Money Growth Variability and Output: Evidence with Credit Card-Augmented Divisia Monetary Aggregates*

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Abstract:

We reexamine the effects of the variability of money growth on output, raised by Mascaro and Meltzer (1983), in the era of the increasing use of alternative payments, such as credit cards. Using a bivariate VARMA, GARCH-in-Mean, asymmetric BEKK model, we find that the volatility of the credit card-augmented Divisia M4 monetary aggregate has a statistically significant negative impact on output from 2006:7 to 2019:3. However, there is no effect of the traditional Divisia M4 growth volatility on real economic activity. We conclude that the balance sheet targeting monetary policies after the financial crisis in 2007-2009 should pay more attention on the broad credit card-augmented Divisia M4 aggregate to address economic and financial stability.

JEL classification: C32; E52; E44.

Keywords: Credit card-augmented Divisia monetary aggregates; Multivariate GARCH-in-mean, Optimal monetary aggregation.

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1 Introduction

This study is stimulated by the balance sheet targeting monetary policy of the Federal Reserve after the 2007-2009 global financial crisis. In this regard, as Istiak and Serletis (2017, p. 115) recently put it, “the mainstream approach to monetary policy is mainly based on the new Keynesian model and is expressed in terms of the interest rate on overnight loans between banks, such as the federal funds rate in the United States. However, in the aftermath of the global financial crisis and Great Recession, short-term nominal interest rates have hardly moved at all, while central bank policies have been the most volatile and extreme in their entire histories. This has discredited the short-term interest rate as an indicator of policy and led central banks to look elsewhere.”

For example, the Federal Reserve and many central banks around the world have departed from the traditional interest-rate targeting approach to monetary policy, focusing on their balance sheets instead, using unconventional monetary policy tools, such as forward guidance, credit easing, quantitative easing, and in some cases negative interest rates at the central bank’s standing deposit facilities. As a result, liquidity measures have become a crucial indicator of monetary policy. Having a proper monetary aggregate has become increasingly important for monetary policy and business cycle analysis.

This raises the question that has been debated for decades: What is the best monetary aggregate? What monetary assets should be included in the monetary aggregate? How should they be grouped? These are chief substantive issues in monetary economics. Until the end of the 1970s, the transactions demand for money was well approximated by simple-sum M1. Since then, a series of regulatory reforms and technological innovations took place in the banking sector, and recently, Barnett (2016), Keating et al. (2018), Jadidzadeh and Serletis (2019), and Dery and Serletis (2019) argue that the Center for Financial Stability (CFS) Divisia M4 monetary aggregate, based on Barnett (1978, 1980), is the most theoretically consistent monetary aggregate that should be used in monetary policy and business cycle analysis.

However, the increased use of alternative payments has changed the way that financial intermediaries operate and reshaped the way people use the banking sector and conduct transactions — see, for example, Teles and Zhou (2005). In fact, credit cards, together with currency and demand deposits, have become one of the three most important payment methods. Therefore, it is necessary to have a monetary aggregate that can include the transaction services provided by credit cards. Ignoring these services would lead to bias in liquidity measures and result in false inference on economic activities. Indeed, Serletis and Rahman (2015) have shown that the inference ability of money on economic activity may vastly depend on the choice of the monetary aggregate. Proper monetary aggregates, which can accurately track the liquidity services in the economy, tend to have stronger inference ability on economic activity.

Despite the fast growth of the credit card transaction services, the credit card-augmented Divisia monetary aggregates are rather young, originated by Barnett et al. (2016), and therefore are still mostly unexplored. The widespread use of credit card transaction services drives interest in many open questions on both monetary policy and economic research. One of the key issues yet to be analyzed is the inference ability of the new CFS credit card-augmented Divisia monetary aggregates. Using GARCH-in-Mean models, we analyze the effects of the variability of credit card-augmented Divisia money growth on output.

