duration of regimes from the transition matrix, and the by considering any smoothed probability bigger than 0.5 from the actual regimes, we defined the Realized Duration. The table (4.2) shows that DM presents a higher duration than MC; thus, the regimes for DM are more persistent than the MC.

3.3. Smoothed Probabilities - Baseline Model

The smoothed probabilities of being in each regime for the baseline model are presented in the figures (4.1) and (4.2). For the MC case, it is clear that regime number 4, where there is no Granger causality, is dominant. Regime 2, where FFR *Temporarily* causes MC, happens mostly during Bernanke's tenure, and regime 4, where MC *Temporarily* causes FFR, dominates during Volcker's tenure.

A similar analysis can be conducted for DM. In this case, both $\psi_1^{(k_1)}$ and $\psi_2^{(k_1)}$ are significant parameters. Thus the Friedman-Cagan effect occurs in a few episodes, particularly during the Volcker mandate. However, FFR is a good predictor of DM growth from Greenspan's appointment ahead. Before Greenspan's appointment, the regime are predominantly of No Granger Causality.

Finally, bi-directional causality was not present for both cases (DM and MC); hence, the cases are either one-direction of causality or no causality.

Figure 4.1 Smoothed Probabilities for Temporary Granger Causality

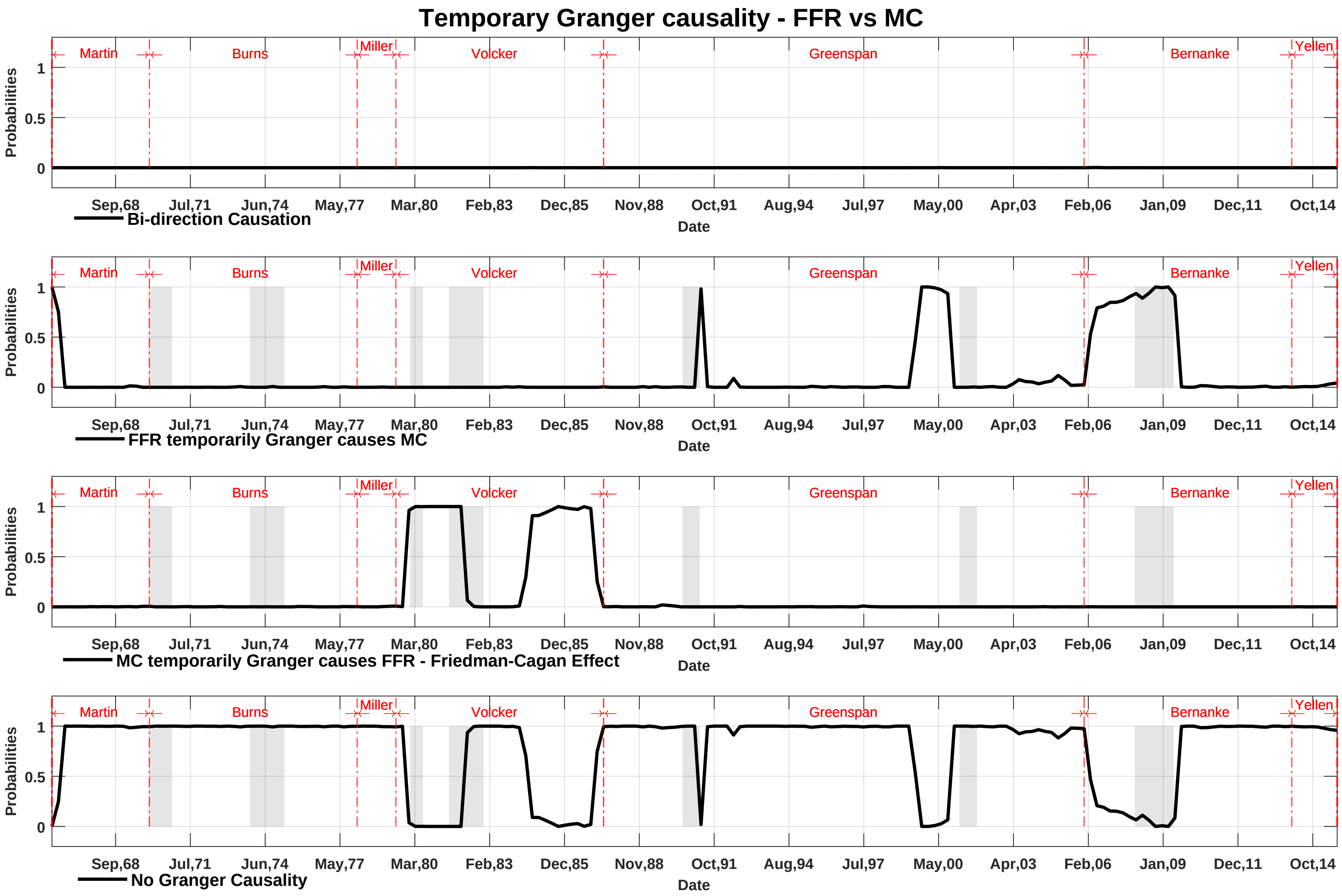
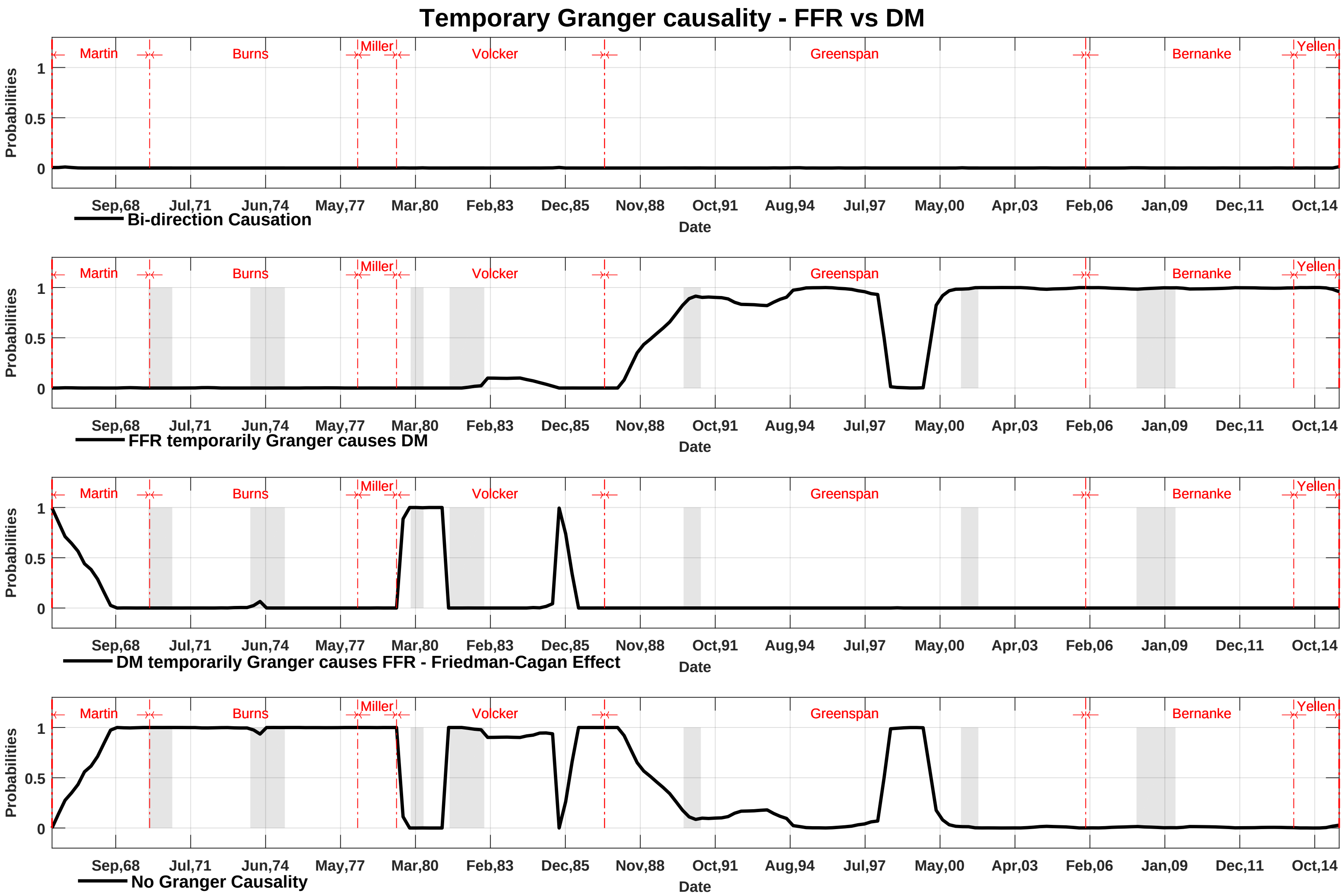
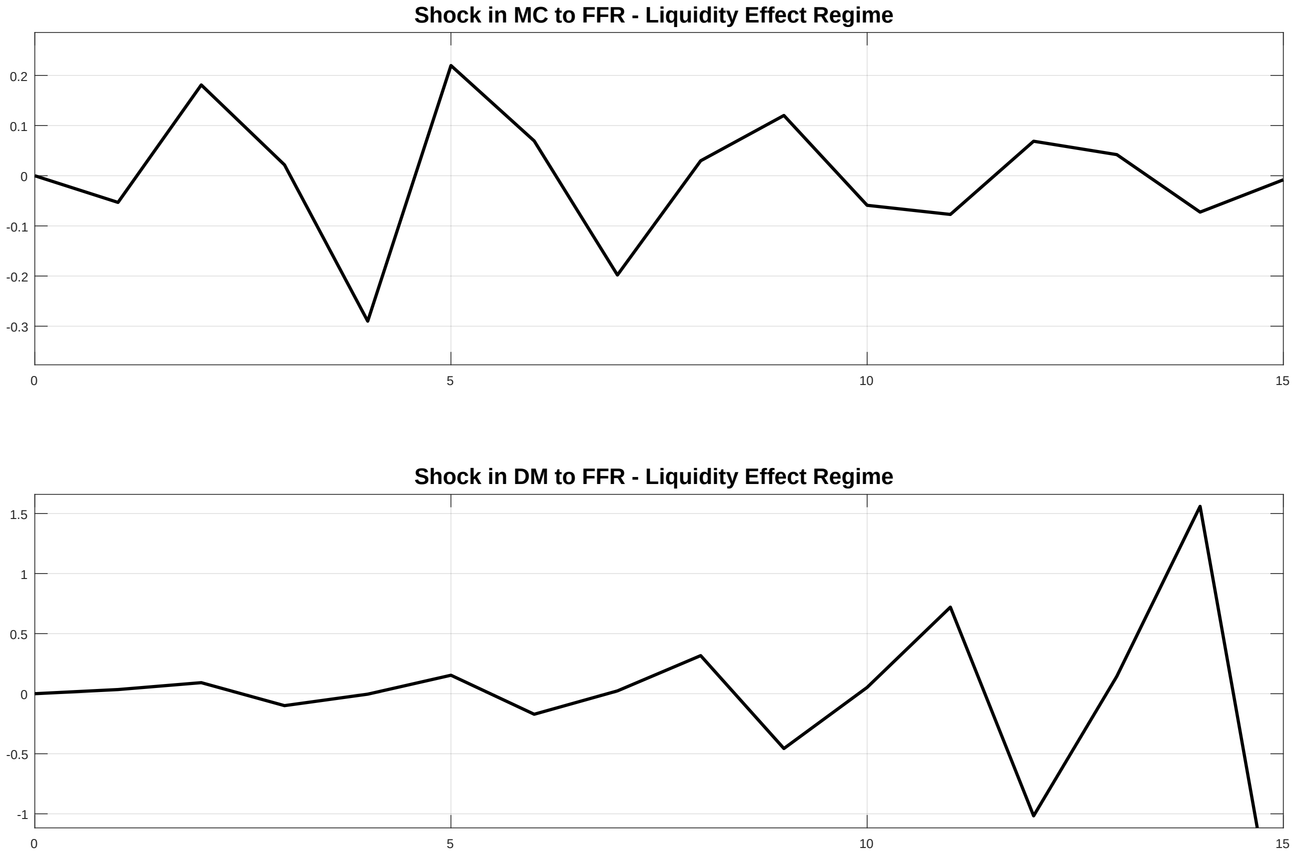


Figure 4.2 Smoothed Probabilities for Temporary Granger Causality



Finally, it is possible to conduct Impulse Response analysis. For this, I will combine the approaches used by Ehrmann et al. (2003) and Elder (2003), where the impulse responses are computed by taking into account the regime and the GARCH-in-mean structure, which imposes a specific form for Impulses Responses[11]. Figure (4.3) shows an overall Friedman-Cagan Effect for MC and DM. A standard deviation positive shock in MC leads to a decrease in the changes of FFR for about 0.3% in the third quarter; therefore, the Liquidity Effect is present for MC. Nonetheless, one standard deviation shock in DM leads to about 0.01% of increase in changes of FFR in the first quarter; accordingly, the results suggest the Expected Inflation Effect. Also, for DM's case, the impulse response behaviour is consistent with the literature on collapsing bubbles as the impulse response exhibits an explosive behaviour.

Figure 4.3 Impulse Response for Liquidity Effect Regime



[11]The derivation of this form is described in Appendix 0.2.

Complete Model

In this section, I present the results of the complete model. Similarly to the baseline model, we set the lags of the Markov-Switching VAR to $h_1 = 4$, and in addition $h_2 = 2$, for the exogenous variables. These choices are further supported by the Ljung-Box test and by the literature, in particular Kapetanios, 2001. The causal estimates are presented in Table (4.3) and the remaining estimates are reported in Appendix 0.3..

Table 4.3 Estimation Results - *Temporary* Granger Causality

			MC	DM
Causal Parameters	$\psi^{(k_1)}_{M\to R}$ Friedman-Cagan Effect	$\psi_1^{(1)}$	0.030* (0.02)	-0.0725*** (0.0253)
		$\psi_1^{(2)}$	0.026 (0.02)	-0.0071 (0.0238)
		$\psi_1^{(3)}$	-0.009 (0.02)	-0.0382* (0.0237)
		$\psi_1^{(4)}$	-0.002 (0.02)	0.0577*** (0.0231)
	$\psi^{(k_1)}_{R\to M}$	$\psi_2^{(1)}$	1.539 (3.02)	-1.3949** (0.6298)
		$\psi_2^{(2)}$	-0.215 (4.09)	-0.0333 (0.6353)
		$\psi_2^{(3)}$	-0.953 (2.16)	-1.7913*** (0.7747)
		$\psi_2^{(4)}$	-5.259** (2.76)	0.8916 (0.7346)

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Table 4.3 shows estimates of parameters associates with *Temporarily* causality between FFR and, either MC or DM. Notice that for both variables the parameters $\psi_2^{(k_1)}$ and $\psi_2^{(k_1)}$ are significant for some lags. For Friedman-Cagan Effect, $\psi_1^{(1)}$, $\psi_1^{(3)}$, and $\psi_1^{(4)}$ are significant for DM, and $\psi_1^{(1)}$ is significant for MC.

Table 4.4 Policy Uncertainty Results - Surprise Effect

		$\sigma_{1,t}$	$\sigma_{2,t}$	MC		DM		
Policy Uncertainty	Regime 1	$\xi_{101}+\xi_{111}$	$\xi_{102}+\xi_{112}$	-0.0103	-0.0373	0.0711	0.0294	R_t
				(0.10)	(0.04)	(0.1402)	(0.0777)	
		$\xi_{201}+\xi_{211}$	$\xi_{202}+\xi_{212}$	-3.6579	-0.6352	-0.7515	1.243*	M_t
				(4.74)	(3.37)	(1.0725)	(0.9521)	
	Regime 2	ξ_{101}	ξ_{102}	0.7750***	0.1155	0.3024**	-0.128	R_t
				(0.27)	(0.31)	(0.1756)	(0.1253)	
		$\xi_{201}+\xi_{211}$	$\xi_{202}+\xi_{212}$	-3.6579	-0.6352	-0.7515	1.243*	M_t
				(4.74)	(3.37)	(1.0725)	(0.9521)	
	Regime 3 Friedman-Cagan Effect	$\xi_{101}+\xi_{111}$	$\xi_{102}+\xi_{112}$	-0.0103	-0.0373	0.0711	0.0294	R_t
				(0.10)	(0.04)	(0.1402)	(0.0777)	
		ξ_{201}	ξ_{202}	0.1141**	-0.0154	0.0156	0.1993	M_t
				(0.07)	(0.21)	(0.1171)	(0.2017)	
	Regime 4	ξ_{101}	ξ_{102}	0.7750***	0.1155	0.3024**	-0.128	R_t
				(0.27)	(0.31)	(0.1756)	(0.1253)	
		ξ_{201}	ξ_{202}	0.1141**	-0.0154	0.0156	0.1993	M_t
				(0.07)	(0.21)	(0.1171)	(0.2017)	

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Table(4.4) shows the estimated parameters for the surprise effect. ξ_{101} and ξ_{102} are significant at 1% and 5% respectively for both variables. Also, ξ_{201} is significant for MC, and the sum of ξ_{202} and ξ_{212} is also significant for DM. Notice that the cross surprises, which is the impact of the interest rates surprise on money supply (or the other way around), happens in DM. This indicates that the interest rate is more sensitive to sudden changes in money than the opposite. Nevertheless, the overall result of the limited cross Surprise Effect might indicate that those variables, in particular DM, are appropriated for the Forward Guidance policy, which means that eventual surprises might be transferred into Liquidity Effect as the theory points out.

Table 4.5 Duration Results

		MC		DM	
		ED[b]	RD[c]	ED[b]	RD[c]
GC[a]	$ED_{M\leftrightarrow R}$	7.06	15	9.62	40
	$ED_{R\rightarrow M}$	3.36	0	5.27	8
	$ED_{M\rightarrow R}$	20.67	150	12.07	88
	$ED_{R\nleftrightarrow M}$	4.52	33	5.86	62

[a] GC stands for Granger Causality .
[b] ED stands for Expected Duration - How many quarters the regime is expected to last.
[c] RD stands for Realized Duration - How many quarters the regime lasted.

The expected duration and the realized duration are in the table 4.5. The expected duration of Friedman-Cagan Effect $ED_{M\rightarrow R}$, is higher for MC than for DM. Therefore, Friedman-Cagan Effect of MC is expected to last for about 20 quarters whereas for DM 12. Also, according to the Smoothed Probabilities, the realized duration, the actual measure of persistence, is high for both variables.

3.4. Smoothed Probabilities and Impulse Response Functions

Plots of the smoothed probabilities of DM and MC that describe *temporary* causality are shown in figures 4.4 and 4.5. Notice in each of the plots the third plot from the top shows how many periods the Friedman-Cagan Effect took place. Regime 1 (Unrestrict VAR) nest regimes 2 and 3. In the figures below, the first plot is the unrestricted VAR, whereas the second and third plots are regimes 2 and 3, respectively. Therefore, it is possible to say, for instance, that the Friedman-Cagan regime is the sum of regimes 1 and 3. Nonetheless, we are going to keep the smoothed probabilities as it is shown. Finally, the shaded areas indicate the recessions periods according to NBER.

In figure 4.4, the Friedman-Cagan effect occurs as $\psi_1^{(1)}$ is statistically different from zero; hence, the regime is dictated by both the autoregressive parameters and by the *Temporary* causality parameters. Our results indicate that for MC, the Friedman-Cagan Effect happens in all FED chairmen periods; however, it seems that the Friedman-Cagan Effect weakens during the recessions, as we can see in the third plot.

Figure 4.5 shows the regimes for DM. As observed in table 4.3, both $\psi_1^{(k_1)}$ and $\psi_2^{(k_1)}$ are significant for some lags; hence all the regimes are separated and dictated by the *Temporary* causality. For this variable, it is possible to observe that the Friedman-Cagan Effect happens most of the periods. Similarly to MC, it seems that this effect weakens during recessions (ellipses in the plots), which is not a theoretical surprise as liquidity constraints tend to be more significant in recessions than in expansions. Nevertheless, in the middle of Greenspan tenure, this effect almost disappeared. The effect seems to take over again after May 2000, and this may be because the FED raised the interest rates six times after the Asian Crisis to accommodate the economy for the sake of a safe landing.

