Recent Monetary Policy and the Credit Card-Augmented Divisia Monetary Aggregates*

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Abstract:

The main objective of this paper is to examine the information content of the credit card-augmented Divisia monetary aggregates and credit card-augmented Divisia inside monetary aggregates, recently produced by the Center for Financial Stability. We compare the inference ability of the credit card-augmented Divisia monetary aggregates and credit card-augmented Divisia inside monetary aggregates to the conventional Divisia monetary aggregates, at all levels of monetary aggregation. Using cyclical correlations analysis and Granger causality tests, we find that both the conventional Divisia monetary aggregates and the credit card-augmented Divisia monetary aggregates are informative in predicting output. Moreover, during, and in the aftermath of the 2007-2009 financial crisis, the credit card-augmented Divisia measures of money are more informative when predicting real economic activity than the conventional Divisia monetary aggregates. We also find that broad Divisia monetary aggregates provide better measures of the flow of monetary services generated in the economy.

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1 Introduction

There is a long tradition in macroeconomics of using models with money to study economic fluctuations, with an influential early example being the discussion of procyclical money supply movements by Friedman and Schwartz (1963a). Friedman and Schwartz (1963b) provide further evidence that monetary instability can be, and in fact has been, an important source of instability in the American economy. However, the real business cycle approach to economic fluctuations posits that postwar business cycles could be explained within a framework that makes no reference to money or indeed to nominal variables at all. Although the New Keynesian model reintroduced a role for monetary policy in stabilizing or destabilizing the economy, strikingly, measures of the money supply remain well behind the scenes in these newest business cycle models and hinder empirical work — see Belongia and Ireland (2016, 2019).

Barnett (1980) demonstrated that simple-sum monetary aggregates produced by the Federal Reserve do not correctly measure the true flow of monetary services generated in an economy where the monetary assets are not perfect substitutes. Barnett (1978, 1980) proposed an alternative measure of money, the Divisia monetary aggregates, that can track changes in the flow of monetary services much more accurately under a lot of circumstances. To illustrate the important role of measurement on inference, both Belongia (1996) and Hendrickson (2014) found that simply replacing the official simple-sum measures of money with their Divisia counterparts suffices to overturn earlier empirical results that suggested that fluctuations in the money supply can be ignored in business cycle analysis. As Belongia (1996) put it, inferences about the effects of money on economic activities may depend importantly on the choice of a monetary index.

Traditionally, the effects of monetary policy on output draw on the hypothesized links between money, interest rates, and output through monetary or credit channels. An extensive literature exists on the policy relevance of the Divisia monetary aggregates, which do not include the liquidity services that credit cards produce. For example, Schunk (2001) has shown that forecasts of U.S. real GDP are most accurate when a Divisia aggregate is included. Belongia and Ireland (2016) extend a New Keynesian model to include roles for monetary aggregates and show that movements in both quantity and price indexes for monetary services correlate strongly with movements in output when the Divisia monetary aggregates are used. Dery and Serletis (2020) show that the inference ability of the Divisia monetary aggregate is even stronger when we use the broad Divisia monetary aggregates.

Taken together, these studies all show that the monetary aggregate that could track liquidity properly has a strong performance in forecasting economic activities. Motivated by this, both theoretical and empirical work on tracking the exact liquidity services are in need to catch up with innovations on alternative payments, such as credit card transaction services. Credit card transactions play a significant role in facilitating the flows of goods and services. Credit cards provide a deferred payment service that is not available from traditional monetary assets — see Barnett and Liu (2019). According to the Center for Financial Stability (CFS), in July 2006, the monthly credit card transactions volume was $146 billion in the U.S. economy. By March 2019, the monthly credit card transactions volume had reached $323 billion. With the rapid growth of credit card transactions, the question is whether the increase in credit card transaction services creates risks to future macroeconomic performance?

In this article, we identify the increase in credit card transaction services and their macroeconomic consequences by using the credit card-augmented Divisia monetary aggregates, recently produced by the CFS, and which account credit card transaction services into liquidity measurement — see Barnett and Su (2018). We reexamine the link between money and economic fundamentals paying attention to money measures that include the transactions services provided by credit cards. In our setting, asking whether the rapid growth in credit card transaction services leads to risks in macroeconomic outcomes boils down to the inference ability of the credit card-augmented Divisia monetary aggregates on macroeconomic fluctuations.

Despite the well established literature on Divisia monetary aggregates, the credit card-augmented Divisia monetary aggregates are rather young. Data are available only since 2006, and therefore they are mostly unexplored. In fact, there is very little empirical evidence available on the relative inference performance of the credit card-augmented Divisia monetary aggregates, although Barnett *et al.* (2016) made the assertion that much of the policy relevance of the Divisia monetary aggregates literature could be strengthened by the use of credit card-augmented Divisia money measures.

The strong inference performance of the conventional Divisia monetary aggregates on macroeconomic activities, together with the rapid growth in the use of credit card transaction services, make it particularly interesting to investigate the inference ability of credit card-augmented Divisia monetary aggregates on key macroeconomic variables. One of the key issues yet to be analyzed is their cyclical movements and inference ability compared to conventional Divisia monetary aggregates. Do the credit card-augmented Divisia monetary aggregates have a stronger correlation with industrial production and economic activity? Do the credit card-augmented Divisia monetary aggregates outperform the conventional Divisia monetary aggregates in forecasting the business cycle?

In this paper, we investigate the cyclical properties of the credit card-augmented Divisia monetary aggregates using Hamilton's (2018) filter and Granger (1969) causality tests. We present a comprehensive comparison of the inference ability of the credit card-augmented Divisia monetary aggregates versus the conventional Divisia monetary aggregates at all levels of monetary aggregation. This paper contributes to the literature in several ways. First, it fills the gap in investigating the cyclical behavior and information content of credit card-augmented Divisia monetary aggregates on economic activities. Second, it examines and compares the performance of the credit card-augmented Divisia monetary aggregates and the traditional Divisia monetary aggregates. We show that both the conventional Divisia monetary aggregates and the credit card-augmented Divisia monetary aggregates are informative in predicting real output. Moreover, the credit card-augmented Divisia monetary aggregates have stronger statistical predictive power. Third, we think this paper constitutes an important step in the direction of quantifying the effects of credit card transaction services on the business cycle. Finally, it also sheds light on the Barnett critique and reinforces the irreplaceable role of money in the conduct of monetary policy.

The remainder of the paper is organized as follows. We begin in Section 2 by providing a brief discussion of the Divisia approach to monetary aggregation, from both the demand side and the supply side, following Barnett *et al.* (2016). Section 3 discusses the data. In Section 4, we undertake an empirical investigation of the cyclical behavior of the conventional Divisia monetary aggregates, the credit card-augmented Divisia monetary aggregates, and the credit card-augmented Divisia inside monetary aggregates, and output. In doing so, we use the Hamilton (2018) filter, the Kydland and Prescott (1990) methodology, and Granger (1969) causality tests. In Section 5, we investigate the predictive content of credit-card services in isolation, with the hope of understanding the grounds in which the standard New-Keynesian model is lacking. The final section concludes the paper and discusses the implications for monetary theory and policy and directions for future work.

2 Divisia Monetary Aggregation

In this section, we review the development of the Divisia monetary aggregates and posit our empirical work on the most recently developed credit card-augmented Divisia money measures.

2.1 (Conventional) 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, derived by Barnett (1978), can be written as

$$\pi_{it}^{a} = \frac{R_t - r_{it}^{a}}{1 + R_t} \tag{1}$$

where R_t is the benchmark asset rate of return measuring the maximum expected rate of return available in the economy, and r^a_{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 ith asset.

With the user cost and quantity data, the expenditure share on monetary asset i is $s_{it} = \pi^a_{it} m^a_{it} / \sum_{i=1}^{I} \pi^a_{it} m^a_{it}$, where m^a_{it} 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

$$d \log M_t = \sum_{i=1}^{I} s_{it} d \log m^a_{it}. \tag{2}$$

Furthermore, Barnett (1978, 1980) demonstrated that the Divisia monetary aggregates represent a superior measurement of liquidity services compared to the simple sum monetary aggregates. As a result, all the modern formal investigations of the impact of money on economic activities are carried out using the Divisia monetary aggregates. See, for example, Belongia (1996), Serletis and Gogas (2014), Hendrickson (2014), and Keating *et al.* (2019). These works carry out two messages for theoretical and empirical work. First, while monetary aggregates have explanatory power regarding the level of economic activity, the Divisia monetary aggregates are superior to the simple sum ones in tracking liquidity measurement. Second, the monetary aggregate that can track the liquidity service properly has the best inference power on macroeconomic activities. In this regard, Jadidzadeh and Serletis (2019) provide evidence that supports and reinforces Barnett's (2016) assertion that we should use, as a measure of money, the broadest Divisia M4 monetary aggregate, as opposed to narrower aggregates such as Divisia M1 or Divisia M2. More recently, Dery and Serletis (2020) also produce inference that favors the group of broad monetary aggregates, Divisia M3, Divisia M4-, and Divisia M4.

2.2 Credit Card-Augmented Divisia Monetary Aggregates

The volume of credit card transaction services has more than doubled in the past decade. Over 80% of American households with credit cards are currently borrowing and paying interest on credit cards. The simple sum monetary aggregates are not able to include credit card transaction services due to accounting conventions. In particular, monetary assets are assets and credit card balances are liabilities, and according to accounting conventions, assets and liability cannot be added together. However, as argued by Barnett *et al.* (2016), economic aggregates should be based on the flows of goods and services, not accounting conventions.

The Divisia monetary aggregates measure flows of services and are not based on accounting conventions. Using economic aggregation and index number theory, the transaction services of credit cards and monetary assets can be aggregated jointly. Barnett *et al.* (2016) derive the Divisia monetary aggregate that can jointly aggregate the services of money and credit cards. They derive the user cost of credit card transaction services, π_{lt}^c, under the assumption of risk neutrality as

$$\pi_{lt}^c = \frac{e_{lt} - R_t}{1 + R_t} \tag{3}$$

where e_{lt} is the expected interest on the credit card transaction l and R_t is as before the rate of return on the benchmark asset. The credit card-augmented Divisia monetary aggregate is then given by

$$d \log M_t = \sum_{i=1}^{I} s_{it} d \log m_{it}^a + \sum_{l=1}^{L} s_{lt} d \log m_{lt}^c \tag{4}$$

where $s_{it} = \pi_{it}^a m_{it}^a / (\sum_{i=1}^{I} \pi_{it}^a m_{it}^a + \sum_{l=1}^{L} \pi_{lt}^c m_{lt}^c)$ is the user-cost-evaluated expenditure share of monetary asset i $(i = 1, ..., I)$ and $s_{lt} = \pi_{lt}^c m_{lt}^c / (\sum_{i=1}^{I} \pi_{it}^a m_{it}^a + \sum_{l=1}^{L} \pi_{lt}^c m_{lt}^c)$ is the user-cost-evaluated expenditure share of credit card transaction l $(l = 1, ..., L)$.

Since the interest rate and risk on credit cards transactions are much higher than those on monetary assets, it is necessary to take the risk adjustment into account when we compute the user cost of credit card transaction services. Barnett and Su (2018) permit risk aversion in the decision of the representative consumer, and derive the user cost of credit cards transaction services from the relevant Euler equations. The user cost and the associated risk adjustment of the credit card transaction services derived by Barnett and Su (2018) are based on consumption capital asset pricing model (CCAPM) under the assumption of intertemporal separability in consumption. However, the CCAPM tends to downward bias the returns in financial and monetary markets, which is also known as the equity premium puzzle. While the downward bias of CCAPM risk adjustments on the user cost of monetary assets might be negligible since they are of low risks, once credit card services are included, that downward bias cannot be ignored, since the interest rates of credit card are high and volatile. Barnett and Liu (2019) believe that extending to intertemporal non-separability could provide a non-negligible risk adjustment. They further extended the theoretical credit card-augmented Divisia under the assumption of intertemporal nonseparability. Moreover, they derived the theoretical framework of the credit card augmented Divisia monetary aggregate under risk with intertemporal nonseparability. The credit card user cost under risk with intertemporal nonseparability is still ongoing research. The credit card augmented Divisia monetary aggregates supplied by the CFS program Advances in Monetary and Financial Measurement (AMFM) are based on the assumption of risk neutrality as derived by Barnett *et al.* (2016).