The effects of money on economic activity rely on the stable relationships involving money demand (Belongia (1984)). Using simple-sum monetary aggregates, Friedman and Schwartz (1983) and Mascaro and Meltzer (1983) found that sharp fluctuations in the short-run growth rate of money have reduced GDP growth. More recently, Serletis and Shahmoradi (2006) and Serletis and Rahman (2015) overwhelmingly suggest that the variability of Divisia money (especially broad Divisia money measures) has a stronger negative impact on output. The reason is that the Divisia monetary aggregate is a more stable monetary index than the conventional simple-sum monetary index and can internalize the pure substitution effects between monetary components.

We contribute to the literature by, for the first time, investigating the effects of the variability of the new CFS credit card-augmented Divisia monetary aggregates on output. Using a bivariate VARMA, GARCH-in-Mean, asymmetric BEKK model, we provide a comparison between the conventional Divisia M4 monetary aggregate and the new credit card-augmented Divisia M4 monetary aggregate. We provide empirical evidence to support Barnett et al. (2016) who argue that much of the policy relevance of the Divisia monetary aggregates literature could be strengthened further by using the credit card-augmented Divisia monetary aggregates.
The paper is organized as follows. Section 2 discusses the Divisia approach to monetary aggregation. Section 3 presents the data and Section 4 provides a brief description of the bivariate VARMA, GARCH-in-Mean, asymmetric BEKK model. Section 5 discusses the empirical results. The final section concludes.

2 Divisia Monetary Aggregates

The monetary aggregates constructed by most central banks around the world are based on the simple-sum index. The simple-sum index has considerable advantages as an accounting measure of the stock of nominal monetary wealth, but has severe problems as a monetary aggregate index to track the liquidity services in the economy. As Barnett (1980) has argued, monetary aggregates should be based on economic theory and index number theory, instead of accounting conventions. Moreover, the inability of the simple-sum monetary aggregates to include credit card transaction services becomes more prominent as the use of credit cards in the economy increases. Credit cards, together with cash and debit cards, have consistently made up approximately 95 percent of the overall transaction preferences. Moreover, in 2017, close to 30 percent of Americans indicated a preference for paying with credit cards. The use of credit cards provides the same liquidity services as cash, but allows for deferred payments, and this is closely associated with the flows of goods and services. Leaving credit cards out of the liquidity measure will cause severe bias as pointed out by Barnett and Liu (2019).

Another problem with the simple-sum approach to monetary aggregation is that it cannot internalize pure substitution effects within the monetary aggregate and views all monetary components as perfect substitutes. This problem becomes more severe when broad monetary aggregates come into consideration. Rather than accounting for the partial liquidity services provided by the broad monetary aggregates, the simple-sum monetary index views all components of the broad monetary aggregates as providing the same liquidity services as currency, although the distant substitutes provide heavily weighted nonmonetary services.

2.1 The Standard Divisia Monetary Aggregates

Barnett (1978, 1980) developed the Divisia monetary aggregates. He argued that the simple-sum monetary aggregates provided by the Federal Reserve are consistent with economic aggregation theory only if the monetary assets are perfect substitutes with the same user cost. However, monetary assets yield interest while currency does not. Thus, the assumption that the simple-sum monetary aggregates are based on is unreasonable. The Divisia monetary aggregates do not assume the perfect substitution between component assets, and hence permit different user costs of the component assets.

Because monetary assets are durable goods that do not perish during the period from use, their prices are their user costs. The formula for the real user cost of a monetary asset $i$, derived by Barnett (1978), can be written as

$$p_{it}^u = \frac{R_t - r_{it}}{1 + R_t}$$

where $R_t$ is the benchmark asset rate of return measuring the maximum expected rate of return available in the economy, and $r_{it}$ is the own rate of return on monetary asset $i$ during period $t$. The user cost can also be interpreted as the opportunity cost of holding a dollar’s worth of the $i$th asset. With the user cost and quantity data, the expenditure share on monetary asset $i$ is

$$s_{it} = p_{it}^u m_{it}^u / \sum_{i=1}^{I} p_{it}^u m_{it}^u$$

where $m_{it}^u$ denotes the real balances of monetary asset $i$ during period $t$. A Divisia monetary aggregate in discrete time computes the growth rate of the aggregate as the share-weighted average of its monetary asset component growth rates as follows

$$d \log M_t = \sum_{i=1}^{I} s_{it} d \log m_{it}^u.$$ (2)
2.2 The Credit Card-Augmented Divisia Monetary Aggregates

