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The Chair of the U.S. Federal Reserve and the Macroeconomic Causality Regimes*

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Abstract

We investigate regime-dependent Granger causality between real output, inflation and monetary indicators and map with U.S. Fed Chairperson's tenure since 1965. While all monetary indicators have causal predictive content in certain time periods, we report that the Federal Funds rate (FFR) and Domestic Money (DM) are substitutes in their role as lead or feedback variables to explain variations in real output and inflation. We provide a comprehensive account of evolution of causal relationships associated with all US Fed Chairpersons we consider.

Keywords: Causality Regimes; Domestic Money; Federal Reserve Chairperson; Markov Switching; Policy Instrument; Vector Autoregression.

JEL classification: C32; C54; C61; E52; E58.

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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 Chairperson had more or less the same policy toolkit to achieve same objectives as described by the mandate. Given this background, at least in principle, unless there are shifts in policy preferences (objectives and/or instruments) or expectations formation, there are no obvious 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 Chairperson's tenure.

There is a good deal of research, that utilizes classical or Bayesian methods, investigating the evolution of the U.S. monetary policy that focuses explicitly on the Federal Funds rate (FFR) or an equivalent short-term rate measure. For instance, in their influential work Sims and Zha (2006) argue that while there are no changes in the parameters of the FFR based 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. The assumption that FFR approximates well the stand of the U.S. monetary policy also 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, are often a side issue. Given the Zero Lower Bound (ZLB) problems since December 2008 and the wide ranging utilization of unconventional monetary policy measures as well as 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)).

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 chairpersons throughout the sample period from 1965 to 2016. Most existing literature, as in for instance Clarida et al. (2000), estimates policy rules based on the structural break premise around early 1980's, when U.S. Federal Reserve under the chairmanship of Volcker implemented contractionary monetary policies. In this paper we use endogenous regime identification methods and do not impose any assumption on the dates of causal regime change. 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) next to 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 Chairperson'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, 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 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 first 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 in certain time periods, these are mostly substitutes in their role as causal lead or feedback variables when used to analyze real output and inflation. That means, broadly speaking, that, when the Federal Funds rate is causally leading inflation and/or output, Domestic Money is not a leading variable, and vice versa.

Second, to give a macroeconomic policy interpretation to our identified regimes, we map these to the corresponding tenures of U.S. Fed chairperson by defining the dominant regimes as the one that prevails at least 75% (or 90%) of the time the relevant chairperson was in office. *Output regimes:* Burns and Volcker in the 1970's and 1980's, respectively, and Bernanke-Yellen (90% of the time) episodes can be characterized as output regimes where the FFR causally leads real output. In contrast, Martin's 1960's and Greenspan's tenures are dominated by output regimes where DM causally leads real output. *Inflation regimes:* We find that DM was causal for inflation variations throughout Martin-Burns-Miller-Volcker tenures without any interruption in the regime identification. There is very little information in FFR to explain inflation variations except during the Burns-Miller tenures in the 1970's, confirming the widely reported failure of FFR to explain variations in inflation (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). *Monetary Rule regimes:* We find few episodes that justify McCallum or Taylor type feedback regimes. Miller-Volcker tenures can be represented as a Taylor type monetary policy regime and the Bernanke-Yellen tenures are identified as McCallum type feedback regimes. Meltzer (2014) suggested that the Federal Reserve followed successful Taylor rule policies after 1985. While there are certain subperiods during Volcker's and Greenspan's chairmanships that are found to be associated with Taylor type feedback rules, with the exception of the Bernanke-Yellen periods, we do not find strong empirical support (i.e. more than 75% of tenure duration) for Meltzer (2014)'s claims.

Third, we 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]. Using a measure of 75% (alternatively 90%) of dominating regime during a Fed chairperson tenure, we find that both monetary indicators have a significant causal lead at the start of Volcker's chairmanship. We also find that Divisia M4 was causally leading inflation during most of Greenspan's tenure. Most significantly, Divisia M4 is strongly associated with Monetary Rule behaviour, successfully accounting for a McCallum type rule during the Volcker and Greenspan periods. M2 serves as a monetary rule dominant regime during the Martin and 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, in an influential paper Friedman and Kuttner (1992) reported that the information content of U.S. monetary aggregates to explain real output and inflation has mostly disappeared after Volcker

[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) for details.

disinflation policies, whereas short term rates 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, 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 show that, when corrected for foreign holdings of U.S. Dollars, the U.S. Domestic Money 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) show that Friedman-Schwartz stylized facts can be replicated when the synthetic money supply measure, Divisia, is used.

Our work is also directly related to the literature that evaluates the causal patterns between money supply measures and macroeconomic variables at recessions/recoveries and expansions. Ever since 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 Switching models. Droumaguet et al. (2017) provide a formal, nevertheless alternative definition of temporary Causality. They develop a Bayesian framework and extend Krolzig (1997) and Warne (2000). They consider a benchmark unrestricted MS-VAR and test the causality on the estimated switching parameters. Their work is about inference. The switching is governed by main parameters of the VAR dating expansions and recessions.[2,3] The main difference between Droumaguet et al. (2017) and our approach is that we do not rely upon any inference on the estimated parameters of the reduced form VAR. Instead, our method constrains the reduced form VAR in order to identify hidden regimes that are directly associated with different causality relationships. These regimes encompass all possible directions of causality within the model and transitions

[2]Similar to Hamilton (1989).

[3]The inference on the parameters in Markov-Switching models has been subject to criticism (See for instance Hansen (1992)).

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 Chairpersons. 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. (2017). 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

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

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

$$D_t = \begin{bmatrix} \mu_{10} + \mu_{11} s_{y,t} \\ \mu_{20} + \mu_{21} s_{\pi,t} \\ \mu_{30} + \mu_{31} s_{m,t} \end{bmatrix}, \quad A_t^{(k)} = \begin{bmatrix} \phi_{10}^{(k)} + \phi_{11}^{(k)} s_{y,t} & \psi_1^{(k)} s_{y,t} & \psi_2^{(k)} s_{y,t} \\ \psi_3^{(k)} s_{\pi,t} & \phi_{20}^{(k)} + \phi_{21}^{(k)} s_{\pi,t} & \psi_4^{(k)} s_{\pi,t} \\ \psi_5^{(k)} s_{m,t} & \psi_6^{(k)} s_{m,t} & \phi_{30}^{(k)} + \phi_{31}^{(k)} s_{m,t} \end{bmatrix}, \tag{2}$$

$\{U_t' = [u_{y,t}, u_{\pi,t}, u_{m,t}]\}$ 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

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

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

$$\Omega_t = \sum_{\ell=1}^{8} \Omega_\ell I(S_t = \ell), \tag{4}$$

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 $P^{(r)} = [p_{i,j}^{(r)}]$, $r = y, \pi, m$, where

$$p_{i,j}^{(r)} = \mathcal{P}(s_{r,t+1} = j | s_{r,t} = i), \quad i, j = 0, 1;\ r = y, \pi, m. \tag{5}$$

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 $P_S = [P_{i,j}]$, $P_{i,j} = \mathcal{P}(S_{t+1} = j | S_t = i)$, $i, j = 1, \ldots 8$, such that

$$P_S = P^{(y)} \otimes P^{(\pi)} \otimes P^{(m)}, \tag{6}$$

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 1 below, is helpful for interpreting the stylized facts.

$$(s_{y,t}, s_{\pi,t}, s_{m,t}) \begin{cases} s_{y,t} = \begin{cases} 1, \text{ then } \pi \text{ and } \Delta m_t \rightarrow \Delta y_t \text{ (Output Regime)} \\ 0, \text{ then } \pi \text{ and } \Delta m_t \nrightarrow \Delta y_t \end{cases} \\ s_{\pi,t} = \begin{cases} 1, \text{ then } \Delta y_t \text{ and } \Delta m_t \rightarrow \pi \text{ (Inflation Regime)} \\ 0, \text{ then } \Delta y_t \text{ and } \Delta m_t \nrightarrow \pi \end{cases} \\ s_{m,t} = \begin{cases} 1, \text{ then } \pi \text{ and } \Delta y_t \rightarrow \Delta m_t \text{ (Monetary Rule Regime)} \\ 0, \text{ then } \pi \text{ and } \Delta y_t \nrightarrow \Delta m_t \end{cases} \end{cases} \tag{7}$$

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 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 follow 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

When	Granger Causality	$P(S_t = j \vert X_t; \Phi)$, j = 1	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)	$\oplus$		$\oplus$	$\oplus$			$\oplus$	
$s_{y,t} = 0$ $s_{\pi,t} = 0$ $s_{m,t} = 0$	$\pi_t \not\longleftrightarrow \Delta y_t \not\longleftrightarrow \Delta m_t$, $\pi_t \not\longleftrightarrow \Delta m_t$ (No Causality)								$\oplus$

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

Table 1: Summary of regime aggregation

of the endogenous variables are causally linked to each other.