2.3 Credit Card-Augmented Divisia Inside Monetary Aggregates

Inside money is a concept from the supply side, defined as the monetary services produced by banks and other financial intermediaries. Although policymakers have highlighted the importance of the interactions between financial intermediaries and liquidity services, they have mostly emphasized the demand side. However, conditions from the supply side of the liquidity services are at least equally important. In fact, inside money is highly relevant to the transmission mechanism of monetary policy and to the indicator value of the resulting service flows. The Federal Reserve's policy of quantitative easing during the financial crisis, with its goal of affecting the supply of liquid assets, appears to impact the inside money directly. Therefore, it is important to account for the monetary services produced by deposit-based financial firms.

In conventional modeling of financial intermediaries and credit supply, a stylized banking sector is added to a model with credit frictions and borrowing constraints — see, for example, Diaz-Gimenez *et al.* (1992). A different approach is to capture the liquidity services produced by financial firms to the money supply and model the propagation of monetary policy accordingly. Barnett (1987) introduced the Divisia supply monetary aggregates, which are based upon supply-side aggregation theory, in the context of a conventional neoclassical model of financial intermediary monetary assets supply. These aggregates highlight the existence of noninterest-bearing required reserves for banks. This is important, because a regulatory wedge is created for the user of the monetary services produced by the banks. Thus the user cost of monetary asset needs to subtract the implicit tax as follows

$$\pi_{it}^{a} = \frac{(1-k_i)R_t - r_{it}}{1+R_t} \tag{5}$$

where k_i is the required reserve ratio on monetary asset i.

Financial firms also produce credit card transaction services as outputs. Barnett and Su (2018) developed the credit card-augmented Divisia inside monetary aggregates from the output supply function of financial intermediaries. In doing so, they assume risk neutrality of bank managers and derive the real expected user cost of produced credit card services as

$$\pi_{lt}^{c} = \frac{e_{lt} - R_t}{1+R_t}. \tag{6}$$

They calculate the credit card-augmented Divisia inside monetary aggregates as in equation (4) with the monetary asset user costs calculated as in equation (5). Thus, the formula for the credit card-augmented Divisia inside monetary aggregates is the same as equation (4), but with quantities demanded, m_{it}^{a}, replaced by quantities supplied and with paid user costs, π_{it}^{a}, replaced by received user costs calculated as in equation (5). As the first step to include credit card services into the inside money measures, the simplifying assumption of risk neutrality of bank managers is made. It is also a very strong assumption, which implies the existence of complete contingent claims perfect markets, suggesting that owners are risk averse, but managers are risk neutral. Future research of inside money measures under risk aversion is ongoing and hopefully will be available soon at the CFS.

3 Data

Belongia and Ireland (2015) argue that the link between Divisia monetary aggregate and economic activity is much stronger in recent years, especially after 2000. Thus, we take a close look at the more recent sample period to examine the relationship between money and economic activity. In doing so, we use monthly data for the United States, from 2006:7 to 2019:3 (a total of 154 monthly observations). The sample period includes the extreme economic events of the 2007-2009 financial crisis and is dictated by the availability of the credit card-augmented Divisia and credit card-augmented Divisia inside monetary aggregates, maintained within the AMFM program at CFS.

We compare the relative information content of the credit card-augmented Divisia monetary aggregates and credit card-augmented Divisia inside monetary aggregates to the conventional Divisia monetary aggregates. We also make comparisons between the narrow Divisia money measures — those at the M1, M2, M2M, MZM, and ALL levels of monetary aggregation — and the broad Divisia money measures — those at the M3, M4-, M4 levels of monetary aggregation. Note that, on the demand side, the Divisia M4- and Divisia M4 aggregates differ only by the inclusion of Treasury bills in Divisia M4. Since Treasury bills are not privately produced inside money, there is no supply side inside-money version of Divisia M4. The broadest Divisia inside money aggregate is therefore Divisia M4-. Our measure of real output is the Industrial Production Index and our interest rate variable is the federal funds rate. We use the Consumer Price Index to account for changes in the level of prices. Data of these three variables are from the St. Louis Federal Reserve Economic Data.

In Figures 1, 2, and 3, we present the logged levels of the conventional Divisia monetary aggregate (as, for example, Divisia M1, at the M1 level of aggregation), the credit card-augmented Divisia monetary aggregate (as Divisia M1A), and the credit card-augmented Divisia inside monetary aggregate (as Divisia M1AI), at three different levels of aggregation levels, M1, M3, and M4, respectively. As can be seen from Figure 1, the narrow Divisia monetary aggregates trend steadily upwards. However, when we look at the broad Divisia monetary aggregates, M3 and M4 in Figures 2 and 3, the difference between the credit card-augmented Divisia and the conventional Divisia is more pronounced, especially in recent years.

Figures 4 to 11 present similar comparisons, at all levels of aggregation (M1, M2, M2M, MZM, ALL, M3, M4-, and M4, respectively), using growth rates to illustrate the consequences of including credit card transaction services into monetary aggregates. There are broad similarities across the growth rates of the monetary aggregates at all aggregation levels, however, the dispersion at turning points has important inference for economic activities. When we zoom in the episode of the 2007-2009 Great Recession (indicated as the shaded area in the figures), the decline of economic activity in 2008 is accompanied with a reduction in the amount of credit available to the private sector as reflected consistently with both the Divisia monetary aggregates and the augmented Divisia monetary aggregates. However, the information content from the narrow Divisia monetary aggregate (in Figures 4 to 7) is less consistent, as the narrow Divisia monetary aggregates are very different from their credit card-augmented counterparts and the inside monetary aggregates during the Great Recession, especially after 2008. The relatively stable structure of U.S. financial markets did not produce large differences among these series after the Great Recession except for Divisia M3.

The Divisia inside monetary aggregate is below the Divisia monetary aggregate at all narrow aggregation levels as can be seen in Figures 4 to 7. It suggests that banking attenuates the response of liquidity to a monetary policy shock; this mainly reflects the presence of a regulatory wedge, which moderates the impact of changes in the policy rate on the liquidity services produced by financial firms. For example, in Figure 4, deviations between Divisia M1 and Divisia M1A inside money are as large as six percentage points during the Great Recession. However, for the broad Divisia monetary aggregates, the deviation between Divisia M3A inside money and the conventional Divisia M3 is not pronounced during the recession at all, but more obvious in recent years when the economy is stable and steadily growing. At the meantime, both Divisia M4 and Divisia M4- are very close with their credit card-augmented counterparts during the whole sample period.

4 Empirical Evidence

The main objective of this section is to examine the relative information content of the credit card-augmented Divisia monetary aggregates in explaining key macroeconomic variations and to provide a comparison between the conventional Divisia monetary aggregates, the credit card-augmented Divisia monetary aggregates, and the credit card-augmented Divisia inside monetary aggregates at different levels of monetary aggregation. We present a comprehensive comparison within two classes of empirical models, cyclical correlations analysis and Granger causality tests, as in Dery and Serletis (2020).

4.1 Cyclical Correlations Analysis

We use the methodology suggested by Kydland and Prescott (1990) to investigate the cyclical properties of the different Divisia monetary aggregates at the different levels of aggregation. In doing so, we decompose each monetary aggregate into trend and cyclical components, using the Hamilton (2018) regression based filter, and then calculate contemporaneous and cross correlation coefficients with the cyclical component of industrial production. We choose the new Hamilton (2018) regression based filter because it can isolate a stationary component from any I(4) series, preserves the underlying dynamic relations and consistently estimates well-defined population characteristics for a broad class of possible data-generating processes.

Our examination is on a time horizon of 24 months. Kydland and Prescott (1990) point out that the duration of business cycles is varying from 1 to 12 years and averaging about 3.5 years. Batini and Nelson (2001) find that it takes over a year before monetary policy actions have their peak effect on inflation and such lag length is not substantially shortened when there are advances in information processing and in financial market sophistication. Indeed, most business cycle analyses are at a horizon of two years or 24 months (see Hamilton (2018)).

According to Hamilton (2018), for a nonstationary monthly time series, y_t, the residuals from an OLS regression of y_t on four lags of itself back shifted 24 months capture the cyclical component of y_t, as follows

$$y_t = \beta_0 + \beta_1 y_{t-24} + \beta_2 y_{t-25} + \beta_3 y_{t-26} + \beta_4 y_{t-27} + v_t.$$

The regression residuals

$$\hat{v}_t = y_t - \hat{\beta}_0 - \hat{\beta}_1 y_{t-24} - \hat{\beta}_2 y_{t-25} - \hat{\beta}_3 y_{t-26} - \hat{\beta}_4 y_{t-27}$$

provide the cyclical component of the series.

We measure the degree of cyclical comovement by the magnitude of the correlation coefficients

$$\rho(M_t, Y_{t+j}), \quad \text{for } j = -24, -18, 12, -9, -6, -3, -2, -1, 0, 1, 2, 3, 6, 9, 12, 18, 24.$$

In particular, the sign of the contemporaneous correlation coefficient, $\rho(M_t, Y_t)$, gives information on the direction of the comovement between a monetary aggregate and output. If $\rho(M_t, Y_t) > 0$, we say that M_t is procyclical, if $\rho(M_t, Y_t) < 0$, we say that M_t is countercyclical, and if $\rho(M_t, Y_t) = 0$, we say that M_t is acyclical. In fact, for data samples of this size, it has been suggested [see, for example, Fiorito and Kollintzas (1994)] that for $0.5 \leq |\rho(M_t, Y_t)| < 1$, $0.2 \leq |\rho(M_t, Y_t)| < 0.5$, and $0 \leq |\rho(M_t, Y_t)| < 0.2$, we say that M_t is strongly contemporaneously correlated, weakly contemporaneously correlated, and contemporaneously uncorrelated with the cycle, respectively. Also, the cross correlation coefficient, $\rho(M_t, Y_{t+j})$ for $j \neq 0$, provides information on the phase shift of M_t. If the absolute value of $\rho(M_t, Y_{t+j})$ is maximum for a positive, zero, or negative j, we say that M_t is leading the cycle by j periods, is synchronous, or is lagging the cycle by j periods, respectively. We report the contemporaneous and cross-correlation coefficients between the cyclical component of each of the monetary aggregates and output in Table 1 (for the narrow Divisia monetary aggregates) and Table 2 (for the broad Divisia monetary aggregates).

As can be seen in Table 1, the Divisia M1, the credit card-augmented Divisia M1, and the credit card-augmented Divisia inside M1 aggregates are weakly procyclical. Compared to the conventional Divisia M1, the credit card-augmented Divisia M1 and the credit card-augmented Divisia inside M1 have stronger correlations with the cyclical component of industrial production. Regarding the phase shift, we find that the Divisia aggregates at the M1 level are all lagging the cycle of industrial production by 6 months while those at the M2 and M2M levels are lagging the cycle by 18 months. On the other hand, the Divisia aggregates at the MZM and ALL levels tend to lead the cycle of output by 12 to 18 months. However, given that these monetary aggregates are generally acyclical, the information value of being leading may be limited.

Table 2 presents similar information for the broad Divisia money measures. All broad Divisia money measures (except for the Divisia M3, Divisia M4, and the credit card- augmented Divisia M4) are weakly procyclical and leading the cycle of industrial production by 12 to 18 months. Comparing the cyclical correlations between the broad Divisia monetary aggregates and industrial production in Table 2 with the cyclical correlations between the narrow Divisia monetary aggregates and industrial production in Table 1, we notice that the Divisia M4-, the credit card-augmented Divisia M4 -, and the credit card-augmented Divisia inside M4- have stronger correlations than those with the narrow Divisia monetary aggregates. This suggests that broad money could be more informative than narrow money in predicting output. Also these results suggest that monetary aggregates augmented with credit card services could be more informative for gauging movements in output. One possible explanation is that credit card-augmented Divisia monetary aggregates provide a wider scope of transmission mechanisms, some of which are not captured by the conventional Divisia monetary aggregates; accordingly we uncover a stronger response of output to the credit card-augmented money supply.