Barnett et al. (2016) further extended the Divisia monetary aggregates to the credit card-augmented Divisia monetary aggregate, which jointly account for the liquidity services provided by monetary assets and credit cards. They derive the money demand aggregate from the consumer’s decision problem

$$\max U(m_t, c_t) = U(M(m^a_t, m^c_t), c_t)$$

(3)

where the utility function of the representative consumer, $U$, is blockwise weakly separable in liquidity services $M_t$ and consumption $c_t$. $M_t$ is the augmented monetary aggregate function (utility function) over the liquidity services provided by monetary assets $m^a_t$ and credit card transaction services $m^c_t$, where $m^a_t = (m^a_{1t}, \ldots, m^a_{at}, \ldots, m^a_{Lt})$ and $m^c_t = (m^c_{1t}, \ldots, m^c_{ct}, \ldots, m^c_{Lt})$. The consumer is subject to the following budget constraint

$$p^*_tc_t = \sum_{i=1}^{L} \left[ (1 + r^a_{i,t-1})p_{i,t-1}^a m^a_{i,t-1} - p^*_t m^a_{it} \right] + \sum_{i=1}^{L} \left[ p^*_t m^c_{it} - (1 + e_{i,t-1})p^*_t m^c_{it-1} \right]$$

$$+ \sum_{i=1}^{L} \left[ p^*_t \frac{e_{i,t}^c}{1 + R_t} - (1 + e_{i,t-1}^c) p^*_t \frac{e_{i,t-1}^c}{1 + R_t} \right] + \left[ (1 + R_{t-1})p^*_t A_{t-1} - p^*_t A_t \right]$$

(4)

where $p^*$ is the price level, $y_t$ measures the wage income during period $t$, $r^a_{i,t}$ is the rate of return on monetary asset $m^a_{it}$, $e_{i,t}^c$ is the expected interest rate on the credit card transaction $m^c_{it}$, $R_t$ is the rate of return of benchmark asset $A_t$ which measures the maximum expected risk free rate of return.

Solving the consumer’s optimization problem, Barnett (1978) derived the user cost of a monetary asset $m^a_{it}$ or the opportunity cost of holding a dollar’s worth of the asset $m^a_{it}$, as in equation (1). Similarly, Barnett et al. (2016) derived the user cost of credit card transaction services $m^c_{it}$ as

$$p^*_t = \frac{e_{it} - R_t}{1 + R_t}$$

The user cost $p^*_t$ can also be interpreted as the opportunity cost of holding a dollar’s worth of the credit card balance $m^c_{it}$.

The user costs are crucial in the credit card-augmented Divisia monetary aggregates. As Stiglitz (1988) put it, it is the opportunity cost that should appear in the money demand equation (and in the LM curve of macroeconomic analysis). Then the credit card-augmented Divisia monetary aggregate growth rate, $d \log M_t$, is the weighted sum of the growth rate of each monetary service demanded, with expenditure shares as the weights (see Barnett et al. (2016))

$$d \log M_t = \sum_{i=1}^{L} s^a_{it} d \log m^a_{it} + \sum_{i=1}^{L} s^c_{it} d \log m^c_{it}$$

where

$$s^a_{it} = \frac{p^*_t m^a_{it}}{\sum_{i=1}^{L} p^*_t m^a_{it} + \sum_{i=1}^{L} p^*_t m^c_{it}}$$

is the user-cost-evaluated expenditure share of monetary asset, $m^a_{it}$, and

$$s^c_{it} = \frac{p^*_t m^c_{it}}{\sum_{i=1}^{L} p^*_t m^a_{it} + \sum_{i=1}^{L} p^*_t m^c_{it}}$$