The parameters of the model defined by equations (1) to (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.[4] When assessing the relevance of monetary indicators, we take a nuanced stand 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 the monetary instrument (currency component of monetary aggregate corrected for foreign holdings of U.S. Dollars) as it has at least two important properties: first it is the monetary aggregate that comes closest to a monetary aggregate as a policy instrument: First, the Federal Reserve knows exactly how much it prints money and tracks closely U.S. Dollar shipments abroad (Porter and Judson (1996)); second, it has a desirable information content to predict 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. 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 (2015)). 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 ($\Delta \text{Divisia} M4$). The data cover the period 1965:1 to 2015:4, except for Divisia M4 for which data is only available

[4] 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.

from 1967:1 onwards.[5,6]

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 full-sample estimates of the parameters that are directly related to the causal link, that is, $\psi_1^{(k)}, \ldots, \psi_6^{(k)}$, $k = 1, 2$. Estimates of the remaining parameters of the various models and the value of the maximized log-likelihood function can be found in Tables 13 and 14 in Appendix B. We note that the 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

[5] For more details on the data see the appendix 1.1.

[6] 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 2.5. for descriptive statistics and unit root tests.

Taylor Regimes: ΔFFR responses to past inflation are not significant.

Causal Effect		FFR	ΔDM
$\pi_t \to y_t$	$\psi_1^{(1)}$	0.1315 (0.3366)	-0.1863 (0.2434)
	$\psi_1^{(2)}$	-0.1294 (0.3177)	-0.0484 (0.2261)
$m_t \to y_t$	$\psi_2^{(1)}$	0.3605*** (0.2125)	0.2215*** (0.0642)
	$\psi_2^{(2)}$	-0.3236 (0.2736)	-0.0051 (0.0654)
$y_t \to \pi_t$	$\psi_3^{(1)}$	-0.0078 (0.0497)	-0.0633 (0.0414)
	$\psi_3^{(2)}$	0.0691 (0.0525)	0.0784* (0.0375)
$m_t \to \pi_t$	$\psi_4^{(1)}$	0.1692 (0.1505)	-0.0501 (0.0458)
	$\psi_4^{(2)}$	0.4785* (0.1494)	0.1023* (0.0452)
$y_t \to m_t$	$\psi_5^{(1)}$	0.1108** (0.0512)	-0.5190*** (0.0615)
	$\psi_5^{(2)}$	0.1703* (0.0356)	-0.1744 (0.1119)
$\pi_t \to m_t$	$\psi_6^{(1)}$	0.0955 (0.2002)	-0.3754*** (0.2206)
	$\psi_6^{(2)}$	0.1110 (0.2316)	1.0423*** (0.2212)

Note: * , **, *** are respectively 5%, 1% and 0.1% significance
Standard errors in the brackets

Table 2: Results for Causality Parameters

3.3. Regime Probabilities

Estimates reported in Table 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 1 estimated probabilities for FFR and DM models together.[7]

We can sketch some broad contours for smoothed probabilities for all models. We first comment on Figure 1. Then, given that regimes switch quite often, in Section 3.4., we map the smoothed probabilities to tenures of Fed Reserve chairpersons and compute the dominant regime (75% or 90% of the tenure duration) for each policy indicator. That way we have a straightforward interpretation of the computed regimes and monetary policy.

First, estimated regime probabilities for the monetary indicators FFR and DM upon which the Federal Reserve has direct control reveal that throughout the sample period controllable monetary indicators causally affect output or inflation or serve as a feedback variable. However, we note that business cycle causal regimes mostly switch across monetary indicators. This means, for instance, that when FFR leads real output, DM in general does not and vice versa.

Specifically, we can distinguish three broad real output regimes: starting from the tenure of Martin, tenures of Burns and Miller were characterized by temporary causality from FFR to real output. This is followed by Volcker and Greenspan tenures up to 1998 where DM causally leads real output that is in turn followed from 2001 onwards by real output regimes where FFR predominantly leads real output including the latter part of Greenspan, Bernanke and Yellen services.

Second, we identify two inflation regimes where either DM causally leads inflation and where it does not. Martin-Burns-Miller-Volcker and Greenspan up until the 1990 recession

[7]Specifically these are the sums of estimated smoothed probabilities associated with the relevant states in the ΔFFR model (Figure 3 in the Appendix), the ΔDM model (Figure 4 in the Appendix). We also report in Figure 2 smooth probabilities for those variables where Federal Reserve has only indirect control ($\Delta M2$ and $\Delta DivisiaM4$)

DM causally leads inflation. After 1990's there is only scant evidence of either DM or FFR causally leading inflation. We note that there is very little evidence of FFR being a causal variable for inflation confirming widely reported failure of FFR alone to explain variations in inflation (see, for instance, Stock and Watson (2007, 2010) and Faust and Wright (2013)).

Third, our analysis indicates that FFR is intermittently a feedback variable (Taylor rule) up until early 2000's that includes Martin-Burns-Miller-Volcker tenures and some episodes of Greenspan era. While as described above the DM is temporary causal for real output and inflation, we only find relevance of DM as a feedback variable to real output and inflation developments (McCallum rule) starting with Greenspan's latter part of service, followed by Bernanke-Yellen tenures associated with the financial crisis and aftermath. To complement this we find fairly strong support for McCallum rules up until the 2000's. While there are certain subperiods during Volcker and Greenspan chairmanship that reveal Taylor rule type feedback rules, with the exception of Bernanke-Yellen periods we do not find strong systematic support for Meltzer (2014)'s claims. Several episodes of Miller, Burns and earlier part of Volcker tenures were also characterized by Taylor rules and these were in conjunction with causal lead regimes of DM to explain variations in both U.S. real output and inflation.