Figure 12 provides a summary of those monetary aggregates that are weakly contemporaneously correlated with output. As can be seen, a few narrow Divisia monetary aggregates (M1, M1A, and M1AI) and most of the broad Divisia monetary aggregates (M3A, M3I, M4-, M4A-, and M4AI-) are weakly contemporaneously correlated with output, as $0.2 \leq |\rho(M_t, Y_t)| < 0.5$. The contemporaneous correlation coefficients between the other Divisia monetary aggregates and output are less than 0.2, which are categorized as uncorrelated according to Fiorito and Kollinzas (1994). It is to be noted that five out of the eight weakly contemporaneously correlated Divisia monetary aggregates are credit card-augmented Divisia monetary aggregates.

So far we have examined the cyclical properties of the different Divisia monetary aggregates. However, cyclical correlations do not imply causality. To further examine the information content of the different Divisia monetary aggregates, in what follows we assess the information content of each monetary aggregate in the context of Granger causality tests in order to investigate the information content of each of the monetary aggregates in predicting real economic activity.

4.2 Granger Causality Tests

Having established the cyclical properties of the different Divisia monetary aggregates, we next perform Granger causality tests to investigate the information content of each of the monetary aggregates in predicting real economic activity. We also assess the information content of the federal funds rate as the benchmark variable. In doing so, we follow Belongia and Ireland (2015) and Dery and Serletis (2020).

We use the following regression equation

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=1}^{q} \theta_j X_{t-j} + \sum_{k=1}^{r} \lambda_k P_{t-k} + e_t \tag{7}$$

where Y_t is a measure of real economic activity (the industrial production index in our case), X_t is a predictor variable (either the federal funds rate, R_t, or a monetary aggregate, M_t, and P_t is the Consumer Price Index which acts as an adjustment variable to remove the effects of general prices from the estimates, as in Bernanke and Blinder (1992) and Belongia and Ireland (2015).

The null hypothesis is that all lags of the predictor variable, X_{t-1}, X_{t-2},..., X_{t-q}, can be excluded from the regression; that is $\theta_j = 0, \forall\ j$. Two most commonly used criteria for specifying the lag length are the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). The BIC is suggested because it provides interesting extremes in the bias/efficiency trade-off. As Thornton and Batten (1985) point out, the BIC tends to select lags that are too short in finite samples. The AIC, on the other hand, gives relatively more importance to unbiasedness over efficiency. Although the AIC is asymptotically inefficient (in the sense that, on average, it selects lags that are too long in large samples), considering that our sample period is relatively short, we choose the AIC for optimal lag length selection to avoid bias — see also Yang (2005) and Burnham and Anderson (2002). We test for Granger causality for a flexible lag structure, optimally chosen by the AIC, after letting each of p, q, and r in equation (7) take values from 1 to 12, thus avoiding the arbitrariness of imposing any arbitrary lag length. The AIC optimal lags and p-values of the Granger causality tests are reported in Table 3. Smaller p-values indicate a stronger role for that nominal variable in predicting industrial production, as in Bernanke and Blinder (1992), Belongia and Ireland (2015), and Dery and Serletis (2020).

It is to be noted that we base our analysis on p-values from the F-distribution assuming asymptotic normality. This, however, may not be valid if some variables are integrated with an order of integration of at least 2. See Sims *et al.* (1990). We therefore investigate the robustness of our results to the use of p-values based on the nonstandard asymptotic distribution, computed as described in Stock and Watson (1989, Appendix B); it has been argued that the latter is more appropriate when using the variables in levels. These bootstrapped p-values are reported in squared brackets in Table 3 (and the rest of the tables); in general, our conclusions are robust to the use of the bootstrapped p-values.

The New Keynesian model places emphasis on the transmission of monetary policy via interest rates. Central banks focus almost entirely on Taylor (1993) type interest rate rules, and the interest rate has been placed at the heart of analyses that interpret and evaluate monetary policies. Thus, we first test the causality from the federal funds rate to industrial production to examine this monetary policy transmission channel. As can be seen in panel 1 of Table 3, we fail to reject the null of no causality with a p-value of 0.586. This provides further evidence of the dangers of a monetary policy strategy that solely targets interest rates, as noted by Belongia and Ireland (2015).

Next, we compare the causal relationships between each Divisia monetary aggregate and industrial production. Table 3 shows that both the conventional Divisia monetary aggregates and the credit card-augmented Divisia monetary aggregates are informative in predicting output at the 10% statistical significance level. Moreover, as shown in panel A of Table 3, all of the narrow credit card-augmented Divisia monetary aggregates and narrow credit card-augmented Divisia inside monetary aggregates are informative for predicting output at the 5% level. The conventional Divisia aggregates, M1, M2, and M2M, are informative for predicting output at the 5% level. This is consistent with the previous section that the cyclical correlations between money and output are higher when we include credit card services into the Divisia monetary aggregates.

In Table 4, we investigate the robustness of our results using monthly growth rates. Part 1 of Table 4 shows that the federal funds rate is not informative in predicting output as we cannot reject the null hypothesis of no Granger causality at any level of statistical significance. For the narrow monetary aggregates, as shown in panel A of Table 4, the Divisia MZM, the credit card-augmented Divisia MZM, the credit card-augmented Divisia ALL, the credit card-augmented Divisia inside MZM, and the credit card-augmented Divisia inside ALL are informative in predicting output at the 5 % statistical significance level. For the broad Divisia monetary aggregates, as shown in panel B of Table 4, all of the aggregates are informative in predicting output at the 1% level.

Finally, it has been argued by Sims (1980) and Litterman and Weiss (1985) that the predictive power of money tends to be absorbed by the interest rate. To investigate if the presence of the federal funds rate reduces the explanatory power of the monetary aggregates on output, we conduct the Granger causality tests while also controlling for the interest rate, in the context of the following regression equation

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=1}^{q} \theta_j X_{t-j} + \sum_{k=1}^{r} \lambda_k P_{t-k} + \sum_{\ell=1}^{s} \phi_\ell R_{t-\ell} + e_t. \tag{8}$$

As before, we allow for a flexible lag structure optimally chosen using the AIC after letting each of p, q, r, and s in equation (8) take values from 1 to 12. We report results in Table 5 using log levels and in Table 6 using growth rates for the optimal lag structures. The optimal lag structures reported in Table 5 are similar to those in Table 3, confirming that we do not fundamentally change the structure of the equation by controlling for the interest rate. It is thus not surprising, but reassuring, that we reach the same conclusions in Table 5 as those that we established in Table 3.

Based on Table 5, when controlling for the federal funds rate, both the conventional Divisia monetary aggregates and the credit card-augmented Divisia monetary aggregates are still informative in predicting output. Comparing the statistical significance levels of the Granger causality tests when controlling for the federal funds rate (as shown in Table 5) to those without controlling for the federal funds rate (as shown in Table 3), the results of the narrow and broad Divisia monetary aggregates are robust when we control for the federal funds rate, and our conclusions in Table 3 still hold. We do not find evidence for Friedman's argument that the explanatory power of money is diminished when the interest rate is taken into account. On the contrary, we show that the broad Divisia monetary aggregates are more informative in predicting economic activity and the results are robust when controlling for the interest rate.

We show that during, and in the aftermath of the 2007-2009 financial crisis, Divisia monetary aggregates are informative in predicting output. Moreover, the credit card-augmented Divisia monetary aggregates have stronger statistical power in predicting output, which is consistent with Barnett *et al.* (2016). Our results are also consistent with Belongia and Ireland (2015), who find that the relation between output and money is stronger than that between the federal funds rate and output in recent years. Our results also corroborate the findings of Dery and Serletis (2020) that broad Divisia monetary aggregates are more informative and robust than the narrow Divisia monetary aggregates in predicting output.

5 Is it Money, Credit, or the Divisia Aggregation?

As already noted, the standard New Keynesian model used for monetary policy and business cycle analysis lacks any formal treatment of either government or private sector money supply. However, there is a large number of recent papers arguing that broad Divisia monetary aggregates have stronger statistical power in predicting output and inflation and, several of these papers, provide a causal link running from innovations in broad Divisia money to macroeconomic aggregates — see, for example, Jadidzadeh and Serletis (2019) and Dery and Serletis (2020). This paper also branches into this recent empirical literature by leveraging credit-card augmented Divisia measures of money. One of our results is that both broad Divisia measures of money with and without credit-card services lead and Granger cause real economic activity. The other (and main) result of the paper is that the credit card-augmented Divisia monetary aggregates have stronger statistical predictive power compared to other Divisia monetary aggregates in predicting real economic activity.

However, while we make a sound case for including credit card services in Divisia measures of money, the mixture of monetary assets and liabilities (credit card balances) very much blends money and credit in terms of the Bernanke and Blinder (1988) dichotomy. In particular, just as we are critical of the standard New-Keynesian model for lacking a serious treatment of money, Bernanke and Blinder (1988) criticized standard macro models for lacking a serious treatment of credit. In this regard, the importance of credit cards in the supply of liquidity services is growing. Traditionally, monetary assets were the dominant suppliers of liquidity services. In particular, cash, debit cards, and checks were used to be the main payment methods, but their role has increasingly been supplanted by credit cards. According to the Federal Reserve Payments Study (2019), credit card payments (combined value of general purpose and private label credit cards) accounted for 34.1 percent of all card payments in 2018 by number. Moreover, credit card payments totaled 44.7 billion with a value of $3.05 trillion in 2018. In fact, from 2015 to 2018, the number and value of credit card payments grew by 9.9 percent per year and 9.3 percent on average per year, respectively.

This then begs the question about the dimensions in which the New Keynesian model is lacking. Is it money, credit, or the Divisia method of aggregation? We address this question by investigating the predictive content of credit card services in isolation. In panel 1 of Table 7, we show that credit card services are procyclical and leading the cycle of industrial production. In panel 2 of Table 7, we examine the information content of credit card services in predicting real economic activity. We show the results for different transformations of the data as well as their robustness to controlling for the interest rate; numbers in brackets are bootstrapped p-values. The test results indicate that we are unable to reject the null hypothesis of no causality from credit card services to real economic activity at conventional significance levels. This holds for both the normal and bootstrapped p-values.

We reach the conclusion that the increased predictive power of the credit card-augmented Divisia monetary aggregates lies in the Divisa method of aggregation and the combined services of monetary assets and credit cards. According to the Barnett critique, measurement matters for inference. For monetary aggregates to be effective monetary policy tools, they must be able to track the liquidity services in the economy. Simple sum monetary aggregates do not and cannot include credit cards due to accounting conventions. Barnett developed the credit card-augmented Divisia monetary aggregates which are able to measure the joint liquidity service flows of monetary assets and credit card transactions. The credit card-augmented Divisia monetary aggregates are able to internalize the substitution effects within monetary assets and credit card transaction services. In this regard, Liu and Serletis (2020), in the context of a credit card-augmented monetary asset demand system based on the Minflex Laurent flexible functional form, find evidence that credit cards are substitutes for traditional monetary assets. They also find that the elasticities of substitution exhibit large swings during the global financial crisis of 2007-2009, a period of erratic monetary policy. In the aftermath of the global financial crisis, however, the elasticities of substitution are small.

6 Conclusion

We examine the relative information content of the credit card-augmented Divisia monetary aggregates and credit card-augmented Divisia inside monetary aggregates, recently produced by the CFS, in comparison to conventional Divisia monetary aggregates. We present a comprehensive comparison within two classes of empirical models, cyclical correlation analysis and Granger causality tests. We find that during, and in the aftermath of the 2007-2009 financial crisis, both the conventional Divisia monetary aggregates and the credit card-augmented Divisia monetary aggregates have predictive power on output. Moreover, the predictive power of credit card-augmented Divisia monetary aggregates is stronger. We also find that broad Divisia monetary aggregates generally provide better measures of the flow of monetary services generated in the economy. Our results favor the group of broad monetary aggregates, including Divisia M3, Divisia M4-, and Divisia M4, and undoubtedly allude to the importance of credit card services and electronic money services in addressing the "Barnett critique." As noted by Barnett and Liu (2019), ignoring credit card services from monetary aggregates can lead to bias in the measurement of the services provided by money.