Figure 4.4 Smoothed Probabilities for Temporary Granger Causality

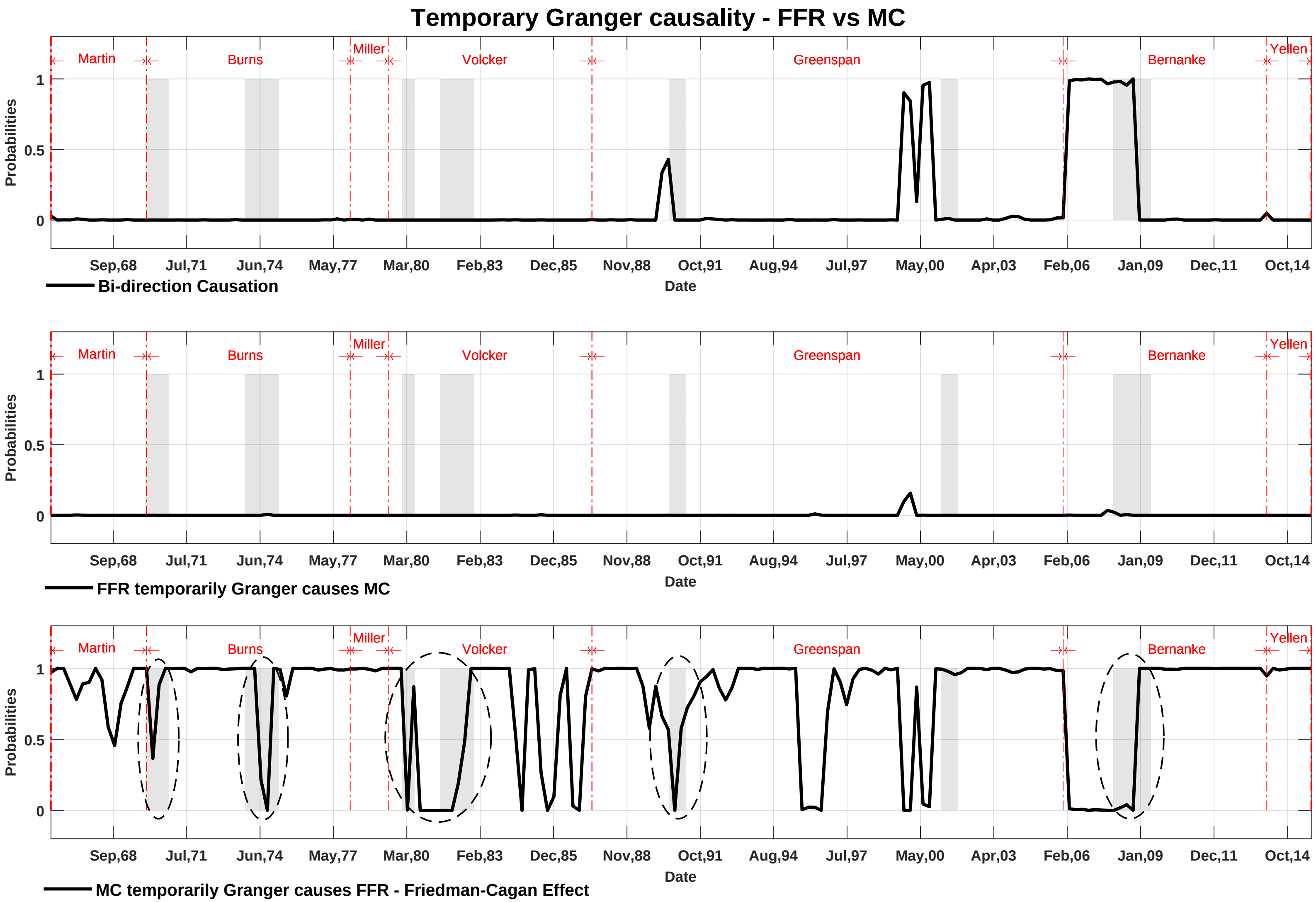
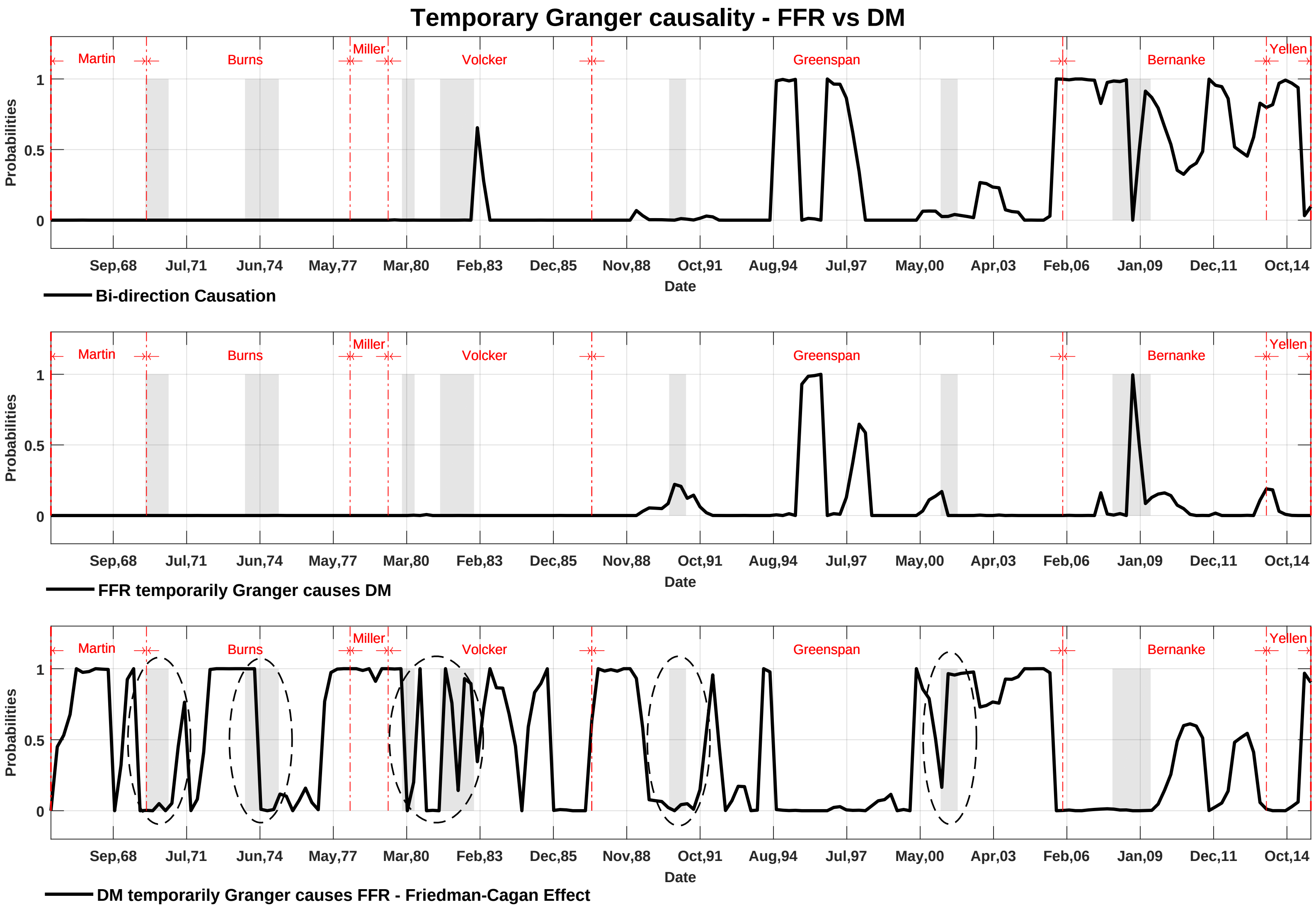


Figure 4.5 Smoothed Probabilities for Temporary Granger Causality



Finally, to distinguish the Friedman-Cagan Effect from the Liquidity Effect and the Expected Inflation Effect, it is necessary to conduct Impulse Response analysis. Figures (4.6) and (4.7) show the Impulse Responses for MC and DM. The upper plots are Impulse Responses of FFR to an one standard deviation shock to Money, and the lower plots show the response of FFR to one standard deviation of Money. Once again, in this approach, I will condition the Impulse Response dynamics on the regime of interest and also, I will take into account the GARCH-in-mean structure into the SVAR.

In figure (4.6), we have the case of MC. Notice that one standard error positive shock leads to a positive response in both cases; hence, there is an increase in Expected Inflation. Therefore, a one standard error positive leads to a shock of almost 0.20% in the annualized growth rate of MC, and the effect will last for 12 quarters. Additionally, one standard error positive shock in MC will lead to a 0.025% increase in the changes of FFR. In contrast, as depicted in figure (4.7), a one standard error positive shock leads to a negative reaction in both cases; in particular, the bottom plot shows a response of -0.12% annual change in the FFR, and then the convergences will happen at a higher level.

By analysing figures (4.6) and (4.7), it is possible to conclude that the effect of an FFR shock is higher than an MC shock, however the opposite when I use DM. By comparing the baseline model presented in section (3.2.), a complete structure matter to observe the liquidity effect for DM; nonetheless, the expected inflation is present for MC.

Finally, I can conclude that the Friedman-Cagan Effect weakens during the recessions in a complete model by considering the smoothed probabilities. And the Regime dependent Impulse Responses indicate that the transmission of the monetary policy differs from DM and MC, which lead me to conclude that foreign holdings are important to define the transmission mechanism.

Figure 4.6 Impulse Response for Friedman-Cagan Effect (Expected Inflation Effect) Regime

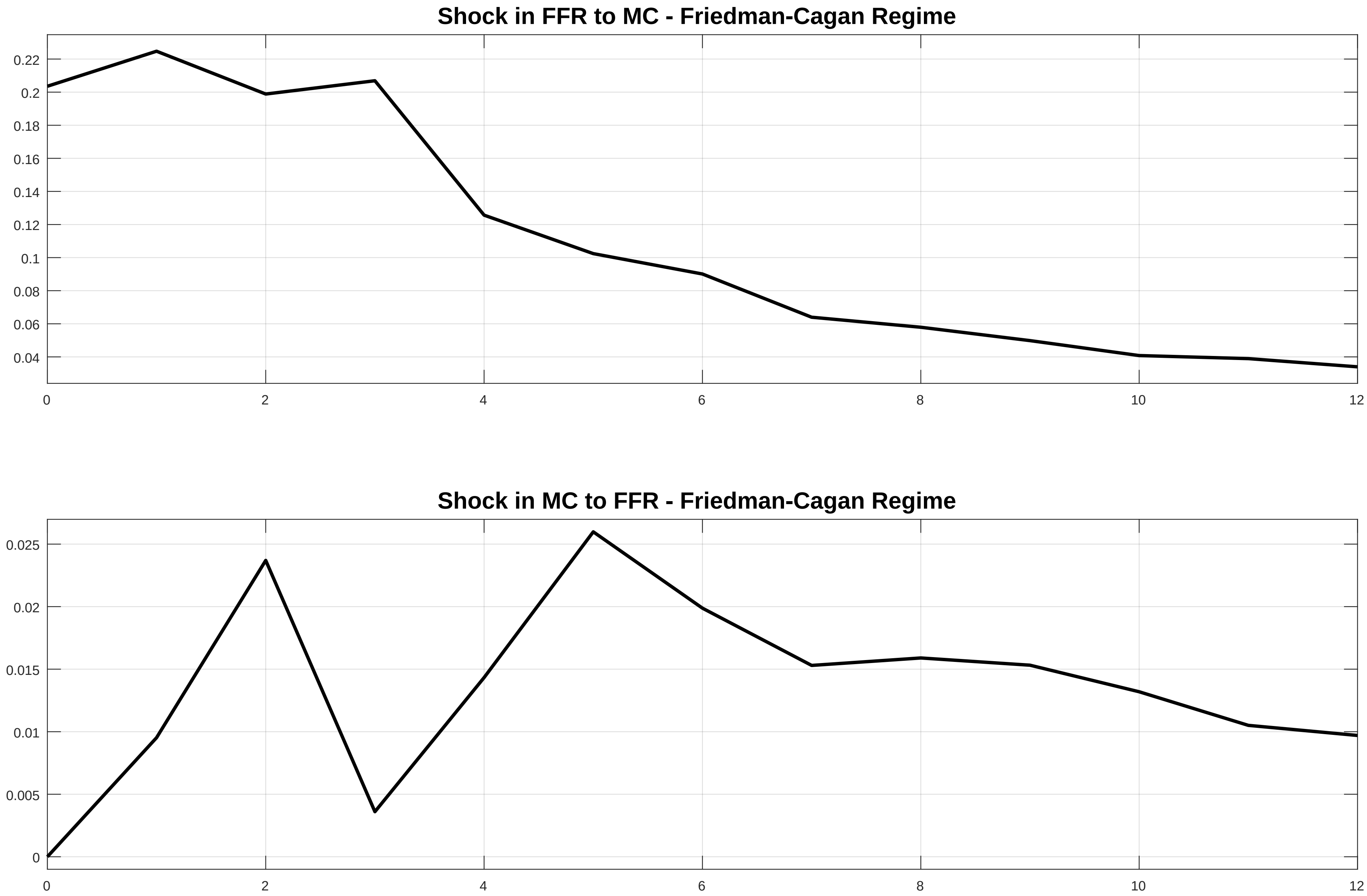
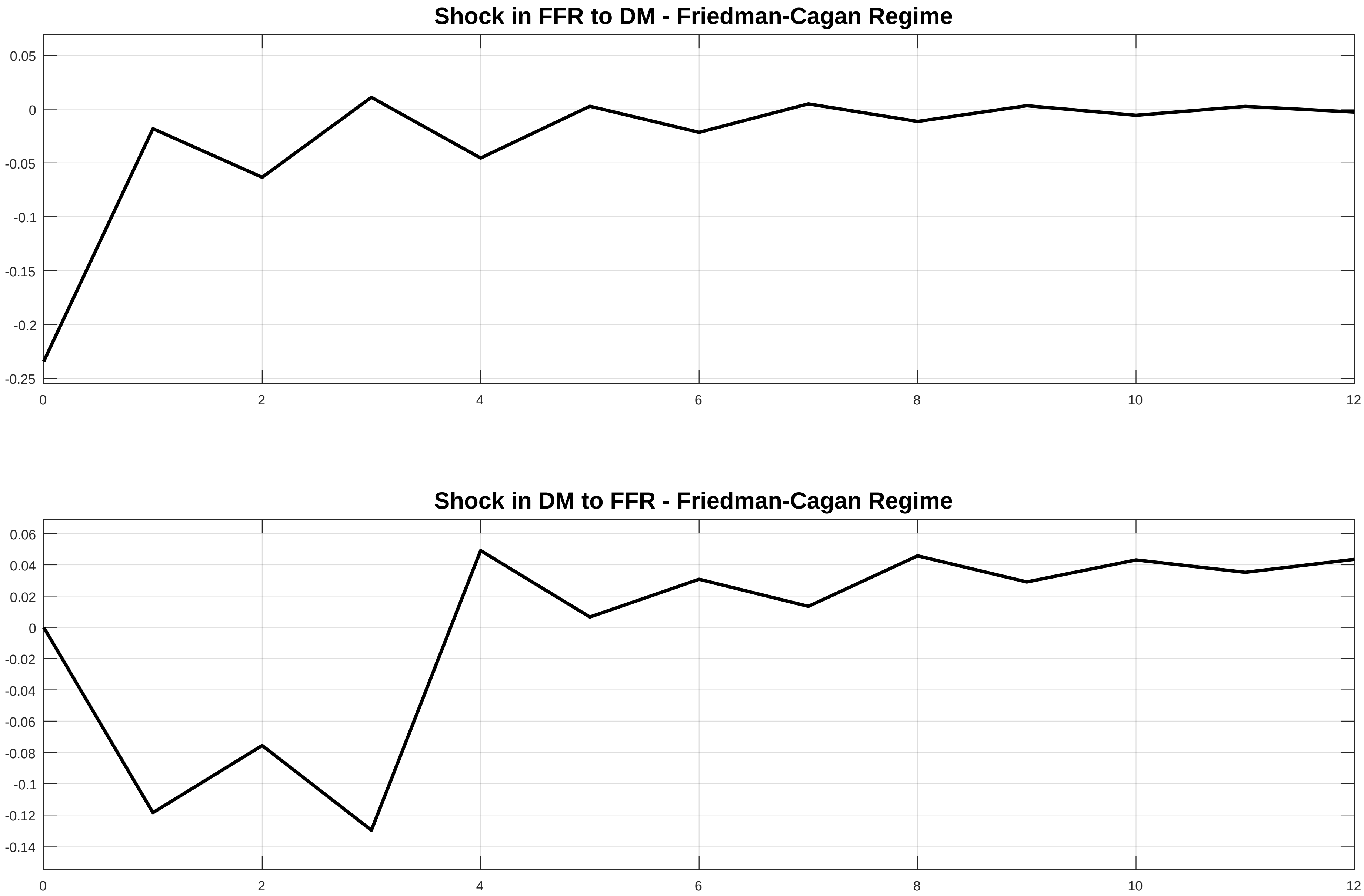


Figure 4.7 Impulse Response for Friedman-Cagan Effect (Liquidity Effect) Regime



4. Broad Definition of Money

Although it is very well documented that the FED does not fully control M1 and M2, for instance, by Bryant (1983) and Gordon and Leeper (1994), many authors such as Meltzer (1963), Cagan (1966) and Cochrane (1989) have used those variables to capture the liquidity effect. For the sake of completeness I will consider these two variables in the complete model.

The estimation results are below.

Table 4.6 Estimation Results

			M1	M2
Causal Parameters	$\psi^{(k_1)}_{M\to R}$ Friedman-Cagan Effect	$\psi_1^{(1)}$	0.0000 (0.0138)	0.1243 (0.1312)
		$\psi_1^{(2)}$	0.0058 (0.0128)	0.0780 (0.1295)
		$\psi_1^{(3)}$	0.0067 (0.0112)	-0.1172 (0.1246)
		$\psi_1^{(4)}$	0.0104 (0.0103)	0.3438* (0.2328)
	$\psi^{(k_1)}_{R\to M}$	$\psi_2^{(1)}$	-1.0205*** (0.3051)	-0.6259*** (0.2196)
		$\psi_2^{(2)}$	-0.2816 (0.2859)	-0.1603 (0.3979)
		$\psi_2^{(3)}$	-0.2550 (0.3317)	-0.3056 (0.2992)
		$\psi_2^{(4)}$	0.0181 (0.1962)	0.1894 (0.2341)

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Notice in Table (4.6) that Friedman-Cagan Effect is weakly present in M2 but not in M1. Among others, Gordon and Leeper (1994) also documented a similar result. Regarding the Duration, M2 seems to be more persistent than M1, except for the bi-directional causality ($ED_{M\leftrightarrow R}$). As will be evident from the smoothed probabilities, Figures (4.8) and (4.9), the plots for M1 seems to be much more unstable than M2.

Table 4.7 Duration Results

		M1		M2	
		ED[b]	RD[c]	ED[b]	RD[c]
GC[a]	$ED_{M\leftrightarrow R}$	5.42	146	3.86	16
	$ED_{R\rightarrow M}$	2.51	30	9.14	81
	$ED_{M\rightarrow r}$	1.07	15	3.83	16
	$ED_{R\nleftrightarrow M}$	1.05	6	8.96	76

[a] GC stands for Granger Causality .
[b] ED stands for Expected Duration - How many quarters the regime is expected to last.
[c] RD stands for Realized Duration - How many quarters the regime lasted.

In Table (4.8), it is possible to observe that the cross Surprise Effect happens in three situations. For M1, as ξ_{102} and ξ_{201} are significant, then the surprise effect of M1 on FFR occurs in Regimes 2 and 4, additionally the surprise effect FFR on M1 in Regimes 3 and 4. For the case of M2, ξ_{202} is significant; therefore, the surprise effect of FFR on M2 happens in Regimes 3 and 4. This results is also expected as it indicates that the FED has limited control of M1 and M2, and hence, those variables might not be the correct choice for policies like Forward Guidance.