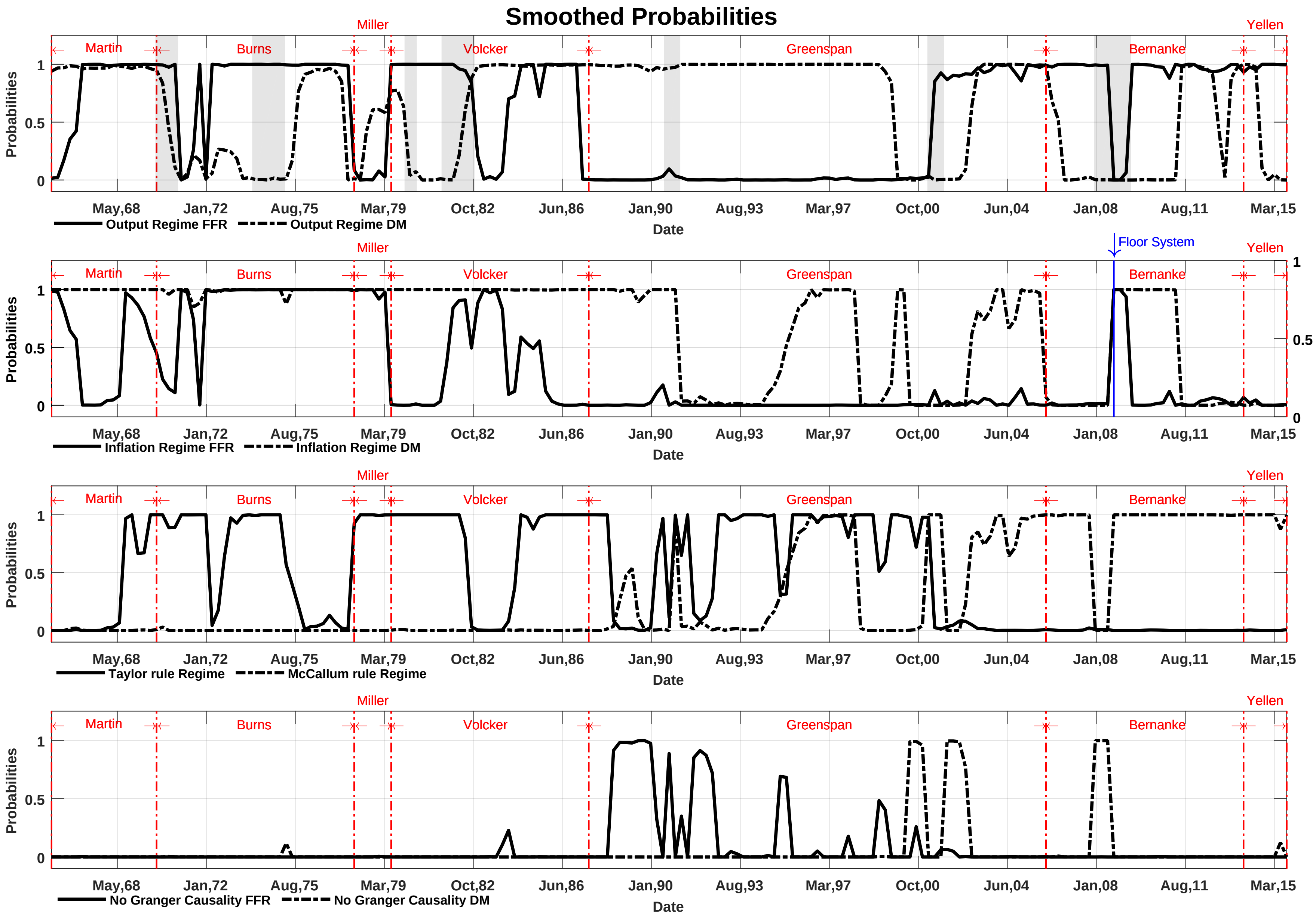

Figure 1: Smoothed Probabilities for Policy Instruments: 'Output Regime' ($S_t = 1, 2, 3, 5$), where the relevant monetary policy indicator causally leads US real output, a 'Inflation Regime' ($S_t = 1, 2, 4, 6$), where the relevant monetary policy indictor causally leads price inflation, a 'Monetary Rule Regime' ($S_t = 1, 3, 4, 7$), where US 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

3.4. 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 $\mathcal{P}(S_t = \ell | X_{1-h}, ..., X_T; \hat{\theta})$, based on the ML estimate $\hat{\theta}$ of the model's parameters, exceeds 1/2. Using this rule, we report in Table 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	121	129
Inflation Regime	57	139
Monetary Rule Regime	97	66
Non-Causality Regime	14	10

Table 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:

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

Similarly to the results in Table 3, the estimated expected durations shown in Table 4 also indicate that the non-causality regime is expected to last the shortest. Regimes other than the non-causality regime exhibit the longest expected durations in a model with DM.

	FFR	ΔDM
Output Regime	24.52	26.19
Inflation Regime	17.15	27.54
Monetary Rule Regime	23.68	24.95
Non-Causality Regime	3.48	5.94

Table 4: Conditional Expected Duration (Quarters)

The expected duration varies from 14 (non-causality) to 121 quarters (output) in the model with the FFR, to 10 (non-causality) to 139 quarters (inflation) in the model with the DM.

An alternative way of looking at the separation of causality regimes is by focusing on which regime has been the dominant regime during a Chairperson'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 to Volcker's mandates was dominated by the Inflation Regime in the case of DM.[8]

Table 5 displays dominant regimes that we match with tenures of each Federal Reserve chairperson. The black and grey bars indicates a dominant regime for more than 90% and 75% of chairperson's tenure time, respectively.

We first note that FFR is causal for output from Burns to Volcker (with the exception of Miller) and later on during Bernanke-Yellen periods and only during Burns-Miller tenure for Inflation. There is very little evidence of Taylor type of rule except for the Miller-Volcker period. Second, DM is indeed the potential policy instrument that is more systematically linked to macro aggregates. During almost the entirety of the tenures of Martin and Greenspan, DM was causal for output. DM was also causal in relation to inflation during Martin-Burns-Miller-Volcker mandates. DM became the relevant feedback variable during Bernanke-Yellen mandates. We conclude that during most of the sample we study FFR and DM are instrument substitutes. It appears that the controllable DM is the relevant monetary variable to describe entire sample studied, whereas FFR is not so much associated

[8]Table 15 in Appendix (B) shows all the results.

with the Greenspan period. As seen from the lens of causal leads, the information content of these two potential instruments switches during the tenures of different Federal Reserve chairpersons, potentially reflecting changes in policy instrument preferences.

In sum, for models with controllable monetary indicators (FFR and ΔDM models) our results suggest that two controllable monetary regularly switch in terms of causal usefulness in explaining variations in inflation and real output. We find that while the DM variations contain useful information to explain variations in real output and inflation up until the turn of the century, it became a feedback variable (McCallum rule) post Global Financial Crisis episodes. Throughout our sample period from 1965 up until end of 2015 DM serves, without any interruption, as a dominant causal or feedback variable. In contrast, while FFR served as an intermittent monetary instrument from the 70s to the end of 80s and only became causal for output during Bernanke-Yellen tenures. In other words, unlike the DM, during the Greenspan period there is no systematic evidence that favours FFR as a causal or feedback policy variable to explain variations in US real output and inflation or vice versa.

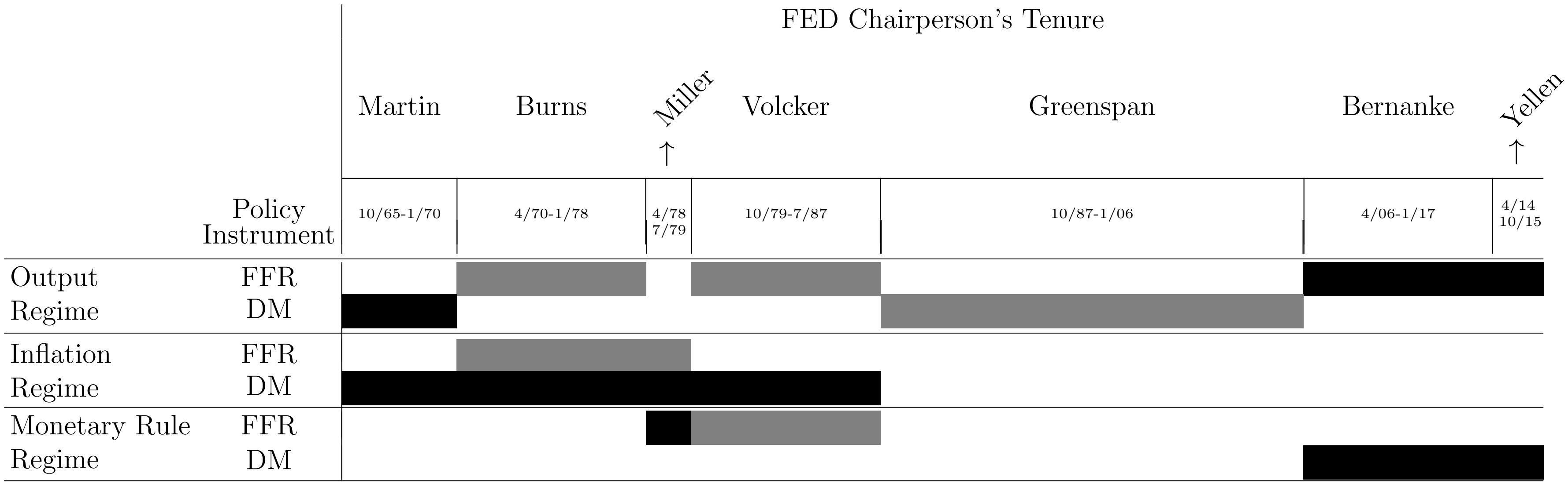

Table 5: Dominant Regime

In the diagram, the black and the grey bars indicate that the regime dominates more than 90% and 75% respectively.

4. Robustness

4.1. Alternative Monetary Indicators

For models with monetary aggregates on which the monetary authority has an indirect control (Figure 2) we obtain smoothed probabilities with relatively well defined cut offs and our results broadly agree with the results for the ΔDM model discussed before. In the case of the $\Delta M2$ model, regime definitions can be separated into two distinct episodes, namely before and after the Volcker disinflations around 1982. Our calculations suggest that before 1982 monetary policy can be characterized by both output and inflation causality regimes and after 1982 by feedback regimes.