This paper is the first paper to empirically examine the inference ability of the credit card-augmented Divisia monetary aggregates. To draw a strong conclusion regarding the relationship between the growth of credit card-augmented Divisia monetary aggregates and output growth, structural models and more sophisticated statistical tests (which are beyond the scope of this paper) could be employed in future research. It is also to be noted that the credit card-augmented Divisia monetary aggregates currently supplied by the CFS have been derived by Barnett *et al.* (2016) under the assumption of risk neutrality and intertemporally separable preferences. Relaxing these assumptions, as in Barnett and Su (2018), with risk adjustment, and Barnett and Liu (2019), with intertemporal non-separability, will undoubtedly improve the information content of the Divisia monetary aggregates and potentially strengthen the statistical links between Divisia money and macroeconomic activity.

Finally, one way to make further progress on identifying the inference behavior of the credit card-augmented Divisia monetary aggregates is to investigate the performance of such credit card-augmented Divisia measures of money in other countries. If the credit card-augmented Divisia monetary aggregates have stronger statistical predictive power on output, as we suggest in this paper, we should expect similar inference patterns of credit card-augmented Divisia measures of money on economic activities in other countries. In this regard, over the years, Divisia monetary aggregates have been widely used all over the world due to their superior performance in tracking liquidity services in the economy. For the United States, the CFS provides the Divisia monetary aggregates through its formal monthly releases; they are also made available to Bloomberg terminal users. The Bank of England provides Divisia monetary aggregates officially for the United Kingdom. The central bank of Poland also provides them for Poland. The European Central Bank provides Divisia monetary aggregates to its Governing Council at its policy meetings, but does not provide them to the public. The Bank of Japan also uses Divisia monetary aggregates for policy purposes, although does not make them available to the public. One can perform similar investigations using credit card-augmented Divisia monetary aggregates for these countries, when data are available, and provide more empirical evidence on the inference ability of credit card-augmented Divisia measures of money.

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Figure 1. Logged Divisia M1 monetary aggregates

