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Barnett, William A. and Tang, Biyan

University of Kansas, University of Kansas

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William A. Barnett and Biyan Tang[1]

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Abstract

Since China's enactment of the Reform and Opening-Up policy in 1978, China has become one of the world's fastest growing economies, with an annual GDP growth rate exceeding 10% between 1978 and 2008. But in 2015, Chinese GDP grew at 7 %, the lowest rate in five years. Many corporations complain that the borrowing cost of capital is too high. This paper constructs Chinese Divisia monetary aggregates M1 and M2, and, for the first time, constructs the broader Chinese monetary aggregates, M3 and M4. Those broader aggregates have never before been constructed for China, either as simple-sum or Divisia. The results shed light on the current Chinese monetary situation and the increased borrowing cost of money.

GDP data are published only quarterly and with a substantial lag, while many monetary and financial decisions are made at a higher frequency. GDP nowcasting can evaluate the current month's GDP growth rate, given the available economic data up to the point at which the nowcasting is conducted. Therefore, nowcasting GDP has become an increasingly important task for central banks. This paper nowcasts Chinese monthly GDP growth rate using a dynamic factor model, incorporating as indicators the Divisia monetary aggregate indexes, Divisia M1 and M2 along with additional information from a large panel of other relevant time series data. The results show that Divisia monetary aggregates contain more indicator information than the simple sum aggregates, and thereby help the factor model produce the best available nowcasting results.

In addition, our results demonstrate that China's economy experienced a regime switch or structure break in 2012, which a Chow test confirmed the regime switch. Before and after the regime switch, the factor models performed differently. We conclude that different nowcasting models should be used during the two regimes.

Keywords: China, Divisia Monetary Index, Borrowing Cost of Money, Nowcasting, Real GDP Growth Rate, Dynamic Factor Model, Regime Switch

JEL classification: C32, C38, C43, E47, E51, O53

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[1] W. A. Barnett
University of Kansas, Lawrence, Kansas, USA; and Center for Financial Stability, NY City, New York, USA
Email: barnett@ku.edu

B. Tang
University of Kansas, Lawrence, Kansas, USA

1. Introduction

In the last three decades, a set of influential studies have placed short-term interest rates at the heart of monetary policy with money supply often excluded from consideration[2]. But doubt has recently been cast on the focus solely on interest rates, as a result of the US Federal Reserve's recent adoption of quantitative easing with its goal of affecting the supply of liquid assets.[3] Central banks around the world normally publish their economies' monetary aggregates as the simple sum of their component assets, ignoring the fact that different asset components yield different liquidity service flows and yield different interest rates, and thus have different opportunity costs or user costs when demanded for their monetary services. Simple sum monetary aggregation implicitly assumes that all the component assets are perfect substitutes for each other.[4] Barnett (1978, 1980) originated and developed the aggregation theoretic monetary aggregates, now provided for the U.S. by the Center for Financial Stability in New York City.

GDP data are published only quarterly and with a substantial lag, while many monetary and financial decisions are made at a higher frequency. GDP nowcasting can evaluate the current month's GDP growth rate, given the available economic data up to the point at which the nowcasting is conducted. Therefore, nowcasting GDP has become an increasingly important task for central banks.

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[2] Gogas and Serletis (2014) find that previous rejections of the balanced growth hypothesis and classical money demand functions can be attributed to mismeasurement of the monetary aggregates.

[3] Istiak,and Serletis (2015) observe "in the aftermath of the global financial crisis and Great Recession, the federal funds rate has reached the zero lower bound and the Federal Reserve has lost its usual ability to signal policy changes via changes in interest-rate policy instruments. The evidence of a symmetric relationship between economic activity and Divisia money supply shocks elevates Divisia aggregate policy instruments to the center stage of monetary policy, as they are measurable, controllable, and in addition have predictable effects on goal variables."

[4] Barnett and Chauvet (2011, p. 8) have observed that "aggregation theory and index theory have been used to generate official governmental data since the 1920s. One exception still exists. The monetary quantity aggregates and interest rate aggregates supplied by many central banks are not based on index number or aggregation theory, but rather are the simple unweighted sums of the component quantities and quantity-weighted or arithmetic averages of interest rate. The predictable consequence has been induced instability of money demand and supply functions, and a series of puzzles in the resulting applied literature."