is the user-cost-evaluated expenditure share of credit card transaction services, $m^c_{it}$. Instead of assigning each monetary component a constant and equal weight as the simple-sum monetary aggregates does, the Divisia monetary aggregate assigns different weights to the monetary components based on their user costs. The substitution effect within the monetary aggregate is internalized through the distribution of the user costs over different monetary services.
The advantage of the credit card-augmented Divisia monetary aggregate is that it includes the services provided by credit cards and internalizes the substitution effects between monetary assets and credit card transaction services. It can be shown that the standard Divisia monetary aggregates are a special case of the credit card-augmented Divisia monetary aggregates; if the growth rates of the credit card transactions are very low and close to zero, then the growth rate of the credit card-augmented Divisia aggregate reduces to the growth rate of the corresponding standard Divisia monetary aggregate. It can also be shown that the simple-sum monetary aggregates are a special case of the Divisia monetary aggregates; if all own rates of return on all monetary assets are the same, then the growth rates of the Divisia monetary aggregates reduce to the growth rates of the corresponding simple-sum monetary aggregates.

It is also to be noted that the credit card-augmented Divisia monetary aggregate derived from the consumer’s optimization problem, reflects the consumer’s response to risk, return, output (income), prices, and monetary and fiscal policy, and contains information about the perceived risks in the economy, so that it has the ability to relate to key macroeconomic variations. We believe that the credit card-augmented Divisia monetary aggregate has stronger inference ability compared to the standard Divisia monetary aggregate, because it can internalize the pure substitution effects between credit cards and monetary assets, and track the liquidity services associated with the flows of goods and services more accurately. If the rate of return on a monetary asset decreases, or, equivalently, there is an increase in its user cost (see equation (3)), consumers will respond by substituting towards the monetary services with relatively decreased user costs. As we have shown in equation (1), the monetary quantity aggregate $M(m^a_t, m^c_t)$ is a utility function of liquidity service flows. Hence the monetary aggregate will change only if the change in the relative prices of $m^a_t$ and $m^c_t$ result in a change in utility. Equivalently, the monetary aggregate will change only if the change in the interest rate has an income effect — see (Barnett (1982). The credit card-augmented Divisia monetary aggregate constructed from index number theory will internalize pure substitution effects between credit card transaction services and monetary assets. When interest rate changes cause shifts in a Divisia aggregate, there could have been no change in the utility level and hence in monetary service flows when credit card transaction services are included.

To summarize, the simple sum monetary aggregates assign the same weight to each monetary asset. They implicitly assume that all the monetary assets provide the same liquidity service and that they are perfect substitutes. The Divisia monetary aggregates do not assume that the monetary assets are perfect substitutes. It is to be noted, however, that the Divisia monetary aggregates that we use in this paper assume that the consumer is making a trade off between return and liquidity services. The weight assigned to each monetary asset depends on its user cost, which is a function of its rate of return and the benchmark interest rate. In fact, as can be seen from the equations for the user cost and the Divisia monetary aggregates, the higher the rate of return of a monetary asset is, the less weight it is assigned in the Divisia aggregate. It is also to be noted that recently Barnett and Su (2018) and Barnett and Liu (2019) extend the Divisia monetary aggregation theory to risk. They assume that the consumer is making a three dimensional trade off among the rate of return, investment purposes, and risk aversion. They developed the risk adjustment (risk premia) of the Divisia monetary aggregates based on the capital asset pricing model. However this is new work and the risk adjusted Divisia monetary aggregate are still under construction at the Center for Financial Stability.

3 The Data

We investigate the relationship between money growth volatility and output growth in the United States, using monthly data for the credit card-augmented Divisia monetary aggregate in comparison to the traditional Divisia monetary aggregate at the broadest level of aggregation, M4. Derry and Serletis (2019) and Liu et al. (2019) have shown that the broad Divisia monetary aggregates have the strongest inference ability in comparison to the narrow Divisia monetary aggregates. Thus, in our study, we focus on the impact of the variability of the standard and credit card-augmented Divisia M4 monetary aggregates on output.

Our data on the monetary aggregates is from the CFS program Advances in Monetary and Financial Measurement (AMFM). Our measure of real output is the industrial production index from the St. Louis Federal Reserve Economic data base. Our sample period is from 2006:7 to 2019:03. This period is chosen for three reasons. First, the Federal Reserve changed its operating target to balance sheet and quantitative
easing during and after the 2007-2009 financial crisis. Second, the use of credit cards grows very fast after the financial crisis as shown in Figures 1 and 2. Third, the CFS credit card-augmented Divisia monetary aggregates are available since 2006.7 Thus, our sample period includes the increased volatility in money supply in the aftermath of the subprime financial crisis and the global recession, with a total of 151 monthly observations. Examining the behavior and properties of the credit card-augmented Divisia monetary aggregates during the volatile period that includes the 2007-2009 financial crisis has important implications, as a relatively stable money demand can have important inference on the economic fluctuations at the turning points — see Liu et al. (2019).