In the case of the $\Delta DivisiaM4$ model, tenures of all Chairmen before the Volcker disinflations are characterized by output regimes and after Volcker and up until the tenure of Bernanke by inflation regimes. The model suggests that this composite monetary indicator is one way or another linked to real output and inflation in a temporarily causal manner throughout, confirming the findings of Belongia and Ireland (2015), but seems to be non-causal around major events such as the Global Financial Crisis.

Causal Effect		$\Delta M2$	$\Delta Divisia M4$
$\pi_t \rightarrow y_t$	$\psi_1^{(1)}$	0.1256 3	-0.6010
		(0.3380)	(0.3804)
	$\psi_1^{(2)}$	-1.1851***	-0.2826
		(0.3118)	(0.3549)
$m_t \rightarrow y_t$	$\psi_2^{(1)}$	0.5703***	0.5954***
		(0.2470)	(0.2114)
	$\psi_2^{(2)}$	0.5461**	0.3143
		(0.2297)	(0.2584)
$y_t \rightarrow \pi_t$	$\psi_3^{(1)}$	0.0092	0.0992***
		(0.0577)	(0.0350)
	$\psi_3^{(2)}$	0.0949**	0.0230
		(0.0435)	(0.0425)
$m_t \rightarrow \pi_t$	$\psi_4^{(1)}$	-0.1882***	-0.1178***
		(0.0422)	(0.0321)
	$\psi_4^{(2)}$	0.0971**	0.0437*
		(0.0389)	(0.0318)
$y_t \rightarrow m_t$	$\psi_5^{(1)}$	-0.3016***	-0.3069*
		(0.0900)	(0.1710)
	$\psi_5^{(2)}$	0.2228**	0.1161
		(0.0764)	(0.2080)
$\pi_t \rightarrow m_t$	$\psi_6^{(1)}$	-0.4359*	-0.0433
		(0.2600)	(0.4586)
	$\psi_6^{(2)}$	0.1693	-0.2358
		(0.2300)	(0.4866)

Note: * , **, *** are respectively 5%, 1% and 0.1% significance

Standard errors in the brackets

Table 6: Results for Causality Parameters

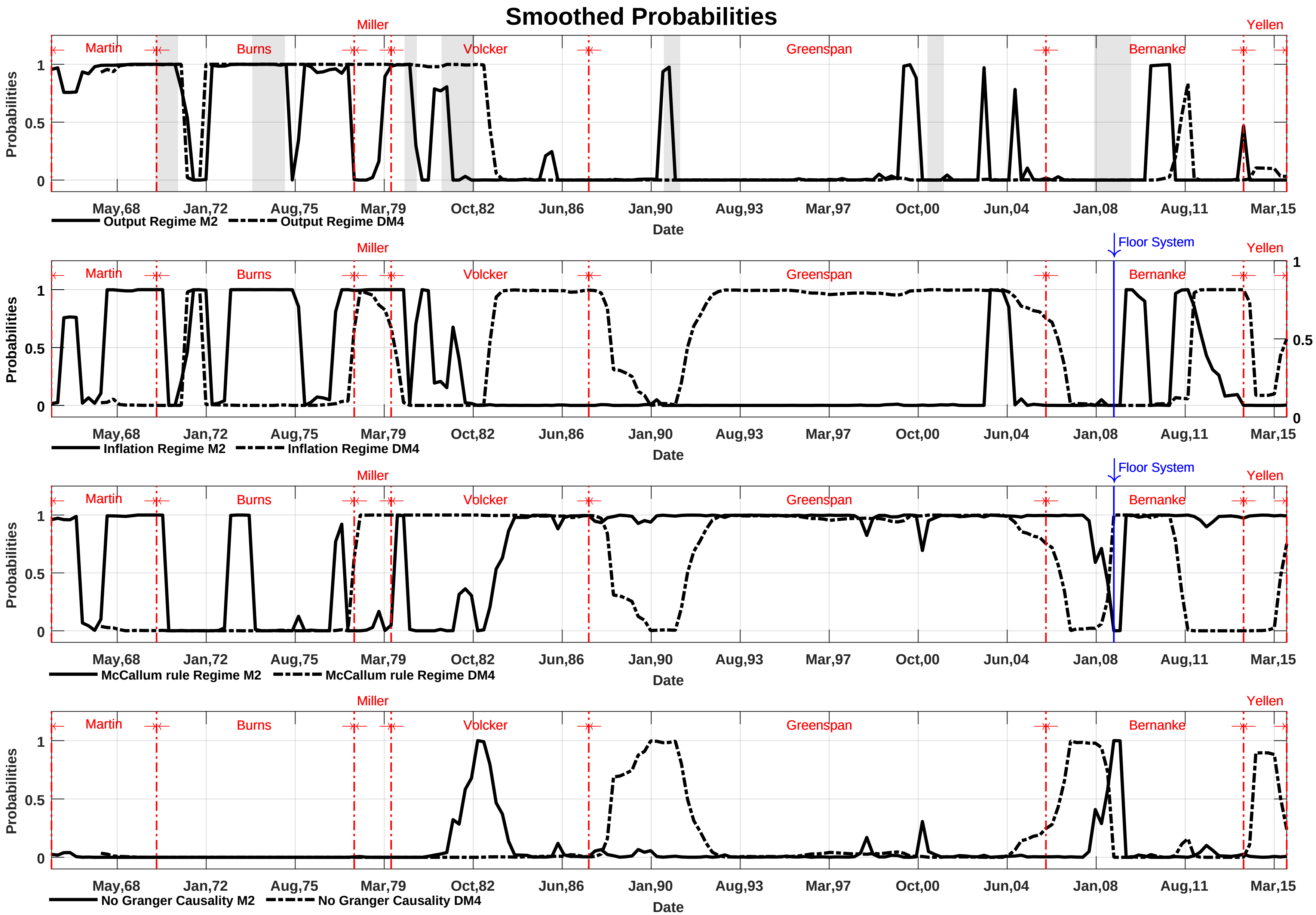

Figure 2: Smoothed Probabilities for Monetary Information Variables 'Indicator-Output Regime' ($S_t = 1, 2, 3, 5$), where the relevant monetary policy indicator causally leads US real output, a 'Indicator-Inflation Regime' ($S_t = 1, 2, 4, 6$), where the relevant monetary policy indictor causally leads price inflation, a 'Monetary Rule Regime' ($S_t = 1, 3, 4, 7$), where US 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

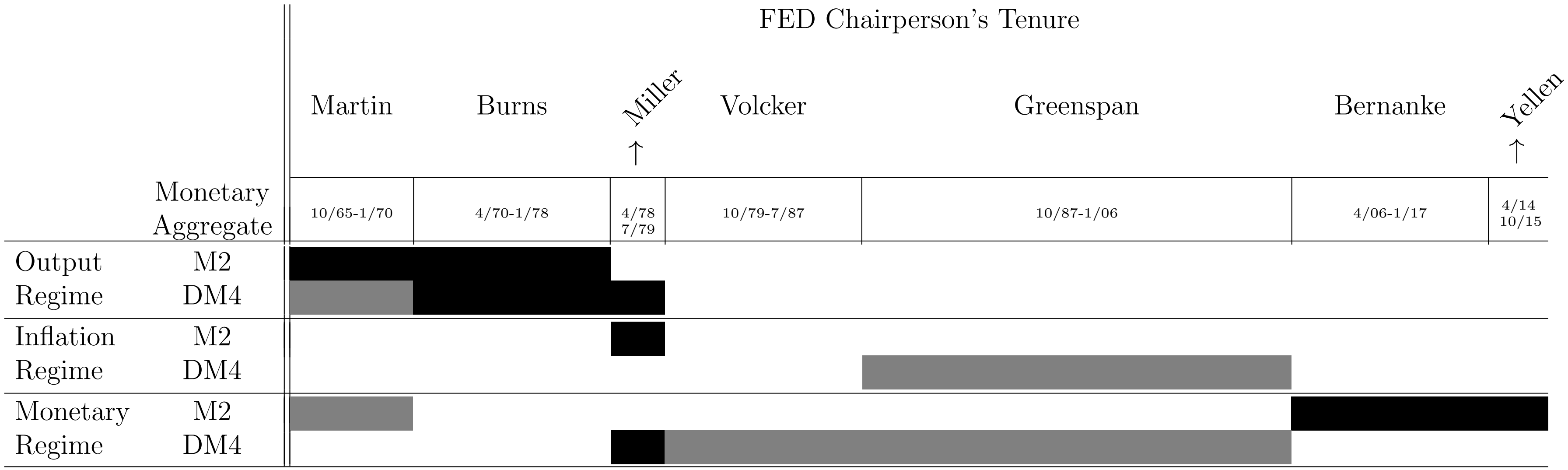

Table 7: Dominant Regime

In Table 7, the black and the grey bars indicate that the regime dominates more than 90% and 75% respectively.