Many empirical studies, such as Barnett and Serletis (2000), Barnett et al. (2008), Gogas et al. (2012), and Belongia and Ireland (2014), find that the Divisia monetary aggregates help in forecasting movements in the key macroeconomic variables and outperform the simple-sum monetary aggregates. Rahman and Serletis (2013, 2015) find that, unlike simple sum monetary growth, increased Divisia money growth volatility is associated with a lower average growth rate of real economic activity, and optimal monetary aggregation can further improve our understanding of how money affects the economy. Barnett et al. (2015) conclude that the Divisia monetary aggregates outperform the simple-sum aggregates in US nominal GDP nowcasting.

In this paper, we explore the liquidity characteristics of the Chinese economy and investigate the implications of the Divisia aggregates for the Chinese economy.

Section 2 and 3 construct the Chinese Divisia monetary aggregates, M1, M2, M3, and M4. The results shed light on the current Chinese monetary situation and the increased borrowing cost of money. Section 4 applies these Divisa indexes to GDP nowcasting in China by using a Dynamic Factor Model. Section 5 describes the data for nowcasting, section 6 discuss the results and finally section 7 concludes. This paper contributes to the literature on the Chinese economy by constructing the Chinese Divisia monetary aggregates, M1, M2, M3, and M4, which are found to provide much information about the economy. We then apply the Divisia indexes in real GDP nowcasting. The Divisia indexes are found to contain more information than the simple sum monetary aggregates in nowcasting. Our results reflect the fact that the Chinese economy experienced a structural break or regime change in 2012.

2. Divisia Monetary Index Literature and Theory

By linking microeconomic theory and statistical index number theory, Barnett (1978, 1980) originated the Divisia monetary aggregates. The index depends upon the prices and quantities of the monetary assets' services, where the prices are measured by the user cost or opportunity costs, since monetary assets are durables. The price of the services of a monetary asset is the interest forgone to consume the services of the asset. The interest forgone depends upon the difference between the interest received by holding the asset and the higher forgone benchmark rate, defined to be the rate of the return on pure investment capital, providing no monetary services. Barnett

(1978, 1980, 1987) derived the user cost formula for demanded monetary services and supplied monetary services.

As derived by Barnett (1978, 1980), the nominal user cost price of the services of monetary asset i during period t is

$$\pi_{it} = p_t^* \frac{R_t - r_{it}}{1 + R_t} \ , \tag{1}$$

Where R_t is the benchmark rate at time t, r_{it} is the rate of return on asset i during period t, and p_t^* is the true cost-of-living index at time t.

Assume $\mathbf{m}_t$ is decision maker's optimal monetary asset portfolio containing the N monetary assets m_{it} for $i = 1, \ldots, N$, and let M be the aggregation-theoretic exact aggregator function over those monetary asset quantities. Depending upon the economic agent's decision problem, the function M could be a category utility function, a distance function, or a category production function. See Barnett (1987). With the necessary assumptions for existence of an aggregate quantity aggregate, the exact quantity monetary aggregate at time t will be $M_t = M(\mathbf{m}_t)$. Its dual user cost price aggregate is $\Pi_t = \Pi(\boldsymbol{\pi}_t)$, where $\boldsymbol{\pi}_t$ is the vector of N user cost prices, π_{it}, for $i = 1, \ldots, N$.

In continuous time, the Divisia price and quantity index can exactly tract the price and quantity aggregator functions, respectively:

$$\frac{d \log \Pi_t}{dt} = \sum_i s_{it} \frac{d \log \pi_{it}}{dt} = \sum_i \frac{\pi_{it} m_{it}}{y_t} \frac{d \log \pi_{it}}{dt} \ , \tag{2}$$

$$\frac{d \log M_t}{dt} = \sum_i s_{it} \frac{d \log m_{it}}{dt} = \sum_i \frac{\pi_{it} m_{it}}{y_t} \frac{d \log m_{it}}{dt} \ , \tag{3}$$

where $y_t = \boldsymbol{\pi}_t' \mathbf{m}_t$ is total expenditure on the portfolio's monetary assets and $s_{it} = \frac{\pi_{it} m_{it}}{y_t}$ is the asset's expenditure share during period t.