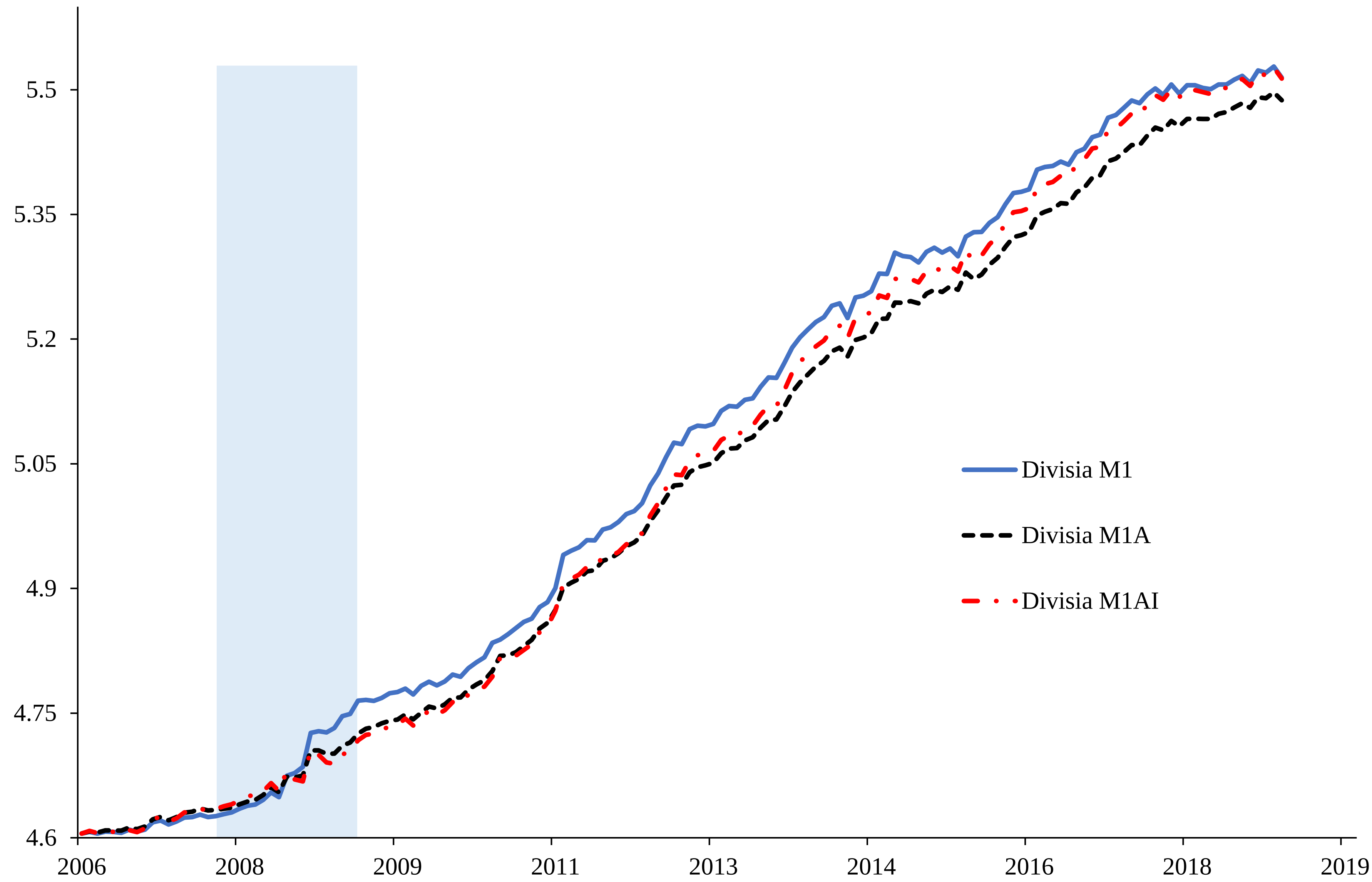

Figure 2. Logged Divisia M3 monetary aggregates

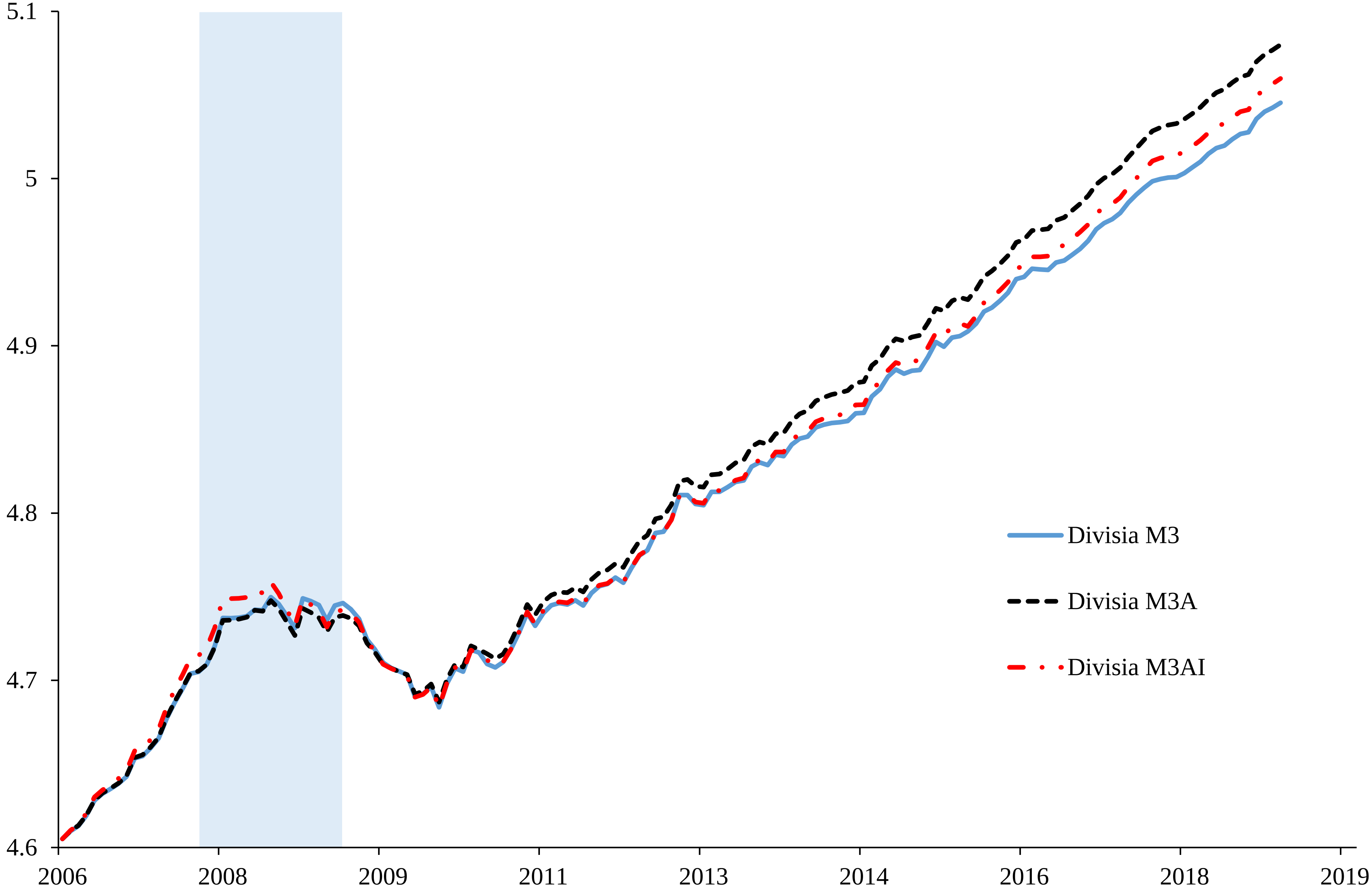

Figure 3. Logged Divisia M4 monetary aggregates

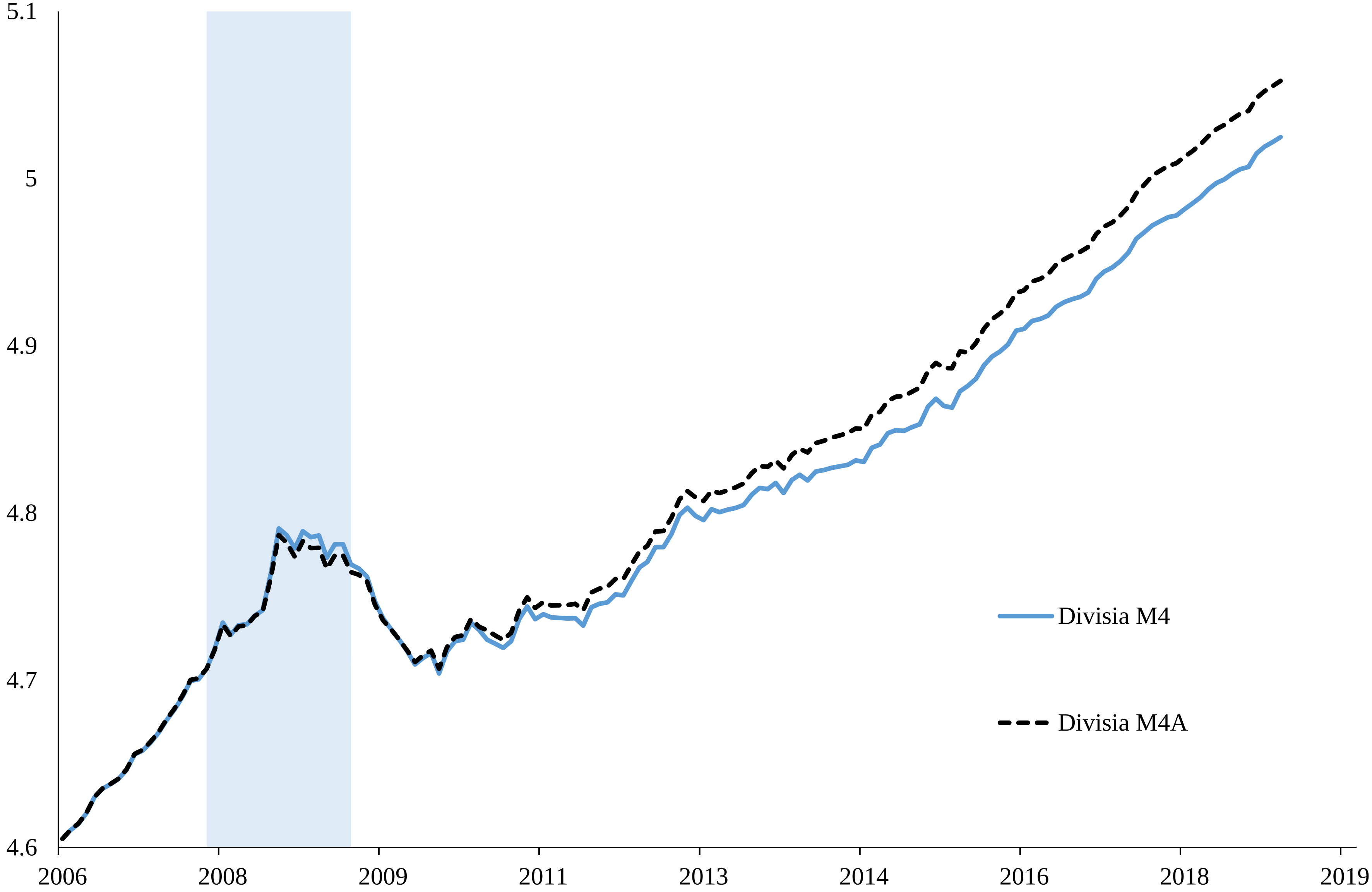

Figure 4. Year-over-year percentage growth rates of Divisia M1 monetary aggregates

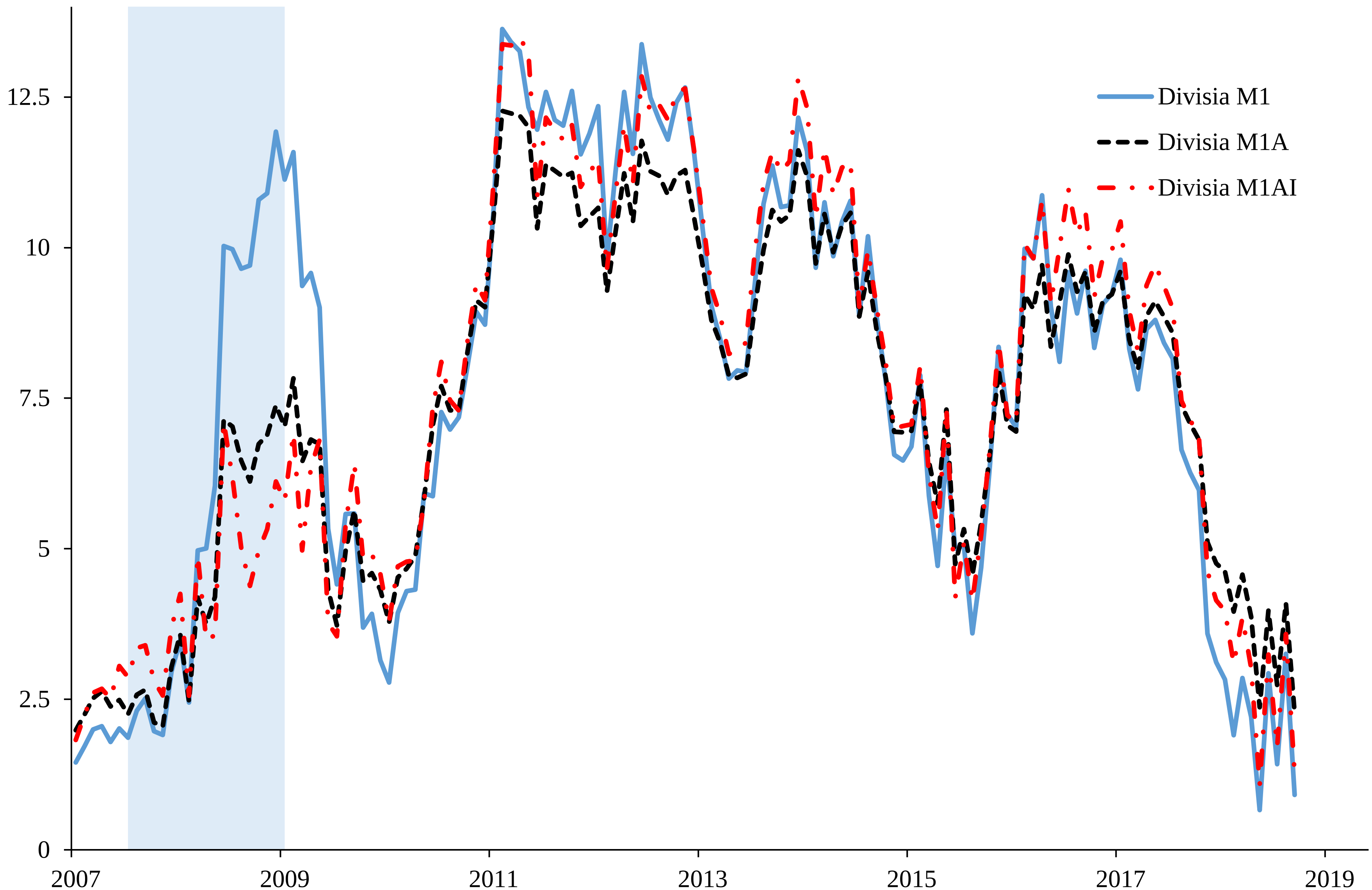

Figure 5. Year-over-year percentage growth rates of Divisia M2 monetary aggregates

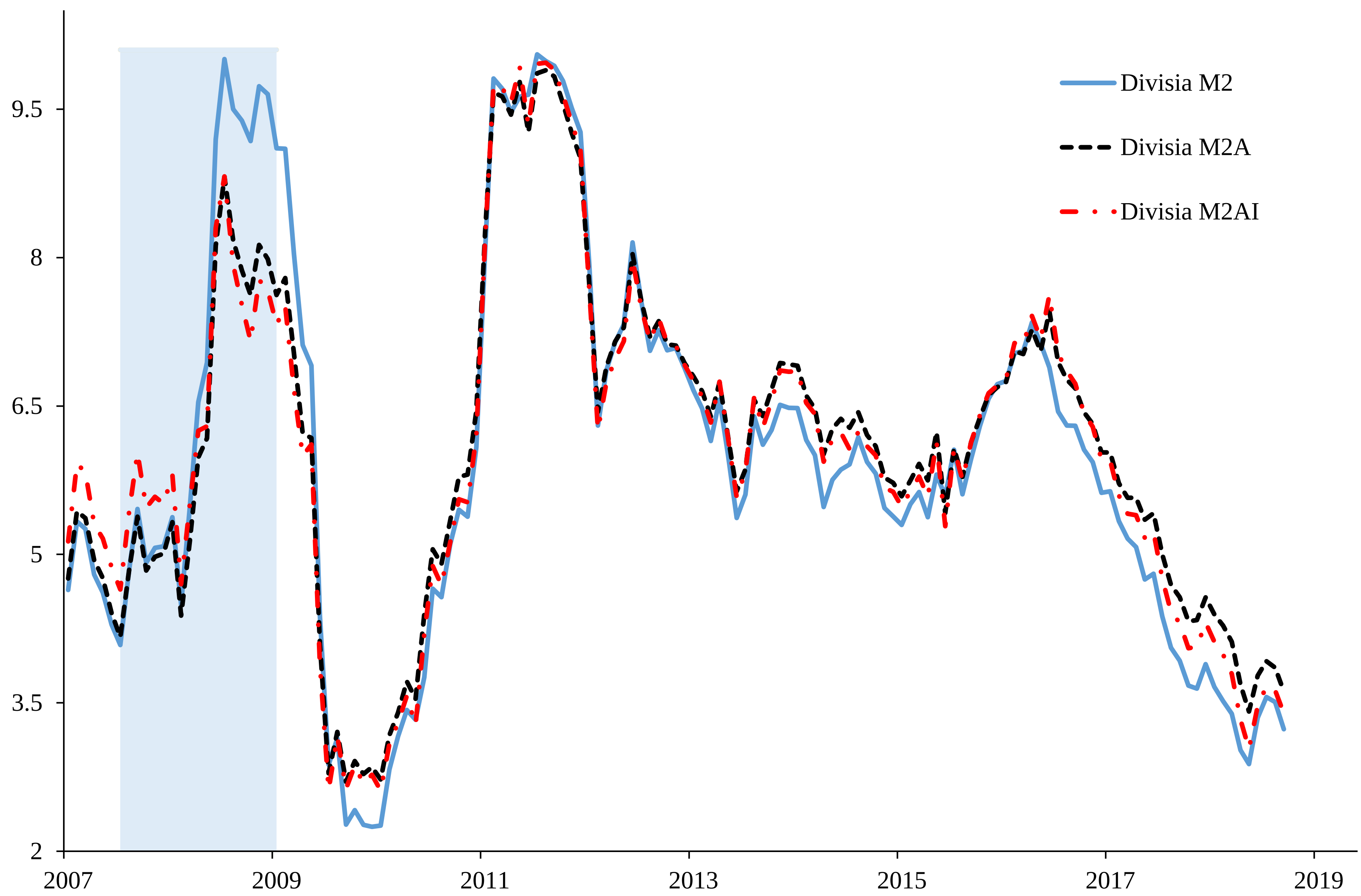

Figure 6. Year-over-year percentage growth rates of Divisia M2M monetary aggregates

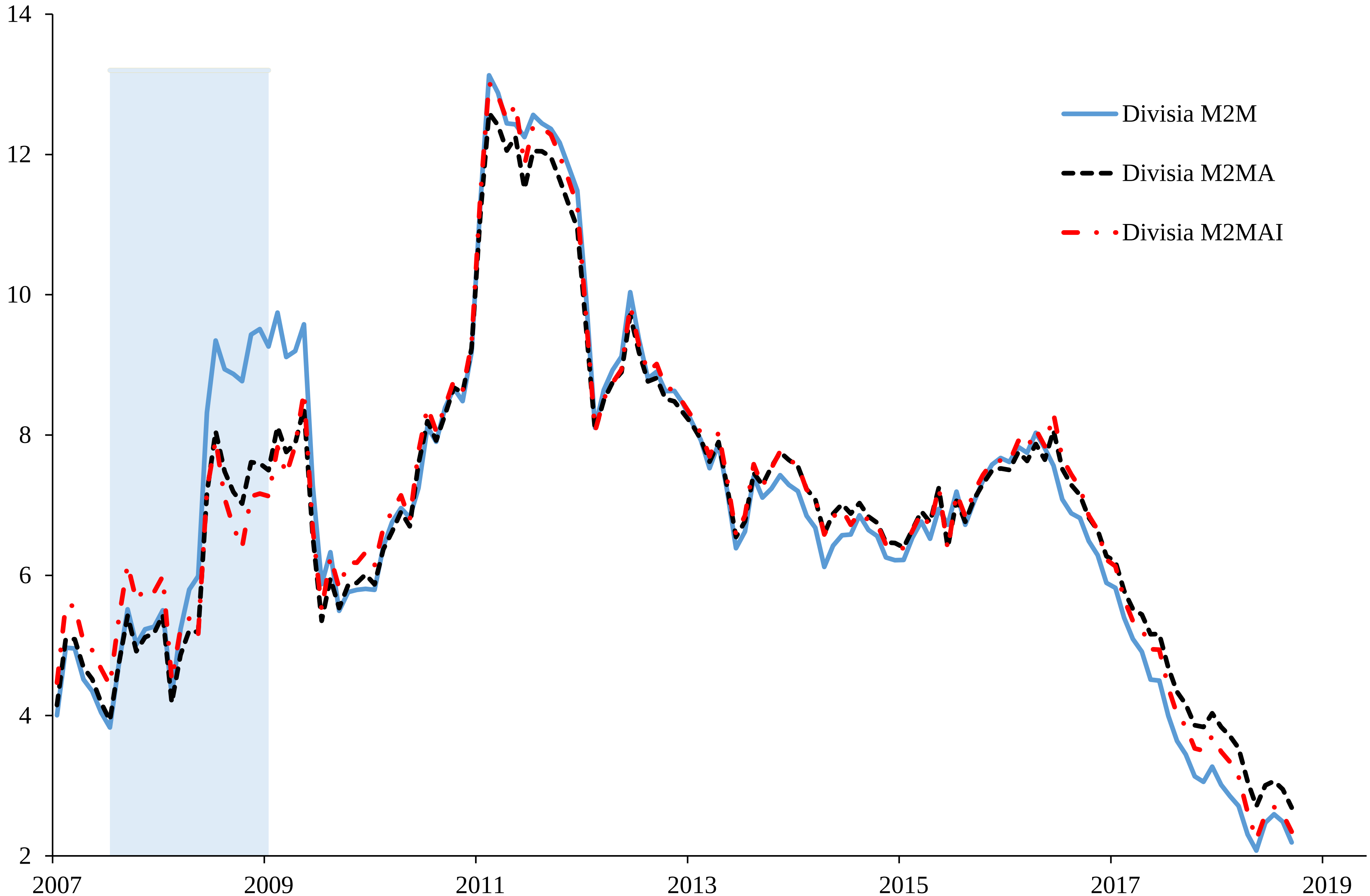

Figure 7. Year-over-year percentage growth rates of Divisia MZM monetary aggregates