	$\Delta M2$	$\Delta DivisiaM4$
Output Regime	63	62
Inflation Regime	57	102
Monetary Rule Regime	149	115
Non-Causality Regime	8	25

Table 8: Number of Quarters Associated with Each Regime

	$\Delta M2$	$\Delta DivisiaM4$
Output Regime	17.82	49.35
Inflation Regime	13.20	53.19
Monetary Rule Regime	18.48	53.40
Non-Causality Regime	3.66	15.48

Table 9: 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 Domestic Money (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

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

where $\hat{\mathcal{P}}(S_t = \ell)$ is either the filtered probability $\mathcal{P}(S_t = \ell | X_{1-h}, ..., X_t; \hat{\theta})$ or the smoothed probability $\mathcal{P}(S_t = \ell | X_{1-h}, ..., X_T; \hat{\theta})$. Note that $0 \leq C_\ell \leq 1$ 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 10. 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.

	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 10: Regime Classification

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 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 11.

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.

	$C_3 = C_1^*$	$C_5 = C_2^*$	$C_7 = C_3^*$	$C_8 = C_4^*$	
	$m_t, \pi_t^E \to y_t$ $y_t, \pi_t^E \to m_t$	$m_t, \pi_t^E \to y_t$	$y_t, \pi_t^E \to m_t$	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 11: Monte Carlo Results

	$C_3 = C_1^*$	$C_5 = C_2^*$	$C_7 = C_3^*$	$C_8 = C_4^*$	
	$m_t \to y_t$ $y_t \to m_t$	$m_t \to y_t$	$y_t \to m_t$	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 12: Monte Carlo Results

The results presented in Table 12 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 the average number of times that the states are identified correctly is very similar to the averages presented in the Table 11. 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. Concluding Remarks

In this paper, we investigate the nonlinear causal relationships between U.S. real output, inflation and a monetary indicator. Our analysis is based on a trivariate VAR model whose parameters are subject to random Markov changes which are directly related to changes in causality. Our findings suggest that causal relationships between key macroeconomic variables and potential policy instruments are often associated with tenures of Federal Reserve Chairpersons.

Our findings suggest that DM and FFR are mostly statistical substitute variables in explaining variations in U.S. real output associated with tenures of Fed chairpersons. As for potential policy instruments, FFR and/or DM were useful in predicting inflation from Martin's to Volcker's tenures. We find little evidence of these two as a feedback variable, with the exception of the Miller and Volcker periods for FFR and the Bernanke-Yellen periods for DM. Divisia M4, on the other hand, reveals strong monetary policy rule properties during the Miller-Volcker-Greenspan period. While we cannot conclude that U.S. monetary policy objectives, instrument preferences, economy-wide inflation or real output expectations change, when there are changes in the Fed management structure, we provide robust evidence that the causal relationships do change in conjunction with these appointments.

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A Appendix

1.1. 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)

B Additional Results

2.1. Temporary Causality

		FFR	$\Delta M2$	ΔDM	$\Delta DivisiaM4$	
y	μ_{10}	1.7842***	1.7800***	1.7285***	1.254**	Mean Parameters
		(0.4938)	(0.3179)	(0.5310)	(0.4425)	
	μ_{11}	-0.0753	-0.2585	-0.3617	2.0181	
		(0.8579)	(1.6636)	(0.8546)	(2.2863)	
π	μ_{20}	0.4093**	0.5236***	1.1449***	0.4536	
		(0.1494)	(0.1328)	(0.1030)	(0.4816)	
	μ_{21}	-0.6413	0.1715	1.0151**	0.1444	
		(0.4131)	(0.3983)	(0.3929)	(0.5031)	
m	μ_{30}	-0.0183	5.6880***	3.6201***	1.9516*	
		(0.0587)	(1.4534)	(1.0300)	(1.0523)	
	μ_{31}	-1.5515	-2.9694*	5.9370***	2.6871	
		(0.4404)	(1.5968)	(1.4075)	(2.1543)	
y	$\mathcal{P}^{(1)}_{0,0}$	0.9726***	0.9800***	0.9874***	0.9750***	Transition Probabilities
		(0.4938)	(0.0241)	(0.0157)	(0.0391)	
	$\mathcal{P}^{(1)}_{1,1}$	0.9587***	0.9940***	0.9700***	0.9871***	
		(0.8579)	(0.0115)	(0.0368)	(0.0251)	
π	$\mathcal{P}^{(2)}_{0,0}$	0.617***	0.8258***	0.9142***	0.9713***	
		(0.1494)	(0.0797)	(0.0439)	(0.0310)	
	$\mathcal{P}^{(2)}_{1,1}$	0.9847***	0.9295***	0.8918***	0.9715***	
		(0.4131)	(0.0359)	(0.0684)	(0.0345)	
m	$\mathcal{P}^{(3)}_{0,0}$	0.9129***	0.9338***	0.9421***	0.9640***	
		(0.0587)	(0.0399)	(0.0390)	(0.0424)	
	$\mathcal{P}^{(3)}_{1,1}$	0.7552***	0.7868***	0.9613***	0.9754***	
		(0.4404)	(0.1145)	(0.0230)	(0.0402)	

Note: * , **, *** are respectively5%, 1% and 0.1% significance
Standard errors in the brackets

Table 13: Results for Mean Parameters and Probabilities

		FFR	$\Delta M2$	ΔDM	$\Delta DivisiaM4$	
y	$\phi_{10}^{(1)}$	0.1918*	0.2162**	-0.0816	0.2558**	Autoregressive Parameters
		(0.1129)	(0.0924)	(0.1353)	(0.1083)	
	$\phi_{11}^{(1)}$	0.0177	-0.9294***	0.4038**	-0.5266*	
		(0.1756)	(0.1817)	(0.1696)	(0.2517)	
	$\phi_{10}^{(2)}$	0.3146***	0.1951*	-0.067	0.2899**	
		(0.0931)	(0.0881)	(0.1510)	(0.1066)	
	$\phi_{11}^{(2)}$	-0.2301	-0.0590	0.1248	-0.3223*	
		(0.1601)	(0.1755)	(0.1896)	(0.1912)	
π	$\phi_{20}^{(1)}$	0.5933***	0.3838***	0.0521	0.7292***	
		(0.0868)	(0.0680)	(0.0674)	(0.1762)	
	$\phi_{21}^{(1)}$	0.1132	0.3201*	0.5444***	-0.2292	
		(0.2150)	(0.1741)	(0.1236)	(0.2122)	
	$\phi_{20}^{(2)}$	0.2446**	0.3790***	0.3824***	0.1399	
		(0.0940)	(0.0595)	(0.0378)	(0.1454)	
	$\phi_{21}^{(2)}$	0.0738	-0.1464	-0.1068	0.0772	
		(0.1873)	(0.1815)	(0.1129)	(0.1711)	
m	$\phi_{30}^{(1)}$	0.4884***	0.1993	0.0904	0.4918**	
		(0.0782)	(0.2422)	(0.1078)	(0.2008)	
	$\phi_{31}^{(1)}$	-0.9719***	0.3641	-0.3616*	-0.2647	
		(0.1599)	(0.2542)	(0.1835)	(0.2504)	
	$\phi_{30}^{(2)}$	-0.0682	0.2884	0.3806***	0.1773	
		(0.0527)	(0.2147)	(0.0950)	(0.1461)	
	$\phi_{31}^{(2)}$	-0.3681***	-0.1909	-0.9387***	-0.0097	
		(0.0967)	(0.2201)	(0.1176)	(0.2068)	
Log-likelihood		-441.5284	-587.1293	-590.9861	-639.3839	

Note: * , **, *** are respectively5%, 1% and 0.1% significance
Standard errors in the brackets