Table 4.8 Policy Uncertainty Results - Surprise Effect

		$\sigma_{1,t}$	$\sigma_{2,t}$	M1		M2		
Policy Uncertainty	Regime 1	$\xi_{101}+\xi_{111}$	$\xi_{102}+\xi_{112}$	0.1550	-0.0160	-0.8007**	0.1598	R_t
				(0.1523)	(0.0197)	(0.4863)	(1.0822)	
		$\xi_{201}+\xi_{211}$	$\xi_{202}+\xi_{212}$	0.1136	-0.2868**	0.0237	0.4620	M_t
				(0.3441)	(0.1500)	(0.1823)	(1.1994)	
	Regime 2	ξ_{101}	ξ_{102}	0.8857***	0.1290*	-0.1175	-0.2229	R_t
				(0.3070)	(0.0836)	(0.1641)	(0.4572)	
		$\xi_{201}+\xi_{211}$	$\xi_{202}+\xi_{212}$	0.1136	-0.2868**	0.0237	0.4620	M_t
				(0.3441)	(0.1500)	(0.1823)	(1.1994)	
	Regime 3 Friedman-Cagan Effect	$\xi_{101}+\xi_{111}$	$\xi_{102}+\xi_{112}$	0.1550	-0.0160	-0.8007**	0.1598	R_t
				(0.1523)	(0.0197)	(0.4863)	(1.0822)	
		ξ_{201}	ξ_{202}	-4.8188*	-0.0410	-0.7409*	0.5279	M_t
				(3.5044)	(1.3597)	(0.4879)	(1.0311)	
	Regime 4	ξ_{101}	ξ_{102}	0.8857***	0.1290*	-0.1175	-0.2229	R_t
				(0.3070)	(0.0836)	(0.1641)	(0.4572)	
		ξ_{201}	ξ_{202}	-4.8188*	-0.0410	-0.7409*	0.5279	M_t
				(3.5044)	(1.3597)	(0.4879)	(1.0311)	

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Figure 4.8 Smoothed Probabilities for Temporary Granger Causality

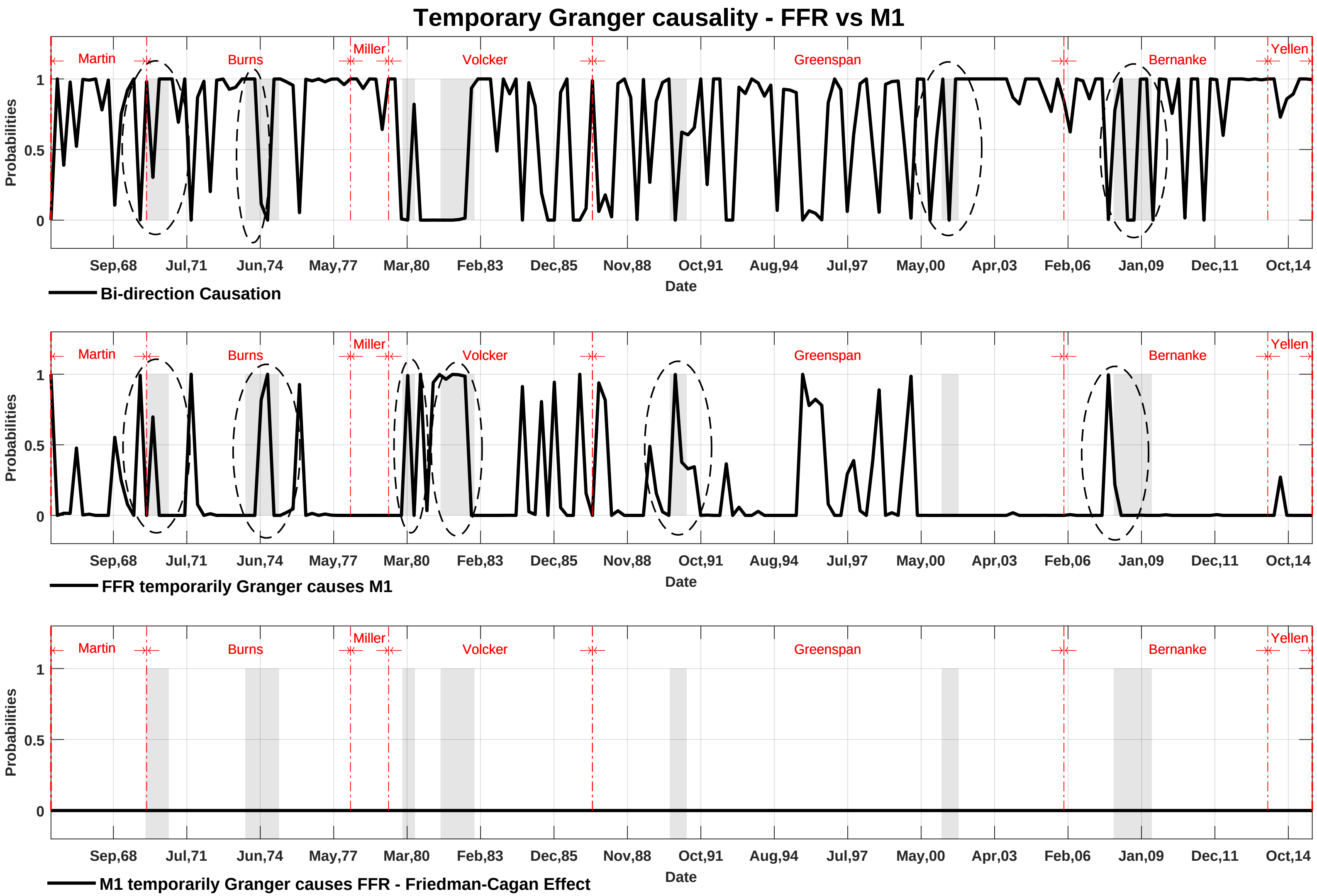
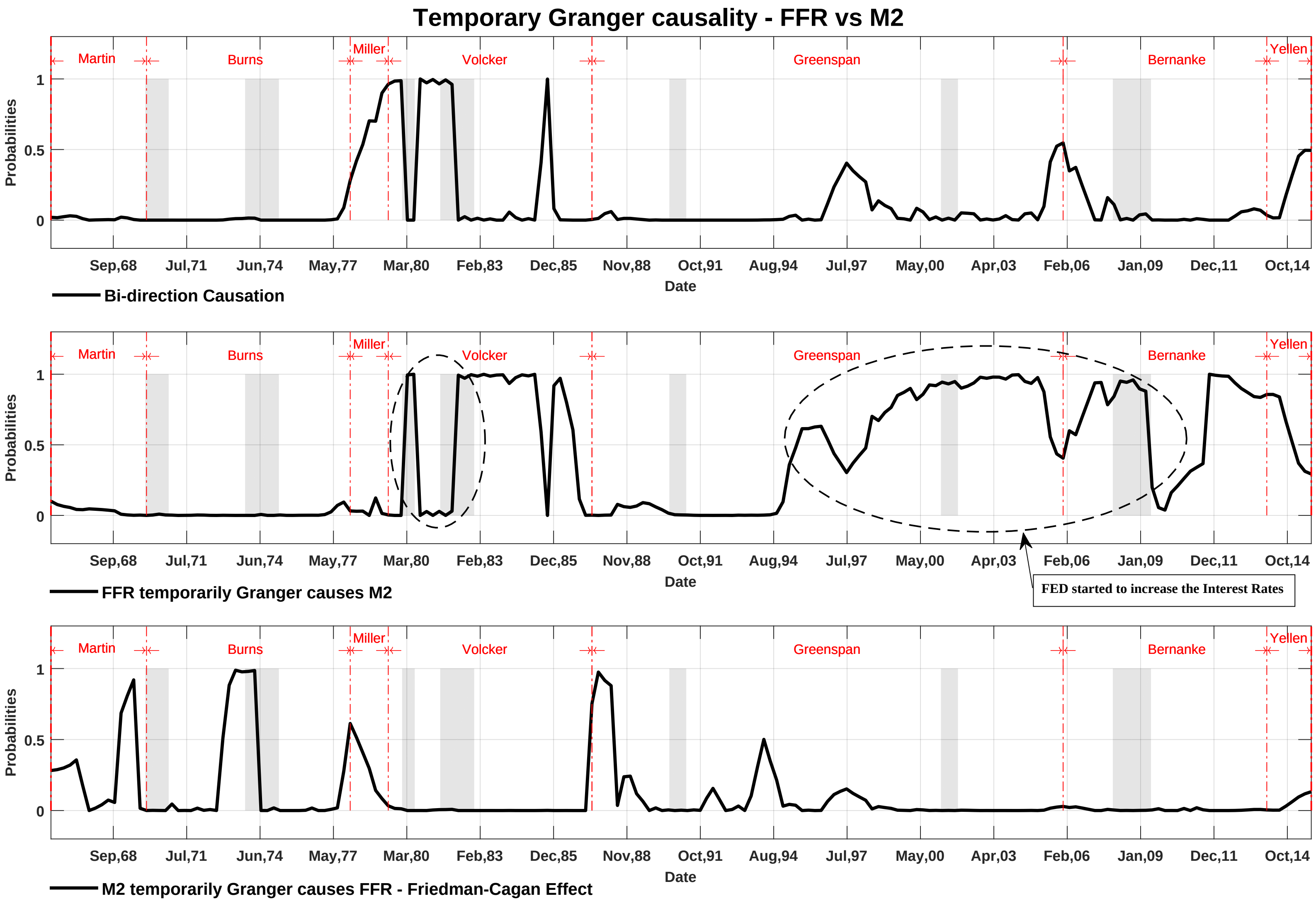


Figure 4.9 Smoothed Probabilities for Temporary Granger Causality



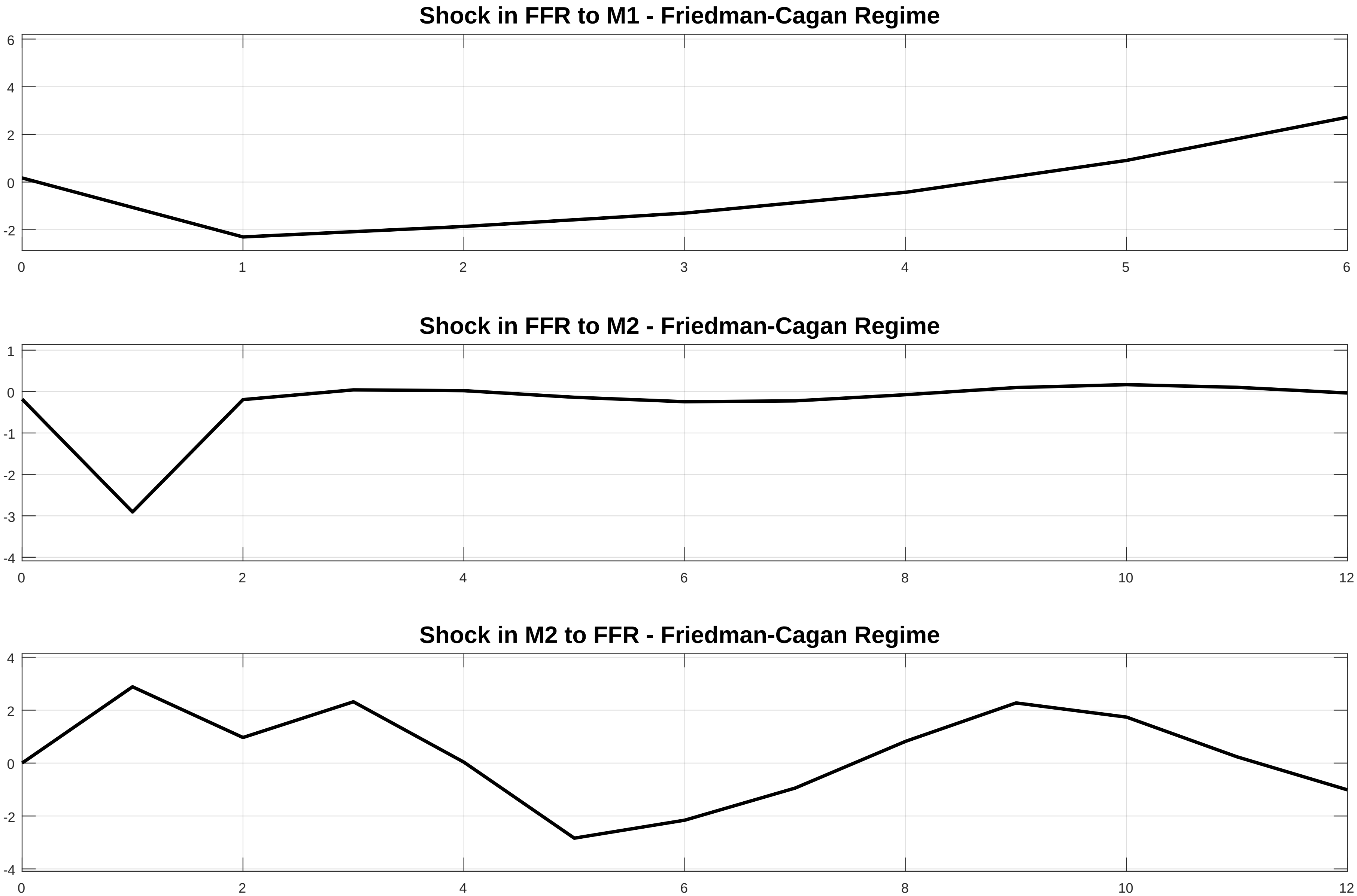
Finally, figures (4.8) and (4.9) show the Smoothed Probabilities for M1 and M2. Notice that in figure (4.8), the Friedman-Cagan Effect Regime reflects the change in the autoregressive parameters, not the Granger causality pattern, because the $\psi_1^{(k_1)}$ parameters are not significant. Therefore, I will consider the smoothed probability of the Friedman-Cagan effect to be zero (the last plot from above).

Differently from the cases of MC and DM, the Friedman-Cagan Effect for M1 and M2 is either not present or happens during some periods of the sample (case of M2), which in principle is not consistent with any stylized facts.

For the case where FFR temporarily causes Money, it seems that recessions trigger this Granger causality pattern (Ellipses in the plot). Nonetheless, for both cases, this conclusion can be very difficult to draw. For M1, the smoothed probabilities vary considerably; therefore, any shock can trigger a change in the regimes. For M2, at the beginning of the 80s, the recession seems to have trigged this Granger Causality pattern. Ultimately lasted until the beginning of Grenspam tenure. The second large period that FFR Granger Caused M2 started in 1994 after the FED had raised the interest rates six times over that year after a stock market boom. Essentially, this Granger Causality pattern lasted until the end of the Great Recession (from 2007 to 2009).Furthermore, based on the Smoothed Probabilities of M1 and M2, it is possible to conclude that changes in FFR are absorbed by the other components of these definitions of money, for instance, the savings deposits of M2. Ultimatelly, it is not related to the open market operations.

Finally, we need to check which effect was dominated. In Figure (4.10), I added the Impulse Responses for M1 and M2. Because M1 did not present the Friedman-Cagan Effect, there is no reason to plot this Impulse Response. The first and second plots show the Impulse Responses of a standard deviation shock in FFR to M1 and M2. For M2, the Expected Inflation Effect dominates the Liquidity Effect because one standard deviation shock in M2 increases the change of FFR by 3%. Additionally, one standard deviation shock in FFR decreases the growth rates of M2 by 3%. Moreover, it is important to notice that an explosive pattern is also present for the case of M1, once again in line with collapsing bubble literature.

Figure 4.10 Impulse Response for Liquidity Effect Regime



5. Conclusions

In this paper, I provide an econometric model for analyzing the relationship between a monetary aggregate and Federal Funds Rate. The paper deals with the sample period sensitivity by endogenizing the Granger Causality pattern in a Vector Autoregression. This method also incorporates a surprise effect by conditioning the model on time-varying predicted volatility. Primarily, for measuring the so-called, Friedman-Cagan Effect, I use the Federal Funds Rates, specifically the shadow rates, and either the currency component of M1 (MC) and MC corrected by foreign holding(DM). Additionally, also two other broader monetary aggregates, M1 and M2.

The findings of this paper are consistent with the theoretical literature and also with some empirical literature. Nonetheless, the results reveal that: (1) The Friedman-Cagan Effect can be separated by regimes, and this effect weakens during the recession periods. (2) Although the literature on Liquidity Effect does not support this effect for quarterly data, by constructing the impulse responses conditional on a particular regime, the currency component of M1 adjusted by US Dollars' foreign holdings (DM) is present in. However, MC is associated with Expected Inflation effect. Moreover, the broad definitions of money either show the Expected Inflation Effect or does not present the Friedman-Cagan Effect.(3) Finally, the results for a broad definition of money suggest that an expansionary or contractionary monetary policy could eventually lead to economic explosiveness. Nevertheless, this explosiveness does not last for long periods due to monetary policy, and these results align with the collapsing bubbles literature.

Chapter 5

Conclusion

This thesis presents some theoretical contributions to the literature on Granger causality in the presence of structural change, together with some macroeconomic and finance applications

The first main chapter sheds some light on the historical Granger causality regimes of the U.S. monetary policy and the role of the seven U.S. Fed chairpersons. This chapter aims to focuses explicitly on the time-varying nonlinear causal information content in two potential monetary policy instruments, Federal Funds Rate (FFR) and Domestic Money (DM), to explain variations in U.S. real output and inflation and vice versa; hence the use of the notion of regime-dependent Granger causality.

The econometric model used identifies episodes of temporary Granger Causality among all variables throughout the sample period from 1965 to 2016. Additionally, the model identifies nonlinear Granger causality regimes with the corresponding U.S. Fed's Chairperson's tenure. The mapping allows for the evaluation of changes in possible policy instrument preferences (FFR or DM) associated with the policymaker in charge of the U.S. monetary policy at the time. Finally, the results of this model also indicate that well-known shocks generate the shift mechanism from one pattern of Granger causality to another, particularly the shocks identified by Romer and Romer (1989); and most importantly, there is a clear shift in terms of the monetary instrument after 2008, in the event of the zero lower bound. These findings are aligned with Bernanke and Reinhart (2004) discussion on alternative instruments for monetary policy during events of very low short-term interest rates.

The second chapter extends the analysis to allow for likelihood functions that are more flexible than the Gaussian and hence potentially more useful for financial data. This chapter uses the GED (Generalized Error) Distribution and examines the relationship between bond yields and stock returns for eight European countries for the application. Two main conclusions emerge from the empirical analysis: First, there is a clear co-movement in the Granger causality direction among the eight European countries, and most importantly, the co-movement is directly related to the stylized facts, for instance, the Financial Crisis. Second, these results, to some extent, can be considered evidence of contagion.

Additionally, the chapter contributes to the empirical finance literature in three ways. First, the exact dates when there are shifts in the causality are found. Second, although the markets are very integrated, the chapter provides evidence that a global (or regional) crisis affects the countries heterogeneously. Third, in terms of price discovery, the evidence indicates that the direction of the causality is mostly from the stock returns to the first difference in sovereign bond yield. The results indicate that economic events, whether they are global or country-specific, can trigger reversals in the causality between these two variables. Additionally, these results contradict the common knowledge that the stock markets always lead the bond markets. The results suggest that the direction of the causality depends on the period, country and nature of the crisis. For instance, the changes in sovereign bond yields cause stock returns in some periods in all countries except Germany.

Finally, the third chapter incorporates time-varying volatility into the econometric framework. The model may be viewed as a multivariate version of a so-called GARCH-*in-Mean*. A bivariate vector autoregression, using federal funds rate and a narrow definition of monetary aggregates, such as currency component of M1 and Domestic Money is estimated. The aim of estimating this bivariate vector autoregression it is to capture the Friedman-Cagan Effect empirically, and more specifically the Liquidity Effect.

The main findings of the empirical analysis are: Friedman-Cagan Effect is triggered by recessions, and the results are robust regardless of whether the currency component of M1 or DM are used. One explanation for this is that central banks may use monetary policy during recessions to stimulate the economy by increasing the rate of change of the money supply, ultimately reducing the downturn and preventing a more severe contraction. Additionally, the impulse response functions are computed. Considering the impulse response functions, it is also possible to conclude that the Liquidity Effect is present in domestic money but not in the currency component of M1, even if the vector autoregression is conditioned on inflation. One possible explanation that may be given for why the currency component of M1 does not observe the Liquidity Effect is because this monetary aggregate contains U.S. Dollars' foreign holdings, which are removed by domestic money.

Furthermore, results for a broad definition of money, such as M1 and M2, are ambiguous, and according to the literature, this is because central banks do not have full control of M1 and M2; therefore the results of these variables could not represent the Liquidity Effect.