Figure 3 shows the logged levels of the conventional Divisia M4 monetary aggregate and the credit card-augmented Divisia M4A monetary aggregate. Both the conventional Divisia and credit card-augmented Divisia M4 aggregates exhibit a strong upward trend, but the credit card-augmented Divisia M4 aggregate grows slower in general. The stability of the credit card-augmented Divisia M4 monetary aggregate is manifested when we compare the year-over-year percentage growth rates which are calculated as $100 \times (\log m_t - \log m_{t-12})$. Figure 4 presents comparisons between the growth rates of the credit card-augmented Divisia M4 monetary aggregate and conventional Divisia M4 aggregate. There are broad similarities between the monetary aggregates growth rates, however, during the financial crisis (indicated the shaded area), the credit card-augmented Divisia M4 monetary aggregate is less volatile than the traditional Divisia M4 monetary aggregate.

To prepare our data for the volatility modeling, we first test the presence of a stochastic trend (a unit root) in the autoregressive representation of each series. We perform a set of unit root and stationarity tests on the growth rates of each monetary aggregate as well as output. The growth rates are calculated as $d \log g_t = 100 \times (\log g_t - \log g_{t-1})$, where $g_t = y_t$, $m_t$ represents the growth rate of output and money, respectively. The null hypothesis of the ADF and DF-GLS tests are rejected and the null hypothesis of the KPSS test cannot be rejected, suggesting that the growth rates of the monetary aggregates and output are stationary, or integrated of order zero, $I(0)$.

4 The Model

We investigate the output effects of the variability of money growth in the context of a bivariate VARMA, GARCH-in-mean asymmetric BEKK model. As pointed out by Tong and Lim (1980), a linear model, such as the AR model, is totally inadequate as a tool to analyze more intricate phenomena such as limit cycles and time irreversibility. In those cases, a linear time series model should give place to a much wider class of models if we are to gain deeper understanding into the structure of the mechanism generating the observed data.

In this paper, the conditional covariance matrix of the output growth and money growth is allowed to vary over time following the generalized autoregressive conditional heteroscedastic (GARCH) process — see Engle (1982), Bollerslev (1986), and Bollerslev et al. (1988). Agents update their estimates of the first and second moments of output growth and money growth each period using the newly revealed information in last period’s output growth and money growth. Thus, agents learn about changes in the covariance matrix only from information on output growth and money growth. There may be other information relevant to agents’ expectations and that would lead to misspecification.

The approach is originated by Bollerslev et al. (1988) in the context of the capital asset pricing model, where they estimate the time-varying risk premium as a function of the conditional variance of asset returns. Grier et al. (2004) also uses a similar approach in addressing the issue of inflation uncertainty and output. As Bollerslev et al. (1988) put it, “the GARCH specification does not arise directly out of any economic theory, but as in the traditional autoregressive moving average time-series analogue, it provides a close and parsimonious approximation to the form of heteroscedasticity typically encountered with economic time-series data (cf. Bollerslev 1986; Engle and Bollerslev 1986).” Our approach can be seen as a statistical examination of the relationship between money growth volatility and output.

Our nonlinear model specification aims to reveal important features of the data-generating process in a parsimonious way by allowing the conditional variance to enter the mean equation directly — see Engle and
Kroner (1995) and Grier et al. (2004). In particular, we use the following model

$$ z_t = \alpha + \Gamma z_{t-1} + \Psi \sqrt{h_t} + \Theta \epsilon_{t-1} + \epsilon_t \quad (5) $$

$$ \epsilon_t | \Omega_{t-1} \sim (0, H_t) , \quad H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} $$

where $\Omega_{t-1}$ is the information set available in period $t-1$ and

$$ z_t = \begin{bmatrix} d \log y_t \\ d \log M_t \end{bmatrix} ; \quad \epsilon_t = \begin{bmatrix} \epsilon_{yt} \\ \epsilon_{mt} \end{bmatrix} ; \quad \alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} ; $$

$$ \Gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} ; \quad \Psi = \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix} ; \quad \Theta = \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix} . $$