Table 14: Results for Autoregressive Parameters

2.2. Dominant Regime

	Policy Instrument	FED Chairperson's Tenure → Martin	Burns	Miller	Volcker	Greenspan	Bernanke	Yellen
Output Regime	FFR	72.2%	84.3%	16.6%	78.1%	25.7%	90.6%	100.0%
	DM	100.0%	28.1%	66.7%	71.9%	83.8%	34.4%	28.6%
	M2	100.0%	81.3%	33.3%	18.8%	9.5%	12.5%	0.0%
	DM4	83.3%	100.0%	100.0%	21.9%	0.0%	6.5%	0.0%
Inflation Regime	FFR	55.5%	87.5%	83.3%	34.4%	0.0%	9.4%	0.0%
	DM	100.0%	100.0%	100.0%	100.0%	54.1%	34.4%	0.0%
	M2	66.7%	62.5%	100.0%	18.8%	5.4%	28.1%	0.0%
	DM4	16.7%	21.9%	0.0%	62.5%	82.4%	35.5%	28.8%
Monetary Rule Regime	FFR	33.3%	62.5%	100.0%	75.0%	55.4%	0.0%	0.0%
	DM	0.0%	0.0%	0.0%	0.0%	40.5%	90.6%	100.0%
	M2	77.8%	21.9%	0.0%	56.3%	100.0%	90.6%	100.0%
	DM4	0.0%	28.1%	100.0%	84.4%	82.4%	38.7%	14.3%

Table 15: Dominant Regime

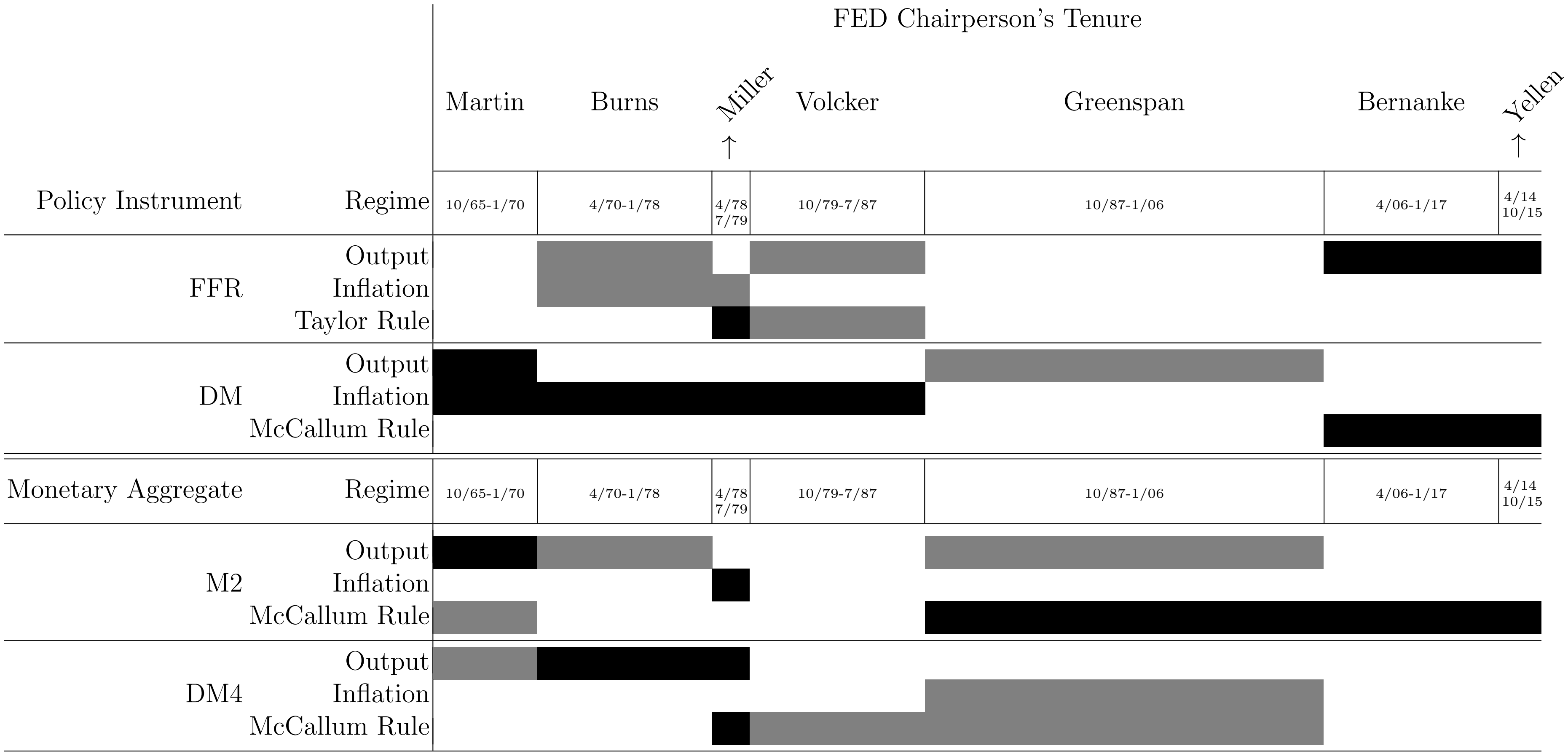

Table 16: Dominant Regime

In the diagram, the black and the grey bars indicate that the regime dominates more than 90% and 75% respectively.

