The Case for Divisia Monetary Statistics: A Bayesian Time-varying Approach

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Abstract

The zero lower bound and quantitative easing policies have rekindled interest in the link between monetary aggregates and the business cycle. This paper argues, on the basis of Bayesian time-varying coefficient VAR models that use Divisia indexes, that money is more closely linked to the business cycle, as well as forecasting economic activity more accurately, than existing literature claims. Moreover, the relationship between money and economic activity is considerably more pronounced during periods of economic distress, such as in the Great Recession.

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1 Introduction

Monetary aggregates have been neglected in the recent macroeconomics literature for two reasons: the emergence of Taylor rules (Taylor, 1993); and, the alleged, weak empirical relationship between monetary aggregates and economic activity (Bernanke and Blinder, 1992). However, the former is no longer operational as a result of the zero lower bound (ZLB) constraint, and quantitative easing policies (QE). Meanwhile, the latter may owe much to the use of standard, simple sum, measures of money and the Great Moderation.

Cracks in the empirical foundations of monetarism surfaced when predictions of inflationary pressures in the US during the 1980s, as a result of surging M1 growth, were not realised. The explanatory power of money was further questioned when Friedman and Kuttner (1992) and Bernanke and Blinder (1992) reported empirical evidence that money's connection with economic activity was a relic of the 1960s and 1970s. As a by-product of Taylor (1993), connecting interest rates to movements in output and inflation, the dominant mainstream macro model during the late 1990s summarised monetary policy entirely by current and future expectations of short-term nominal interest rates (Clarida et al., 1999).

However, Barnett (2012) argues that the disconnect between money and economic activity observed during the 1980s and 1990s, is a result of measurement error. In light of this, Hendrickson (2014) over-turns the results of Friedman and Kuttner (1992) and Bernanke and Blinder (1992), simply by replacing the Federal Reserve's simple sum monetary statistics with Divisia indexes of money. In doing so, they uncover a strong link between money and eocnomic activity. Belongia and Ireland (2016b) re-confirm the strong connection between Divisia monetary aggregates and economic activity using more recent data, and Barnett and Chauvet (2011) suggest that Divisia measures of money act as better signals for financial crises.

Despite the theoretical appeal of Divisia money aggregates, central banks still focus their attention on atheoretical simple sum monetary aggregates. More specifically, Divisia indices weight component assets of money in accordance with their usefulness in making transactions. Simple sum aggregation embeds the presumption that the services component assets provide are constant over time; and exactly equal. Therefore simply adding the component assets of a monetary aggregate together, a priori, implies that they are perfect one-for-one substitutes.

In reality, the component assets of money provide different services and therefore yield different returns. These returns change over time, thereby implying the opportunity costs–in terms of foregone interest–are time-varying. In estimating macroeconomic and macro-econometric models, it is both theoretically consistent, and intuitive to use aggregated data that are coherent with the assumptions of the model. Failing to do so may lead to distorted statistical inference; and ultimately, misguided policy implications.

The key contribution of this paper is to assess the relative empirical benefits of Divisia indices relative to their simple sum counterparts. Departing from the majority of literature within this field, Bayesian time-varying parameter VAR models are employed in order to track the possibility of any variation in the relevance of Divisia aggregates throughout time. An important feature of this modelling strategy is that it allows for heterogeneity across boom and bust periods. By providing comprehensive reduced-form and structural analyses, this study is the first of its kind to utilise Divisia indices in non-linear Bayesian framework. In the spirit of Benati and Mumtaz (2007), this paper uses US data spanning 1976Q1 to 2016Q3.

Understanding the reduced-form and structural implications of weighting money in a theoretically consistent manner is important for at least three reasons. First, there is mixed evidence on the forecasting performance of Divisia aggregates, relative to their simple sum counterparts (Schunk, 2001; Albuquerque et al., 2015; Barnett et al., 2016). This study complements the existing literature, such as Belongia and Ireland (2016b), by uncovering a stronger link between Divisia money and economic activity throughout time, and over different frequencies.

Second and perhaps more importantly, the prior structural VAR literature incorporating Divisia indices use constant parameter VAR models (Belongia and Ireland, 2015, 2016b). A well known feature of the data is the stark change in macroeconomic volatility; particularly following the Great Inflation (Canova et al., 2007; Bianchi et al., 2009; Benati and Mumtaz, 2007). In general the results are not conflicting, macroeconomic volatility changes over time. Furthermore, the latter argues that the sources of this change was predominantly down to good luck; not successful monetary policy. This is echoed in Barnett and Chauvet (2011) who document that monetary policy preceding the 2001 Recession was in fact too expansionary; and in response, too contractionary. Throughout the Great Moderation, monetary policies are argued to have been guided by defective data inconsistent with modern aggregation theory.

Building on Belongia and Ireland (2015), this paper focuses on the time-varying influence of money in the monetary policy rule. In particular, results uncover economically meaningful differences in the influence of Divisia money, relative to simple sum aggregates, for monetary policy rules. However, structural variance decompositions of monetary policy shocks over the business cycle show negligible differences across comparable models. Furthermore, all models imply the Great Moderation was not as a result of improved monetary policy, and that monetary policy shocks played little role in driving depth or length of the Great Recession.

Third, simple sum monetary aggregates embed measurement error of unknown magnitude; due to the inability of these measures to capture internal substitution effects across component assets. It is of paramount importance to understand the empirical implications of measurement error, and this study quantifies these in a flexible econometric model.Complementary to the results in Barnett et al. (2009), the implications of measurement error are prominent during periods of economic distress, and high interest rates.

The main results of this study may be summarised into four main findings. First, model evaluation exercises provide statistical support in favour of replacing simple sum measures of money with their Divisia counterparts. Second, a close link between money and economic activity over the business cycle is re-established. In particular, the relationship is considerably stronger when using Divisia aggregates. Third, out of sample (pseudo) forecasting performance of models using Divisia aggregates surpasses those using analogous simple sum measures; particularly during periods of recession. Finally, allowing for Divisia aggregates within estimated Taylor rules implies a closer connection between macroeconomic variables and the interest rate throughout time, and over the business cycle. Overall, the results from this paper reveal that measurement error is most harmful during periods of high interest rates and recessions.

This paper contributes to the monetary economics literature by quantifying the relative empirical benefits of using Divisia monetary statistics using time-varying coefficient VAR models. Reduced-form analysis conforms with the findings of Belongia and Ireland (2016b) and Barnett et al. (2016), by showing that systems using Divisia aggregates outperform those using simple sum counterparts. Building on the structural results in Belongia and Ireland (2015) and Belongia and Ireland (2016b), this paper quantifies the impact of money in monetary policy rules within a time-varying framework. The implication of this study suggests that Divisia aggregates are important for forecasting economic activity, and have a role to play in monetary policy. In accounting for time-variation, this study builds on the existing literature by showing that parameter, and volatility, evolution is an important factor to consider when conducting empirical analysis. Therefore the Federal Reserve, and indeed other central banks, should replace atheoretical simple sum aggregates in favour of Divisia indices when producing economic forecasts, and changing their monetary policy stance.

The remainder of this paper is organised as follows: Section 2 describes the data and econometric specification. Section 3 presents the empirical analysis. Finally, Section 4 offers concluding remarks.

2 Data, Econometric Specification and Structural Identification

2.1 Data

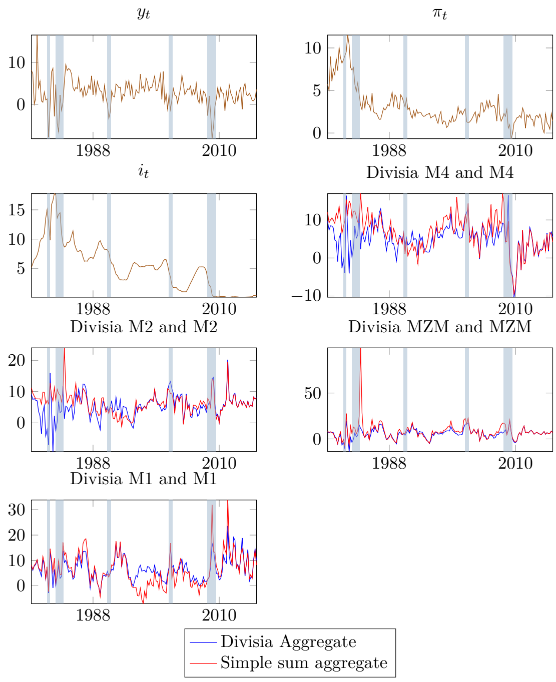

Figure 1: **US Macroeconomic data from 1977 to 2016**
Notes: This figure plots quarterly growth rates of US macroeconomic data from 1977Q3–2016Q3. The first three plots report y_t is annualised quarterly real GDP growth; π_t is annualised quarterly GDP deflator inflation; i_t is the Federal Funds rate. The remaining plots show the annualised quarterly growth rates of: Divisia M4 and simple sum M4; Divisia M2 and simple sum M2; Divisia MZM and simple sum MZM; and Divisia M1 and simple sum M1, respectively. Grey bars indicate NBER recession dates.