The quantity and user cost duals satisfy Fisher's (1922) factor reversal test in continuous time:

$$\Pi_t M_t = \boldsymbol{\pi}_t' \mathbf{m}_t \ . \tag{4}$$

For use with economic data, the discrete time representation of the Divisia index is needed. The Tornqvist-Theil approximation is a second order approximation to the continuous time Divisia index. See Tornqvist (1936) and Theil (1967). When applied to the above Divisia indices, the discrete time approximations become

$$\log \mathit{\Pi}_t - \log \mathit{\Pi}_{t-1} = \sum_{i=1}^{N} s_{it}^{*} (\log \pi_{it} - \log \pi_{i,t-1}), \tag{5}$$

$$\log M_t - \log M_{t-1} = \sum_{i=1}^{N} s_{it}^{*} (\log m_{it} - \log m_{i,t-1}) \tag{6}$$

where $s_{it}^{*} = \frac{1}{2}(s_{it} + s_{i,t-1})$ is the average of the current and the lagged expenditure shares, s_{it} and $s_{i,t-1}$.

Equations (5) and (6) can be interpreted as share-weighted averages of user-cost and quantity growth rates respectively. From equation (6), the Tornqvist-Theil discrete time Divisia monetary index, M_t, can alternatively be written as

$$\frac{M_t}{M_{t-1}} = \prod_{i=1}^{n} \left(\frac{m_{it}}{m_{i,t-1}}\right)^{s_{it}^{*}} . \tag{7}$$

Dual to the aggregate's quantity index, the aggregate's user-cost index can be directly computed from Fisher's factor reversal test, (4), as follows

$$\mathit{\Pi}_t = \frac{\pi_t^{'} m_t}{M_t} = \frac{\sum_{i=1}^{N} \pi_{it} m_{it}}{M_t} . \tag{8}$$

The price aggregates produced from equation (5) and (8) are not exactly the same in discrete time. However, the differences are third order and typically smaller than the round-off error in the component data.[5]

3. The Chinese Divisia Index

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[5] See Barnett (1982) for a rigorous discussion on this topic. For nonmathematical explanations, see Barnett (2008).

The Center for Financial Stability in New York City provides the Divisia monetary aggregates for the United States. The European Central Bank, the Bank of England, the Bank of Japan, the Bank of Israel, the National Bank of Poland, and the International Monetary Fund (IMF) also maintain Divisia monetary aggregates, but do not necessarily provide them to the public.[6]

Limited initial work has appeared on the construction of Divisia monetary aggregates for China.[7] In our research, we construct and provide Divisia monetary aggregates for China at many levels of aggregation and begin investigation of their implications for China's monetary policies.

3.1. Data Sources

The data we used in constructing the Chinese Divisia monetary aggregates come from various sources. Data on official simple sum aggregates, M0, M1, and M2, come from the People's Bank of China, which is the central bank of China. Deposit interest and bank loan rates come from the same source. The components of our broader Divisia aggregate, M3, include the components in M2 along with short-term corporate bonds, financial institution bonds, central bank bills, and money market funds. The components of M4 include the components of M3 along with national and local government bonds. The data on both the quantities and rates of return on those bonds and money market funds come from three sources: (1) the China Central Depository and Clearing Corporation Limited (CCDC)[8], (2) the Asset Management Association of China, and (3) the China Securities Depository and Clearing Corporation Limited (CSDC).

The Chinese central bank categorizes the primary component of the simple sum monetary aggregate, M0, as "currency in circulation." We assume the return on currency is zero. The narrow money aggregate, M1, consists of currency in circulation and corporate demand deposits, which accrue demand deposit interest. Simple sum M2 includes all of the components in M1, along with corporate deposits, personal deposits, and other deposits. Six maturities of time deposits exist with

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[6] The information and links to all such sources can be found in the web site of the Center for Financial Stability's program, Advances in Monetary and Financial Measurement (AMFM), http://www.centerforfinancialstability.org/amfm.php. This website provides a detailed directory of the literature on Divisia monetary aggregates covering 40 countries in the world. Also see Barnett and Alkhareif (2013).