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Appendix A

Appendix - Chapter 1

0.1. Data Description

-For Domestic Money

- Rest of the world; currency; asset, Level, Millions of Dollars, Quarterly, Not Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (ROWCURQ027S)
- Currency Component of M1, Billions of Dollars, Quarterly, Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (CURRSL)

-For Interest rate

- Effective Federal Funds Rate, Percent, Quarterly (End of the Period from Daily -DFF), Not Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (DFF)
- Shadow rates (Estimated): From January of 2009 - Source: Center for quantitative economic research -Federal Reserve of Atlanta

-For other monetary aggregates

- M2 Money Stock, Billions of Dollars, Quarterly, Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (M2)
- Divisia M4 - Source: Center for Financial Stability

-For other Macroeconomic aggregates

- Real GDP - Real Gross Domestic Product, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate -Source: FRED, Federal Reserve Bank of St. Louis (GDPC96) - Vintage: 29/26/2017
- Inflation - Gross Domestic Product: Implicit Price Deflator, Index 2009=100, Quarterly, Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (GDPDEF)

0.2. Additional Results

Temporary Causality

		FFR	ΔDM	$\Delta M2$	$\Delta DivisiaM4$	
y	μ_{10}	1.1154** (0.5276)	1.5709*** (0.5051)	1.4324*** (0.3583)	1.3051*** (0.5395)	Mean Parameters
	μ_{11}	1.6686* (1.1939)	-1.2800 (1.1363)	3.3117*** (1.2205)	-8.3433* (5.1485)	
π	μ_{20}	0.8243*** (0.1511)	1.0523*** (0.3414)	0.6926*** (0.1967)	0.7305*** (0.2224)	
	μ_{21}	-0.5144 (0.4772)	-1.6661*** (0.4655)	-0.2337 (0.4493)	0.3986 (1.0616)	
m	μ_{30}	0.0353 (0.0589)	4.6067*** (1.2282)	6.2695*** (1.5924)	7.9079** (4.1472)	
	μ_{31}	-1.0210*** (0.4169)	5.4725*** (1.7714)	-4.6537*** (1.8266)	-4.0717 (4.3203)	
y	$\mathscr{P}^{(1)}_{0,0}$	0.9839*** (0.0173)	0.9786*** (0.0199)	0.9937*** (0.0199)	0.9759*** (0.0479)	Transition Probabilities
	$\mathscr{P}^{(1)}_{1,1}$	0.9844*** (0.0181)	0.9665*** (0.0401)	0.9955*** (0.0187)	0.9941*** (0.0150)	
π	$\mathscr{P}^{(2)}_{0,0}$	0.9248*** (0.0429)	0.9645*** (0.0348)	0.8561*** (0.0755)	0.9759*** (0.0601)	
	$\mathscr{P}^{(2)}_{1,1}$	0.9345*** (0.0408)	0.9760*** (0.0208)	0.9497*** (0.0364)	0.9868*** (0.0295)	
m	$\mathscr{P}^{(3)}_{0,0}$	0.9571*** (0.0346)	0.9796*** (0.0349)	0.9858*** (0.0260)	0.9878*** (0.0356)	
	$\mathscr{P}^{(3)}_{1,1}$	0.9333*** (0.0422)	0.9869*** (0.0224)	0.9525*** (0.0502)	0.9706*** (0.0676)	

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Table A.1 Results for Mean Parameters and Probabilities

		FFR	ΔDM	$\Delta M2$	$\Delta DivisiaM4$	
y	$\phi_{10}^{(1)}$	0.4992***	0.2468**	0.3194***	0.3012***	Autoregressive Parameters
		(0.1473)	(0.1114)	(0.0976)	(0.1057)	
	$\phi_{11}^{(1)}$	-0.3675**	0.0752	-0.7199***	-0.4378*	
		(0.2089)	(0.1724)	(0.2004)	(0.3404)	
	$\phi_{10}^{(2)}$	0.0919	0.0293	0.1592*	0.2734***	
		(0.1397)	(0.1192)	(0.0982)	(0.1081)	
	$\phi_{11}^{(2)}$	0.0071	0.2711*	-0.0446	-0.0458	
		(0.2353)	(0.1923)	(0.2149)	(0.2670)	
π	$\phi_{20}^{(1)}$	0.5370***	0.3752**	0.3570***	0.4831***	
		(0.0963)	(0.2079)	(0.0726)	(0.0911)	
	$\phi_{21}^{(1)}$	0.0705	0.3384	0.3536**	0.0696	
		(0.1859)	(0.2141)	(0.1761)	(0.2643)	
	$\phi_{20}^{(2)}$	0.1103*	0.0358*	0.3395***	0.2018**	
		(0.0738)	(0.1931)	(0.0768)	(0.1014)	
	$\phi_{21}^{(2)}$	0.2546*	0.1634	-0.1871	-0.0256	
		(0.1965)	(0.2004)	(0.1798)	(0.2247)	
m	$\phi_{30}^{(1)}$	0.3852***	0.1821*	0.4234**	-0.0264	
		(0.0981)	(0.1181)	(0.2164)	(0.4416)	
	$\phi_{31}^{(1)}$	-0.6687***	-0.4250**	0.3591*	0.5097	
		(0.1540)	(0.2207)	(0.2400)	(0.4504)	
	$\phi_{30}^{(2)}$	0.0050	0.1857**	-0.1012	0.1289	
		(0.0659)	(0.1036)	(0.2141)	(0.2538)	
	$\phi_{31}^{(2)}$	-0.3018***	-0.7443***	0.0126	-0.0239	
		(0.1270)	(0.1679)	(0.2336)	(0.2713)	
Log-likelihood		-444.8361	-601.5506	-599.5977	-648.3909	

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Table A.2 Results for Autoregressive Parameters

Dominant Regime

	Policy Instrument	Fed Chair's Tenure → Martin	Burns	Miller	Volcker	Greenspan	Bernanke	Yellen
Output Regime	FFR	0.0%	62.5%	100.0%	37.50%	71.6%	78.1%	100.0%
	DM	0.0%	0.0%	0.0%	53.1%	59.5%	9.4%	57.1%
	M2	100.0%	78.1%	16.7%	0.0%	14.9%	3.13%	0.0 %
	DM4	33.3%	100.0%	100.0%	18.8%	9.5%	6.5%	0.0%
Inflation Regime	FFR	33.3%	96.9%	100.0%	62.5%	0.0%	34.4%	0.0%
	DM	100.0%	100.0%	100.0%	100.0%	63.5%	6.3%	0.0%
	M2	83.3%	75.0%	100.0%	37.5%	0.0%	25.0%	0.0%
	DM4	100.0%	100.0%	50.0%	0.0%	0.0%	0.0%	0.0 %
Monetary Rule Regime	FFR	55.6%	21.9%	16.7%	68.8%	83.8%	0.0%	0.0%
	DM	0.0%	0.0%	0.0%	0.0%	59.5%	100.0%	100.0%
	M2	83.3%	21.9%	0.0%	53.1%	100.0%	84.4%	100.0%
	DM4	66.7%	25.0%	50.0%	81.3%	100.0%	83.9%	100.0%

Table A.3 Dominant Regime

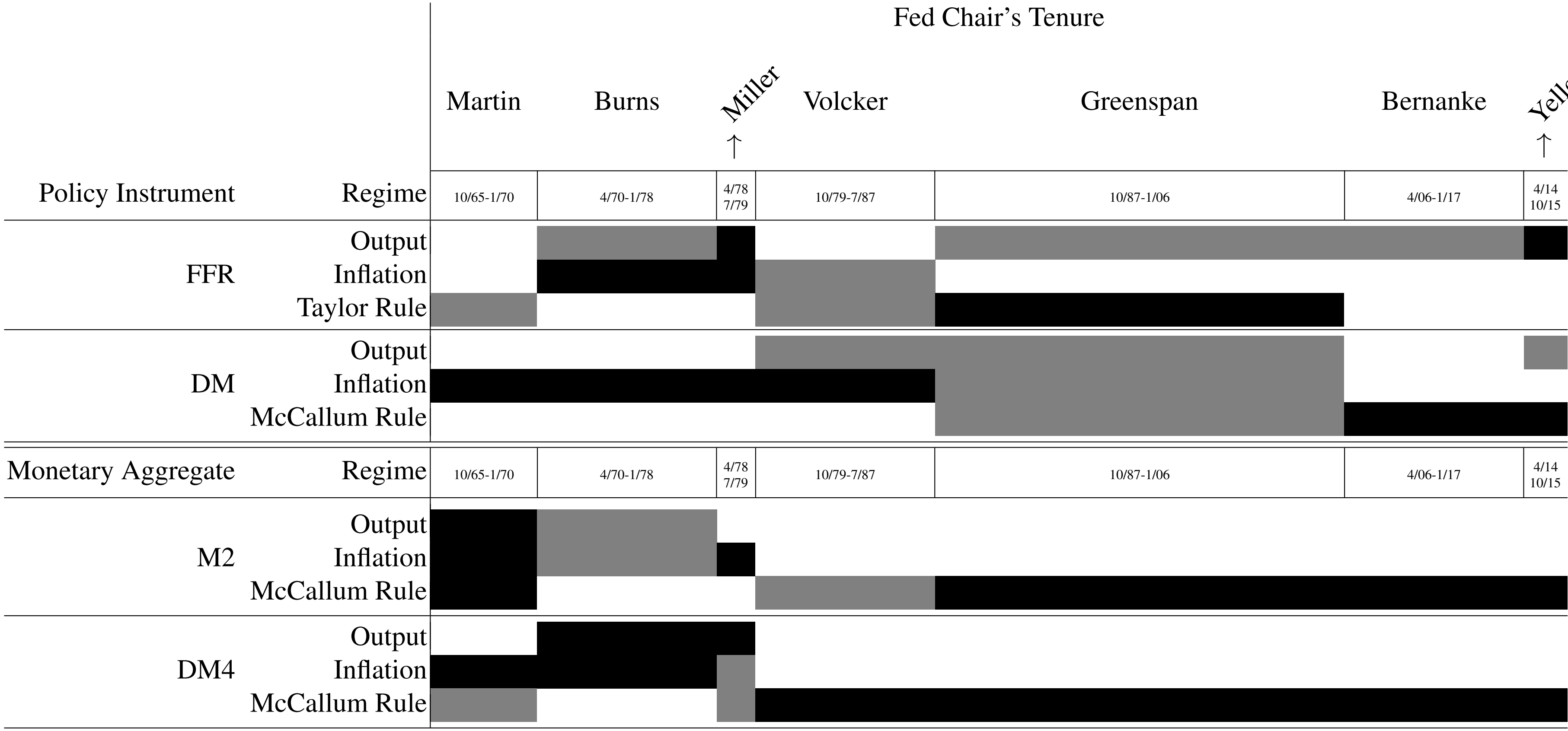


Table A.4 Dominant Regime

In the diagram, the black and the grey bars indicate that the regime dominates more than 80% and 50% respectively.