This study uses US macroeconomic data on real GDP; GDP deflator inflation; the Federal Funds rate. The monetary aggregates used are: M4; M2; Money-Zero-Maturity (MZM); and M1[1]. The time series sample spans 1967Q1 to 2016Q3. All variables enter the model as annualised quarterly growth rates except for the Federal Funds rate; this is left untransformed. Figure 1 plots US macroeconomic variables from 1977Q3 to 2016Q3. In the Supplementary

[1]The Federal Reserve discontinued publication of its broadest aggregate, "L" in 1998, which the Centre for Financial Stability's Divisia M4 index is comparable to. Therefore, analysis comparing Divisia M4 and with simple sum M4 required obtaining the component assets that comprise the Divisia M4 index and simply adding them together. Implicitly adding these components together implies perfect substitutability among distant assets for money as to currency. This is regarded as far worse than imposing no weight on highly liquid substitutes for money; an issue that arises with narrower aggregates such as those used in this paper.

Appendix, Table A1 report the sources for data used in this paper.

2.2 A Time–varying Parameter VAR with Stochastic Volatility

Analysis begins by using the following TVP VAR model with p lags and M variables:

$$Y_t \quad = \quad \beta_{0,t} + \beta_{1,t} Y_{t-1} + \cdots + \beta_{p,t} Y_{t-p} + \epsilon_t \equiv X_t^{'} \theta_t + \epsilon_t \tag{1}$$

where Y_t is defined as $Y_t \equiv [y_t,\, \pi_t,\, i_t,\, m_t]^{'}$, with y_t being annualised quarterly real GDP growth, π_t is the annualised quarterly rate of GDP deflator inflation, i_t is the short term interest rate, and m_t is the annualised quarterly growth of the Divisia or simple sum monetary aggregate. $X_t^{'}$ contains lagged values of Y_t and a constant. Therefore in this study, $M = 4$, and the lag length is set to $p = 2$, which is consistent with Benati and Mumtaz (2007). The VAR's time–varying parameters are collected in θ_t and evolve as

$$p(\theta_t|\theta_{t-1}, Q) = I(\theta_t) f(\theta_t|\theta_{t-1}, Q) \tag{2}$$

where $I(\theta_t)$ is an indicator function that rejects unstable draws. Thereby imposing a stability constraint on the VAR where, conditional on the roots of the VAR polynomial lying outside the unit circle, $f(\theta_t|\theta_{t-1}, Q)$ follows a random walk[2]

$$\theta_t = \theta_{t-1} + \nu_t \tag{3}$$

where $\nu_t \backsim N(0, Q)$. The innovations in (1) follow $\epsilon_t \backsim N(0, \Omega_t)$. Ω_t is the time–varying covariance matrix which is factored as

$$Var(\epsilon_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})^{'} \tag{4}$$

with A_t being a lower triangular matrix with unit diagonal elements, zeros above the main diagonal, and the contemporaneous relations below. H_t is a diagonal matrix containing the stochastic volatility innovations. Collecting the diagonal elements of H_t and the non-unit non-zero elements of A_t in the vectors, $h_t \equiv [h_{1,t},\, h_{2,t}, ..., h_{4,t}]'$ and $\alpha_t \equiv [\alpha_{21,t},\, \alpha_{31,t}, \ldots, \alpha_{43,t}]'$, they

[2] As Cogley and Sargent (2005) note, adding an indicator function that rejects draws for the coefficient matrices in every t truncates and renormalises the prior. This stability constraint imposes a belief, a priori, that explosive representations of real GDP growth, inflation, the interest rate and money growth are implausible. Galí and Gambetti (2009) labels this constraint as imposing local stationarity for all time periods, t.

evolve as a geometric random walk and random walk respectively

$$\ln h_{i,t} = \ln h_{i,t-1} + \eta_t, \quad \eta_t \backsim N(0, W) \tag{5}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t, \quad \zeta_t \backsim N(0, S) \tag{6}$$

The innovations in the model are jointly Normal and the structural shocks, u_t are such that, $\epsilon_t \equiv A_t^{-1} H_t^{\frac{1}{2}} u_t$. S is a block diagonal matrix, which implies that the non–zero and non–unit elements of A_t in each row evolve independently. This is a simplifying assumption that allows estimation of A_t equation by equation. The initial conditions of the model are calibrated using the OLS point estimates of a time invariant VAR model using the first 10 years of data. Therefore, the effective sample is from 1977Q3-2016Q3. Appendix B provides specific information with regards to the choice of priors and an outline of the Markov-Chain Monte Carlo posterior simulations algorithm; as well as reporting convergence diagnostics of the MCMC.

2.3 Structural Identification

Table 1: Identification Restrictions

Shock:	**Supply** u_t^S	**Demand** u_t^D	**Monetary Policy** u_t^{MP}	**Money Demand** u_t^{MD}
Variable				
y_t	$\geq$	$\geq$	$\leq$	$\leq$
π_t	$\leq$	$\geq$	$\leq$	$\leq$
i_t	x	$\geq$	$\geq$	$\geq$
m_t	x	$\geq$	$\leq$	$\geq$

Notes: This table reports the sign restrictions imposed on the contemporaneous impact of identified structural shocks on to GDP growth, y_t; inflation, π_t; the interest rate, i_t; and Divisia money growth, m_t. The term x denotes no restriction imposed on the contemporaneous impact of the structural shock to the respective variable.

Mapping to the structural model utilises Algorithm 1 in Arias et al. (2018) incorporated with Rubio-Ramirez et al. (2010), by imposing sign restrictions on the contemporaneous impact of the four identified shocks. Similar to Benati and Mumtaz (2007), the structural shocks are characterised as: supply, u_t^S; demand non-policy, u_t^D; monetary policy, u_t^{MP}; and money demand shocks, u_t^{MD}.

Table 1 summarises the impact of a positive structural shock on the endogenous variables;

it can be shown that these restrictions are sufficient to separate the shocks from one another. Appendix C of the Supplmentary Appendix provides details on the procedure to obtain the structural impact matrices, and an outline of the algorithm to compute generalised impulse response functions following Koop et al. (1996).

From a theoretical perspective, the sign restrictions associated to supply, demand and monetary policy are non-controversial (see e.g. Clarida et al. (2000)). On impact a supply shock is assumed to raise GDP growth and lower inflation, with the response of the interest rate and money left unconstrained. A demand shock causes increases in all variables on impact. The identified monetary policy shock causes contemporaneous contractions in GDP, inflation, and money; whilst increasing the interest rate.

However, the restrictions imposed on variables with respect to a money demand shock requires further discussion, and is motivated by a simple transaction demand for money model allowing for money in the utility function. Following Benati (2017), the first-order conditions of the household's optimisation problem imply:

$$\frac{P_t C_t}{M_t} \approx \theta R_t$$

The left hand side of the approximation is the velocity of money. Note also that consumption and GDP are cointegrated implies that long-term properties of velocity defined in terms of consumption are equivalent to those defined in terms of GDP. On this premise, the velocity of money, and therefore its inverse (i.e. money as a fraction of GDP), to a function of the nominal interest rate.

This model essentially links velocity to the natural rate of interest, and shows that the velocity of M1 is a close approximation to the permanent component of the short interest rate. Upon estimating a bivariate system and identifying a permanent and transitory shock, it is shown that M1 velocity increases in line with the short rate with respect to transitory shocks. This justifies our identifying assumption that both money and the interest rate increase with respect to a money demand shock. Note also that these results suggest that any disequilibrium between M1 velocity (and therefore M1 balances) and the interest rate arise from the interest rate itself.

Furthermore, the only ways in which velocity increases are: i) money balances increase; ii) GDP falls; iii) money increases while GDP falls; or iv) the increase in money is greater than that of the increase in GDP. Arguably, iv) can be disregarded, since it is shown that a disequilibrium between velocity and the short-term interest rate implies future movements of the interest rate. Thus, as the interest moves toward equilibrium this does not signal inflation. In the presence of rising interest rates, the implication here is that inflation, and GDP, falls. Regarding the latter, the fact that demand for money to make transactions incorporates a forward looking component (Andrés et al., 2009), implies that agents may hold money for transactions in future periods. In turn, this suggests that current GDP falls. Therefore, the imposition of negative signs on GDP growth and inflation are credible in the context of a transaction demand for money model.