[7] On Chinese Divisia monetary index, see Yu and Tsui (1990) and Hongxia (2007). But availability of Chinese Divisia monetary indexes is very limited

[8] For detailed websites, see http://www.chinabond.com.cn, http://www.amac.org.cn and http://www.chinaclear.cn respectively.

different interest rate returns: three-months, six-months, one-year, two-years, three-years, and five-years. This paper assumes that consumers balance their budgets monthly. Despite having six different maturity horizons, we impute the same three-month time deposit interest rate to all of the time deposits as the "holding period" yield on each, in accordance with term structure theory and our theory's use of holding period yields, rather than yields to maturity. The monetary component and interest rate data are available on the website of the People's Bank of China, dating back to December 1999.

To measure the true cost of living index, we use the monthly all citizen's consumer price index level. The CPI data are monthly with the initial period index normalized to 100. The CPI data are available on the website of National Bureau of Statistics of the People's Republic of China.[9]

3.2. Benchmark Rate

The benchmark after-tax interest rate cannot be lower than the yield on a monetary asset, since a monetary assets provides liquidity services, while the benchmark asset provides only its financial yield. In addition, interest paid on pure investment capital in China is taxed at a lower rate than the interest rate on monetary assets. In this paper, we follow Barnett et al. (2013) in using the short-term bank loan rate as the benchmark rate. Specifically we adopt as the benchmark rate the one-month loan rate, which is a universal loan rate in China and is determined by the People's Bank of China. For banks to profit on loans, the loan rate should always be higher than the rate of return the banks pay to depositors. In fact, the one-month bank loan rate in China is always higher than the five-year time deposit interest rate and the five-year Treasury bond rate.[10] Hence, our benchmark rate always exceeds the rates of return on monetary assets.

3.3 Results

We constructed monthly Chinese Divisia M0, M1, and M2 from December 1999 to February, 2015 with the index normalized to 100 at the first period. Based on the data availability of the broader aggregates' components, the Divisia M3 index starts in January 2002, while Divisia M4 begins in March 2006, since some of its components' rates of return are not available before March 2006.

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[9] See the website at http://www.stats.gov.cn/english/

[10] See the following website, http://www.pbc.gov.cn/publish/zhengcehuobisi/627/index.html, for the available data on the bank loan rate.

The components of our Divisia M0, M1, and M2 are the same as the official simple sum counterparts. The broader Divisia M3 contains components from M2 along with deposits excluded from M2 and the following bonds: political bank AAA rating bonds, commercial financial bonds rated AAA, corporation bonds of AAA rating, asset backed bonds, and currency funds. The included bonds are short to medium term. The rates of return on these bonds are their one-year inter-bank rates.

The broadest Divisia M4 is defined as M3 plus Treasury bonds and local bonds, with the 6 months interest rate on Treasury bonds imputed to all Treasury bonds as the holding period yield; and the 1 year interest rate on local bonds is imputed to all local bonds.

Figures 1-3 provide levels of the Chinese Divisia monetary aggregates, M0, M1, M2, and the corresponding simple sum aggregates. Figures 4, 5, and 6 display growth rate paths.