Regime Separation by Monetary Indicator

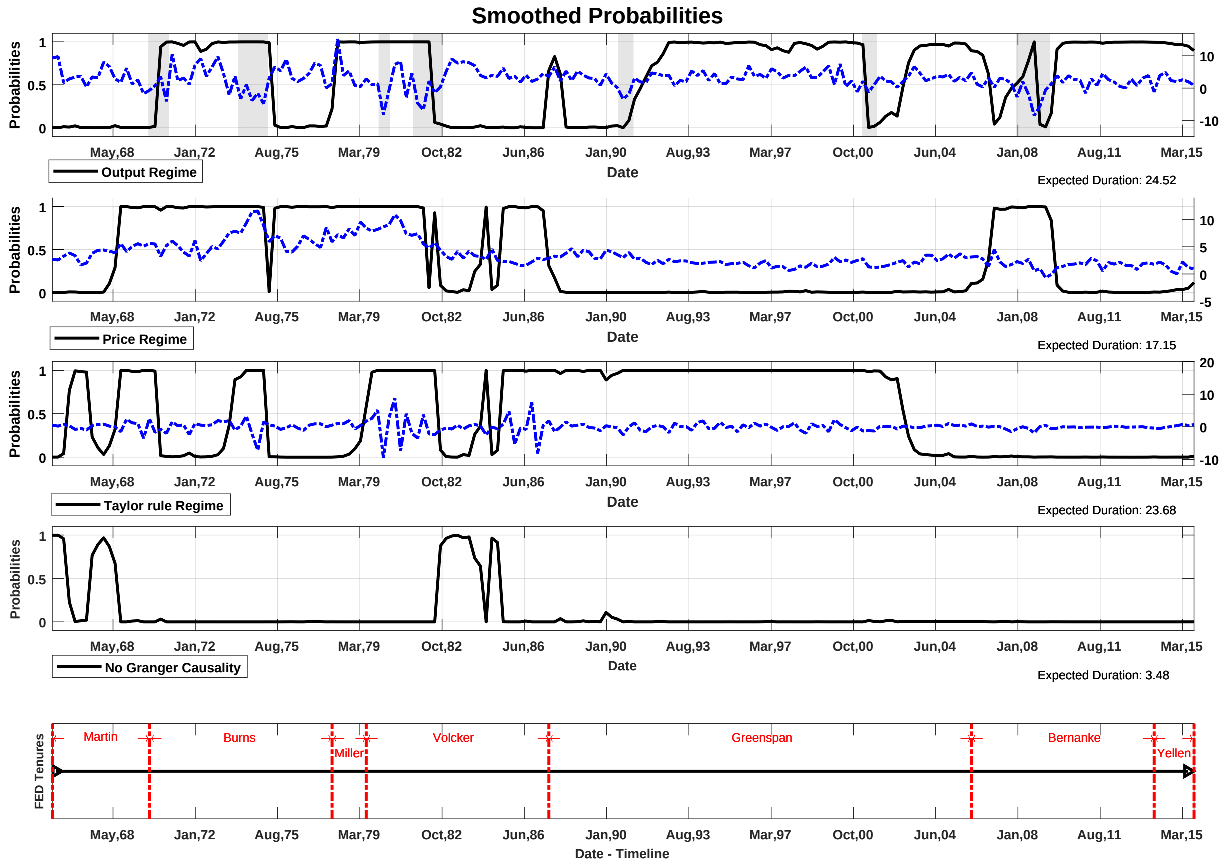


Figure A.1 Smoothed Probabilities for Federal Funds Rate

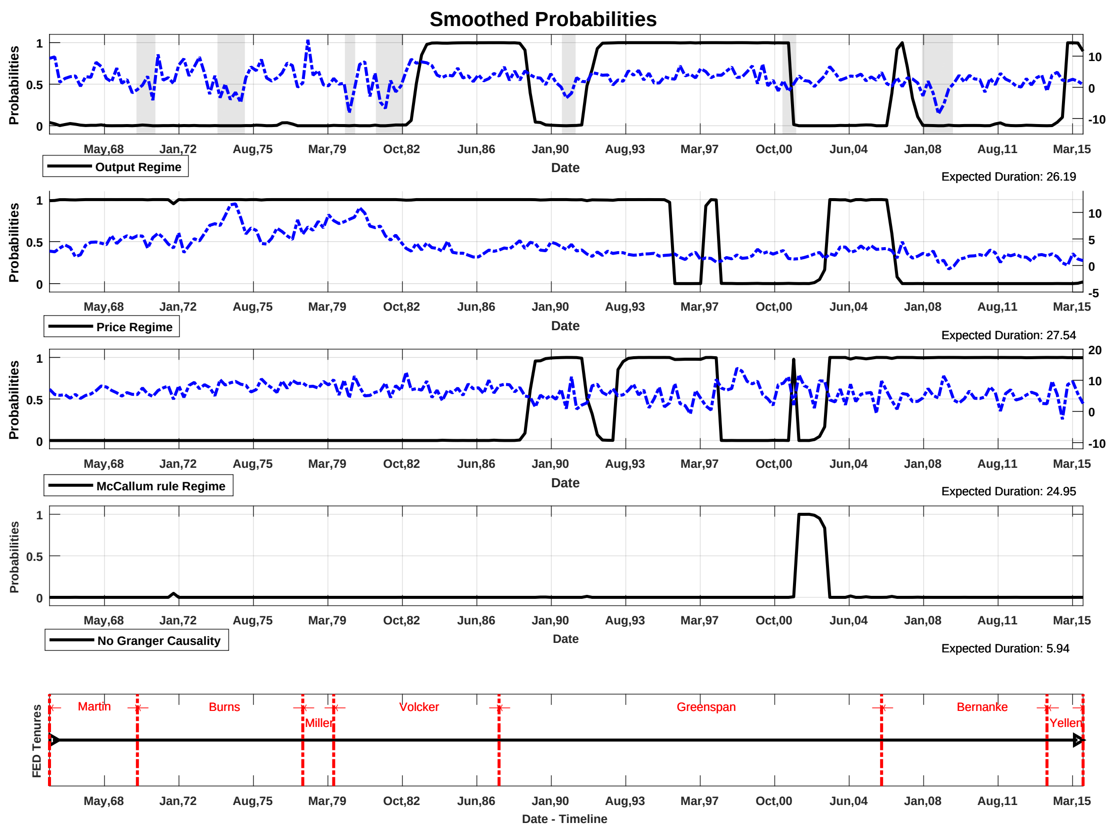


Figure A.2 Smoothed Probabilities for Domestic Money

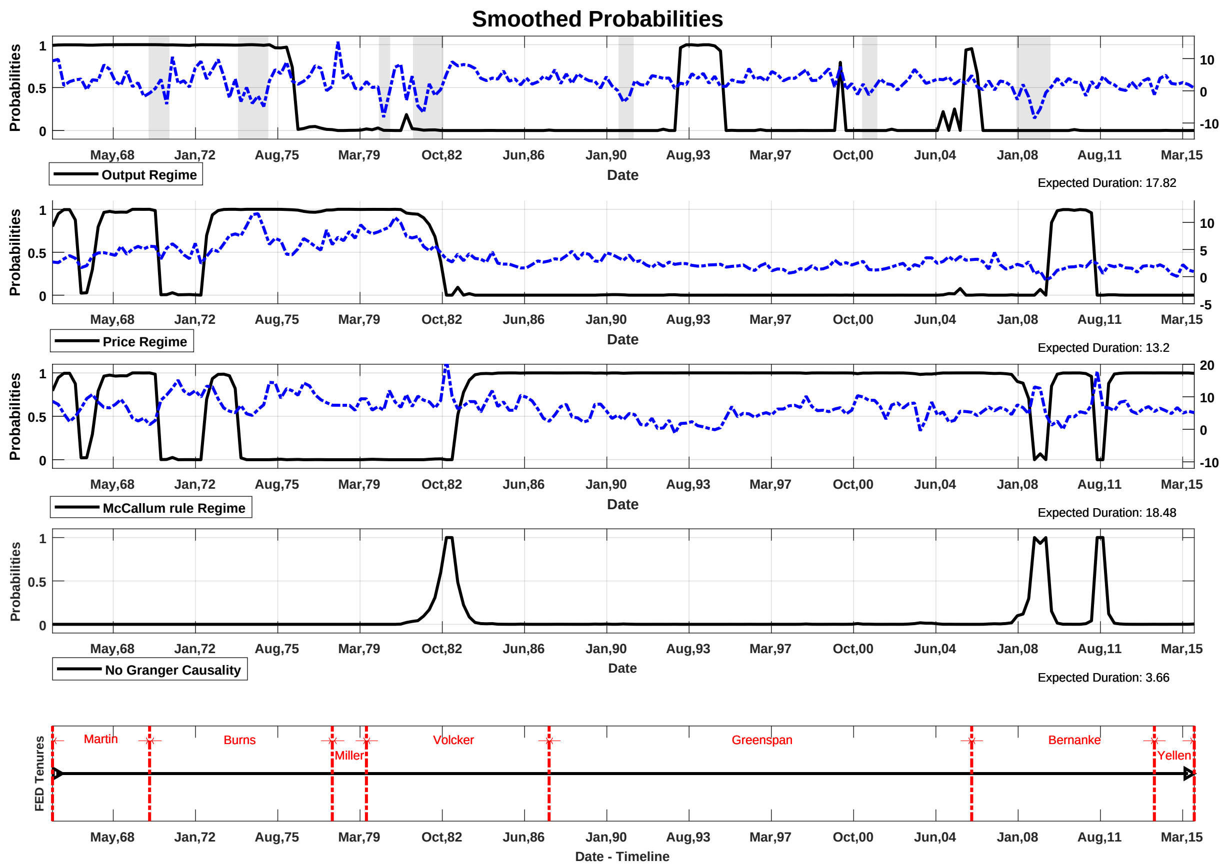


Figure A.3 Smoothed Probabilities for M2

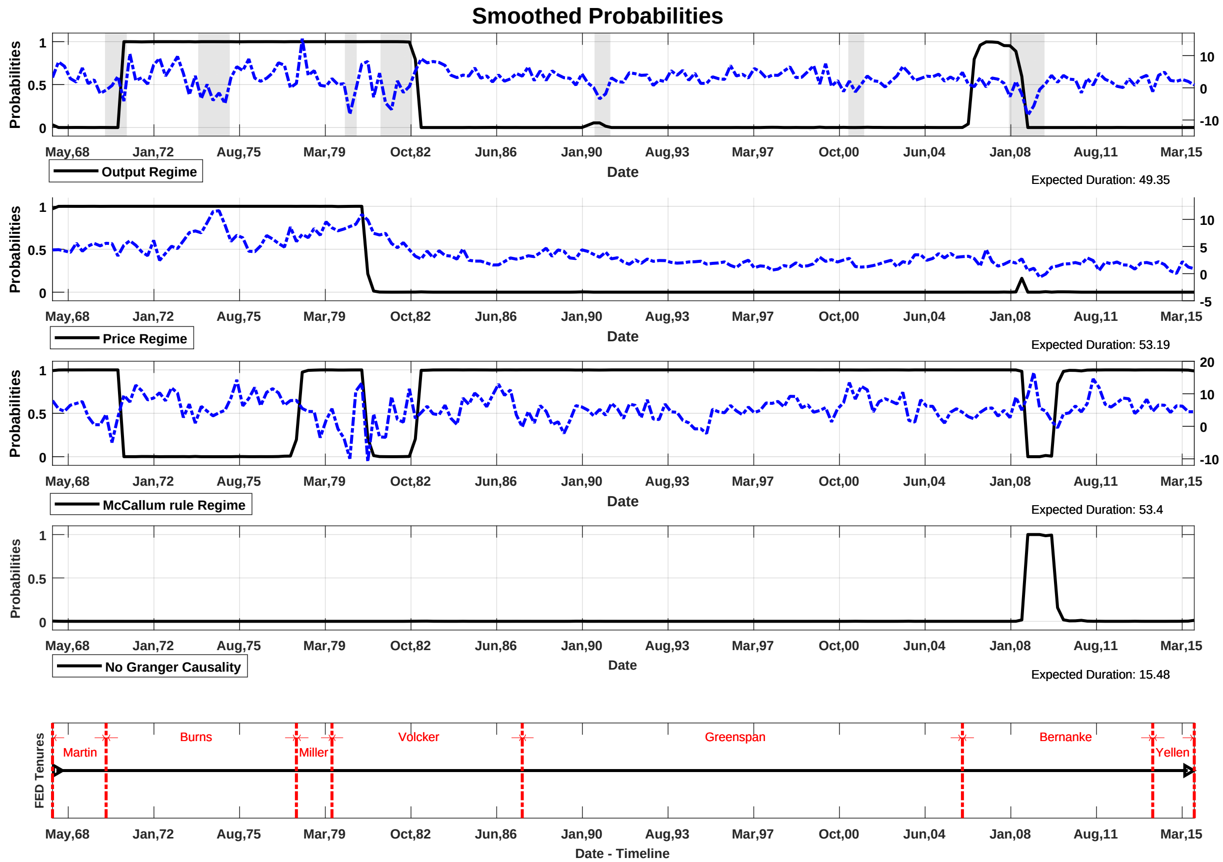


Figure A.4 Smoothed Probabilities for Divisia M4

Subsample Granger Causality Tests

As has been indicated throughout the main text, our modelling approach is designed to handle situations in which conventional full-sample analysis of Granger Causality is inappropriate due to causality patterns being different in different subsamples. As further sensitivity analysis, we now carry out conventional Granger Causality tests in some of the subsamples identified by our MS-VAR models. The subsamples we focus on are those in which at least 20 consecutive quarters are identified, on the basis of the smoothed regime probabilities, as belonging to the same regime. In each subsample, the tests are based on a linear VAR model the order of which is selected by the Akaike information criterion.

The results of the tests can be found in A.5, where, for each monetary variable indicated at the left of the plot, the p-value of a test of no Ganger causality is shown above for each of the subsamples under consideration. It is clear that the results of conventional causality tests are consistent with the causality patterns identified through the regime-switching models. For example, with respect to M2 in the Inflation Regime, the smoothed probabilities indicate no Granger Causality, which is corroborated by the conventional causality test; in the case of DM from 1982 to 2000 and for the Output Regime, both the smoothed probabilities and the conventional test indicate Granger Causality.

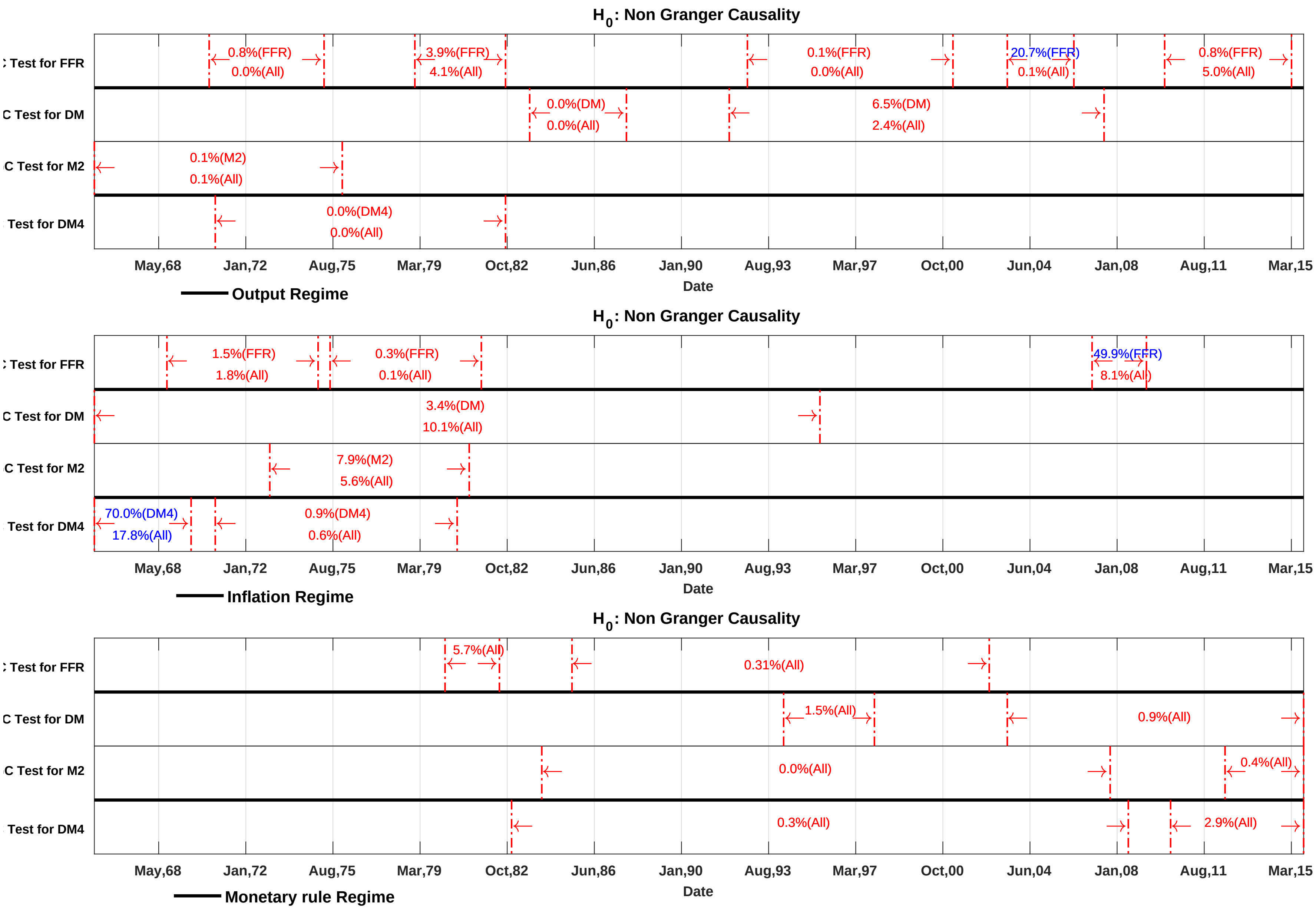


Figure A.5 Block Granger Causality Test for all variables. H_0 : is for No–Granger Causality and the Blocks were defined according to the Smoothed Probabilities estimates.

Unit Root tests

	Variable					
	Δy	$\Delta\pi$	FFR	$\Delta M2$	ΔDM	$\Delta DivisiaM2$
Mean	2.85	3.51	-0.02	6.60	6.28	5.43
Standard Deviation	3.29	2.35	1.90	3.44	2.79	4.01
Unit Root Test	Reject [-10.13]	Reject [-3.90]	Reject [-15.99]	Reject [-6.92]	Reject [-4.06]	Reject [-4.11]

Note: Null of has a Unit root - Rejection rule: $P - Value < 0.05$

Table A.5 Descriptive Statistics and Unit Root Test

Appendix B

Appendix - Chapter 2

0.1. Data

1. Sovereign (government) bond yields: The 10-year sovereign bond yields are obtained from the Datastream. The weekly data are generally for the last trading day of the week. Changes are defined as the first differences of the sovereign bond yields. (ΔYLD)

2. Stock Index Returns: The stock market returns are the weekly weighted return obtained from the Datastream. Stock returns are defined as the logarithmic changes of the stock index and the numbers have been multiplied by 100 to express the index's return as a percentage. (R_t= Log of Stock Price) (ΔR_t = Stock Returns)

Figure B.1 Changes in Sovereign Bond Yields, All Countries

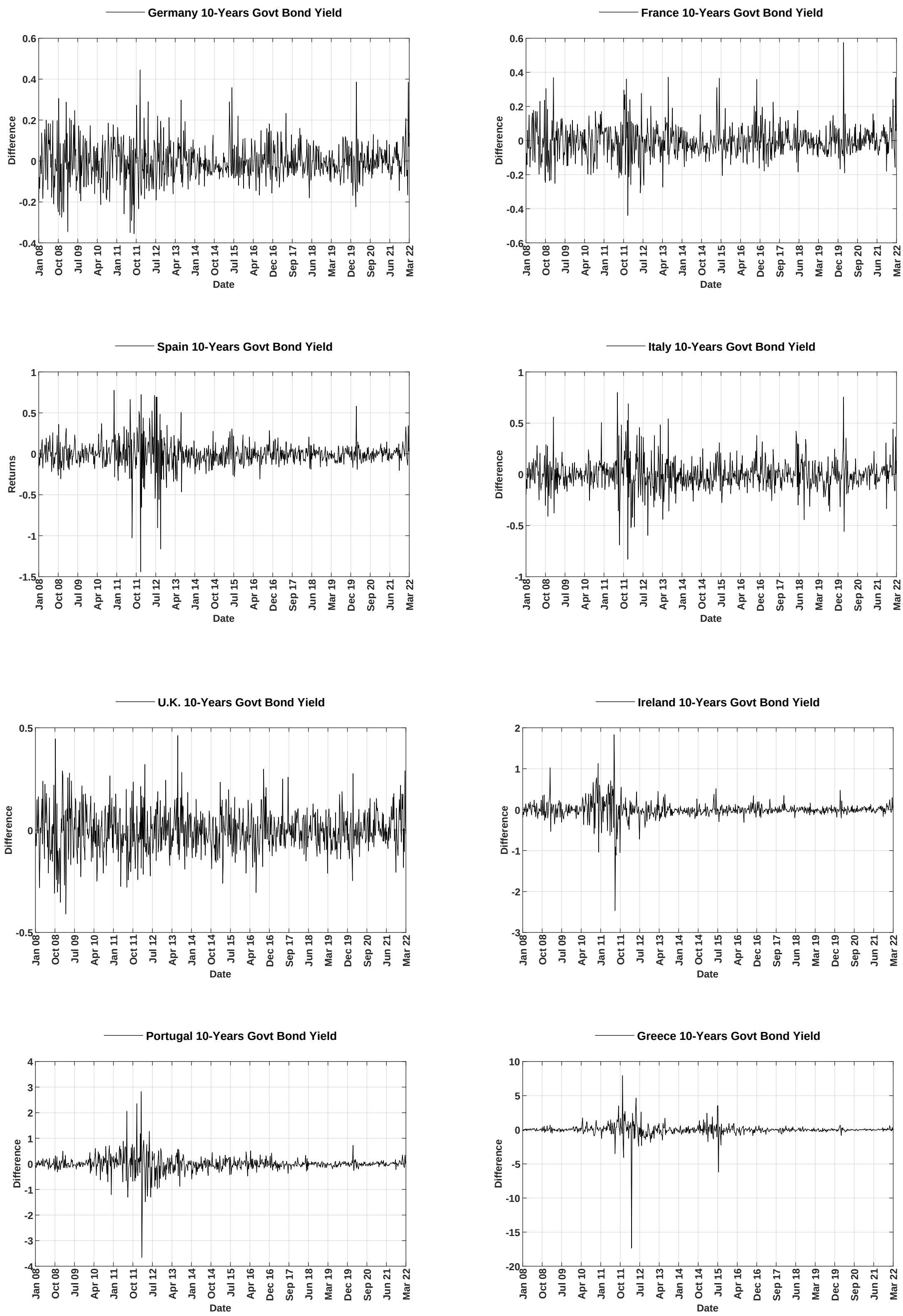
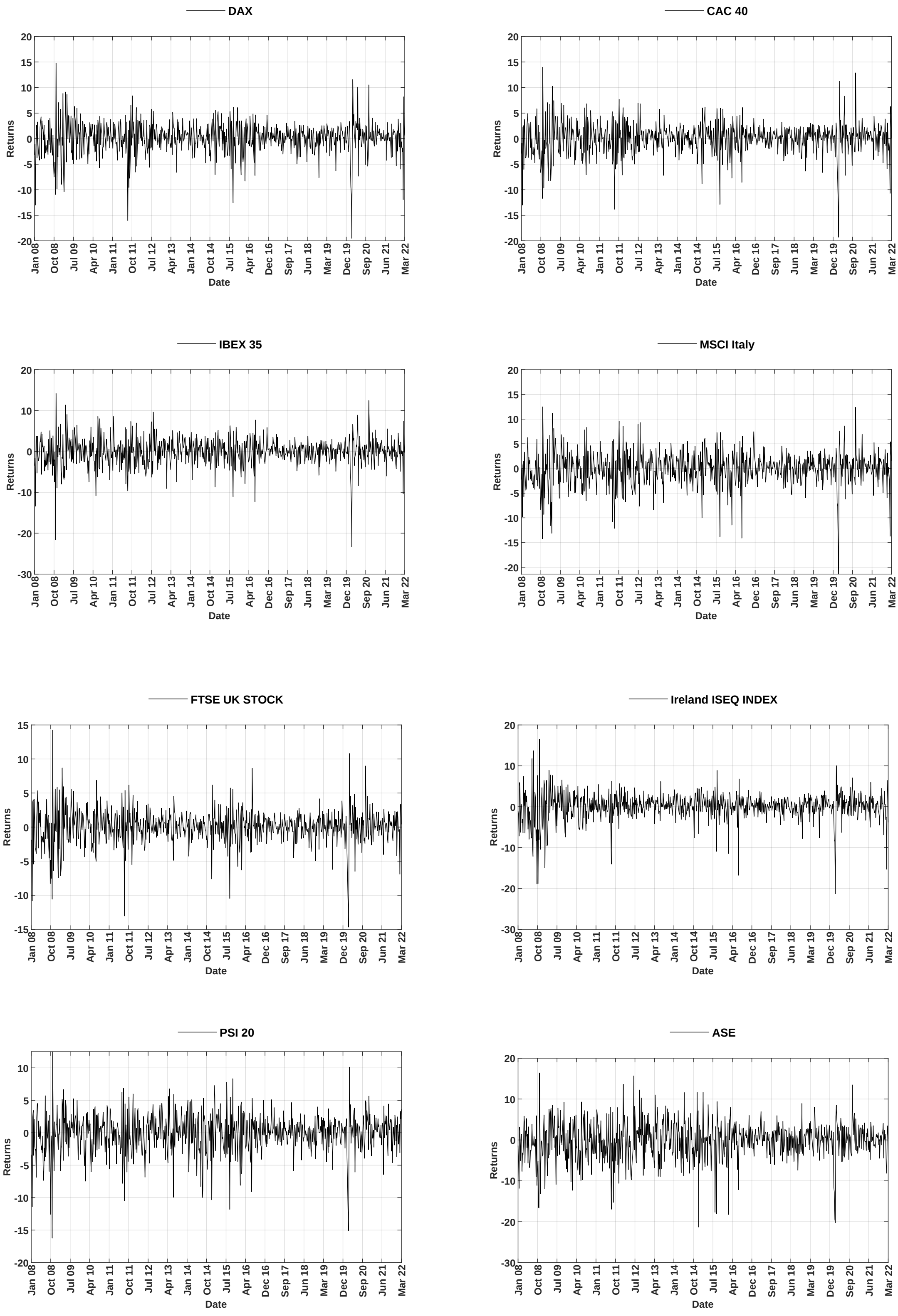


Figure B.2 Stock Returns, All Countries



0.2. *Temporary* Granger Causality - Additional Results

	Germany	France	Spain	Italy	U.K.	Ireland	Portugal	Greece	
μ_{10}	0.0878	0.0117	-0.0241	-0.045	0.0441	-0.1218	-0.1560	-1.6996	Mean Parameters
	(0.01)	(0.35)	(0.24)	(0.12)	(0.01)*	(0.14)	(0.26)	(0.00)	
μ_{11}	0.0609	0.0234	0.1410	0.2079	0.1070	0.0069	0.1534	0.1092	
	(0.00)	(0.00)	(0.00)	(0.00)*	(0.01)*	(0.18)	(0.00)	(0.00)	
μ_{20}	-0.115	0.0292	0.2528	-0.115	0.0393	0.0719	0.0793	1.6192	
	(0.02)	(0.39)	(0.08)	(0.16)	(0.02)*	(0.26)	(0.37)	(0.00)	
μ_{21}	0.0009	0.3140	-0.1182	-0.209	0.0283	0.2938	-0.1405	-0.0869	
	(0.48)	(0.00)	(0.00)	(0.00)*	(0.01)*	(0.00)	(0.00)	(0.00)	
$p^{(1)}_{1,1}$	0.9843	0.8506	0.9852	0.9241	0.0460	0.9339	0.9781	0.9376	Trans. Probabilities
	(0.00)	(0.00)	(0.00)	(0.00)*	(0.05)*	(0.00)	(0.00)	(0.00)	
$p^{(1)}_{0,0}$	0.9773	0.9571	0.9767	0.8408	0.1030	0.9784	0.9575	0.9659	
	(0.00)	(0.00)	(0.00)	(0.00)*	(0.10)*	(0.00)	(0.00)	(0.00)	
$p^{(2)}_{1,1}$	0.8853	0.9465	0.9080	0.9637	0.0438	0.9834	0.9948	0.9952	
	(0.00)	(0.00)	(0.00)	(0.00)*	(0.04)*	(0.00)	(0.00)	(0.00)	
$p^{(2)}_{0,0}$	0.9475	0.9776	0.9757	0.9842	0.0777	0.9623	0.9864	0.9860	
	(0.00)	(0.00)	(0.00)	(0.00)*	(0.07)*	(0.00)	(0.00)	(0.00)	
$\varphi_{1,10}$	-0.0151	0.0287	-0.0531	0.0401	0.2906	0.0956	0.0024	0.0405	VIX
	(0.38)	(0.26)	(0.09)*	(0.18)	(0.28)	(0.06)*	(0.49)	(0.24)	
$\varphi_{1,11}$	-0.0535	0.0196	-0.0297	0.0035	0.0104	-0.0131	-0.0726	-0.0884	
	(0.12)	(0.32)	(0.21)	(0.47)	(0.01)*	(0.40)	(0.14)	(0.00)*	
$\varphi_{1,20}$	-0.1143	-0.045	-0.1935	-0.120	0.0155	-0.1329	-0.0251	-0.0566	
	(0.13)	(0.29)	(0.02)*	(0.07)*	(0.03)*	(0.04)*	(0.37)	(0.20)	
$\varphi_{1,21}$	0.0385	-0.165	0.0775	0.1357	0.2593	-0.0105	0.1341	0.1031	
	(0.32)	(0.02)*	(0.22)	(0.07)*	(0.33)	(0.44)	(0.04)*	(0.01)*	
$\varphi_{2,10}$	-0.0597	-0.093	-0.1667	-0.342	0.0001	-0.0972	-0.1373	-0.0578	Euribor
	(0.17)	(0.01)*	(0.00)*	(0.00)*	(0.00)*	(0.01)*	(0.00)*	(0.07)*	
$\varphi_{2,11}$	0.0056	-0.111	-0.1863	-0.319	0.0042	0.0217	-0.1828	-0.0926	
	(0.46)	(0.00)*	(0.00)*	(0.00)*	(0.01)*	(0.27)	(0.00)*	(0.01)*	
$\varphi_{2,20}$	-0.0542	-0.407	0.0825	0.2506	0.0103	-0.3596	0.0000	0.0903	
	(0.25)	(0.00)*	(0.12)	(0.00)*	(0.01)*	(0.00)*	(0.50)	(0.10)*	
$\varphi_{2,21}$	-0.1369	-0.259	0.1226	0.2543	0.0011	-0.4716	0.1359	0.1153	
	(0.02)*	(0.00)*	(0.04)*	(0.00)*	(0.00)*	(0.00)*	(0.01)*	(0.05)*	
$\sigma_{11,S_t=1}$	0.0057	-0.047	-0.0240	0.0143	-0.0123	-0.0080	0.0194	-0.0272	Distribution Parameters (Σ and κ)
$\sigma_{12,S_t=1}$	0.0018	0.0284	0.0249	0.0318	0.0384	0.0148	0.0052	0.0094	
$\sigma_{22,S_t=1}$	0.0006	0.0002	0.0038	0.0005	0.0032	0.0022	0.0004	0.0008	
$\sigma_{11,S_t=2}$	0.0018	0.0007	0.0043	0.0019	0.0049	0.0269	0.0061	0.0959	
$\sigma_{12,S_t=2}$	1.5640	0.0032	0.0049	0.0076	0.0073	1.8851	0.1007	11.0659	
$\sigma_{22,S_t=2}$	0.0003	0.0002	0.0004	0.0005	0.0001	0.0003	0.0004	0.0014	
$\sigma_{11,S_t=3}$	0.0028	-0.001	0.0082	0.0067	0.0010	0.0010	0.0037	0.0105	
$\sigma_{12,S_t=3}$	0.0313	0.0150	0.1545	0.0874	0.0117	0.0034	0.0305	0.0766	
$\sigma_{22,S_t=3}$	0.0630	0.0369	0.0311	0.0498	0.0237	0.0189	0.0265	-0.0350	
$\sigma_{11,S_t=4}$	0.1025	0.0656	0.1265	0.0978	0.0906	-0.1688	0.8554	0.7243	
$\sigma_{12,S_t=4}$	0.0144	0.0021	-0.0115	-0.010	0.0043	0.0035	-0.0088	-0.0242	
$\sigma_{22,S_t=4}$	0.0228	0.0163	0.0215	0.0199	0.0126	0.0200	0.0227	0.0428	
κ	1.7873	1.2379	1.5483	1.0997	1.6128	0.8377	0.8564	0.8707	

Table B.1 Estimation Results - Mean and Probabilities Parameters

Note: The terms in parenthesis are the p-values. κ is the distributional parameter, and σ_{11},σ_{22} and σ_{12} defines Σ and both are regime dependent.