Structural analysis proceeds on this premise using M1 aggregates. This is becuase the component assets (i.e. currency and demand deposits) that comprise the aggregate are for making transactions. The reason for this is that it may not be the case that a money demand shock, when focussing on broader monetary aggregates yields the same impact on the economy[3]. Component assets of money included in broader monetary aggregates provide different liquidity services beyond holding money for transaction purposes. However, in the Supplementary Appendix structural analysis for all models is provided, and in general results and conclusions are consistent with those presented below.

3 Results

3.1 Model Selection and Evaluation

In order to justify the use of a TVP VAR, it is necessary to conduct a model selection exercise. To provide statistical credibility, a battery of restricted and alternative Bayesian VAR models are estimated using US economic data and the Divisia M4 aggregate[4]. All models are then tested in terms of statistical fit using the Bayesian Deviance Information Criterion (DIC) proposed in Spiegelhalter et al. (2002). Specifically, the DIC is given by

$$\mathrm{DIC} = \bar{D} + p_D \tag{7}$$

where $\bar{D} = -2E(\ln \mathrm{L}(\Lambda_i))$ which is -2 multiplied by the expected value of the log likelihood evaluated at draws of the parameters, Λ_i, for each iteration of the MCMC. The second term,

[3] I would like to thank an anonymous reviewer for this suggestion.

[4] For the sake of brevity, model selection results for models using Divisia and simple sum M2, MZM, or M1 are not reported. Note that these results are consistent with those presented in the main text and are available on request.

$p_D = \bar{D} - D(\bar{\Lambda})$, where $D(\bar{\Lambda}) = -2 \ln \mathrm{L}(E(\Lambda_i))$, is a measure of model complexity. The lower the DIC, the better the model fit. Estimating (7) requires calculating the likelihood function for each run of the MCMC[5].

Table 2: Bayesian DIC Statistics for Competing VAR Models using Divisia M4

Model	**DIC**
TVP VAR with time-varying covariance matrix	**1075.52**
TVP VAR with constant covariance matrix	2198.927
Two-Regime Markov Switching VAR	2535.012
Linear Bayesian VAR with time-varying covariance matrix	1186.087
Linear Bayesian VAR with stochastic volatility	1163.065
Linear Bayesian VAR with constant covariance matrix	3028.721

Notes: This table reports the DIC estimates from a battery of VAR models using US real GDP growth, GDP deflator inflation, the Federal Funds rate, and Divisia M4 from 1967Q3-2016Q3. The value highlighted in bold font indicates the model with the lowest DIC statistic, and therefore the model that fits the data best.

Table 2 reports the DIC statistics from restricted variants of the TVP VAR specification, and from a two-regime Markov Switching VAR (MSVAR) model. Posterior parameter estimates are obtained using Bayeisan methods by incorporating standard priors and posterior simulation algorithms.[6]. It is evident that TVP VAR specification fits the data better relative to all restricted variants of the baseline specification; as well as the MSVAR that, based on posterior parameter estimates, captures boom and bust periods over the estimation sample[7]. From an economic perspective, the TVP VAR allows for a break at every observation. Thereby departing from the assumption that all recessions, and indeed booms, are homogeneous; something the DIC statistics support is present within the data.

Having established that the TVP VAR specification fits the data most favourably, it is also worth considering whether there is statistical evidence in favour of replacing simple sum monetary aggregates with their Divisia counterparts. Therefore, to evaluate the potential statistical benefits of using Divisia indexes, the DIC statistics of TVP VARs using Divisia and simple sum: M4; M2; MZM; and M1 are reported in Table 3. In Panel A results for models using M4 are presented, meanwhile in Panels B to D show results from models using M2, MZM, and M1

[5] A particle filter evaluates the likelihood function of each TVP VAR to deal with the non-linear interaction of the stochastic volatilities.

[6] Prior specifications and posterior simulation algorithms are not discussed or reported as they are widely available (see e.g. the website of Haroon Mumtaz https://sites.google.com/site/hmumtaz77/code).

[7] These results are available on request. Note also that the DIC statistics for models using narrow measures of Divisia provide values greater than 2000, these are substantially higher than those estimates from analogous TVP VAR specifications presented in Table 3 below.

respectively. It is clear that there is non-conflicting statistical evidence in favour of replacing simple sum measures of money with their theoretically superior Divisia counterparts.

To complement this statistical evaluation, it is noteworthy to mention that simply replacing simple sum measures with their Divisia counterparts yields substantial saves in the computation time taken to obtain the structural results. More specifically, replacing simple sum M4, M2, MZM ,and M1 with Divisia M4, M2, MZM, and M1 yields an 87.25%, 15.8%, 23.2%, and 30.8% save in respective computation time. The average save in computation time across all models is 39 hours[8].

Table 3: DIC statistics for Competing Measures of Money

	A: M4		**B: M2**		**C: MZM**		**D: M1**	
	Divisia	**Simple**	**Divisia**	**Simple**	**Divisia**	**Simple**	**Divisia**	**Simple**
DIC	**1075.52**	1113.17	**1045.78**	1082.50	**1112.13**	1164.57	**1133.37**	1236.71

Notes: This table reports the DIC estimates from the 8 estimated TVP VAR models. Panels A, B, C, and D contain results from models using Divisia and simple sum: M4; M2; MZM; and M1, respectively. Values highlighted in bold font indicate a lower DIC estimate from the model using a Divisia monetary aggregate, relative to its simple sum analogue.

Taken together, the above provides statistical evidence to: i) justify the econometric model; ii) support the use of Divisia aggregates; and iii) using these measures of money results in substantial saves in structural computation time. Therefore, even at the outset, it is clear there is a strong statistical case for replacing simple sum monetary aggregates.

3.2 Reduced-Form Evidence

3.2.1 Money and Macroeconomic Variables over the Business Cycle

In order to study the link between money and macroeconomic fundamentals, the coherence and gain statistics are computed from the time-varying spectral density matrices at frequency ω. The time-varying spectral density matrices at frequency ω are

$$\hat{f}_{t|T}(\omega) = (I_4 - \hat{\theta}_{t|T}e^{-i\omega})^{-1}\frac{\Omega_{t|T}}{2\pi}\left[(I_4 - \hat{\theta}_{t|T}e^{-i\omega})^{-1}\right]' \tag{8}$$

[8]The reason for this is that the models estimated using simple sum measures of money resulted in more frequent rejections of explosive draws. Estimation of the models was carried out on a HP Z440 Workstation with 32GB DDR4-2400 RAM and an Intel Xeon E5-1650v4 3.60GHz 15MB 2400 6C CPU processor.

where $\hat{\theta}_{t|T}$ are the time-varying coefficient matrices, $\Omega_{t|T}$ are the time-varying reduced-form VAR covariance matrices and $\omega \in [0 \quad \pi]$ denotes the frequency window. Note that the off-diagonal elements of the spectral density matrix evaluate the connection between the endogenous variables in the TVP VAR over different cycles. Coherence and gain are defined as

$$\hat{\delta}_{ij,t|T}(\omega) = \sqrt{\frac{\left[\hat{c}_{ij,t|T}(\omega)\right]^2 + \left[\hat{q}_{ij,t|T}(\omega)\right]^2}{\hat{f}^{ii}_{t|T}(\omega)\hat{f}^{jj}_{t|T}(\omega)}}, \quad 0 \leq \hat{\delta}_{ij,t|T}(\omega) \leq 1 \tag{9}$$

$$\hat{\mathrm{g}}_{ij,t|T}(\omega) = \sqrt{\frac{\left[\hat{c}_{ij,t|T}(\omega)\right]^2 + \left[\hat{q}_{ij,t|T}(\omega)\right]^2}{\hat{f}^{jj}_{t|T}(\omega)}} \tag{10}$$

in (9) $\hat{c}_{ij,t|T}(\omega)$ and $\hat{q}_{ij,t|T}(\omega)$ denote the co-spectrum and quadrature spectrum respectively. The co-spectrum, $\hat{c}_{ij,t|T}(\omega)$, is the real component of the off-diagonal elements of $\hat{f}_{t|T}(\omega)$. Meanwhile the quadrature spectrum, $\hat{q}_{ij,t|T}(\omega)$, is the imaginary component of the off-diagonal elements of $\hat{f}_{t|T}(\omega)$, and $\hat{f}^{ii}_{t|T}(\omega)$, $\hat{f}^{jj}_{t|T}(\omega)$ are the spectral densities of variable i and j respectively. The co-spectrum measures the covariance between the variables over different frequencies whereas the quadrature spectrum contains information on the possibility that the series of interest are at different phases of the cycle. The coherence between two series is the magnitude to which the series' are jointly influenced by cycles at a given frequency. Large values of $\hat{\delta}_{ij,t|T}(\omega)$ imply series i and j share a common cycle at frequency ω. The gain statistics in (10) report the slope of the relationship between variable i and j at frequency ω; which is analogous to the OLS coefficient at a given frequency.