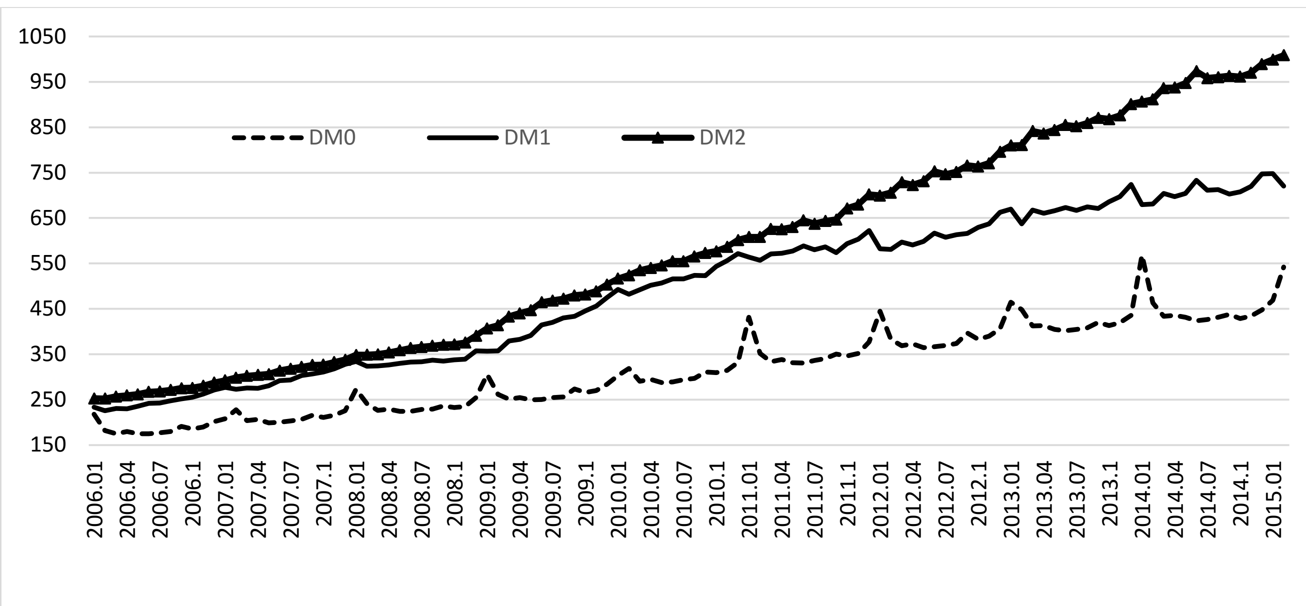

Figure 1: Divisia Index Level for M0, M1, M2 with December 1999 Set at 100.

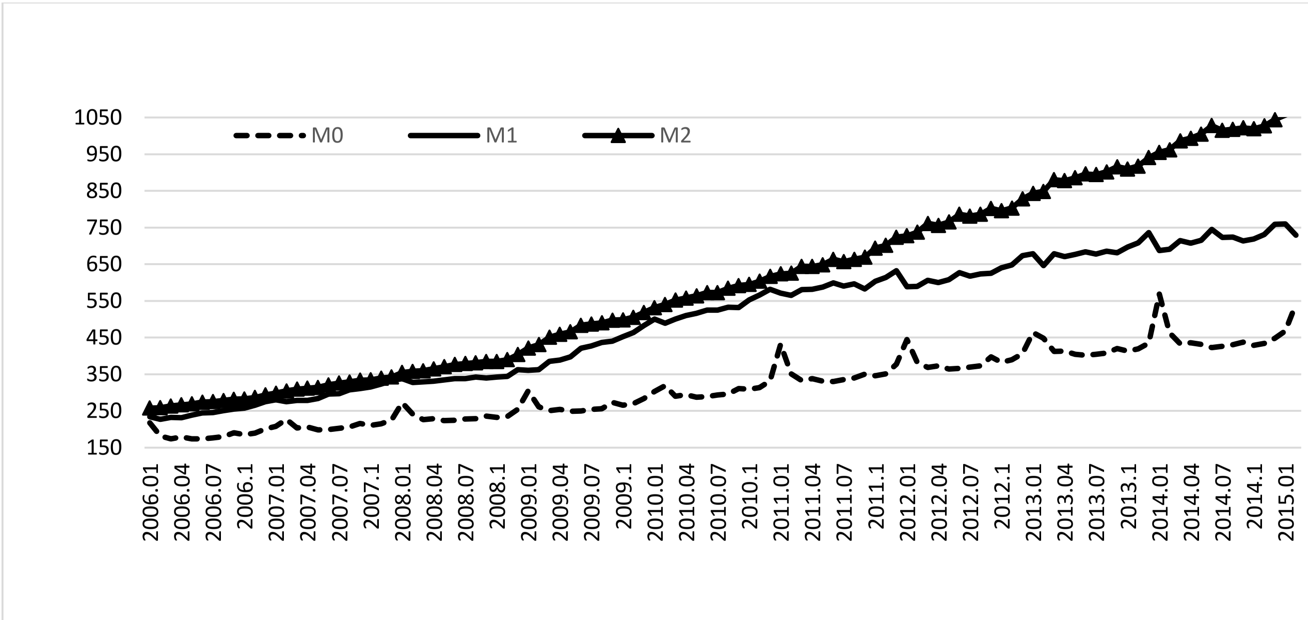

Figure 2: Simple Sum M0, M1, M2 Level with December 1999 Set at 100.