0.3. *Temporary* Smoothed Probabilities - Synchronization

Figure B.3 Smooth Probabilities for Temporary Granger Causality and Synchronization

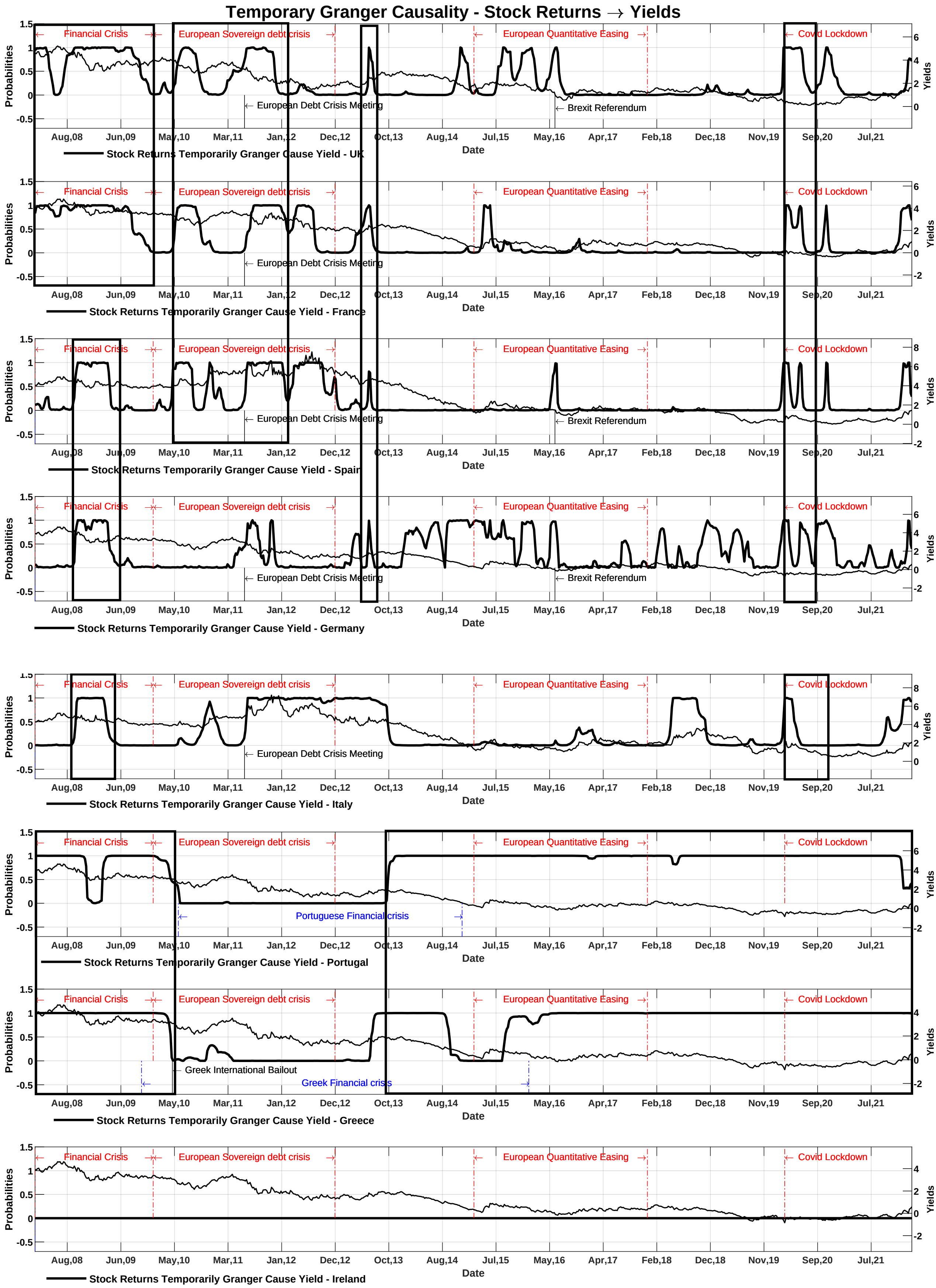
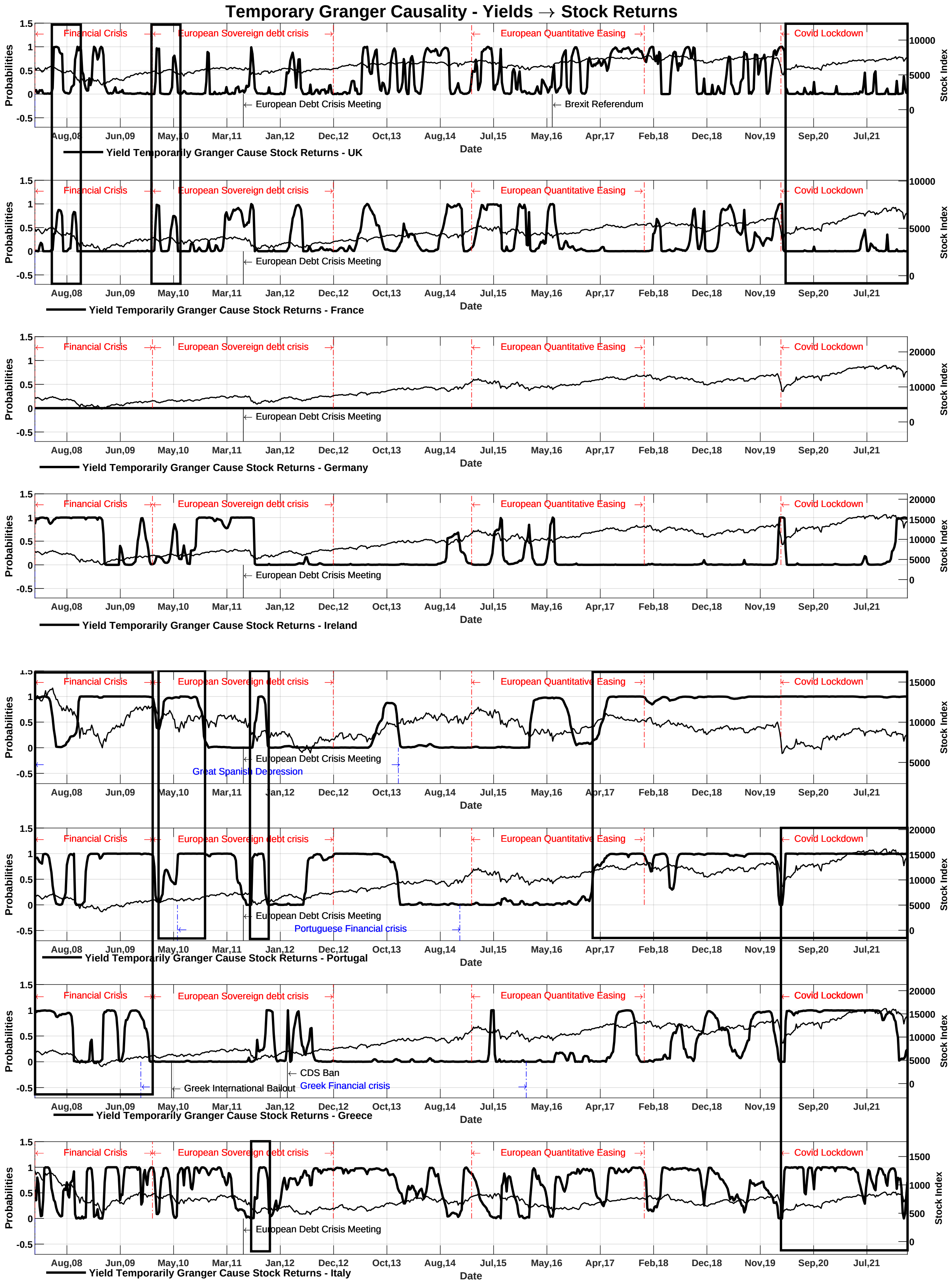


Figure B.4 Smooth Probabilities for Temporary Granger Causality and Synchronization



0.4. *Temporary* Smoothed Probabilities - New Results

Figure B.5 Smooth Probabilities for Temporary Granger Causality ($\Delta R_t \rightarrow \Delta YLD_t$)

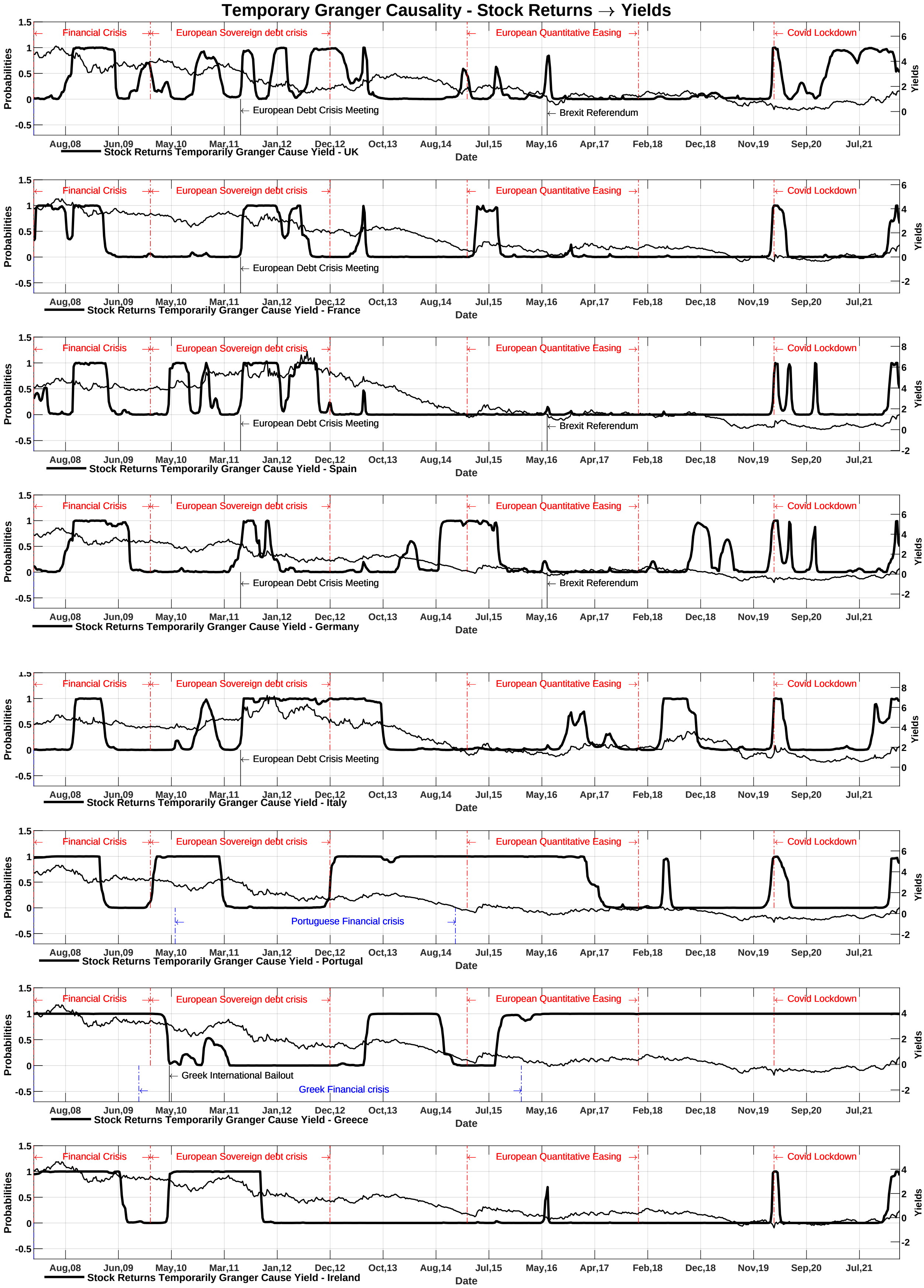
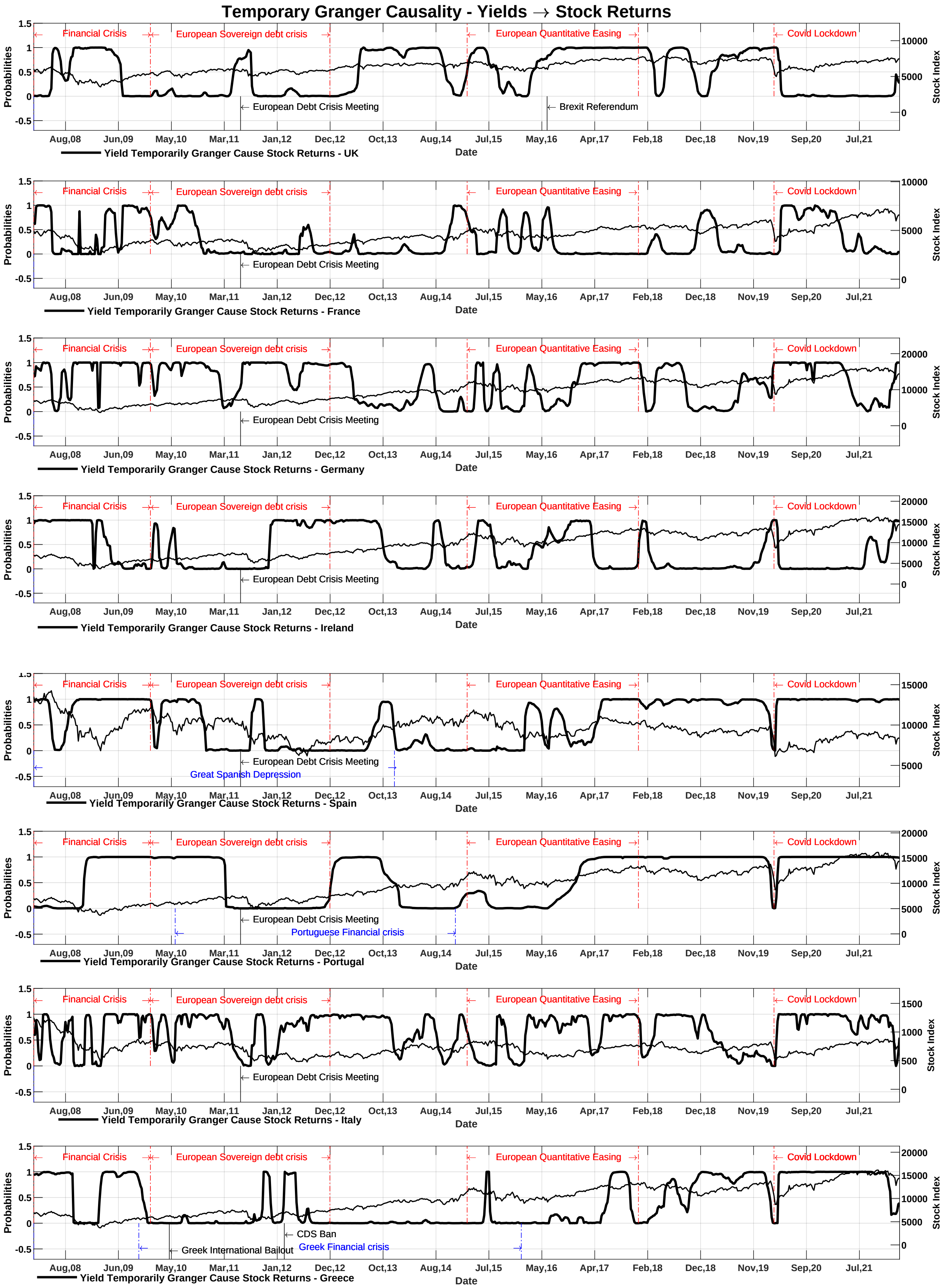


Figure B.6 Smooth Probabilities for Temporary Granger Causality ($\Delta YLD_t \rightarrow \Delta R_t$)



Appendix C

Appendix - Chapter 3

0.1. Data Description

-For Domestic Money

- Rest of the world; currency; asset, Level, Millions of Dollars, Quarterly, Not Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (ROWCURQ027S)
- Currency Component of M1, Billions of Dollars, Quarterly, Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (CURRSL)

-For Interest rate

- Effective Federal Funds Rate, Percent, Quarterly (End of the Period from Daily -DFF), Not Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (DFF)
- Shadow rates (Estimated): From January of 2009 - Source: Center for quantitative economic research -Federal Reserve of Atlanta

-For other monetary aggregates

- Currency Component of M1, Billions of Dollars, Quarterly, Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (CURRSL)
- M1 Money Stock, Billions of Dollars, Quarterly, Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (M1)
- M2 Money Stock, Billions of Dollars, Quarterly, Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (M2)
- Divisia M4 - Source: Center for Financial Stability

-For other Macroeconomic aggregates

- Real GDP - Real Gross Domestic Product, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate -Source: FRED, Federal Reserve Bank of St. Louis (GDPC96) - Vintage: 29/26/2017
- Inflation - Gross Domestic Product: Implicit Price Deflator, Index 2009=100, Quarterly, Seasonally Adjusted - Source: FRED, Federal Reserve Bank of St. Louis (GDPDEF)

0.2. Impulse Response Functions

$$BY_t = \Omega_t + \sum_{k_1=1}^{h_1} \Phi_t^{(k_1)} Y_{t-k_1} + \Xi_t diag(H_t) + \sum_{k_2=1}^{h_2} \left\{ \Theta_{t,1}^{(k_2)} y_{t-k_2} + \Theta_{t,2}^{(k_2)} \pi_{t-k_2} \right\} + U_t,$$

$$\underbrace{Y_t}_{N\times 1} = \underbrace{C_{S_t}}_{N\times 1} + \sum_{k_1=1}^{h_1} \underbrace{A_{S_t}^{(k_1)}}_{N\times N} \underbrace{Y_{t-k_1}}_{N\times 1} + \underbrace{\Xi_{S_t}^T}_{N\times N} \underbrace{diag(H_t)}_{N\times 1} + \sum_{k_2=1}^{h_2} \left\{ Z_{S_t,1}^{(k_2)} y_{t-k_2} + Z_{S_t,2}^{(k_2)} \pi_{t-k_2} \right\} + \underbrace{B^{-1} U_t}_{N\times 1},$$

$$Y_t = C_{S_t} + A_{S_t}(L) Y_t + \Xi_{S_t}^T diag(H_t) + Z_{S_t,1}(L) y_t + Z_{S_t,2}(L) \pi_t + B^{-1} U_t,$$

$$Y_t - A_{S_t}(L) Y_t = C_{S_t} + \Xi_{S_t}^T diag(H_t) + Z_{S_t,1}(L) y_t + Z_{S_t,2}(L) \pi_t + B^{-1} U_t,$$

$$[I - A_{S_t}(L)] Y_t = C_{S_t} + \Xi_{S_t}^T diag(H_t) + Z_{S_t,1}(L) y_t + Z_{S_t,2}(L) \pi_t + B^{-1} U_t,$$