Decomposing the degree of association between money and macroeconomic variables in the frequency domain, approximates a link between time series that may not be obvious using conventional correlation coefficients; or non-parametric filters like those proposed in Baxter and King (1999). The benefit of computing frequency domain statistics are that relationships at horizons relevant for policy makers can be established throughout time. For example the reduced-form estimates from each TVP VAR can provide information on how these variables co-move over the business cycle.

Figure 2 reports heatmaps of the time-frequency dynamics of money and macroeconomic variables over the business cycle; business cycle frequencies are defined over a 6 to 32 quarter horizon. Specifically, the posterior median coherence statistics between money and macroeconomic variables stemming from models using Divisia M4 are in Panel A, and models using Divisia M2, MZM, and M1 are in Panels B, C, and D respectively. The strength of the connection is shown by the colour, and the areas of black denote the time and frequency bands where the coherence is greater from models using analogous simple sum monetary statistics.

Three factors emerge from Figure 2. First, with the exception of Divisia M1 and GDP, the association between Divisia money and GDP growth over the business cycle, predominantly, is closer than that of simple sum aggregates. Panels A, B, and C show that the coherence between Divisia M4, M2, and MZM over the business cycle outweighs the degree of association between GDP and comparable simple sum measures. Models using Divisia M4, M2, and MZM yield larger connections between money and GDP over 85% of the estimation sample. It is clear that the coherence between money and GDP falls sharply during the Volcker disinflation (i.e. the early-mid 1980s), thereby indicating a sharp transition in the connectedness between all measures of money and GDP growth over the business cycle. For example, during the late 1970s and 1980s, the coherence between Divisia M4 and GDP, Divisia M2 and GDP, and Divisia MZM and GDP is greater than the second half of the sample. This is indicative of the break in the volatility of macroeconomic variables that is confluent with the beginning of the Great Moderation.

Second, the connection between Divisia money and inflation is stronger than that of simple sum analogues; particularly for Divisia M4 and M2. Across all models, the coherence statistics from models using Divisia are greater over 75% of the sample. It is also evident that at longer horizons the connection between Divisia money and inflation intensifies throughout the estimation sample. In general, the connection between Divisia money and inflation is substantially larger for horizons beyond 15 quarters. To illustrate, the coherence statistics between Divisia M4 and inflation during the most recent recession at a 6 quarter horizon are around 0.4. Comparing this to the 30 quarter horizon, where the estimated connection reaches highs of 0.7, shows that the influence of a common cycle between money and inflation is at lower frequencies of the business cycle. Building on the former, it is evident that there is also considerable time variation in the degree of association between Divisia M4 and inflation; the analogous statistics for Divisia MZM and inflation during the mid 1990s at lower frequencies of the business cycle (i.e. 20 quarter horizons and greater) are around 0.4.

Finally, the coherence between all measures of Divisia money and the Federal funds rate is closer than that of their simple sum counterparts. In particular, the posterior median coherence between the Federal funds rate and money from models using Divisia M4, M2, and M1 are greater across more than 95% of the estimation sample. From each plot, the connectedness

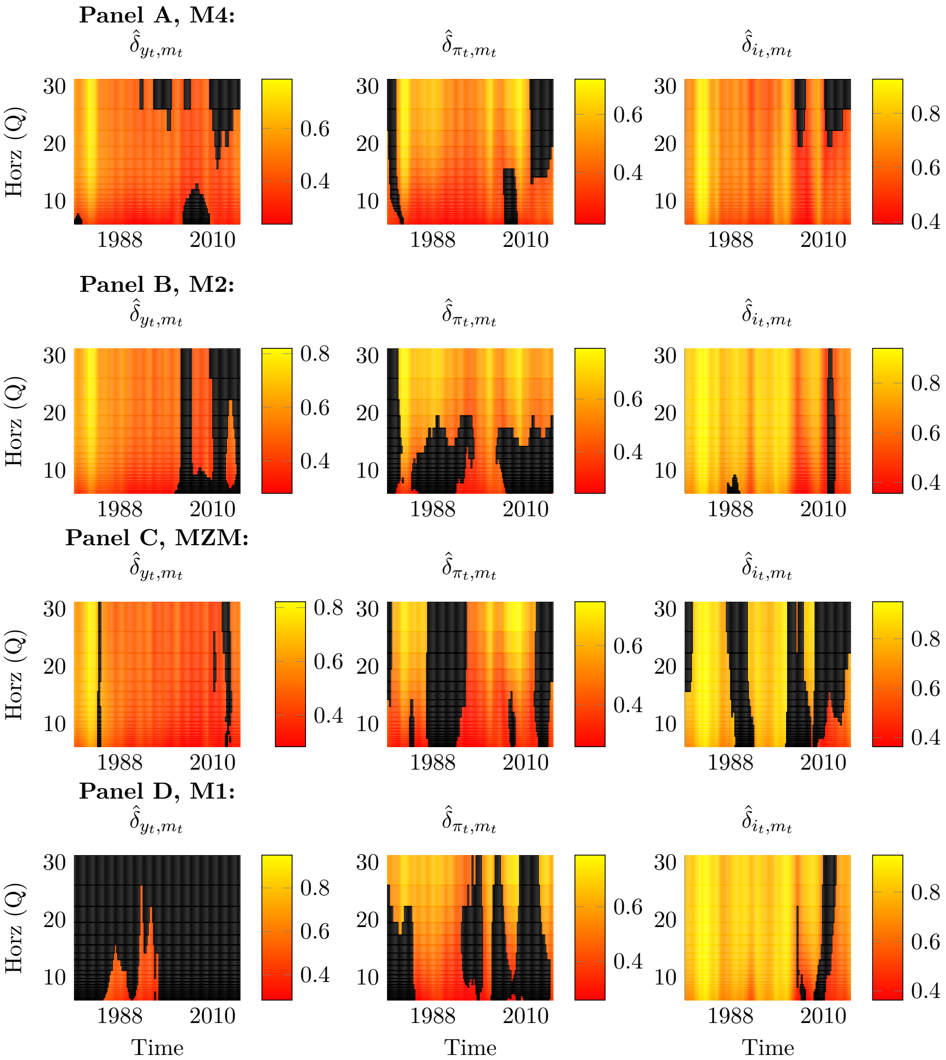

Figure 2: **The Time-Frequency Dynamics between Money and Macroeconomic Variables. Coherence over the Business Cycle from 1977 to 2016**

Notes: This figure reports heatmaps of the time frequency dynamics of the posterior median coherence statistics between money and macroeconomic variables from 1977Q3-2016Q3. Panel A contains results from models using Divisia M2, and Panels B and C report results from models using Divisia MZM and M1 respectively. The strength of the connection is shown by the colour. The areas in black mark the time and frequency bands where the (posterior median) coherence statistic is greater from models using analogous simple sum monetary statistics. These heatmaps represent a three dimensional space of coherence over time (x-axis), frequency (y-axis), and strength (colour).

between money and interest rates seems to be relatively constant over the business cycle. However, there is a clear break in this link during the early 2000s where the coherence halves from 0.8 to 0.4 across all frequencies.