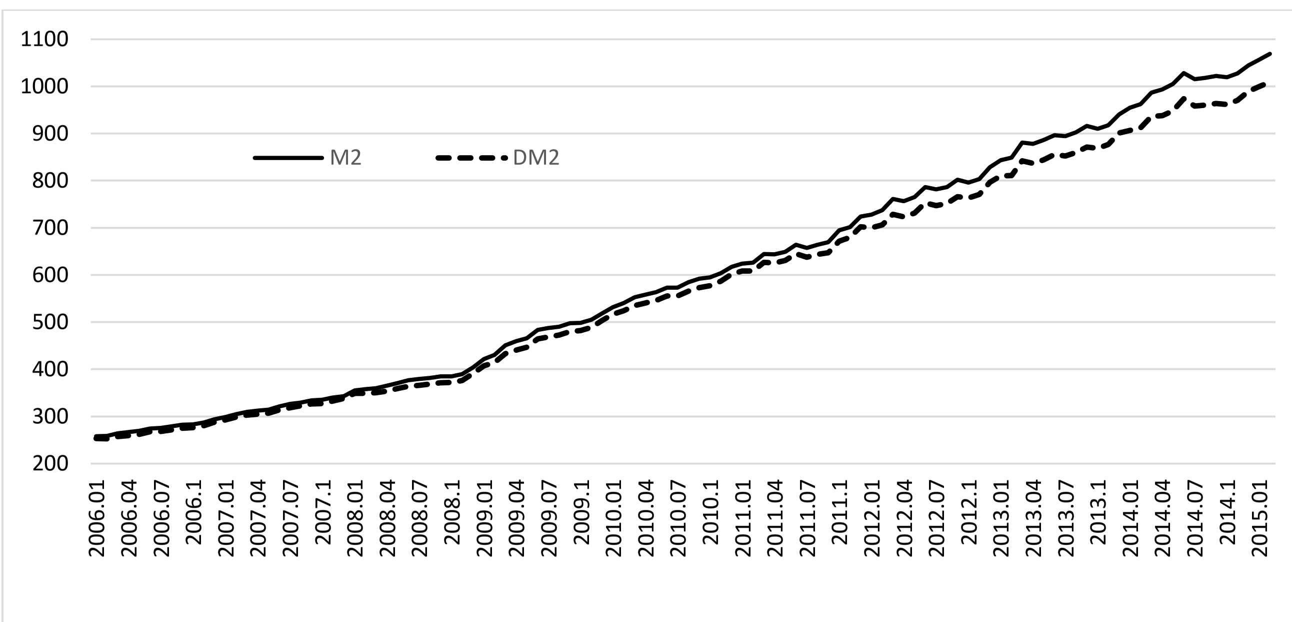

Figure 3: Divisia M2 and Simple Sum M2 with December 1999 Set at 100.