Where $[I - A_{S_t}^{(k_1)}(L)] = I - A_{S_t}^{(1)} L - A_{S_t}^{(2)} L^2 - \ldots - A_{S_t}^{(k_1)} L^{k_1} = \Lambda_{S_t}(L^{k_1})$

$$\Lambda_{S_t}(L^{k_1}) Y_t = C_{S_t} + \Xi_{S_t}^T diag(H_t) + Z_{S_t,1}(L) y_t + Z_{S_t,2}(L) \pi_t + B^{-1} U_t,$$

$$Y_t = \Lambda_{S_t}^{-1}(L^{k_1}) \left[C_{S_t} + \Xi_{S_t}^T diag(H_t) + Z_{S_t,1}(L) y_t + Z_{S_t,2}(L) \pi_t + B^{-1} U_t \right] \tag{C.1}$$

$$Y_t = \frac{C_{S_t}}{\Lambda_{S_t}(L^{k_1})} + \frac{\Xi_{S_t}^T}{\Lambda_{S_t}(L^{k_1})} diag(H_t) + \frac{Z_{S_t,1}(L)}{\Lambda_{S_t}(L^{k_1})} y_t + \frac{Z_{S_t,2}(L)}{\Lambda_{S_t}(L^{k_1})} \pi_t + \frac{B^{-1} U_t}{\Lambda_{S_t}(L^{k_1})},$$

$$Y_t = \Phi_{S_t}^{-1}(L^{k_1}) C_{S_t} + \Lambda_{S_t}^{-1}(L^{k_1}) \Xi_{S_t}^T diag(H_t) + \Lambda_{S_t}^{-1}(L^{k_1}) Z_{S_t,1}(L) y_t + \Lambda_{S_t}^{-1}(L^{k_1}) Z_{S_t,2}(L) \pi_t + \Lambda_{S_t}^{-1}(L^{k_1}) B^{-1} U_t,$$

$$Y_t = \delta_{S_t}^{(1)} + \delta_{S_t}^{(2)} y_t + \delta_{S_t}^{(3)} \pi_t + \underbrace{\delta_{S_t}^{(4)} diag(H_t) + \delta_{S_t}^{(5)} B^{-1} U_t}_{U_t \text{ Dependent}}, \tag{C.2}$$

Notice that:

$$vec(H_t) = h_t = \Gamma + \sum_{i=1}^{g} F_i vec(U_{t-i} U_{t-i}') + \sum_{j=1}^{n} G_j h_{t-j}$$

But we know that the contemporaneous disturbances are uncorrelated, so can simply by expressing in diagonal form:

$$diag(H_t) = \underbrace{h_t}_{N\times 1} = \underbrace{\Gamma}_{N\times 1} + \sum_{i=1}^{g} \underbrace{F_i}_{N\times N} \times \underbrace{diag(U_{t-i} U_{t-i}')}_{N\times 1} + \sum_{j=1}^{n} \underbrace{G_j}_{N\times N} \times \underbrace{h_{t-j}}_{N\times 1} \tag{C.3}$$

Lets consider $g = n = 1$:

$$diag(H_t) = h_t = \Gamma + F diag(U_{t-1} U_{t-1}') + G h_{t-1}$$

Moving forward:

$$h_{t+1} = \Gamma + F diag(U_t U_t') + G h_t \tag{C.4}$$

$$h_{t+2} = \Gamma + F diag(U_{t+1} U_{t+1}') + G h_{t+1} \tag{C.5}$$

Then, taking the conditional expected value of equations (C.4) and (C.5) up to $\mathscr{F}_t$:

$$\begin{aligned}
E[h_{t+1}|\mathscr{F}_t] &= \Gamma + FE[diag(U_tU_t')|\mathscr{F}_t] + GE[h_t|\mathscr{F}_t] \\
&= \Gamma + Fh_t + Gh_t \\
&= \Gamma + (F+G)h_t
\end{aligned}$$

$$\begin{aligned}
E[h_{t+2}|\mathscr{F}_t] &= \Gamma + FE[diag(U_{t+1}U_{t+1}')|\mathscr{F}_t] + GE[h_{t+1}|\mathscr{F}_t] \\
&= \Gamma + Fh_{t+1} + GE[h_{t+1}|\mathscr{F}_t]
\end{aligned}$$

By the Law of iterated expectations:

$$\begin{aligned}
E[E[h_{t+1}|\mathscr{F}_t]] &= \Gamma + (F+G)E[h_t] \\
E[h_{t+1}] &= \Gamma + (F+G)E[h_t]
\end{aligned}$$

$$\begin{aligned}
E[E[h_{t+2}|\mathscr{F}_t]] &= \Gamma + FE[h_{t+1}] + GE[E[h_{t+1}|\mathscr{F}_t]] \\
&= \Gamma + FE[h_{t+1}] + GE[h_{t+1}] \\
E[h_{t+2}] &= \Gamma + (F+G)E[h_{t+1}]
\end{aligned}$$

Therefore we can conclude:

$$E[h_{t+3}] = C + (F+G)E[h_{t+2}]$$

Then, we have:

$$\begin{aligned}
E[h_{t+2}] &= \Gamma + (F+G)E[h_{t+1}] \\
&= \Gamma + (F+G)\Big[C + (F+G)E[h_t]\Big] \\
&= \Gamma + (F+G)C + (F+G)^2E[h_t] \\
&= \Gamma\Big[1 + (F+G)\Big] + (F+G)^2E[h_t]
\end{aligned}$$

Now for $E[h_{t+3}]$:

$$\begin{aligned}
E[h_{t+3}] &= \Gamma + (F+G)\Big[C\Big[1 + (F+G)\Big] + (F+G)^2E[h_t]\Big] \\
&= \Gamma + (F+G)C\Big[1 + (F+G)\Big] + (F+G)^3E[h_t] \\
&= \Gamma\Big[1 + (F+G) + (F+G)^2\Big] + (F+G)^3E[h_t]
\end{aligned}$$

Generalizing and conditioning:

$$\begin{aligned}
E[h_{t+3}] &= \sum_{j=0}^{2}\Gamma(F+G)^j + (F+G)^3E[h_t] \\
E[h_{t+k-\tau}] &= \sum_{j=0}^{k-\tau-1}\Gamma(F+G)^j + (F+G)^{k-\tau}E[h_t]
\end{aligned}$$

$$
\begin{aligned}
E[h_{t+k-\tau}|\mathscr{F}_t] &= \sum_{j=0}^{k-\tau-1} \Gamma(F+G)^j + (F+G)^{k-\tau} E[h_t|\mathscr{F}_t] \\
&= \sum_{j=0}^{k-\tau-1} \Gamma(F+G)^j + (F+G)^{k-\tau} h_t
\end{aligned}
$$

Or:

$$
E[h_{t+k-\tau}|\mathscr{F}_t] = \sum_{j=0}^{k-\tau-2} \Gamma(F+G)^j + (F+G)^{k-\tau-1} h_{t+1} \tag{C.6}
$$

Considering equation (C.1):

$$
Y_t = \Lambda_{S_t}^{-1}(L^{k_1})\left[C_{S_t} + \Xi_{S_t}^{(T)} diag(H_t) + Z_{S_t,1}(L)y_t + Z_{S_t,2}(L)\pi_t + B^{-1}U_t\right]
$$

$$
Y_t = \sum_{\tau=0}^{\infty} \underbrace{\Pi_{S_t}^{(\tau)}}_{N\times N}(L)\left[C_{S_t} + \Xi_{S_t}^{(T)} diag(H_{t-\tau}) + Z_{S_t,1}(L)y_{t-\tau} + Z_{S_t,2}(L)\pi_{t-\tau} + B^{-1}U_{t-\tau}\right]
$$

Considering k steps ahead:

$$
Y_{t+k} = \sum_{\tau=0}^{\infty} \Pi_{S_{t+k}}^{(\tau)}(L)\left[C_{S_{t+k}} + \Xi_{S_{t+k}} diag(H_{t+k-\tau}) + Z_{S_{t+k},1}(L)y_{t+k-\tau} + Z_{S_{t+k},2}(L)\pi_{t+k-\tau} + B^{-1}U_{t+k-\tau}\right]
$$

$$
\begin{aligned}
Y_{t+k} &= \sum_{\tau=0}^{k-1} \Pi_{S_{t+k}}^{(\tau)}(L)\left[C_{S_{t+k}} + \Xi_{S_{t+k}} diag(H_{t+k-\tau}) + Z_{S_{t+k},1}(L)y_{t+k-i} + Z_{S_{t+k},2}(L)\pi_{t+k-\tau} + B^{-1}U_{t+k-\tau}\right] \\
&+ \sum_{\tau=k}^{\infty} \Pi_{S_{t+k}}^{(\tau)}(L)\left[C_{S_{t+k}} + \Xi_{S_{t+k}} diag(H_{t+k-\tau}) + Z_{S_{t+k},1}(L)y_{t+k-\tau} + Z_{S_{t+k},2}(L)\pi_{t+k-\tau} + B^{-1}U_{t+k-\tau}\right]
\end{aligned}
$$

Taking the expectation of equation (C.4) with respect to $\mathscr{F}_t$ and considering $S_{t+k} = S_{t+k-1} = S_{t+k-2} = \ldots = S_t$; nevertheless the variance equation is not subject to regime change, therefore, there is no reason for conditioning the H_t by S_t, then:

$$
\begin{aligned}
E(Y_{t+k}|\mathscr{F}_t, S_t) &= \sum_{\tau=0}^{k-1} \Pi_{S_t}^{(\tau)}(L)\Big[C_{S_t} + \Xi_{S_{t+k}} diag(E(H_{t+k-\tau}|\mathscr{F}_t)) \\
&+ Z_{S_t,1}(L)y_{t+k-i} + Z_{S_t,2}(L)\pi_{t+k-\tau} + B^{-1}U_{t+k-\tau}\Big] \\
&+ \sum_{\tau=k}^{\infty} \Pi_{S_t}^{(\tau)}(L)\Big[C_{S_{t+k}} + \Xi_{S_t} diag(H_{t+k-\tau}) \\
&+ Z_{S_t,1}(L)y_{t+k-\tau} + Z_{S_t,2}(L)\pi_{t+k-\tau} + B^{-1}U_{t+k-\tau}\Big]
\end{aligned}
$$

$$
\begin{aligned}
E(Y_{t+k}|\mathscr{F}_t,S_t) &= \sum_{\tau=0}^{k-1}\Pi_{S_t}^{(\tau)}(L)\Big[C_{S_t}+\Xi_{S_t}diag(E(H_{t+k-\tau}|\mathscr{F}_t))\\
&+ Z_{S_t,1}(L)y_{t+k-i}+Z_{S_t,2}(L)\pi_{t+k-\tau}+B^{-1}U_{t+k-\tau}\Big]\\
&+ \sum_{\tau=k}^{\infty}\Pi_{S_t}^{(\tau)}(L)\Big[C_{S_t}+\Xi_{S_t}diag(H_{t+k-\tau})\\
&+ Z_{S_t,1}(L)y_{t+k-\tau}+Z_{S_t,2}(L)\pi_{t+k-\tau}+B^{-1}U_{t+k-\tau}\Big]\\
E(Y_{t+k}|\mathscr{F}_t,S_t) &= \sum_{\tau=0}^{k-1}\Pi_{S_t}^{(\tau)}(L)\Big[C_{S_t}+\Xi_{S_t}E(h_{t+k-\tau}|\mathscr{F}_t))\\
&+ Z_{S_t,1}(L)y_{t+k-i}+Z_{S_t,2}(L)\pi_{t+k-\tau}+B^{-1}U_{t+k-\tau}\Big]\\
&+ \sum_{\tau=k}^{\infty}\Pi_{S_t}^{(\tau)}(L)\Big[C_{S_t}+\Xi_{S_t}h_{t+k-\tau}\\
&+ Z_{S_t,1}(L)y_{t+k-\tau}+Z_{S_t,2}(L)\pi_{t+k-\tau}+B^{-1}U_{t+k-\tau}\Big] \qquad \text{(C.7)}
\end{aligned}
$$

Taking the derivative of equation (C.6) with respect to U_t we have:

$$\frac{\partial E[h_{t+k-\tau}|U_{i,t},\mathscr{F}_{t-1}]}{\partial U_{i,t}}=(F+G)^{k-\tau-1}\frac{\partial h_{t+1}}{\partial U_{i,t}}$$

Recall from equation (C.4) that:

$$h_{t+1}=\Gamma+F diag(U_tU_t')+Gh_t$$

Then:

$$\frac{\partial E[h_{t+k-\tau}|U_{i,t},\mathscr{F}_{t-1}]}{\partial U_{i,t}}=(F+G)^{k-\tau-1}F\underbrace{\frac{\partial diag(U_tU_t')}{\partial U_{i,t}}}_{2U_{i,t}} \qquad \text{(C.8)}$$

$$\frac{\partial E[h_{t+k-\tau}|U_{i,t},\mathscr{F}_{t-1}]}{\partial U_{i,t}}=\underbrace{(\underbrace{F}_{N\times N}+\underbrace{G}_{N\times N})^{k-\tau-1}\underbrace{F}_{N\times N}\underbrace{\frac{\partial diag(U_tU_t')}{\partial U_{i,t}}}_{2\times U_{i,t}-\text{Scalar}}}_{N\times N}$$

Taking the derivative of equation (C.7) with respect to U_t we have:

$$
\begin{aligned}
\frac{\partial E(Y_{t+k}|U_{i,t},\mathscr{F}_{t-1},S_t)}{\partial U_{i,t}} &= \sum_{\tau=0}^{k-1}\Pi_{S_t}^{(\tau)}(L)\Big[\Xi_{S_t}\Big[\frac{\partial E(h_{t+k-\tau}|\mathscr{F}_t)}{\partial U_{i,t}}\Big]+B^{-1}\frac{\partial U_{t+k-\tau}}{\partial U_{i,t}}\Big]\\
&+ \sum_{\tau=k}^{\infty}\Pi_{S_t}^{(\tau)}(L)\Big[\Xi_{S_t}\Big[\frac{\partial h_{t+k-\tau}}{\partial U_{i,t}}\Big]+B^{-1}\frac{\partial U_{t+k-\tau}}{\partial U_{i,t}}\Big]
\end{aligned}
$$

From equation (C.8), we have:

$$\frac{\partial E(Y_{t+k}|U_{i,t},\mathscr{F}_{t-1},S_t)}{\partial U_{i,t}} = \sum_{\tau=0}^{k-1}\Pi_{S_t}^{(\tau)}(L)\Big[\Xi_{S_t}\Big[(F+G)^{k-\tau-1}F\underbrace{\frac{\partial diag(U_tU_t')}{\partial U_{i,t}}}_{2U_{i,t}}\Big]\Big]+\underbrace{\Pi_{S_t}^{(k)}(L)B^{-1}\underbrace{\frac{\partial U_t}{\partial U_{i,t}}}_{U_{i,t}}}_{\text{Original IRF}}$$

$$\frac{\partial E(Y_{t+k}|U_{i,t},\mathscr{F}_{t-1},S_t)}{\partial U_{i,t}} = \sum_{\tau=0}^{k-1}\Pi_{S_t}^{(\tau)}(L)\Big[\Xi_{S_t}(F+G)^{k-\tau-1}F\Big[\underbrace{\frac{\partial diag(U_tU_t')}{\partial U_{i,t}}}_{2U_{i,t}}\Big]\Big]+\underbrace{\underbrace{\Pi_{S_t}^{(k)}(L)}_{N\times N}B^{-1}\underbrace{\frac{\partial U_t}{\partial U_{i,t}}}_{Scalar}}_{N\times N}$$

Implementation

Let $k=1,2,...,11,12$ and $\tau=0,...,k-1$, then:

$$\begin{aligned}\frac{\partial E(Y_{t+k}|U_{i,t},\mathscr{F}_{t-1},S_t)}{\partial U_{i,t}} &= \sum_{\tau=0}^{k-1}\Pi_{S_t}^{(\tau)}(L)\Big[\Xi_{S_t}(F+G)^{k-\tau-1}F\Big[\frac{\partial diag(U_tU_t')}{\partial U_{i,t}}\Big]\Big]\\ &+ \Pi_{S_t}^{(k)}(L)B^{-1}\frac{\partial U_t}{\partial U_{i,t}}\end{aligned}$$

If $k=1$, then:

$$\begin{aligned}\frac{\partial E(Y_{t+1}|U_{i,t},\mathscr{F}_{t-1},S_t)}{\partial U_{i,t}} &= \sum_{\tau=0}^{0}\Pi_{S_t}^{(\tau)}(L)\Big[\Xi_{S_t}(F+G)^{-\tau}F\Big[\frac{\partial diag(U_tU_t')}{\partial U_{i,t}}\Big]\Big]\\ &+ \Pi_{S_t}^{(k)}(L)B^{-1}\frac{\partial U_t}{\partial U_{i,t}}\\ &= \underbrace{\Pi_{S_t}^{(0)}(L)}_{\text{Initial Shock}}\Big[\Xi_{S_t}F\Big[\frac{\partial diag(U_tU_t')}{\partial U_{i,t}}\Big]\Big]\\ &+ \Pi_{S_t}^{(1)}(L)B^{-1}\frac{\partial U_t}{\partial U_{i,t}}\end{aligned}$$

If $k=2$, then:

$$\begin{aligned}\frac{\partial E(Y_{t+2}|U_{i,t},\mathscr{F}_{t-1},S_t)}{\partial U_{i,t}} &= \sum_{\tau=0}^{1}\Pi_{S_t}^{(\tau)}(L)\Big[\Xi_{S_t}(F+G)^{1-\tau}F\Big[\frac{\partial diag(U_tU_t')}{\partial U_{i,t}}\Big]^{1/2}\Big]\\ &+ \Pi_{S_t}^{(k)}(L)B^{-1}\frac{\partial U_t}{\partial U_{i,t}}\\ &= \Pi_{S_t}^{(1)}(L)\Big[\Xi_{S_t}F\Big[\frac{\partial diag(U_tU_t')}{\partial U_{i,t}}\Big]^{1/2}\Big]\\ &+ \Pi_{S_t}^{(0)}(L)\Big[\Xi_{S_t}(F+G)F\Big[\frac{\partial diag(U_tU_t')}{\partial U_{i,t}}\Big]^{1/2}\Big]\\ &+ \Pi_{S_t}^{(2)}(L)B^{-1}\frac{\partial U_t}{\partial U_{i,t}}\end{aligned}$$

If $k = 3$, then:

$$
\begin{aligned}
\frac{\partial E(Y_{t+3}|U_{i,t}, \mathscr{F}_{t-1}, S_t)}{\partial U_{i,t}} &= \sum_{\tau=0}^{2} \Pi_{S_t}^{(\tau)}(L)\Big[\Xi_{S_t}(F+G)^{2-\tau}F\Big[\frac{\partial diag(U_t U_t')}{\partial U_{i,t}}\Big]\Big] \\
&+ \Pi_{S_t}^{(k)}(L)B^{-1}\frac{\partial U_t}{\partial U_{i,t}} \\
&= \Pi_{S_t}^{(2)}(L)\Big[\Xi_{S_t}F\Big[\frac{\partial diag(U_t U_t')}{\partial U_{i,t}}\Big]\Big] \\
&+ \Pi_{S_t}^{(1)}(L)\Big[\Xi_{S_t}(F+G)F\Big[\frac{\partial diag(U_t U_t')}{\partial U_{i,t}}\Big]\Big] \\
&+ \Pi_{S_t}^{(0)}(L)\Big[\Xi_{S_t}(F+G)^2F\Big[\frac{\partial diag(U_t U_t')}{\partial U_{i,t}}\Big]\Big] \\
&+ \Pi_{S_t}^{(3)}(L)B^{-1}\frac{\partial U_t}{\partial U_{i,t}}
\end{aligned}
$$