2.3. Regime Separation by Monetary Indicator

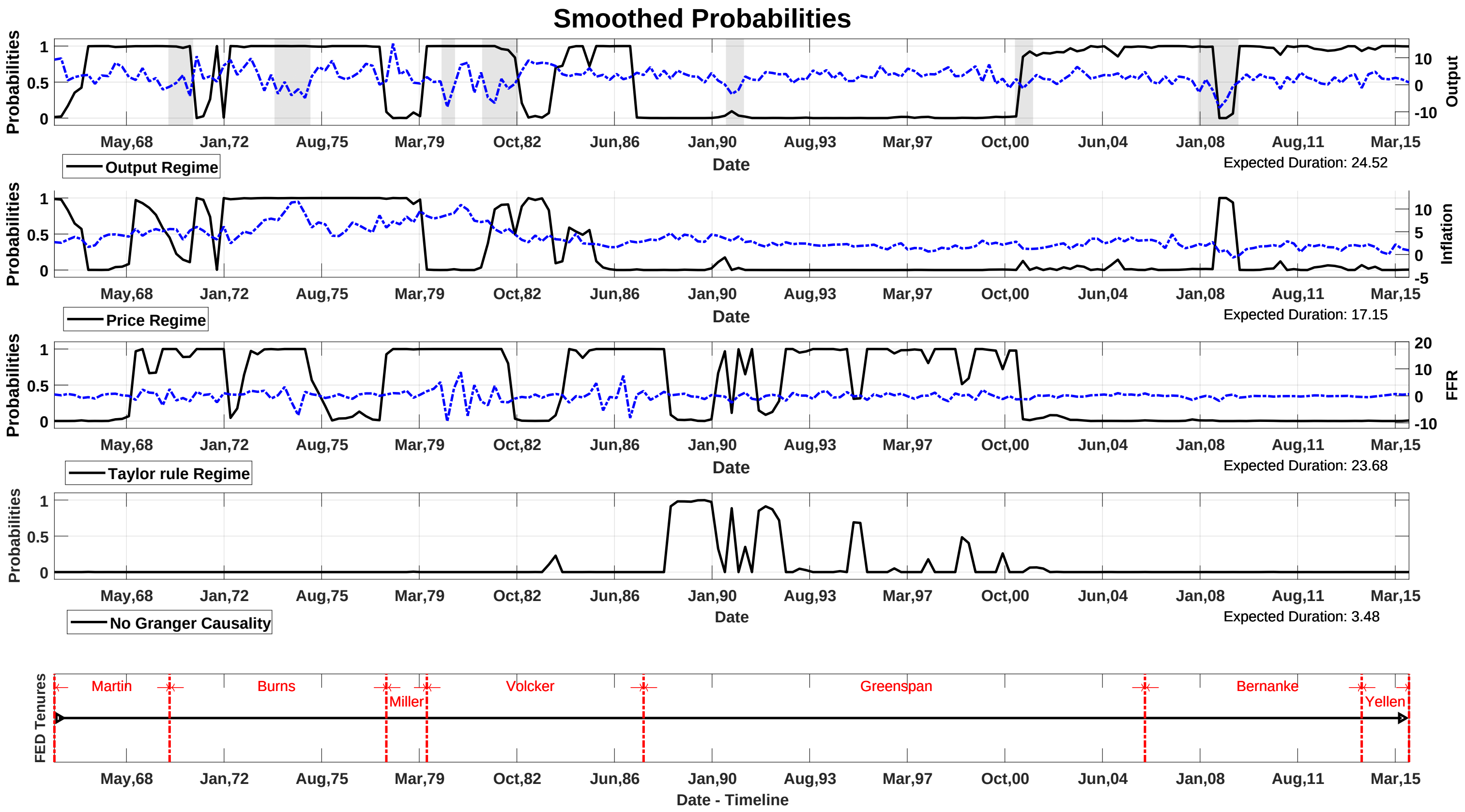

Figure 3: Smoothed Probabilities for Federal Funds Rate

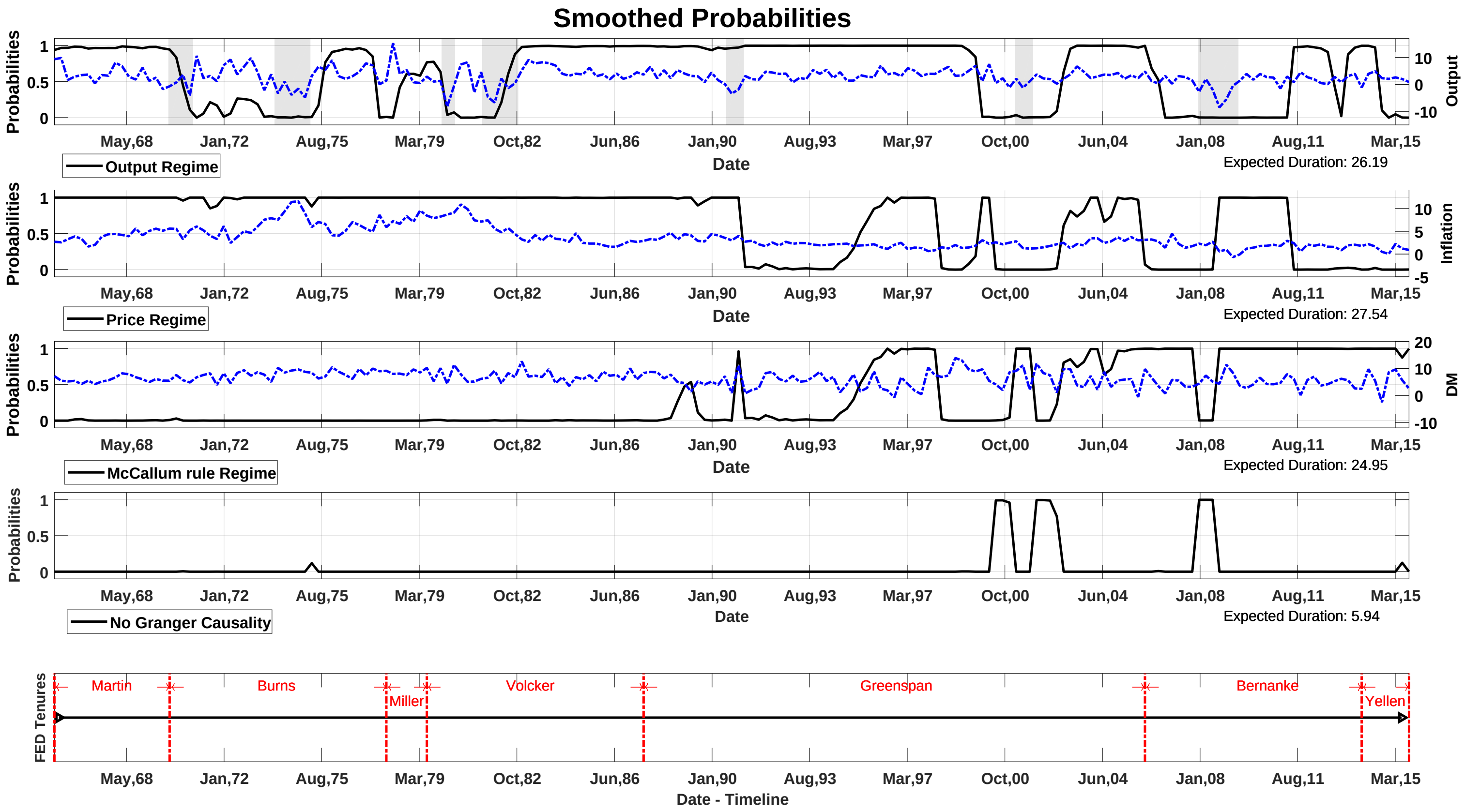

Figure 4: Smoothed Probabilities for Domestic Money

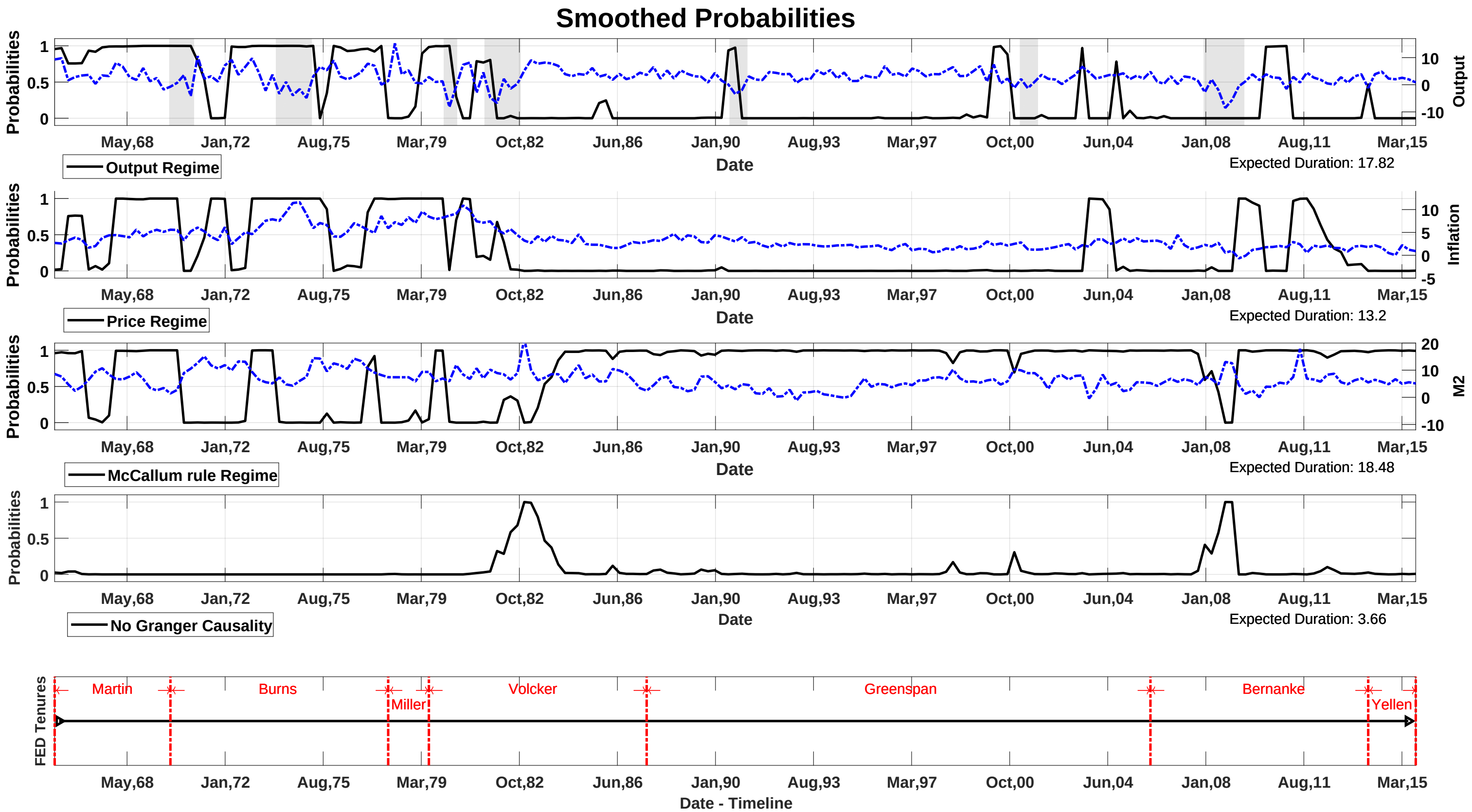

Figure 5: Smoothed Probabilities for M2

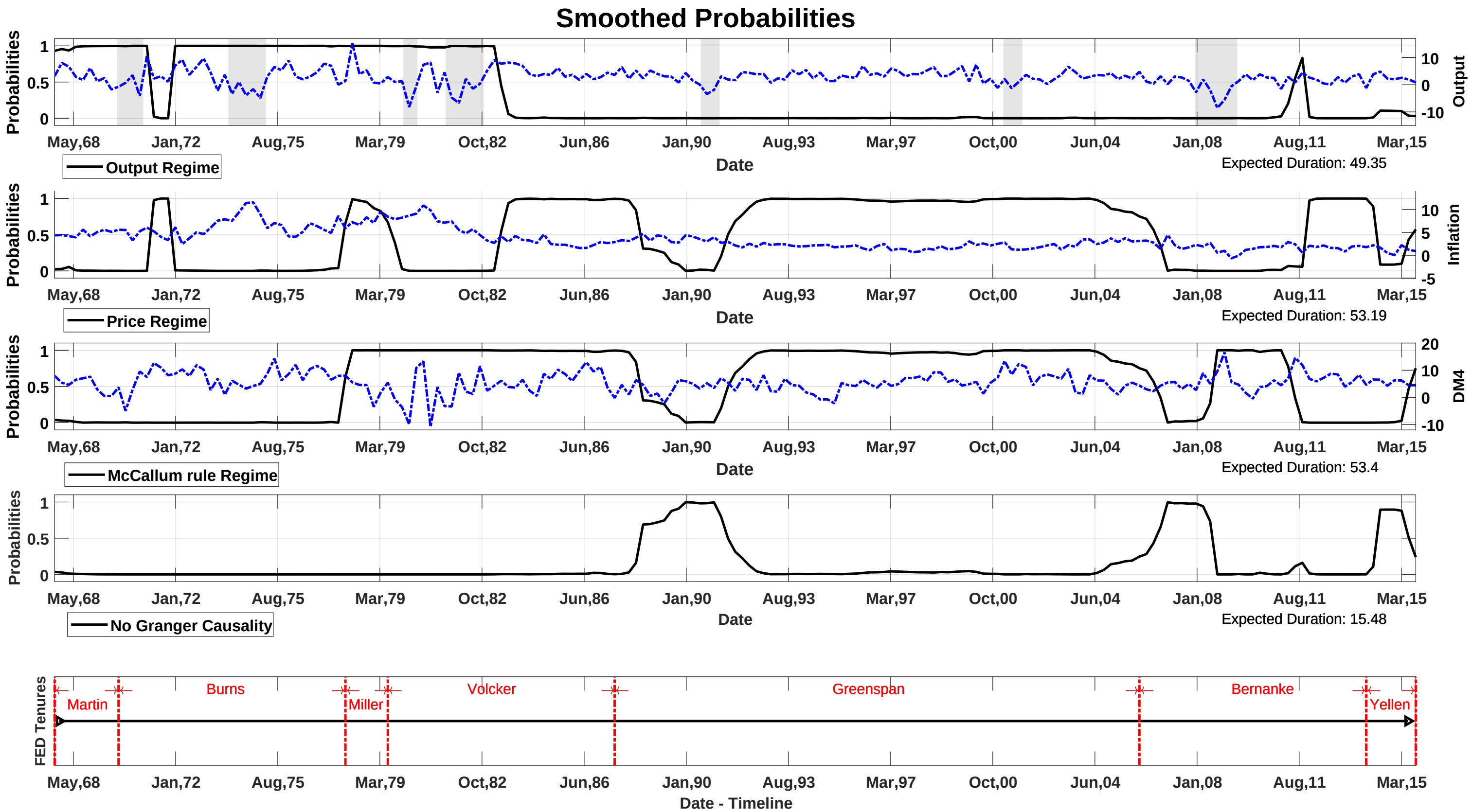

Figure 6: Smoothed Probabilities for Divisia M4

2.4. 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 7, 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.