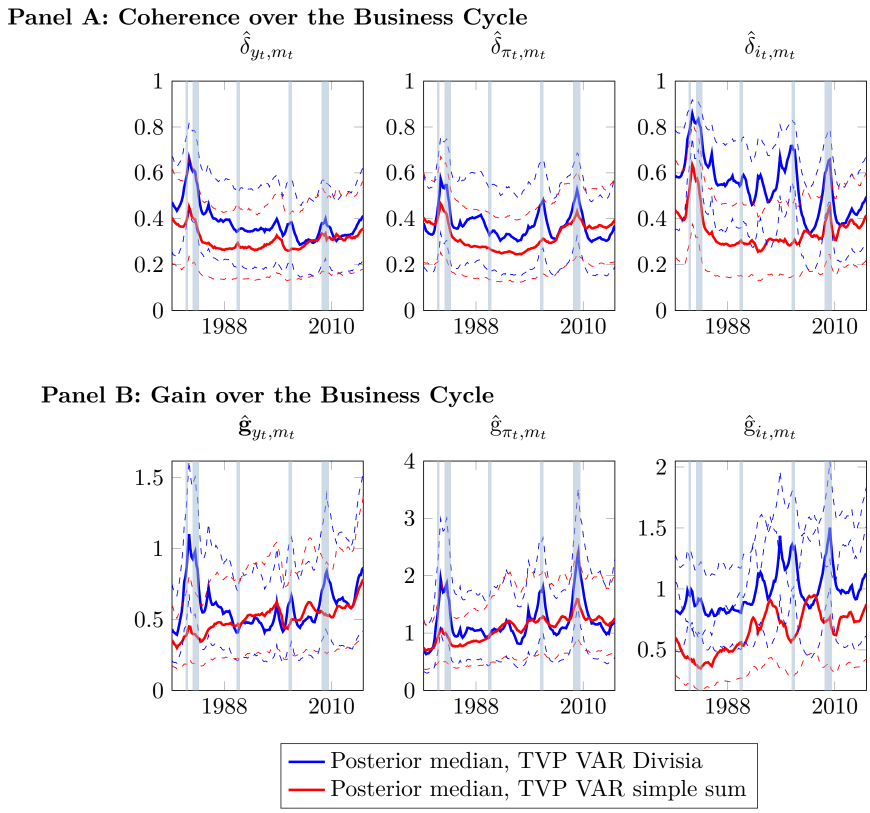

Figure 3: **Coherence and Gain Aggregated over the Business Cycle from Models using Divisia and Simple Sum M4 from 1977 to 2016**
Notes: Panel A of this figure reports the posterior median and 68% equal-tailed point-wise probability bands of the coherence statistics between: Divisia/simple sum M4 and GDP growth (top left panel); Divisia/simple sum M4 and GDP deflator inflation (top middle panel); and Divisia/simple sum M4 and the Federal Funds rate (top right panel), over the business cycle. Panel B of this figure reports the posterior median and 68% equal-tailed point-wise probability bands of the gain statistics between: Divisia/simple sum M4 and GDP growth (bottom left panel); Divisia/simple sum M4 and GDP deflator inflation (bottom middle panel); and Divisia/simple sum M4 and the Federal Funds rate (bottom right panel), over the business cycle. Business cycle frequencies are defined over a 6-32 quarter horizon. Grey bars indicate NBER recession dates.

To provide an idea of the overall impact over the business cycle, Panels A and B of Figure 3 present the coherence and gain statistics aggregated over the business cycle between money and macroeconomic variables, respectively; focussing on models using Divisia and simple sum M4. The gain statistics show how the slope of the relationship between money and macroeconomic variables has evolved throughout time[9]. Overall, it is clear that the connection between Divisia

[9]The gain is computed by taking the numerator of (10) and dividing by the spectral density of variable j. This can be interpreted as the frequency domain regression coefficient. Available on request are analogous statistics computed from models using Divisia and simple sum M2, MZM, and M1. The results in general are similar to those presented here although the differences become smaller the narrower the measure of money used.

M4 and macroeconomic variables is stronger relative to simple sum M4. This observation is more prominent during periods of recession. Note also from Panel B that the gain statistics from models using Divisia M4 is substantially stronger during economic downturns.

These results provide strong evidence of a closer link between macroeconomic variables and Divisia aggregates relative to their simple sum counterparts. Furthermore, they also reveal that the connection between money and macroeconomic fundamentals varies not only over various stages of the business cycle, but also over different periods of time; something that time invariant methods implicitly ignore. Figure 2 confirms a closer link between Divisia aggregates and macroeconomic variables throughout the estimation sample; whilst also highlighting the importance of accounting for time variation in macro-econometric modelling.

On the whole, the above provides strong support for Friedman's conjectures that the lag between monetary growth and the economy's response being long and variable. Consistent with the proposals in Friedman and Schwartz (1963), money seems to have had some influence in generating business cycles during the late 1970s and early 1980s. The emphasis on using properly measured monetary statistics, when examining a monetary explanation of business cycles over the Great Moderation, is clearly supported by the results in Figure 2. As stated by Belongia and Ireland (2016b), perhaps business cycle theorists would have been less averse to including money within their models had they been looking at Divisia aggregates.

This analysis enriches our understanding of the time-frequency dynamics of money and macroeconomic fundamentals over the business cycle. Taking this further, the Supplementary Appendix provides a detailed pseudo forecasting exercise that assesses the relative performance of Divisia aggregates with their simple sum counterparts. On the whole, these results show that simply replacing simple sum aggregates with their Divisia alternatives produce more precise (pseudo)forecasts; this observation is particularly prominent during recessions.

3.3 Money and Monetary Policy Shocks

As noted earlier, structural analysis focuses on models using Divisia and simple sum M1. Figure 4 plots the point-wise posterior median and 80% equal-tailed point-wise probability bands (i.e. posterior credible sets) of the generalised impulse response functions of macroeconomic variables to monetary policy shocks from models using Divisia M1 and simple sum M1. The responses have been normalised such that a monetary policy shock causes a 0.25% increase in the Federal funds rate on impact. Impulse response functions are plotted over a 20 quarter horizon and reported at 10 year intervals that span the estimation sample.

It is clear from these plots that the transmission of monetary policy shocks throughout the estimation sample are similar across models using Divisia M1 and simple sum M1. furthermore, the time-variation in the responses of GDP, inflation, and money is predominantly in the magnitude of the contractions. However, there are two notable differences. First, there is a larger degree of posterior uncertainty around impulse response functions from the model using simple sum M1. This suggests a lower level of precision in the estimated response of variables to monetary policy shocks when using simple sum M1 over its Divisia alternative. Second, simple sum M1 growth is more sensitive than Divisia M1 with respect to monetary policy shocks in the middle of the estimation sample.

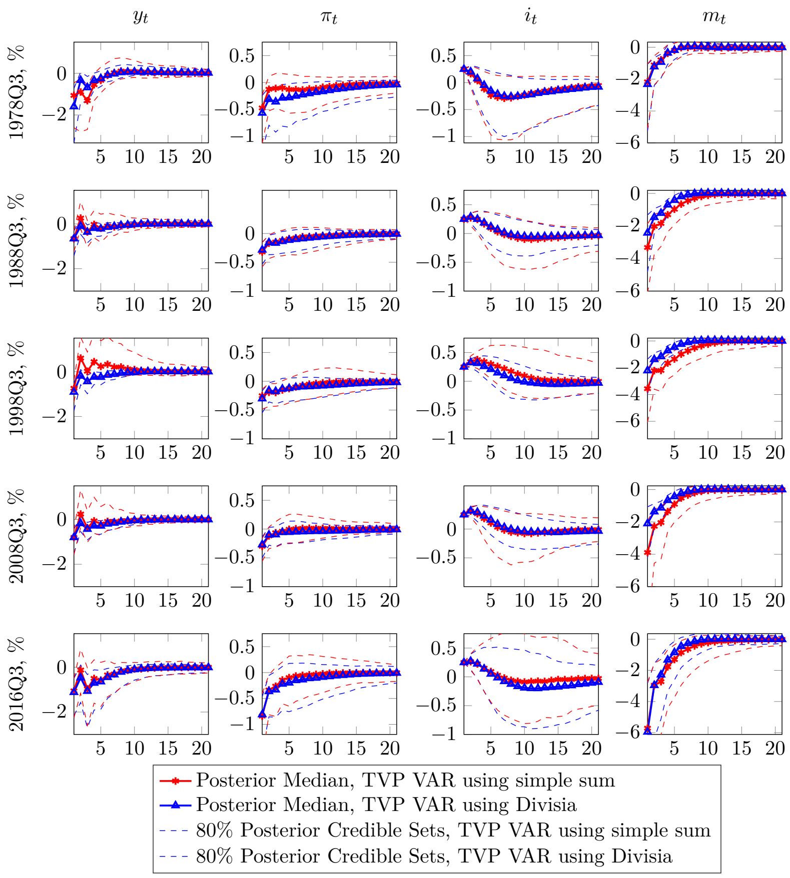

Figure 4: **Impulse Response Functions of Macroeconomic Variables to Monetary Policy Shocks: TVP VARs using M1 over Selected Dates**
Notes: This figure plots the point-wise posterior median and the 80% equal-tailed point-wise probability bands (i.e. posterior credible sets) for the impulse response functions of GDP growth, y_t; inflation, π_t; the Federal funds rate, i_t; and Divisia/simple sum M1, m_t across selected dates. Impulse response functions are plotted over a 20 quarter horizon and are normalised such that monetary policy shocks result in a 0.25% increase in the Federal funds rate on impact.

3.3.1 Structural Monetary Policy Rules

Structural monetary policy rules are obtained from the reduced-form estimates by factoring the reduced-form covariances matrices (details provided in Appendix C of the Supplementary Materials) as

$$\Omega_t = \bar{P}_t^{-1} \bar{D}_t \bar{D}_t' \bar{P}_t^{-1} \tag{11}$$

where $\bar{P}_t$ is a matrix with unit diagonal elements and the structural impact coefficients within the equations of the model. The $\bar{D}_t$ matrix contains the volatility of the structural innovations. The structural representation may be written as

$$\bar{P}_t Y_t = \Gamma_{0,t} + \Gamma_{1,t} Y_{t-1} + \Gamma_{2,t} Y_{t-2} + \bar{D}_t u_t \tag{12}$$

where $\Gamma_{0,t} = \bar{P}_t \beta_{0,t}$ and $\Gamma_{j,t} = \bar{P}_t \beta_{j,t}$ for $j = 1, 2$. and u_t is the 4×1 vector of structural innovations where $u_t \backsim N(0, I_4)$. The third row of (12) delivers the structural monetary policy rule. The third row of $\bar{P}_t$ contains the structural impact coefficients within the monetary policy rule associated to GDP growth, $\rho_t^{i,y}$; inflation, $\rho_t^{i,\pi}$; and money growth, $\rho_t^{i,m}$. These coefficients represent the contemporaneous response of the interest rate to movements in inflation, GDP and money.