0.3. *Temporary* Granger Causality - Additional Results

Table C.1 Estimation Results - Baseline Model

		MC	DM
Autoregressive Parameters	$\phi_{10}^{(1)}$	0.0002 (0.00)	-0.0354 (0.09)
	$\phi_{10}^{(2)}$	0.0066 (0.01)	0.0241 (0.09)
	$\phi_{10}^{(3)}$	0.0147 (0.05)	-0.0403 (0.06)
	$\phi_{10}^{(4)}$	0.2576*** (0.05)	0.2862*** (0.06)
	$\phi_{11}^{(1)}$	-1.1141*** (0.28)	-0.7054*** (0.21)
	$\phi_{11}^{(2)}$	-1.1350*** (0.40)	-1.7557*** (0.28)
	$\phi_{11}^{(3)}$	-0.6631** (0.34)	-0.0108 (0.34)
	$\phi_{11}^{(4)}$	-0.3729** (0.20)	-1.6630*** (0.44)
	$\phi_{20}^{(1)}$	0.4166*** (0.09)	0.2817** (0.11)
	$\phi_{20}^{(2)}$	0.2586*** (0.08)	0.3173* (0.14)
	$\phi_{20}^{(3)}$	0.1604** (0.09)	-0.0745 (0.13)
	$\phi_{20}^{(4)}$	-0.2185*** (0.07)	0.2073* (0.10)
	$\phi_{21}^{(1)}$	-0.0432 (0.27)	-0.3629* (0.16)
	$\phi_{21}^{(2)}$	-0.2633 (0.31)	-0.5029** (0.18)
	$\phi_{21}^{(3)}$	0.0134 (0.09)	0.1667 (0.19)
	$\phi_{21}^{(4)}$	0.0436 (0.14)	0.1039 (0.15)

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Table C.2 Estimation Results - Complete Model

		MC	DM
Autoregressive Parameters	$\phi_{10}^{(1)}$	-1.2772***	-0.8195***
		(0.13)	(0.11)
	$\phi_{10}^{(2)}$	-1.6805***	-0.6758***
		(0.22)	(0.11)
	$\phi_{10}^{(3)}$	-0.4230**	-0.5608***
		(0.21)	(0.10)
	$\phi_{10}^{(4)}$	-0.5385***	0.0865
		(0.10)	(0.09)
	$\phi_{11}^{(1)}$	1.4474***	1.2968***
		(0.16)	(0.17)
	$\phi_{11}^{(2)}$	1.7171***	0.5638***
		(0.24)	(0.15)
	$\phi_{11}^{(3)}$	0.6022***	0.7372***
		(0.22)	(0.15)
	$\phi_{11}^{(4)}$	0.8338***	-0.1441
		(0.11)	(0.11)
	$\phi_{20}^{(1)}$	0.4373***	0.1211
		(0.09)	(0.10)
	$\phi_{20}^{(2)}$	0.1213***	0.2997***
		(0.08)	(0.11)
	$\phi_{20}^{(3)}$	0.2085***	-0.0824
		(0.08)	(0.09)
	$\phi_{20}^{(4)}$	-0.2117***	0.1433*
		(0.07)	(0.10)
	$\phi_{21}^{(1)}$	0.3262	-0.2307*
		(0.86)	(0.17)
	$\phi_{21}^{(2)}$	0.2264	-0.7176***
		(0.54)	(0.16)
	$\phi_{21}^{(3)}$	0.2313	0.1385
		(0.80)	(0.17)
	$\phi_{21}^{(4)}$	0.0279	0.0377
		(0.89)	(0.18)

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Table C.3 Estimation Results - Broader Definition of Money

		M1	M2
Autoregressive Parameters	$\phi_{10}^{(1)}$	-1.2097***	0.1394***
		(0.19)	(0.05)
	$\phi_{10}^{(2)}$	-1.5138***	0.1064***
		(0.24)	(0.03)
	$\phi_{10}^{(3)}$	-0.4582***	-0.2552***
		(0.19)	(0.06)
	$\phi_{10}^{(4)}$	-0.1799	0.1556***
		(0.12)	(0.05)
	$\phi_{11}^{(1)}$	1.4215***	0.7607***
		(0.23)	(0.23)
	$\phi_{11}^{(2)}$	1.5685***	-0.0353
		(0.26)	(0.25)
	$\phi_{11}^{(3)}$	0.5706***	0.0432
		(0.21)	(0.23)
	$\phi_{11}^{(4)}$	0.3794***	-0.5729***
		(0.15)	(0.19)
	$\phi_{20}^{(1)}$	1.0514	0.9841***
		(0.82)	(0.16)
	$\phi_{20}^{(2)}$	1.5841***	-0.2280
		(0.67)	(0.19)
	$\phi_{20}^{(3)}$	-0.0224	0.1584
		(0.62)	(0.20)
	$\phi_{20}^{(4)}$	-1.3062**	-0.1117
		(0.64)	(0.13)
	$\phi_{21}^{(1)}$	-0.8647	-0.7801***
		(0.81)	(0.21)
	$\phi_{21}^{(2)}$	-1.2609**	0.0596
		(0.67)	(0.23)
	$\phi_{21}^{(3)}$	0.2507	0.0000
		(0.62)	(0.00)
	$\phi_{21}^{(4)}$	1.3674**	-0.0002
		(0.64)	(0.04)

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Temporary Granger Causality - Additional Results - Complete Model

Table C.4 Estimation Results - Mean and Probabilities Parameters

	MC	DM	M1	M2	
ω_{10}	-5.857***	-0.948*	-4.770***	0.708	Mean Parameters
	(1.46)	(0.60)	(1.13)	(2.02)	
ω_{11}	2.940***	2.289**	10.532	-0.579	
	(0.89)	(1.29)	(15.02)	(4.53)	
ω_{20}	5.517***	0.938	4.694***	-1.399	
	(1.50)	(0.82)	(1.18)	(4.95)	
ω_{21}	4.079	0.293	-6.463	3.247	
	(10.31)	(3.67)	(15.07)	(6.94)	
$p^{(1)}_{1,1}$	0.883***	0.967***	0.884***	0.967***	Trans. Probabilities
	(0.08)	(0.02)	(0.05)	(0.04)	
$p^{(1)}_{0,0}$	0.979***	0.990***	0.073	0.964***	
	(0.02)	(0.01)	(0.12)	(0.03)	
$p^{(2)}_{1,1}$	0.972***	0.926***	0.923***	0.767***	
	(0.01)	(0.03)	(0.02)	(0.07)	
$p^{(2)}_{0,0}$	0.795***	0.838***	0.681***	0.921***	
	(0.06)	(0.05)	(0.12)	(0.03)	

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Table C.5 Estimation Results: $GARCH - in - Mean$, and Exogenous Variables Parameters

	MC	DM	M1	M2	
$\theta^{(1)}_{10,1}$	-0.344**	0.1099*	-0.074	0.125***	Δy_t
	(0.16)	(0.0681)	(0.17)	(0.04)	
$\theta^{(1)}_{11,1}$	0.291**	-0.2379***	0.019	-0.577***	
	(0.16)	(0.0910)	(0.19)	(0.14)	
$\theta^{(1)}_{20,1}$	-0.058	-0.1169	-0.499	-0.201	
	(0.06)	(0.0987)	(1.28)	(0.17)	
$\theta^{(1)}_{21,1}$	0.833	-0.0062	0.490	-0.056	
	(3.14)	(0.4256)	(1.31)	(0.30)	
$\theta^{(1)}_{10,2}$	-0.865	-0.2632	-0.608	-0.130***	π_t
	(0.13)	(0.0529)	(0.09)	(0.03)	
$\theta^{(1)}_{11,2}$	0.831	0.2593	0.596	0.170**	
	(0.13)	(0.0655)	(0.10)	(0.09)	
$\theta^{(1)}_{20,2}$	-0.010	-0.0090	1.243	0.119*	
	(0.05)	(0.0635)	(0.97)	(0.09)	
$\theta^{(1)}_{21,2}$	0.924	0.4293	-1.038	0.036	
	(1.19)	(0.1679)	(1.01)	(0.14)	

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Table C.6 Estimation Results - $GARCH(1,1)$ and Covariance Parameters

	MC	DM	M1	M2	
ρ	0.025	0.2130	-1.106***	-0.603***	Constant
	(0.16)	(0.1897)	(0.36)	(0.23)	Correlation
c_y	0.014	0.0086	0.006	0.460***	$GARCH(1,1)$
	(0.03)	(0.0104)	(0.01)	(0.08)	
c_x	0.428**	0.2347**	0.185**	0.357***	
	(0.20)	(0.1212)	(0.08)	(0.12)	
f_y	0.372***	0.6042***	0.606***	0.000	
	(0.09)	(0.1996)	(0.20)	(0.00)	
f_x	1.201*	1.0061*	2.078	1.177	
	(0.83)	(0.7710)	(1.31)	(1.36)	
g_y	0.250	0.4140	0.810	0.000	
	(0.37)	(0.4671)	(3.08)	(0.01)	
g_x	0.434	0.6007	0.635**	0.732***	
	(0.57)	(0.5531)	(0.32)	(0.31)	

Note: * , **, *** are respectively 10%, 5% and 1% significance
Standard errors in the brackets

Temporary Granger Causality - Additional Results - GARCH-M Plots

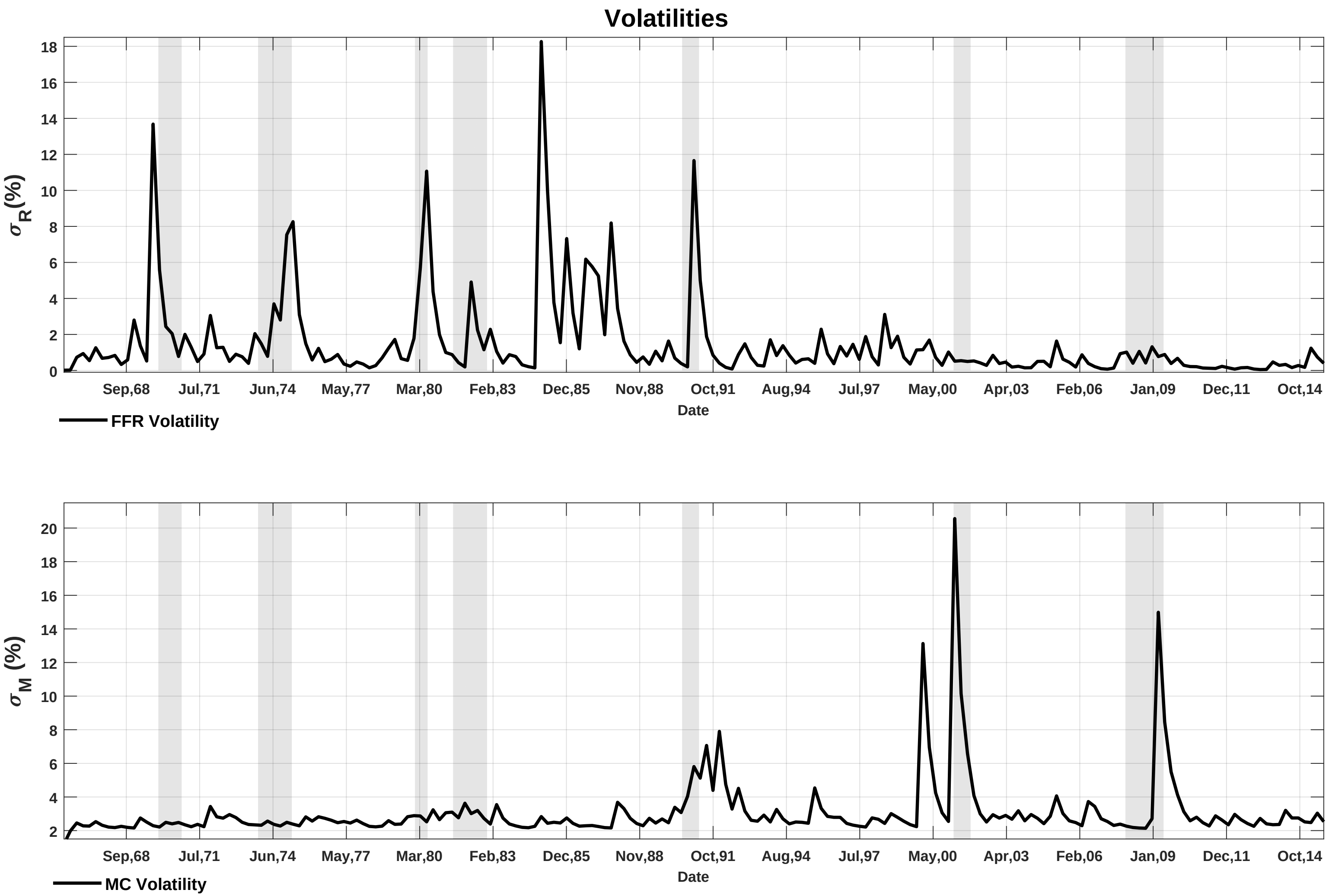


Figure C.1 $GACH(1,1) - M$ for Temporary Granger Causality Model

Figure C.2 $GACH(1,1)-M$ for Temporary Granger Causality Model

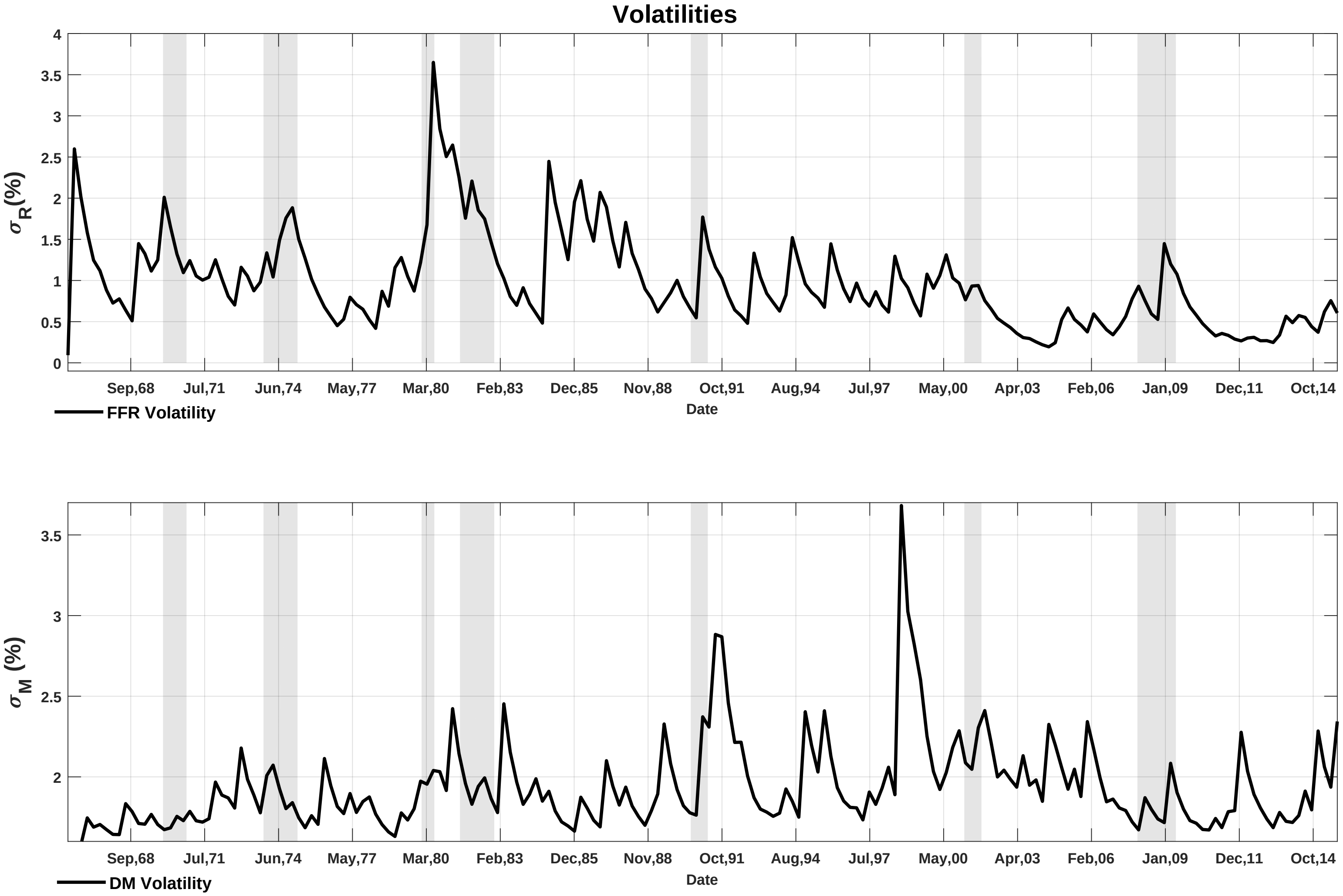


Figure C.3 $GACH(1,1)-M$ for Temporary Granger Causality Model

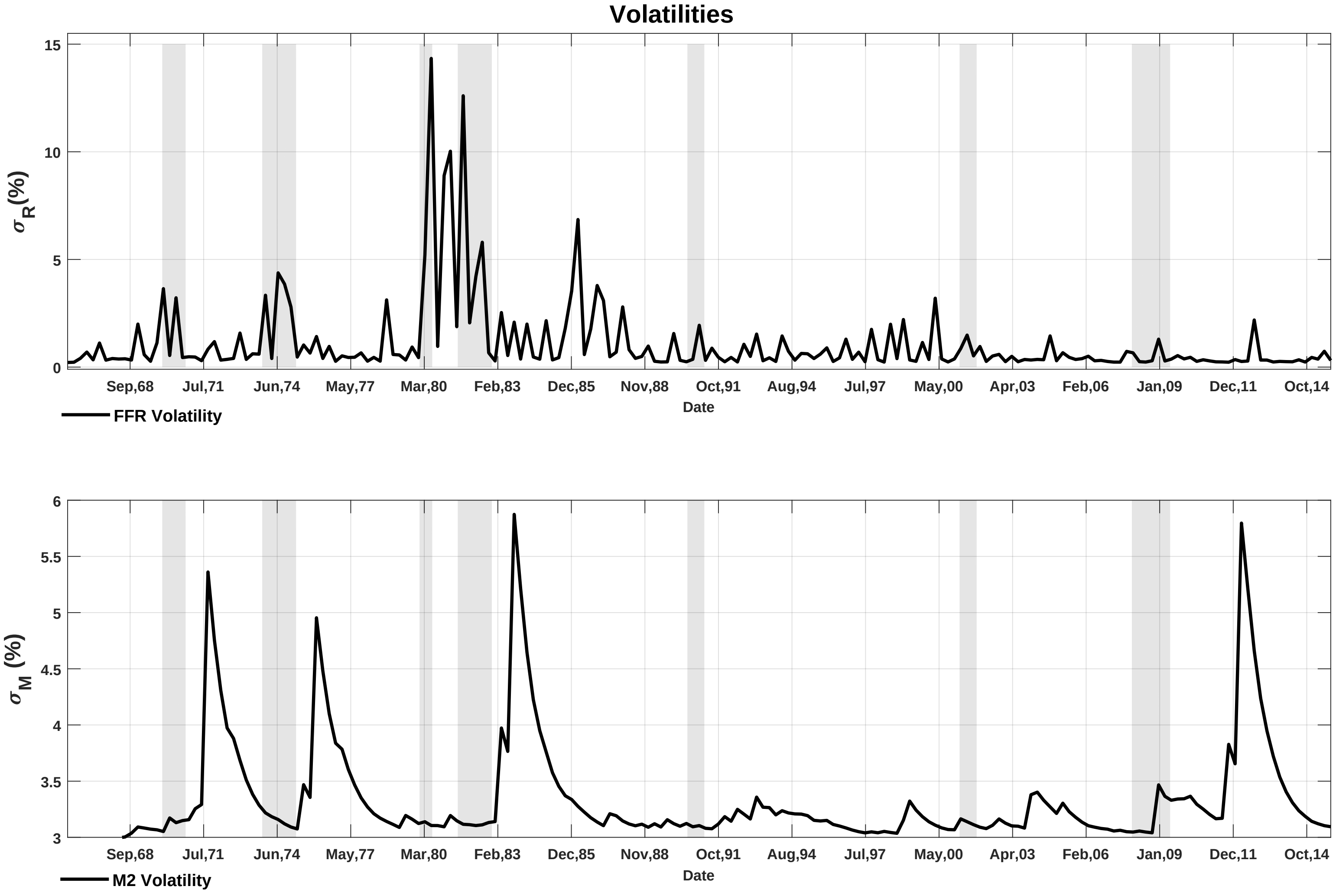


Figure C.4 $GACH(1,1)-M$ for Temporary Granger Causality Model