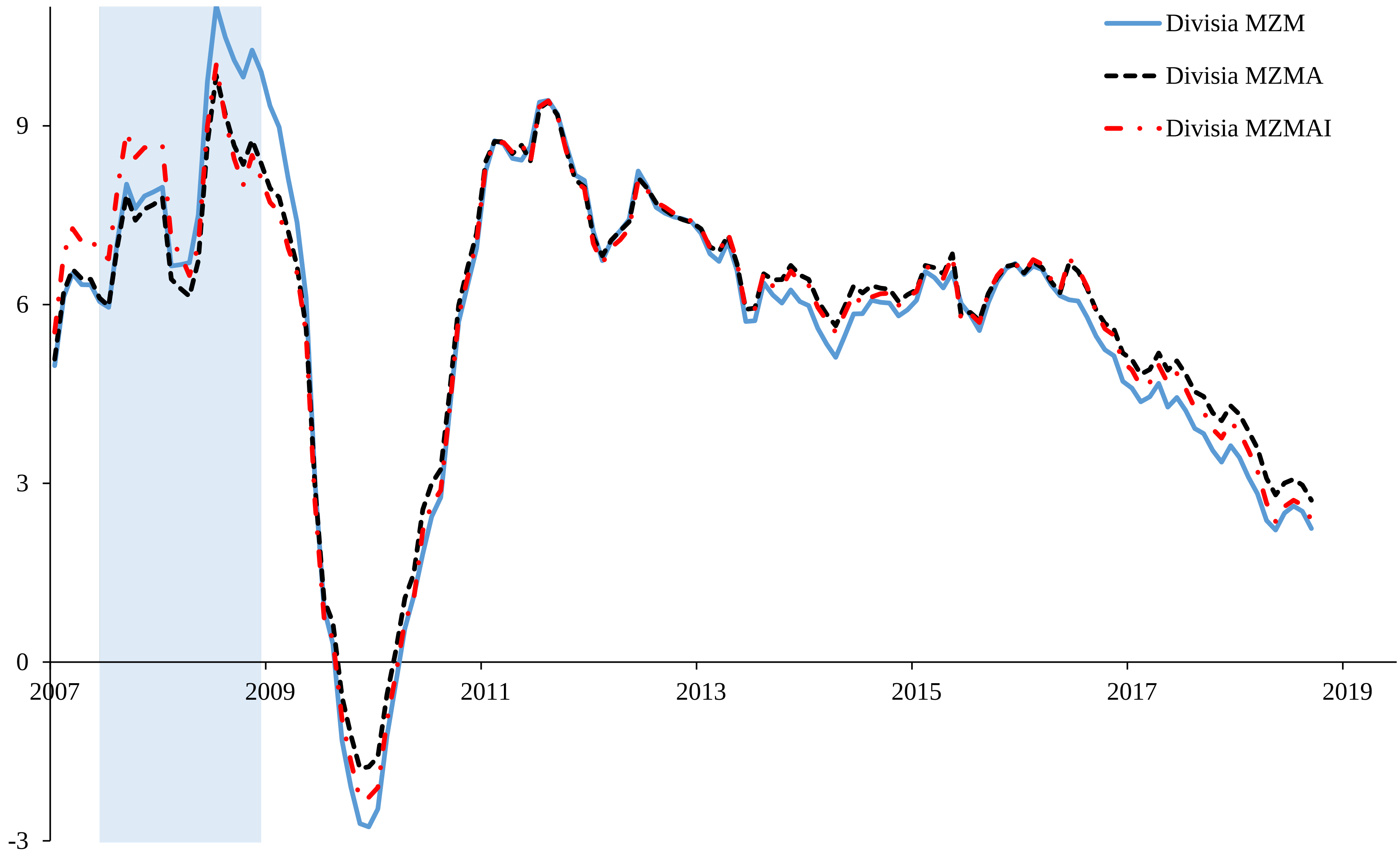

Figure 8. Year-over-year percentage growth rates of Divisia ALL monetary aggregates

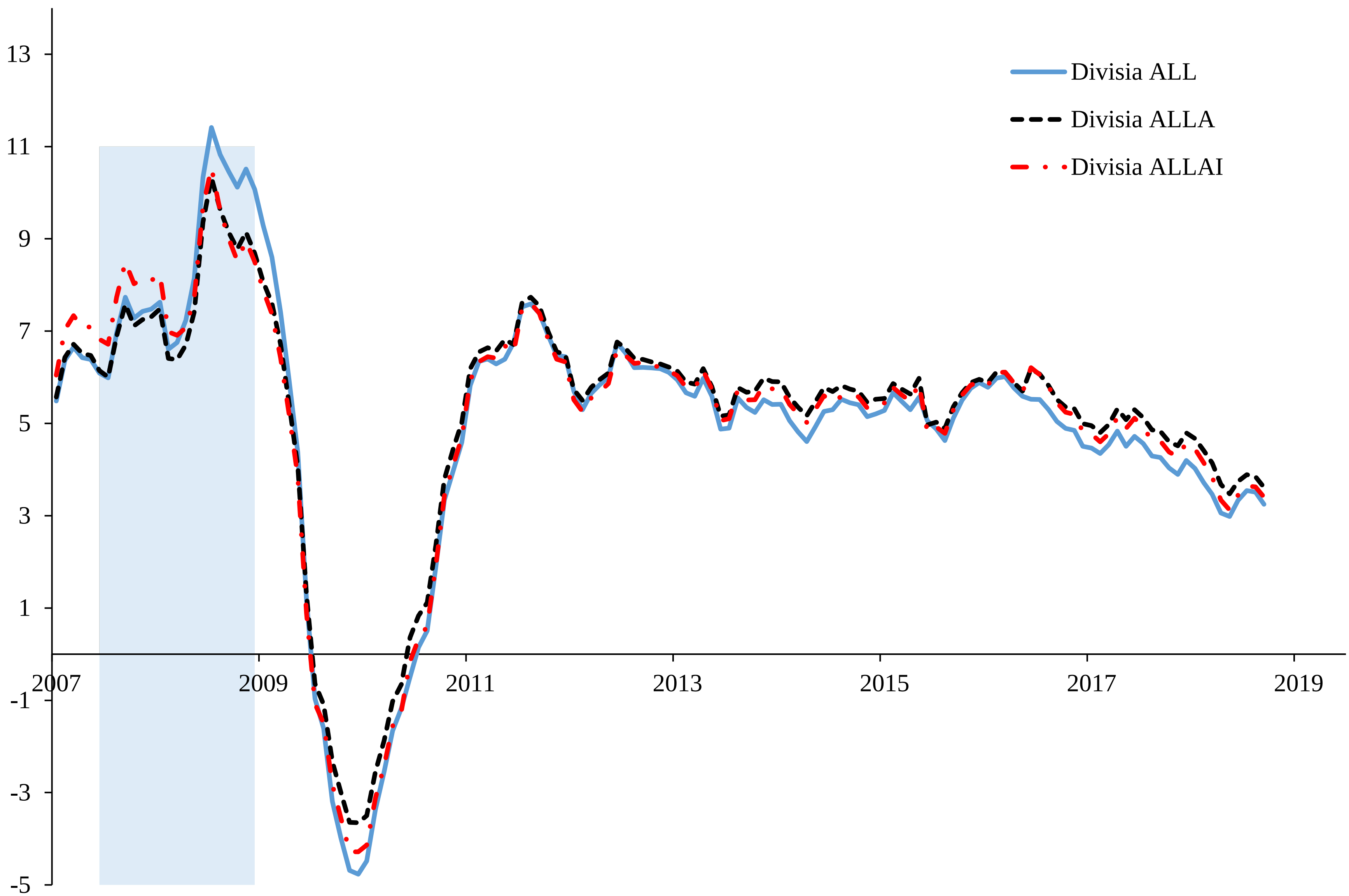

Figure 9. Year-over-year percentage growth rates of Divisia M3 monetary aggregates

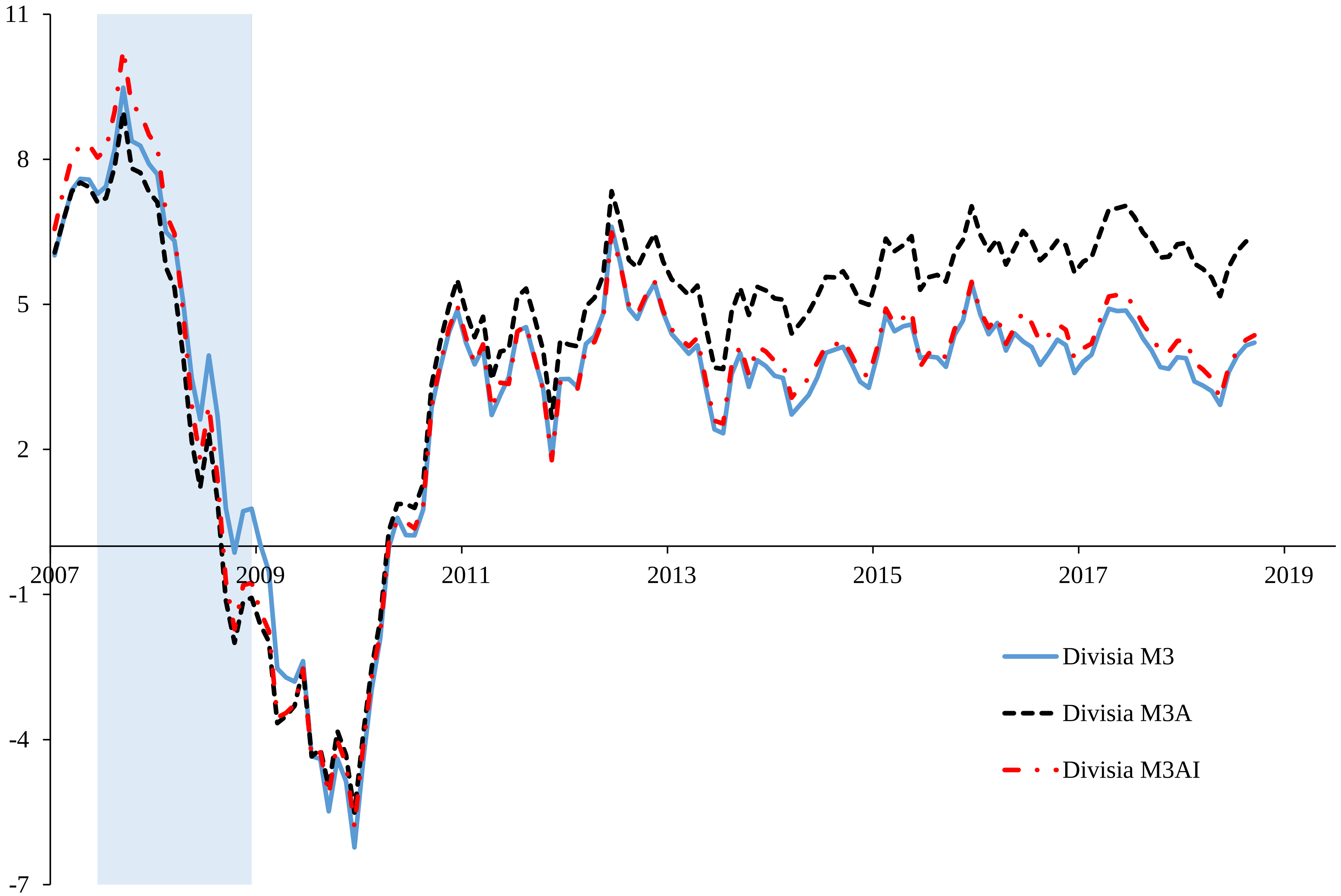

Figure 10. Year-over-year percentage growth rates of Divisia M4- monetary aggregates