The sources of variability in nominal output growth can be the unforeseen changes in the growth of output and money, $\epsilon_t$. The variability can also arise from monetary policy which is used in an attempt to offset real shocks. Such operations, if successful, decrease the variability caused by temporary real shocks, but, if improperly timed or excessive, they can increase variability.

We use the asymmetric version of the BEKK model, introduced by Grier et al. (2004), for the variance equation

$$ H_t = C'C + B'H_{t-1}B + A'_{t-1} \epsilon \epsilon_{t-1}' A + D'u_{t-1}u_{t-1}'D $$

where $C$, $B$, $A$, and $D$ are $2 \times 2$ matrices with $C$ being a triangular matrix to ensure positive definiteness of $H$. This specification sums the sources of variability that we just discussed, as it allows past volatilities of output and money, $H_{t-1}$, as well as lagged values of shocks $\epsilon \epsilon'$ and $uu'$, to affect the current volatility of the money and output growth rates. The asymmetry vector is defined as $u_{t-1} = \epsilon_{t-1} \circ I_{\epsilon<0} \epsilon_{t-1}$ where $\circ$ denotes the elementwise product of vectors.

We use the quasi-maximum likelihood estimation method to estimate our model. Thus, even if the standardized residuals are not normally distributed, the quasi-maximum likelihood estimator asymptotic standard errors would still be valid — see Bollerslev and Wooldridge (2007). All the estimations are performed in RATS 9.2. We obtain the initial conditions by performing several iterations using the simplex algorithm and we use the BFGS (Broyden, Fletcher, Goldfarb and Shanno) estimation algorithm to maximize the nonlinear log likelihood function.

5 Empirical Evidence

Tables 1 and 2 report the estimated coefficients. The mean effect of the conditional volatility in the money growth rate on output growth is given by $\hat{\psi}_{12}$. As we can see in Panel A of Table 1, the null hypothesis $H_0: \hat{\psi}_{12} = 0$ is rejected. Specifically, the effect of the conditional volatility in the money growth rate on the growth rate of output for Divisia M4A is $-0.326$ (with a $p$-value of 0.055). The decrease in output growth is proportional to the risks in monetary aggregate growth, which is measured by the covariance of the money growth with the output growth. However, for the conventional Divisia M4 counterpart, the money growth variability does not have any statistically significant impact on output as shown in Table 2.

We wonder if the volatility in money growth rate will cause uncertainty in output growth. The variance effect of the conditional volatility in money growth rate on the variance of output growth is given by $\hat{b}_{12}$. As we can see from Panel C of Table 1, $\hat{b}_{12}$ is not statistically significant, indicating the presence of the volatility in money does not have a persistent effect on the volatility of output. Finally, the $D$ matrix presents the asymmetric ARCH effects. The coefficient $\hat{d}_{12}$ of the $D$ matrix in Panel C of Tables 1 suggests that contractionary monetary policy (negative money growth shocks) are associated with more volatility in output, compared with expansionary monetary policy (positive money growth shocks).

Panel B of Tables 1 and 2 presents the diagnostic tests on the standardized residuals of the model. The key diagnostics are for the standardized residuals $z_{jt} = \hat{z}_t / \sqrt{h_t}$ for $j = \Delta \ln y$, $\Delta \ln m$. The Ljung and Box (1979) $Q$ statistic and the adjusted $Q^2$ statistic show that the null hypothesis of no autocorrelation cannot
be rejected at the 1 percent level for the values and the squared values of the standardized residuals in various lags of up to 10, suggesting that there is no significant evidence of serial correlation left in the system residuals. This provides further support for the specification of the bivariate VARMA, GARCH-in-Mean BEKK model, as it absorbs most of the ARCH and GARCH effects.