The monetary policy rule, ignoring the constant; shocks; and the volatility of shocks, may be written as

$$i_t = \Gamma_t^i(L) i_{t-s} + \Gamma_t^{i,\pi}(L) \pi_{t-k} + \Gamma_t^{i,y}(L) y_{t-k} + \Gamma_t^{i,m}(L) m_{t-k} \tag{13}$$

where $\Gamma_t^i(L)$ denote lag polynomials of structural coefficients associated to lagged interest rate values. $\Gamma_t^{i,\pi}(L)$, $\Gamma_t^{i,y}(L)$, $\Gamma_t^{i,m}(L)$ are lag polynomials of structural coefficients attributed to GDP growth, inflation, and money for $s = \{1, 2\}$, $k = \{0, 1, 2\}$, respectively[10]. This policy rule augments that postulated in Taylor (1993), by allowing the Federal funds rate to be dictated by movements in inflation, GDP growth, and money. The specification is flexible in a sense that allows for sufficient dynamics through time-varying volatilities and coefficients, but also captures interest rates smoothing; something that central banks tend to implement.

The left hand side plots in Figure 5 report the point-wise posterior median and 68% posterior credible sets of the structural impact coefficients associated to inflation, GDP growth, and M1

[10]Note at $k = 0$, the parameters correspond to the sturctural impact coefficients

money growth respectively. The right hand side plots report posterior median and one standard deviation percentiles of relative structural impact coefficients. These are obtained by taking the ratio of the k^{th} draw, at time t, of the structural impact coefficient associated to variable $x = \{y_t, \pi_t, m_t\}$ that stems from the TVP VAR using simple sum M1, and dividing this by the analogous impact coefficient from the TVP VAR using Divisia M1. Statistical differences are observed when the one standard deviation percentiles do not include one.

From models using both Divisia and simple sum M1, there are negligible differences in the structural impact coefficients associated to inflation and GDP growth. However turning our attention to the (contemporaneous) response of the Federal funds rate to money growth, it is clear that there are differences during the late 70s and early 80s. From posterior median estimates during the 1981-82 recession the impact of money on the Federal funds rate from the TVP VAR using Divisia M1 is 0.71; whereas the analogous value stemming from the model using simple sum M1 is 0.45. Addign to this, there is a statistically credible difference in the contemporaneous impact of Divisia M1, relative to simple sum M1, on the Federal funds rate during the 2008 recession. In particular, it is clear that Divisia M1 exerts an economically and statistically larger effect on the Federal Funds rate[11].

Overall, the structural impact coefficients from both models report a steady decline in the policy response of macroeconomic variables throughout the estimation sample; however surges are observed during recessionary periods. The sharpest decline coincides with the Volcker disinflation and the beginning of the Great Moderation. These estimates imply that the policy response to GDP growth hovered around zero during the 1990s, before increasing prior to the burst of the dot-com bubble. Throughout the Great Moderation, the implication is that the emphasis of monetary policy response was on inflation and money growth. From 2000-2007, and consistent with Belongia and Ireland (2016a), monetary policy seems to respond less to inflation relative to GDP growth.

Table 4 reports the point-wise posterior median and 68% equal-tailed point-wise probability bands of the long-run coefficients from the estimated monetary policy rules. Estimates are reported at 10 year intervals spanning the estimation sample; Panel A and B contain results

[11]Note also that statistical differences are observed from models using MZM. The differences in the contemporaneous response of the Federal funds rate to Divisia MZM coincide with the "Monetarist Experiment" that was implemented from 1979Q4 to 1982Q4. As discussed in Barnett and Chauvet (2011), Divisia growth rates over this period were substantially lower than their simple sum analogues; with the policy producing a negative shock that spurred an unintended recession. This finding corresponds with Barnett et al. (2009) who show there are important differences between simple sum and Divisia aggregates both during periods of high interest rates, and around the beginnings and ends of recessions.

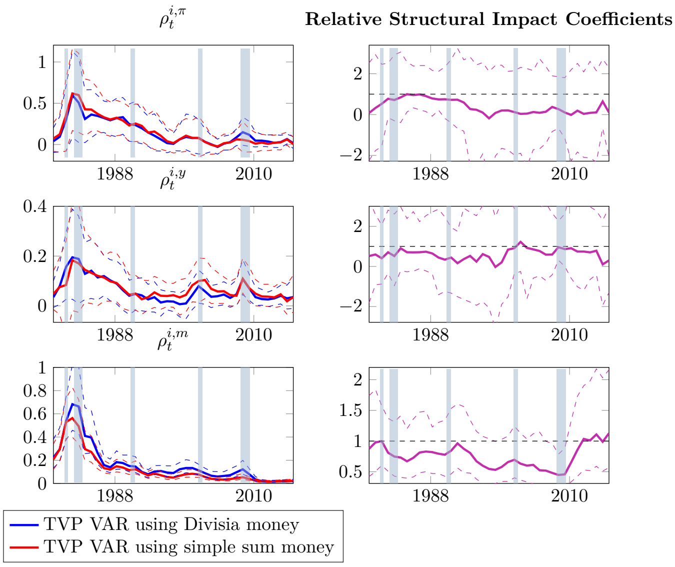

Figure 5: **Structural Impact Coefficients in Structural Monetary Policy Rules from Models Using M1; 1977 to 2016**

Notes: Graphs on the left hand side of this figure plot the posterior median and 68% posterior credible sets for the distribution of the impact coefficients in the structural monetary policy rules implied by models using M1. The top left plot reports the impact coefficients of inflation, $\rho_t^{i,\pi}$; the middle left plot reports the impact coefficients of GDP growth, $\rho_t^{i,y}$; and the bottom left plot reports the impact coefficients of money growth, $\rho_t^{i,m}$. Graphs on the right hand side of this figure plot the posterior median and one standard deviation percentiles for the relative structural impact coefficients associated to inflation (top right), GDP growth (middle right), and money growth (bottom right) from 1977Q3-2016Q3. Grey bars indicate NBER recession dates.

Table 4: Long-run Coefficients Implied by Structural Monetary Policy Rules from 1978 to 2016

Panel A: Divisia M1			
	π_t	y_t	m_t
1978Q3	1.06 [-0.81 2.65]	0.43 [-1.94 2.80]	1.01 [-2.82 3.73]
1988Q3	1.89 [-0.03 4.29]	0.82 [-1.09 2.95]	0.97 [-0.26 3.59]
1998Q3	1.19 [0.48 2.71]	0.54 [-0.40 1.48]	0.60 [0.05 1.91]
2008Q3	1.63 [0.29 3.87]	1.02 [-0.25 3.09]	0.81 [-0.12 3.05]
2016Q3	1.43 [0.84 2.33]	0.90 [0.19 2.09]	-0.03 [-0.41 0.45]
Panel B: Simple sum M1			
	π_t	y_t	m_t
1978Q3	1.32 [-0.96 3.14]	0.36 [-2.71 3.26]	0.57 [-0.65 2.76]
1988Q3	1.91 [0.61 3.82]	0.73 [-0.17 2.41]	0.48 [0.03 1.29]
1998Q3	1.32 [0.63 2.34]	0.45 [-0.17 1.45]	0.14 [-0.14 0.66]
2008Q3	1.59 [0.67 3.28]	0.95 [0.18 2.57]	0.40 [0.05 1.14]
2016Q3	1.61 [0.89 2.56]	0.77 [-0.02 2.14]	-0.04 [-0.50 0.36]

Notes: This table reports the posterior median and 68% posterior credible sets of long-run coefficients implied by the time-varying structural monetary policy rules from TVP VARs using Divisia M1 (Panel A) and simple M1 (Panel B). The long-run coefficients are reported over 10-year intervals from 1978Q3 to 2016Q3. These coefficients represent the estimated response of the interest rate to a permanent 1% increase in: inflation, π_t; GDP growth, y_t and money growth, m_t.

from models using Divisia M1 and simple sum M1 respectively. These coefficients measure the theoretical impact of a permanent one percentage point rise in inflation, GDP growth or money growth.

From posterior median estimates, it is clear that the long-run coefficients on inflation from the TVP VAR using Divisia M1 and simple sum M1 are similar. In both cases, the long-run coefficient on inflation where all exceed 1, whilst displaying statistical credibility (from 1998 onwards) and substantial time-variation. Note that the long-run coefficients on inflation, GDP growth and money surge during the 2008 recession, relative to a decade earlier. Consistent with the reduced-form evidence, this implies a closer link between macroeconomic fundamentals during periods of economic distress[12].