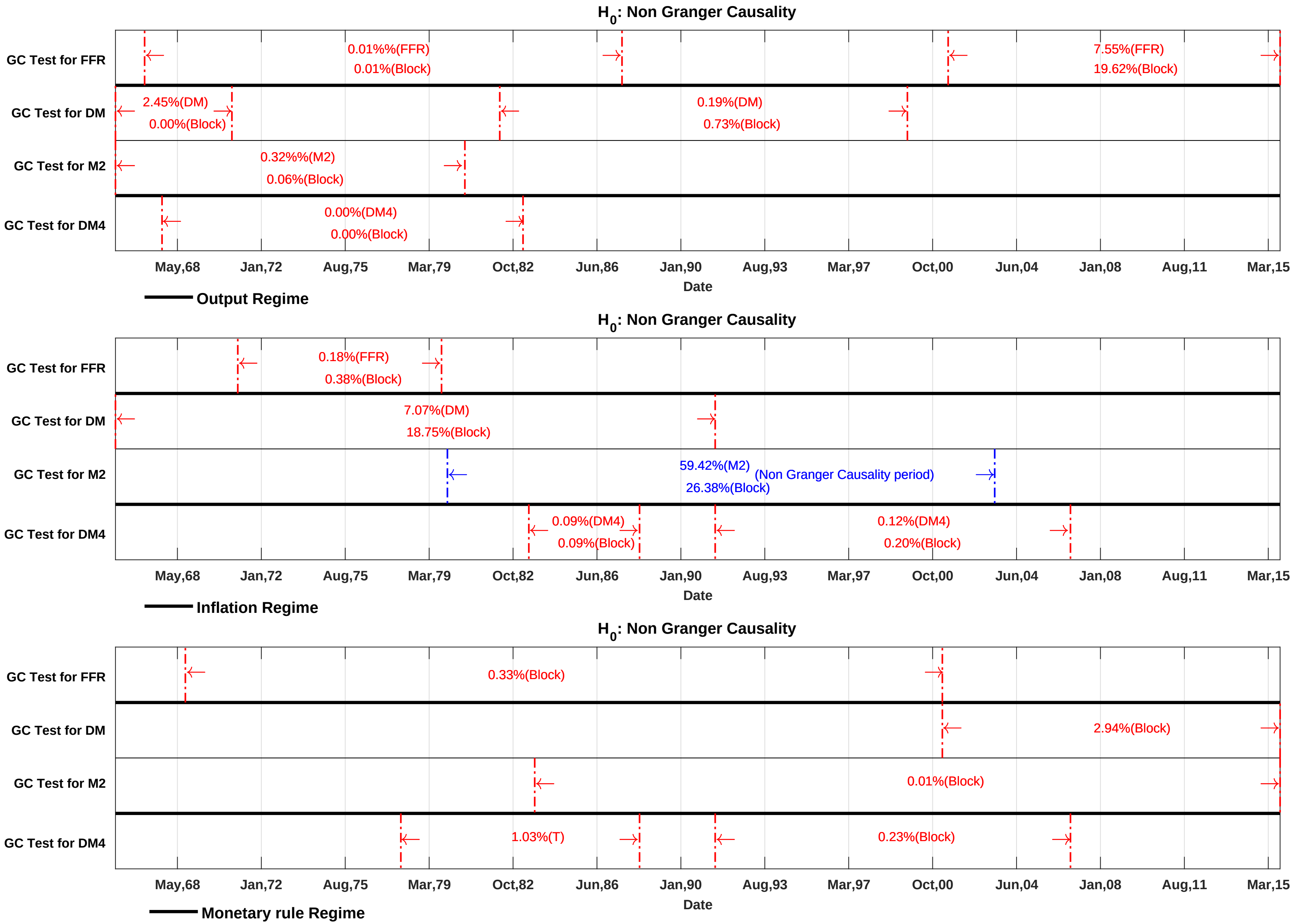

Figure 7: Block Granger Causality Test for all variables. H_0 : is for No–Granger Causality and the Blocks were defined according to the Smoothed Probabilities estimates.

2.5. 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	Reject	Reject	Reject	Reject	Reject
	[-10.13]	[-3.90]	[-15.99]	[-6.92]	[-4.06]	[-4.11]

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

Table 17: Descriptive Statistics and Unit Root Test