Overall, we find that the increased uncertainty of the growth rate of the credit card-augmented Divisia M4 monetary aggregate has a statistically significant negative effect on output. There are volatility spillovers from surprise changes in the growth rate of money to the volatility of output, although the effect is not persistent. However, there are no effects of the corresponding traditional Divisia M4 money growth volatility on real economic activity. The results suggest that the credit card-augmented Divisia M4 monetary aggregate has a stronger inference ability on output, and the Fed’s balance sheet targeting monetary policies should consider the broad credit card-augmented Divisia M4 monetary aggregates.

Our main result is that an increase of uncertainty about the growth rate of the credit card-augmented Divisia M4 monetary aggregate is associated with lower average growth rates of output in the US. In this regard, monetary growth uncertainty reflects the risks in the economy and can be a proxy for risk and uncertainty in general. A higher level of risk or uncertainty reduces consumer spending and firm investment. A lower level of economic activity leads to lower demand for assets and asset prices fall, which leads to a decline in leverage of market-based financial intermediaries, as noted by Adrian and Shin (2010). In fact, in more anxious time, massive deleveraging may lead to a credit crunch and tighter borrowing constraints. This is the same mechanism through which overall financial market volatility measures such as the VIX (or financial instability measures) could be related to output growth rates.

6 Conclusion

In this paper, we investigate the effects of credit card-augmented Divisia money growth uncertainty on real economic activity in the United States in the context of a bivariate VARMA, GARCH-in-Mean, asymmetric BEKK model, over the period from 2006:7 to 2019:3. We find that the increased uncertainty about the growth rate of the Divisia M4A monetary aggregate is associated with a lower average growth rate of output in the United States.

Although Serletis and Rahman (2015) find that the money variability/output relationship is robust to Divisia monetary aggregates for a longer time period since 1967, here we find that after the 2007-2009 financial crisis, the money variability/output relationship is negative and statistically significant only with broad credit card-augmented Divisia monetary aggregate, Divisia M4A. Most importantly, the statistically insignificant money variability/output relationship of the conventional Divisia M4 monetary aggregate, highlights that excluding credit cards from liquidity measures would lead to biases on economic inference. The effects of money growth variability are more pronounced in the system when credit cards are taken into liquidity considerations. We, therefore, conclude that the credit card-augmented Divisia M4 monetary aggregate has stronger inference ability on economic activity in the United States compared to the traditional Divisia M4 aggregate.

The evidence is consistent with that in Liu et al. (2019) who provide a comprehensive comparison within two classes of empirical models: cyclical correlations analysis and Granger causality tests. They show that during, and in the aftermath of the 2007-2009 financial crisis, broader Divisia monetary aggregates provide better measures of the flow of monetary services generated in the economy, and that the credit card-augmented Divisia monetary aggregates are more informative when predicting real economic activity than the conventional Divisia monetary aggregates.

To conclude, our results suggest that the Federal Reserve using the flawed unstable simple-sum M1 and M2 monetary aggregates will not maintain output stability, but on the contrary, create instability. The policies based on the ill-defined simple-sum monetary aggregates increase the risk that individuals and society bear, and result in less certain policy outcomes.
References


Figure 1. Number of Noncash payments

Figure 2. Value of credit card payments

Figure 3. Logged Divisia M4 and Divisia M4A
Figure 4. Year-over-year percentage growth rates of Divisia M4 and Divisia M4A
Table 1. Parameter Estimates with Divisia M4A

A. Conditional mean equation

\( a = \begin{bmatrix} 0.403 \ (0.000) \\ 0.000 \ (0.996) \end{bmatrix}; \Gamma = \begin{bmatrix} 0.714 \ (0.000) & -0.519 \ (0.001) \\ 0.063 \ (0.086) & 0.769 \ (0.000) \end{bmatrix}; \)

\( \Psi = \begin{bmatrix} -0.148 \ (0.459) & -0.326 \ (0.055) \\ 0.363 \ (0.005) & -0.284 \ (0.004) \end{bmatrix}; \Theta = \begin{bmatrix} -0.844 \ (0.000) & 0.590 \ (0.000) \\ -0.144 \ (0.000) & -0.783 \ (0.000) \end{bmatrix}. \)