Figure 11. Year-over-year percentage growth rates of Divisia M4 monetary aggregates

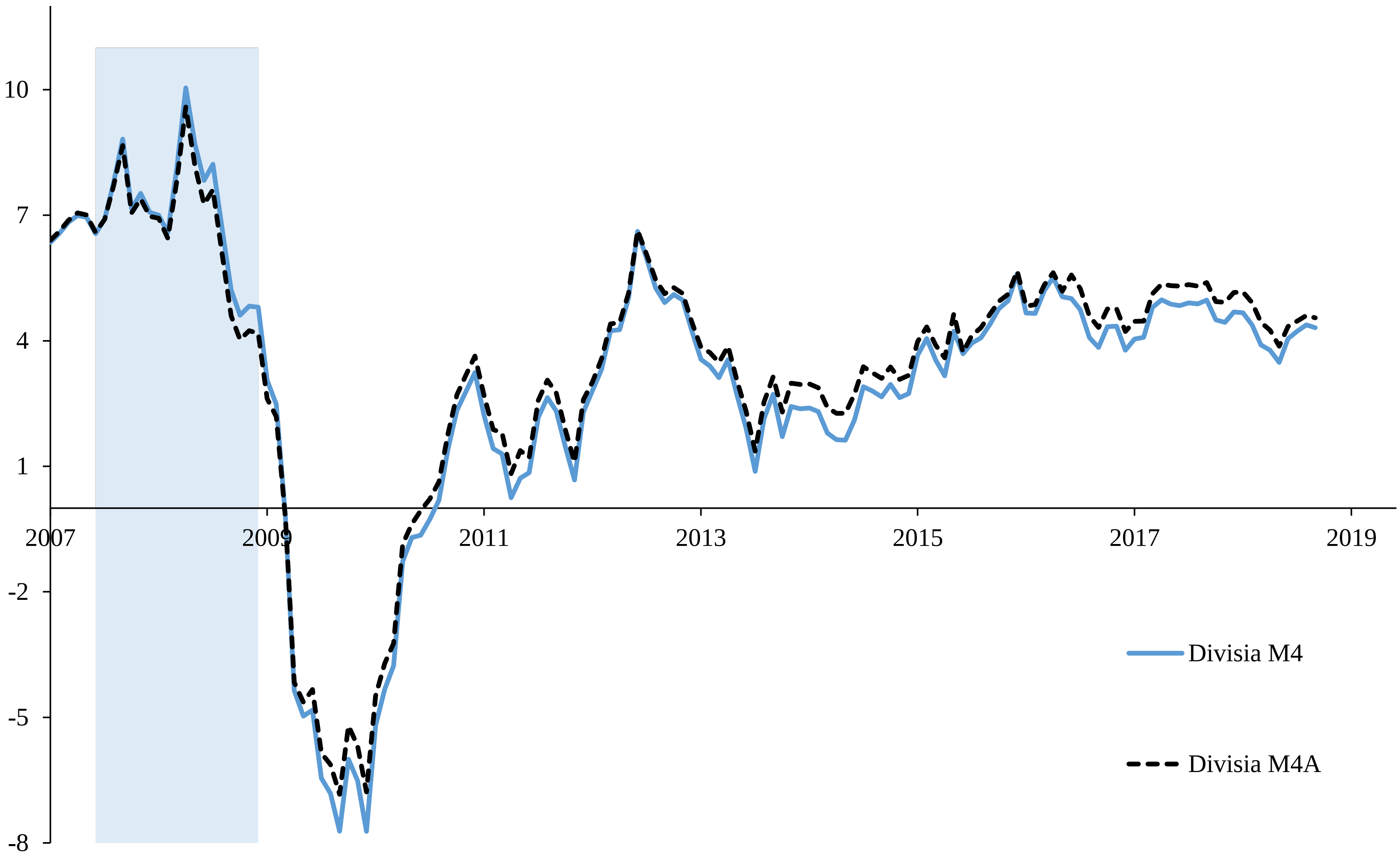

Table 1. Cyclical correlations between narrow Divisia monetary aggregates and industrial production

$\rho(x_t, y_{t+j}),\ \mathrm{j} = -24, -18, -12, -9, -6, -3, -2, -1,\ 0,\ 1,\ 2,\ 3,\ 6,\ 9,\ 12,\ 18,\ 24$

Series	j = -24	j = -18	j = -12	j = -9	j = -6	j = -3	j = -2	j =-1	j =0	j = 1	j = 2	j = 3	j = 6	j = 9	j = 12	j = 18	j= 24
Divisia M1	0.175	0.279	0.383	0.408	**0.411**	0.347	0.317	0.275	0.222	0.191	0.166	0.146	0.101	0.088	0.079	0.052	-0.036
Divisia M1A	0.180	0.267	0.376	0.408	**0.424**	0.388	0.368	0.337	0.290	0.264	0.243	0.223	0.161	0.087	0.087	-0.015	-0.161
Divisia M1AI	0.188	0.275	0.385	0.417	**0.434**	0.408	0.393	0.365	0.321	0.301	0.282	0.265	0.201	0.159	0.105	-0.032	-0.176
Divisia M2	0.226	**0.309**	0.304	0.256	0.203	0.117	0.085	0.046	0.009	0.000	-0.001	0.005	0.058	0.123	0.186	0.267	0.212
Divisia M2A	0.248	**0.312**	0.307	0.273	0.234	0.167	0.139	0.107	0.076	0.071	0.072	0.079	0.122	0.172	0.214	0.229	0.106
Divisia M2AI	0.241	**0.307**	0.295	0.254	0.207	0.140	0.114	0.086	0.059	0.060	0.066	0.078	0.134	0.193	0.242	0.260	0.134
Divisia M2M	0.311	**0.365**	0.359	0.342	0.324	0.240	0.199	0.150	0.100	0.071	0.047	0.027	-0.004	-0.010	-0.004	-0.040	-0.140
Divisia M2MA	0.306	**0.345**	0.344	0.336	0.331	0.268	0.233	0.191	0.148	0.124	0.103	0.083	0.044	0.026	0.014	-0.069	-0.195
Divisia M2MAI	0.313	**0.352**	0.348	0.338	0.330	0.271	0.237	0.197	0.155	0.134	0.115	0.096	0.057	0.035	0.016	-0.085	-0.208
Divisia MZM	0.154	0.213	0.151	0.092	0.024	-0.040	-0.053	-0.065	-0.071	-0.051	-0.022	0.013	0.154	0.300	0.420	**0.514**	0.424
Divisia MZMA	0.173	0.221	0.160	0.106	0.045	-0.009	-0.020	-0.029	-0.032	-0.010	0.020	0.056	0.192	0.329	0.436	**0.489**	0.359
Divisia MZMAI	0.171	0.220	0.157	0.100	0.035	-0.022	-0.034	-0.043	-0.046	-0.023	0.008	0.045	0.186	0.328	0.439	**0.496**	0.370
Divisia ALL	0.038	0.092	0.031	-0.020	-0.080	-0.118	-0.118	-0.111	-0.098	-0.067	-0.027	0.017	0.178	0.342	0.480	**0.616**	0.561
Divisia ALLA	0.055	0.099	0.036	-0.013	-0.072	-0.104	-0.104	-0.095	-0.080	-0.047	-0.005	0.040	0.201	0.362	0.494	**0.603**	0.516
Divisia ALLAI	0.056	0.133	0.127	0.084	0.033	-0.048	-0.067	-0.090	-0.105	-0.097	-0.073	-0.036	0.115	0.278	**0.387**	0.373	0.189

Notes: Sample period, monthly data: 2006:07 - 2019:03. Cyclical components are obtained using the Hamilton (2018) filter.

Table 2. Cyclical correlations between broad Divisia monetary aggregates and industrial production

$$\rho(x_t, y_{t+j}),\ \mathrm{j} = -24\,, -18, -12, -9, -6, -3, -2, -1,\ 0,\ 1,\ 2,\ 3,\ 6,\ 9,\ 12,\ 18,\ 24$$

Series	j = -24	j = -18	j = -12	j = -9	j = -6	j = -3	j = -2	j =-1	j =0	j = 1	j = 2	j = 3	j = 6	j = 9	j = 12	j = 18	j= 24
Divisia M3	0.139	0.174	0.106	0.065	0.042	0.078	0.105	0.146	0.184	0.238	0.292	0.346	0.498	0.614	**0.658**	0.525	0.284
Divisia M3A	0.154	0.179	0.114	0.077	0.057	0.099	0.126	0.167	0.204	0.258	0.312	0.365	0.509	0.614	**0.644**	0.480	0.218
Divisia M3AI	0.156	0.185	0.125	0.091	0.076	0.125	0.155	0.198	0.238	0.293	0.347	0.401	0.543	0.644	**0.668**	0.493	0.234
Divisia M4-	0.184	0.224	0.192	0.176	0.179	0.234	0.264	0.308	0.347	0.398	0.445	0.491	0.611	0.688	**0.701**	0.519	0.238
Divisia M4A-	0.195	0.224	0.192	0.178	0.182	0.239	0.269	0.311	0.350	0.400	0.446	0.491	0.605	0.673	**0.675**	0.471	0.176
Divisia M4AI-	0.199	0.235	0.213	0.205	0.217	0.282	0.314	0.359	0.399	0.449	0.494	0.538	0.647	0.709	**0.705**	0.490	0.200
Divisia M4	0.036	0.099	0.056	0.016	-0.021	-0.006	0.019	0.061	0.101	0.147	0.198	0.251	0.407	0.544	0.629	**0.632**	0.478
Divisia M4A	0.042	0.095	0.046	0.002	-0.040	-0.025	-0.001	0.042	0.082	0.130	0.183	0.239	0.398	0.538	**0.620**	0.610	0.435

Notes: Sample period, monthly data: 2006:07 - 2019:03. Cyclical components are obtained using the Hamilton (2018) filter.