Turning our attention to the long-run impact of money for the Federal funds rate, there are clear differences in the posterior median coefficients, with relatively larger coefficients associated to Divisia M1. For example in 1998Q3, a permanent one percentage point increase in Divisia M1 growth implies a 0.6 percentage point rise in the Federal funds rate. In the very same period, the model using simple sum M1 indicates the Federal funds rate would increase by 0.14 percentage points. The increased sensitivity of the interest rate to Divisia M1 may stem from the ability of Divisia aggregates to capture internal substitution effects that simple sum measures are unable to. This is justified in the findings of Barnett and Chauvet (2011), who provide evidence that Divisia aggregates more accurately reflect monetary policy stance than their simple sum counterparts[13].

3.3.2 The Economic Importance of Monetary Policy Shocks to the Variance of US Macroeconomic Fundamentals over the Business Cycle

To examine the importance of monetary policy shocks for macroeconomic variation, a frequency domain structural variance decomposition of monetary policy shocks is computed over the estimation sample; details are provided in Appendix C[14]. Panel A of Figure 6 reports heatmaps of the percent attributable to monetary policy shocks over business cycle frequencies for the

[12] Long-run coefficients from all models are reported in the Supplmentary Appendix. Note also, the profile and magnitude of the long-run coefficients on macroeconomic variables are consistent with those reported in Benati and Mumtaz (2007).

[13] It is worth commenting on the relatively large posterior probability bands for the long-run coefficients from models using Divisia M1. These coefficients are computed as a ratio provided in Appendix C of the Supplementary Materials. The distribution of the denominator of these ratios largely fluctuates around zero thereby increasing the scope for and driving this amount of posterior uncertainty.

[14] Available on request are structural variance decompositions of all identified shocks from the estimated models. The implication of these results regarding the Great Moderation are consistent with Benati and Mumtaz (2007).

variation of GDP growth, inflation, the Federal funds rate, and Divisia M1 money growth. The areas in black mark the time and frequency bands where the (posterior median) coherence statistic is greater from models using analogous simple sum M1. Panel B reports posterior median and 68% equal-tailed point-wise posterior probability bands of the aggregate importance of monetary policy shocks for macroeconomic variables over the business cycle. These are obtained by summing the impacts from a 6 to 32 quarter horizon.

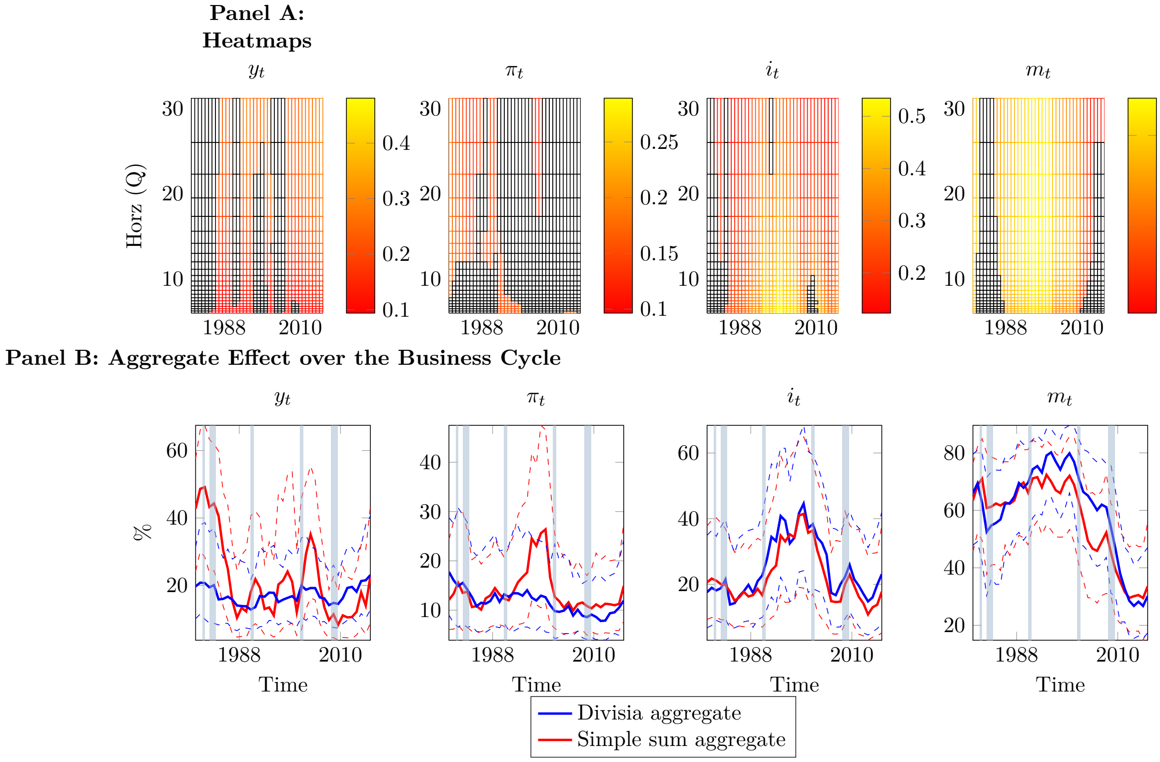

Figure 6: **The Economic Importance of Monetary Policy Shocks at Business Cycle Frequencies from 1977 to 2016**
Notes: Panel A of this figure reports the posterior median percent contribution of monetary policy shocks to the variance of: real GDP growth; inflation; the interest rate; and money growth, from 1977Q3 to 2016Q3 over business cycle frequencies. The areas in black mark the time and frequency bands where the (posterior median) coherence statistic is greater from models using analogous simple sum monetary statistics. These heatmaps represent a three dimensional space of time (x-axis), frequency (y-axis), and strength (colour). Panel B of this figure reports the posterior median, and 68% equal-tailed point-wise probability bands of the percent contribution of monetary policy shocks to the variance of: real GDP growth; inflation; the interest rate; and money growth, from 1977Q3 to 2016Q3 over the business cycle. Business cycle frequencies are defined over a 6-32 quarter horizon. Grey bars indicate NBER recession dates.

As can be seen from Panel A, the contribution of monetary policy shocks to GDP variation over the business cycle is relatively larger across time, and frequencies, when using Divisia M1. For inflation however, monetary policy shocks stemming from the model using Divisia M1 is larger across the business cycle throughout the second half of the sample. It is also evident that the influence monetary policy shocks have on Divisia M1 variation is relatively larger than these shocks have on M1 variation both throughout time, and over the business cycle. Panel B reports the aggregated influence of monetary policy shocks over the business cycle. In particular although this reveals that although there are substantial differences in posterior median estimates, there are no statistical differences in the economic importance of monetary policy shocks over the business cycle. It is worth noting that the model using Divisia M1 generates a substantially more stable the time profile of the percent contribution of monetary policy shocks for GDP growth and inflation variations. In general, these results suggest there are negligible statistical differences in the economic importance of monetary policy shocks when replacing simple sum aggregates with their theoretically superior Divisia counterparts.

In general, the results using Divisia M1 conform with the findings in Benati and Mumtaz (2007), by supporting the view that monetary policy shocks played a negligible role for the variance in GDP growth, and inflation, during the Great Moderation. Examining variance decompositions of all identified shocks shows that the Great Inflation and Great Moderation were due to bad luck and good luck, respectively. In accounting for the Great Recession and subsequent recovery period, this study shows that the drivers of the depth, and persistence, of the most recent recession was a mixture of demand non-policy and supply shocks[15].

3.3.3 Policy Counterfactuals

Figure 7 plots results from two different counterfactual simulations. Panel A plots reports the posterior median and 80% point-wise equal-tailed probability bands of the counterfactual minus actual paths of macroeconomic variables where structural monetary policy rules identified during the Chairmanship of Alan Greenspan have been imposed throughout the entire sample. Panel B reports analogous statistics to Panel A with the exeception that the counterfactual paths impose structural monetary policy rules identified during the Chairmanship of Paul Volcker[16] [17].

Panel A reveals two main results. First, toward the end of the Great Inflation, monetary policy would have been more contractionary than observed, which would have translated into

[15]These results are available on request.

[16]Alan Greenspan's tenure was from August 11, 1987 to January 31, 2006. Paul Volcker's Chairmanship tenure spanned August 6, 1979 to August 11,1987.

[17]Counterfactual simulations are computed in the following manner: For each simulation $k = 1, 2, \dots, K$ at every quarter $t = p + 1, p + 2, \dots, T$ three random numbers are drawn over appropriate uniform distributions. τ indexes the quarter of the Chairmanship from which the elements of the structural monetary policy rule are obtained; and κ_τ, and κ_t index the iterations of the Gibbs sampler at times τ and t, respectively. Thus, the elements from the structural monetary policy rule are taken at iteration κ_τ of quarter τ while all other elements are taken from iteration κ_t for quarter t. Each counterfactual is conditional on the first p actual historical values.