B. Residual diagnostics

<table>
<thead>
<tr>
<th></th>
<th>Mean Variance</th>
<th>( Q(5) )</th>
<th>( Q^2(5) )</th>
<th>( Q(10) )</th>
<th>( Q^2(10) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( z_{yt} )</td>
<td>-0.014</td>
<td>1.022</td>
<td>5.660( \text{(0.340)} )</td>
<td>4.810( \text{(0.440)} )</td>
<td>10.910( \text{(0.365)} )</td>
</tr>
<tr>
<td>( z_{mt} )</td>
<td>0.008</td>
<td>1.010</td>
<td>3.880( \text{(0.567)} )</td>
<td>3.390( \text{(0.639)} )</td>
<td>8.470( \text{(0.583)} )</td>
</tr>
</tbody>
</table>

C. Conditional variance-covariance structure

\( C = \begin{bmatrix} 0.424 \ (0.000) & -0.015 \ (0.641) \\ -0.000 \ (1.000) \end{bmatrix}; \quad B = \begin{bmatrix} 0.008 \ (0.932) & -0.024 \ (0.854) \\ 0.031 \ (0.778) & 0.888 \ (0.000) \end{bmatrix}; \)

\( A = \begin{bmatrix} -0.119 \ (0.381) & 0.256 \ (0.023) \\ -0.042 \ (0.289) & 0.360 \ (0.000) \end{bmatrix}; \quad D = \begin{bmatrix} 0.913 \ (0.000) & -0.196 \ (0.283) \\ -0.261 \ (0.004) & 0.391 \ (0.004) \end{bmatrix}. \)

Notes: Sample period is from 2006:7 to 2019:3 (T=153). Numbers in parentheses are p-values.
Table 2. Parameter Estimates with Divisia M4

A. Conditional mean equation
\[
\begin{align*}
a &= \begin{bmatrix} 0.503 (0.039) \\ 0.499 (0.019) \end{bmatrix};& \quad \Gamma &= \begin{bmatrix} 1.008 (0.000) & -1.101 (0.102) \\ 0.504 (0.090) & -0.575 (0.061) \end{bmatrix}; \\
\Psi &= \begin{bmatrix} 0.219 (0.531) & -0.656 (0.195) \\ 0.817 (0.010) & -1.142 (0.000) \end{bmatrix};& \quad \Theta &= \begin{bmatrix} -1.059 (0.000) & 1.027 (0.138) \\ -0.468 (0.107) & 0.642 (0.039) \end{bmatrix}.
\end{align*}
\]

B. Residual diagnostics

<table>
<thead>
<tr>
<th>Mean</th>
<th>Variance</th>
<th>(Q(5))</th>
<th>(Q^2(5))</th>
<th>(Q(10))</th>
<th>(Q^2(10))</th>
</tr>
</thead>
<tbody>
<tr>
<td>(z_{yt})</td>
<td>-0.006</td>
<td>1.004</td>
<td>6.130(0.294)</td>
<td>5.530(0.355)</td>
<td>12.990(0.224)</td>
</tr>
<tr>
<td>(z_{mt})</td>
<td>0.002</td>
<td>1.007</td>
<td>10.260(0.068)</td>
<td>2.150(0.828)</td>
<td>18.060(0.054)</td>
</tr>
</tbody>
</table>

C. Conditional variance-covariance structure
\[
\begin{align*}
C &= \begin{bmatrix} 0.276 (0.000) & -0.027 (0.425) \\ 0.000 (1.000) & \end{bmatrix};& \quad B &= \begin{bmatrix} 0.613 (0.000) & -0.020 (0.905) \\ -0.217 (0.043) & -0.925 (0.000) \end{bmatrix}; \\
A &= \begin{bmatrix} -0.167 (0.211) & 0.188 (0.103) \\ -0.009 (0.854) & 0.306 (0.000) \end{bmatrix};& \quad D &= \begin{bmatrix} 0.832 (0.000) & 0.033 (0.843) \\ -0.094 (0.303) & -0.201 (0.183) \end{bmatrix}.
\end{align*}
\]

Notes: Sample period is from 2006:7 to 2019:3 (T=153). Numbers in parentheses are p-values.