Figure 12: Weakly contemporaneous cyclical correlations between Divisia monetary aggregates and industrial production

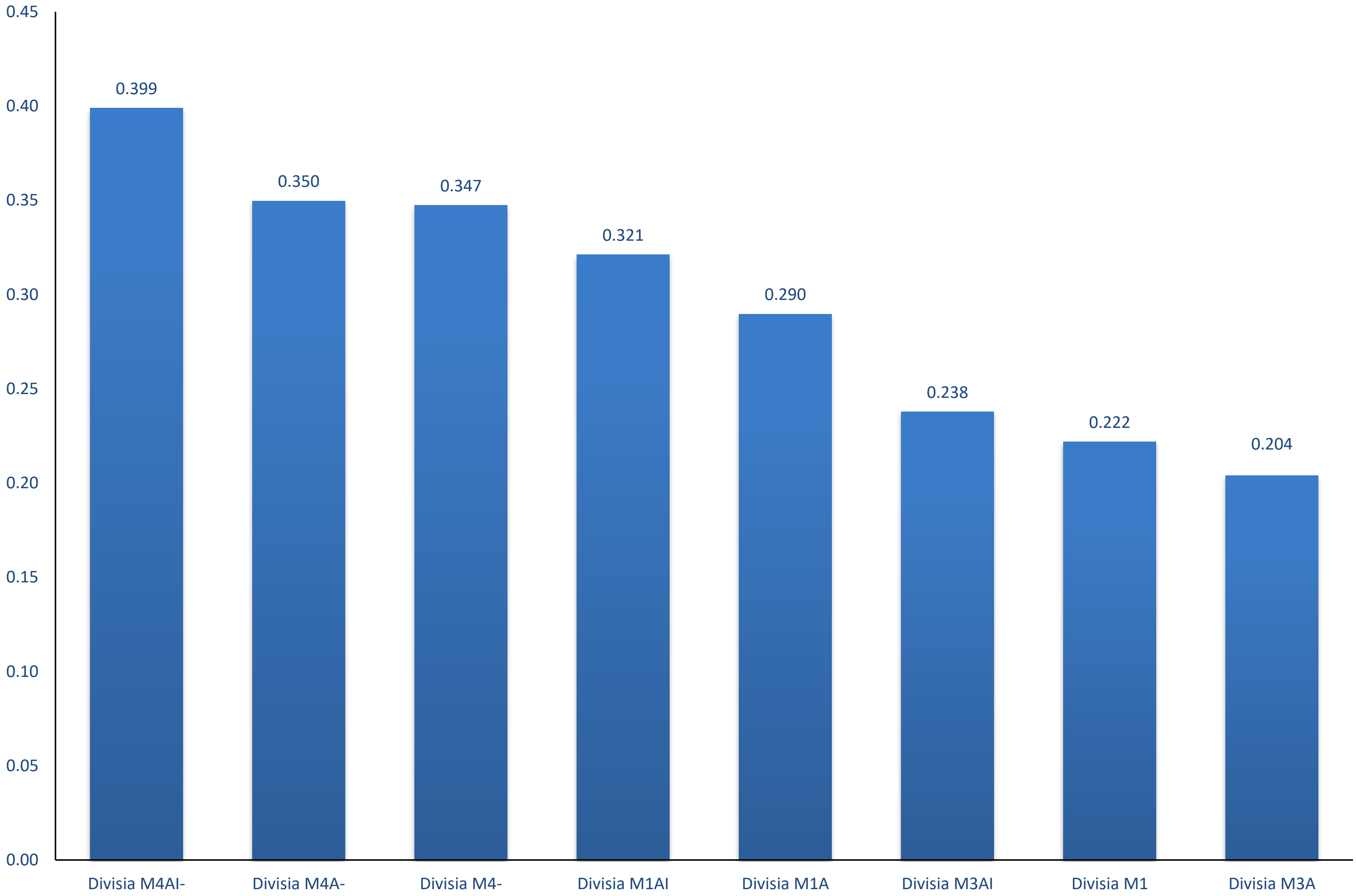

Table 3. Granger causality tests with data in logged levels

1. Interest rate and industrial production

	AIC optimal lags	p-value
Fed fund rate	(7,1,11)	0.586 [0.653]

2. Divisia money and industrial production

	Original Divisia		Augmented Divisia		Augmented Divisia inside money	
	AIC optimal lags	p-value	AIC optimal lags	p-value	AIC optimal lags	p-value
A. Narrow monetary aggregates						
Divisia M1	(8,1,2)	**0.012** [**0.027**]	(8,1,2)	**0.017** [**0.035**]	(8,1,2)	**0.017** [**0.037**]
Divisia M2	(8,1,2)	**0.033** [0.059]	(8,1,2)	**0.038** [0.068]	(8,1,2)	**0.043** [0.074]
Divisia M2M	(8,1,2)	**0.035** [0.072]	(8,1,2)	**0.035** [0.070]	(8,1,2)	**0.040** [0.079]
Divisia MZM	(8,1,2)	0.059 [0.100]	(7,9,9)	**0.009** [**0.017**]	(7,9,9)	**0.016** [**0.030**]
Divisia ALL	(7,9,2)	0.051 [0.079]	(7,10,9)	**0.011** [**0.020**]	(7,10,9)	**0.017** [**0.032**]
B. Broad monetary aggregates						
Divisia M3	(8,7,2)	**0.031 [**0.060]	(8,7,2)	**0.014** [**0.030**]	(8,7,2)	**0.012** [**0.029**]
Divisia M4-	(8,7,2)	0.093 [0.155]	(8,7,2)	0.068 [0.103]	(8,7,2)	0.056 [0.104]
Divisia M4	(8,7,2)	**0.022** [**0.047**]	(8,7,2)	**0.014** [**0.031**]		

Notes: Sample period, monthly data: 2006:07 - 2019:03. Numbers are marginal significance levels. Numbers in brackets are p-values based on bootstrap Granger causality tests. Bold numbers indicate significance at the 5% level.

Table 4. Granger causality tests with data in monthly growth rates

1. Interest rate and industrial production

	AIC optima lags	P-value
Fed fund rate	(7,1,1)	0.210 [0.200]

2. Divisia money and industrial production

	Original Divisia		Augmented Divisia		Augmented Divisia inside money	
	AIC optima lags	P-value	AIC optima lags	P-value	AIC optima lags	P-value
A. Narrow monetary aggregates						
Divisia M1	(6,1,10)	0.218 [0.196]	(6,1,10)	0.313 [0.300]	(7,1,1)	0.222 [0.217]
Divisia M2	(6,1,10)	0.571 [0.568]	(6,1,10)	0.754 [0.750]	(6,1,10)	0.802 [0.801]
Divisia M2M	(6,1,10)	0.308 [0.307]	(6,1,10)	0.439 [0.441]	(6,1,10)	0.462 [0.461]
Divisia MZM	(6,8,8)	**0.029** [**0.029**]	(12,8,8)	**0.007** [**0.009**]	(12,8,8)	**0.011** [**0.013**]
Divisia ALL	(7,1,1)	0.105 [0.108]	(12,12,8)	**0.009** [**0.007**]	(12,8,8)	**0.011** [**0.011**]
B. Broad monetary aggregates						
Divisia M3	(7,6,1)	**0.003** [**0.004**]	(7,6,1)	**0.001** [**0.001**]	(7,6,1)	**0.001** [**0.001**]
Divisia M4-	(7,6,1)	**0.006** [**0.007**]	(7,6,1)	**0.004** [**0.005**]	(7,6,1)	**0.003** [**0.004**]
Divisia M4	(7,6,1)	**0.001** [**0.001**]	(7,6,1)	**0.001** [**0.000**]		

Notes: Sample period, monthly data: 2006:07 - 2019:03. Numbers are marginal significance levels. Numbers in brackets are p-values based on bootstrap Granger causality tests. Bold numbers indicate significance at the 5% level.

Table 5. Granger causality tests with log levels and controlling for the interest rate

	Original Divisa		Augmented Divisia		Augmented Divisia inside money	
	AIC optimal lags	P-value	AIC optimal lags	P-value	AIC optimal lags	P-value
			A. Narrow monetary aggregates			
Divisia M1	(8,1,2,1)	**0.012** [**0.037**]	(8,1,2,1)	**0.018** [**0.046**]	(8,1,2,1)	**0.018** [**0.047**]
Divisia M2	(8,1,2,1)	**0.035** [0.073]	(8,1,2,1)	**0.041** [0.082]	(8,1,2,1)	**0.047** [0.090]
Divisia M2M	(8,1,2,1)	**0.030** [0.071]	(8,1,2,1)	**0.034** [0.078]	(8,1,2,1)	**0.038** [0.090]
Divisia MZM	(8,1,2,1)	0.064 [0.123]	(7,9,9,1)	**0.009** [**0.022**]	(7,9,9,1)	**0.017** [**0.035**]
Divisia ALL	(7,9,2,1)	0.051 [0.083]	(7,10,9,1)	**0.012** [**0.024**]	(7,10,9,1)	**0.019** [**0.036**]
			B. Broad monetary aggregates			
Divisia M3	(8,7,2,1)	**0.034** [0.055]	(8,7,2,1)	**0.016** [**0.028**]	(8,7,2,1)	**0.013** [**0.024**]
Divisia M4-	(8,7,2,1)	0.099 [0.137]	(8,7,2,1)	0.062 [0.092]	(8,7,2,1)	0.058 [0.090]
Divisia M4-	(8,7,2,1)	**0.024** [**0.043**]	(8,7,2,1)	**0.016** [**0.030**]		

Notes: Sample period, monthly data: 2006:07 - 2019:03. Numbers are marginal significance levels. Numbers in brackets are p-values based on bootstrap Granger causality tests. Bold numbers indicate significance at the 5% level.

Table 6. Granger causality tests with monthly growth rates and controlling for the interest rate

	Original Divisia		Augmented Divisia		Augmented Divisia inside money	
	AIC optimal lags	P-value	AIC optimal lags	P-value	AIC optimal lags	P-value
			A. Narrow monetary aggregates			
Divisia M1	(6,1,10,3)	0.153 [0.150]	(8,1,1,1)	0.172 [0.174]	(8,1,1,1)	0.157 [0.155]
Divisia M2	(12,6,10,3)	0.144 [0.148]	(12,6,10,3)	0.090 [0.094]	(12,6,10,3)	0.107 [0.111]
Divisia M2M	(8,1,1,1)	0.367 [0.368]	(8,1,1,1)	0.288 [0.286]	(8,1,1,1)	0.296 [0.299]
Divisia MZM	(12,8,8,3)	**0.027** [**0.039**]	(12,12,8,3)	**0.007** [**0.007**]	(12,12,8,3)	**0.011** [**0.011**]
Divisia ALL	(7,2,1,1)	0.145 [0.148]	(12,12,8,3)	**0.008** [**0.008**]	(12,12,8,3)	**0.011** [**0.011**]
			B. Broad monetary aggregates			
Divisia M3	(8,6,2,2)	**0.002** [**0.002**]	(8,6,2,2)	**0.001** [**0.001**]	(8,6,1,1)	**0.001** [**0.001**]
Divisia M4-	(7,6,1,1)	**0.007** [**0.009**]	(7,6,1,1)	**0.005** [**0.005**]	(7,6,1,1)	**0.003** [**0.004**]
Divisia M4	(7,6,1,2)	**0.001** [**0.002**]	(7,6,1,1)	**0.001** [**0.001**]		

Notes: Sample period, monthly data: 2006:07 - 2019:03. Numbers are marginal significance levels. Numbers in brackets are p-values based on bootstrap Granger causality tests. Bold numbers indicate significance at the 5% level.

Table 7. Credit cards services

1. Cyclical correlations between credit cards services and industrial production

$$\rho(x_t, y_{t+j}),\ \text{j} = -24, -18, -12, -9, -6, -3, -2, -1,\ 0,\ 1,\ 2,\ 3,\ 6,\ 9,\ 12,\ 18,\ 24$$

Series	j = -24	j = -18	j = -12	j = -9	j = -6	j = -3	j = -2	j =-1	j =0	j = 1	j = 2	j = 3	j = 6	j = 9	j = 12	j = 18	j= 24
Credit Cards	0.277	0.268	0.345	0.406	0.485	0.572	0.591	0.605	0.613	**0.617**	0.612	0.602	0.535	0.425	0.277	-0.071	-0.341

Notes: Sample period, monthly data: 2006:07 - 2019:03. Cyclical components are obtained using the Hamilton (2018) filter.

2. Granger causality tests

Log levels		Monthly growth rate		Log levels and controlling for the interest rate		Monthly growth rates and controlling for the interest rate	
AIC optimal lags	p-value	AIC optimal lags	p-value	AIC optimal lags	p-value	AIC optimal lags	p-value
(8,4,2)	0.140 [0.182]	(6,1,10)	0.467 [0.457]	(8,1,2,1)	0.160 [0.239]	(8,1,1,1)	0.549 [0.536]

Notes: Sample period, monthly data: 2006:07 - 2019:03. Numbers are marginal significance levels. Numbers in brackets are p-values based on bootstrap Granger causality tests. Bold numbers indicate significance at the 5% level.