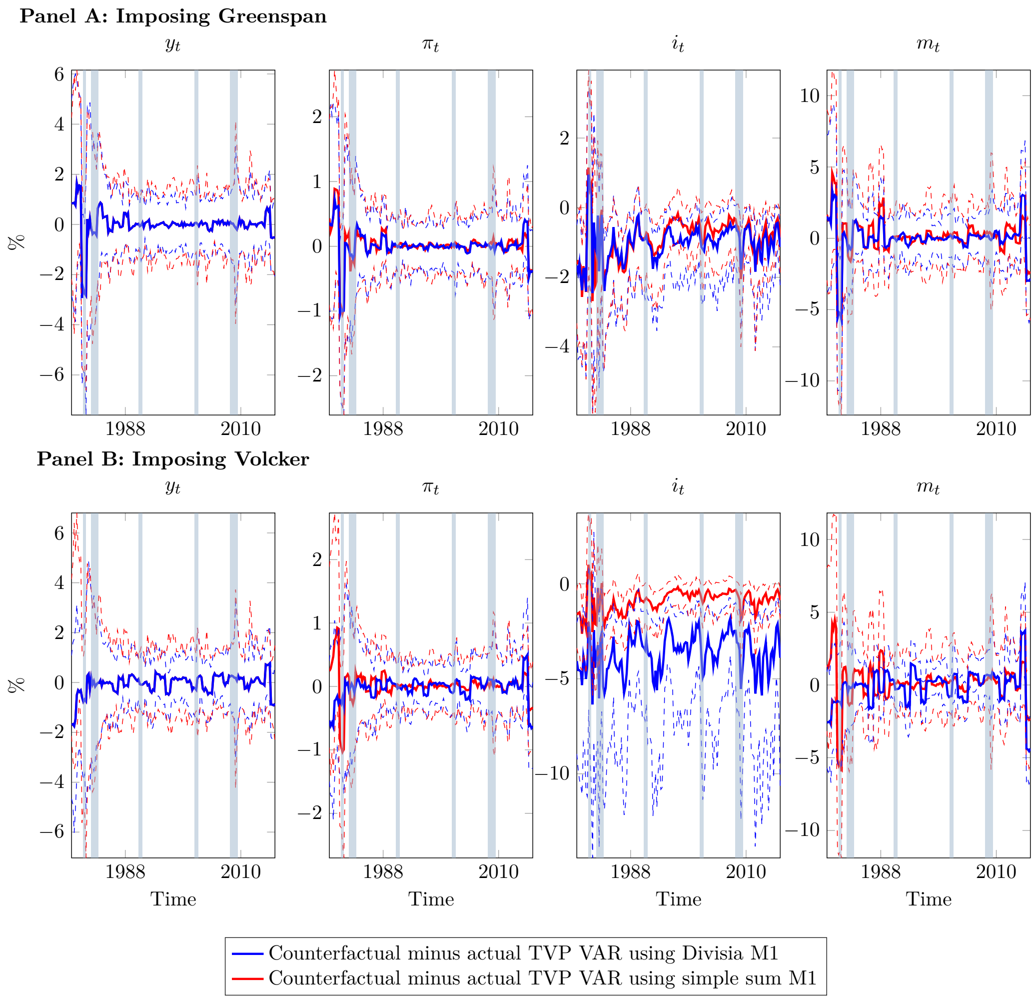

Figure 7: **Policy Counterfactuals: Imposing Greenspan and Volcker from 1977 to 2016**

Notes: This figure plots the posterior median and 80% equal-tailed point-wise probability bands of the difference between the counterfactual path of macroeconomic variables and the actual simulated history from 1977Q3-2016Q3. Panel A reports the counterfactual path minus the actual simulated history of: real GDP growth, y_t; inflation, π_t; the Federal funds rate, i_t; and Divisia/simple sum M1 money growth, m_t by imposing structural monetary policy rules from the Greenspan era (i.e. 1987Q3–2006Q1). Panel B reports the counterfactual path minus the actual simulated history of: real GDP growth, y_t; inflation, π_t; the Federal funds rate, i_t; and Divisia/simple sum M1 money growth, m_t by imposing structural monetary policy rules from the Volcker period (i.e. 1979Q3–1987Q2). Grey bars indicate NBER recession dates.

GDP growth and inflation being around 2.5 and 1.05 percentage points lower than observed, respectively. Second, imposing Greenspan over the estimation sample shows that negligible differences in GDP growth and inflation during the 2008 recession. It is clear, from posterior median estimates, that the difference between the counterfactual and actual paths of GDP growth and inflation fluctuate around zero. Turning attention to Panel B, imposing Volcker implies that monetary policy would have been more expansionary, particularly from the model using Divisia M1, during the Great Moderation with negligible differences in the observed values of GDP growth and inflation. Specifically, throughout the Great Moderation the difference in GDP fluctuates around +/-1% of the actual value; meanwhile the differences in inflation are in the range of +/- 0.5 percentage points.

On the whole, these counterfactuals suggest three noteworthy findings. First, consistent with Benati and Mumtaz (2007) and many others, the end of the Great Inflation and the Great Moderation cannot be attributed to the conduct of monetary policy. This suggests that the systematic component of monetary policy was not the underlying factor which led to the Great Moderation. Therefore, the Great Moderation was either down to non-systematic policy or plain luck (i.e. a substantial decline in the volatility and magnitude of non-policy shocks). Second, the Federal Reserve departing from the systematic behaviour of Greenspan was not a contributing factor to the boom-bust cycle around the 2008 recession. Finally, utilising theoretically superior monetary aggregates in place of their simple sum counterpart does not over-turn the conclusion that the conduct of monetary policy was not a driver of the end of the Great Inflation, or Great Moderation.

However these results do contradict other studies, such as Canova and Gambetti (2009), who maintain that had monetary policy could have been successful in hindering inflation during the 1970s; had it been more aggressive[18]. Their results show that the cost in terms of output growth would have been too damaging to feasibly implement. Nevertheless it is important to attempt to highlight why differences emerge. The counterfactuals presented here rely on imposing Volcker and Greenspan over the entire sample period through random draws of the structural monetary policy rules from the relevant periods whilst holding other parameters at their (randomly drawn) current states. This is inherently different to the counterfactuals of Canova and Gambetti (2009) who rely on counterfactuals using impulse response analysis.

[18]Others conclude that monetary policy failed in stabilising inflation during the 1970s (see e.g. Boivin and Giannoni (2006)).

Adding to this, Galí and Gambetti (2009) present reduced form evidence that documents changes in conditional and unconditional second moments, as well as impulse response analysis. They conclude that the sources of the Great Moderation may be more complex than a result of Good Luck. However, it is important to note that their model analyses labour market dynamics and does not focus on the conduct of monetary policy.

Finally Barnett and Chauvet (2011) and many others, conform to the view that measurement error was the underlying cause for bad policy. The results presented here may differ from the conclusions of the former, since the counterfactual experiments stem from a structural VAR. Whereas the former provides a qualitative reduced form assessment of monetary statistics. Indeed, much of the reduced form analysis in this study advocates the importance of accounting for measurement error when examining links over the business cycle, or (pseudo) forecasting purposes.

4 Conclusions

This paper assesses the relative empirical benefits of Divisia monetary aggregates by fitting time-varying coefficient VAR models to US data from 1967Q1 to 2016Q3. Consistent with Belongia and Ireland (2015), and Belongia and Ireland (2016b), results uncover a link between money and economic activity that was previously rejected (Friedman and Kuttner, 1992; Bernanke and Blinder, 1992). This paper conforms to view that measurement matters, and re-emphasises the importance of theoretically consistent monetary aggregation; particularly during periods of economic turbulence.

The results are summarised as follows. First, model evaluation using Bayesian DIC statistics presents a strong case for replacing replacing simple sum measures of money with their Divisia counterparts. Second, reduced-form evidence indicates a strong link between Divisia money and economic activity over business cycle that is substantially less prominent when using simple sum aggregates. Third, out of sample (pseudo) forecasts of economic activity from models using Divisia aggregates surpasses those using analogous simple sum measures. This is particularly prominent during periods of recession. Finally, incorporating Divisia monetary aggregates within Taylor rules yields economically closer connections between macroeconomic variables and the interest rate throughout time; with the most prominent differences occurring during both periods of high interest rates and economic distress. Overall, these findings indicate that the issues of measurement error are most prevalent, and indeed most harmful, during periods of economic turbulence. For policymakers, Divisia aggregates are shown to be an essential consideration when conducting economic forecasts and implementing monetary policy during periods of sustained macroeconomic volatility, high interest rates, and recessions.

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