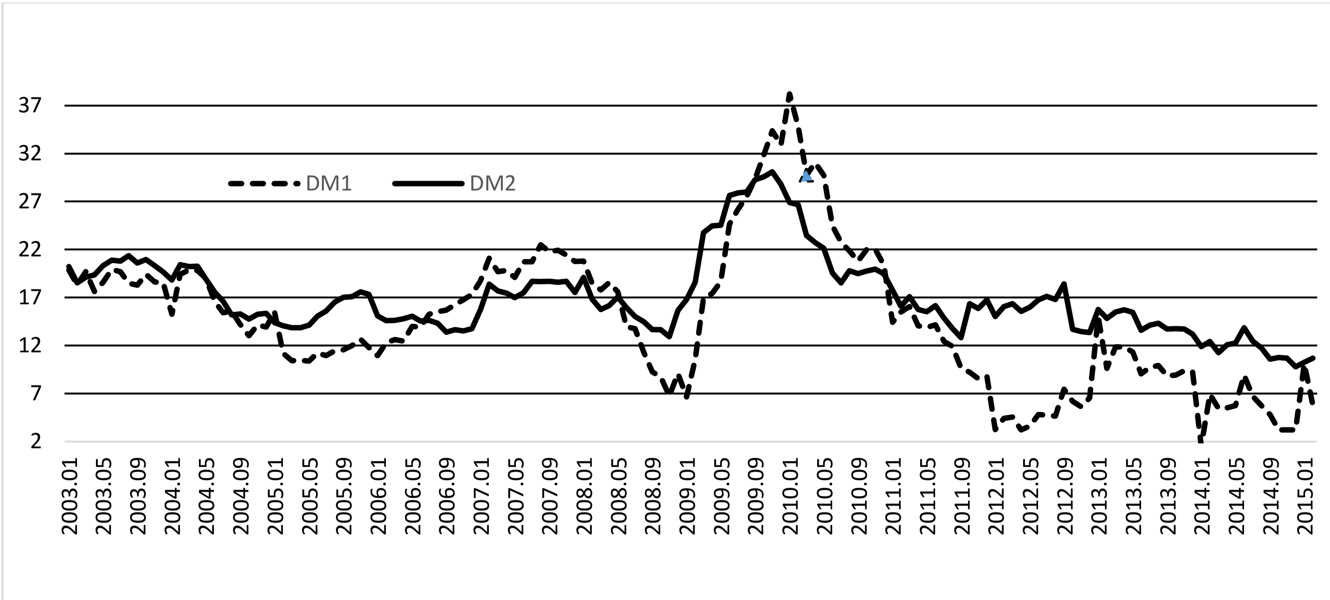

Figure 4: Divisia M1, M2 Monthly Year-Over-Year Growth Rate (%) from January 2003 to February 2015.

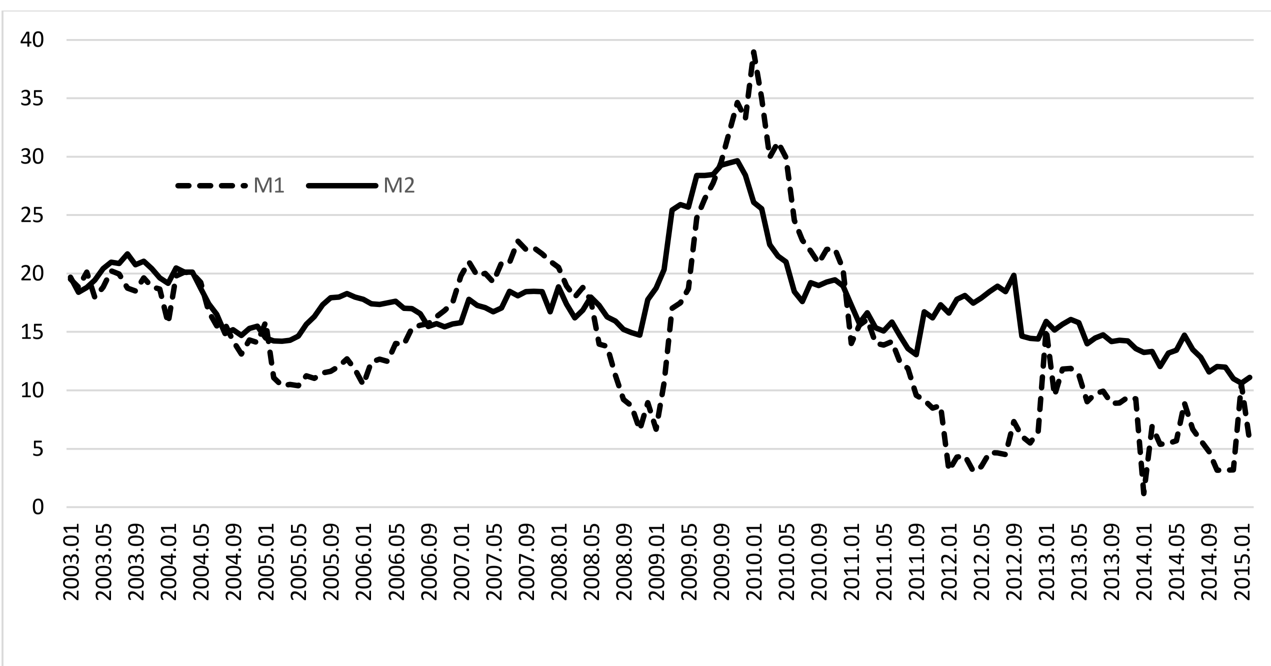

Figure 5: Simple Sum Monetary Aggregates M1, M2 Monthly Year-Over-Year Growth Rates (%) from January 2003 to February 2015.

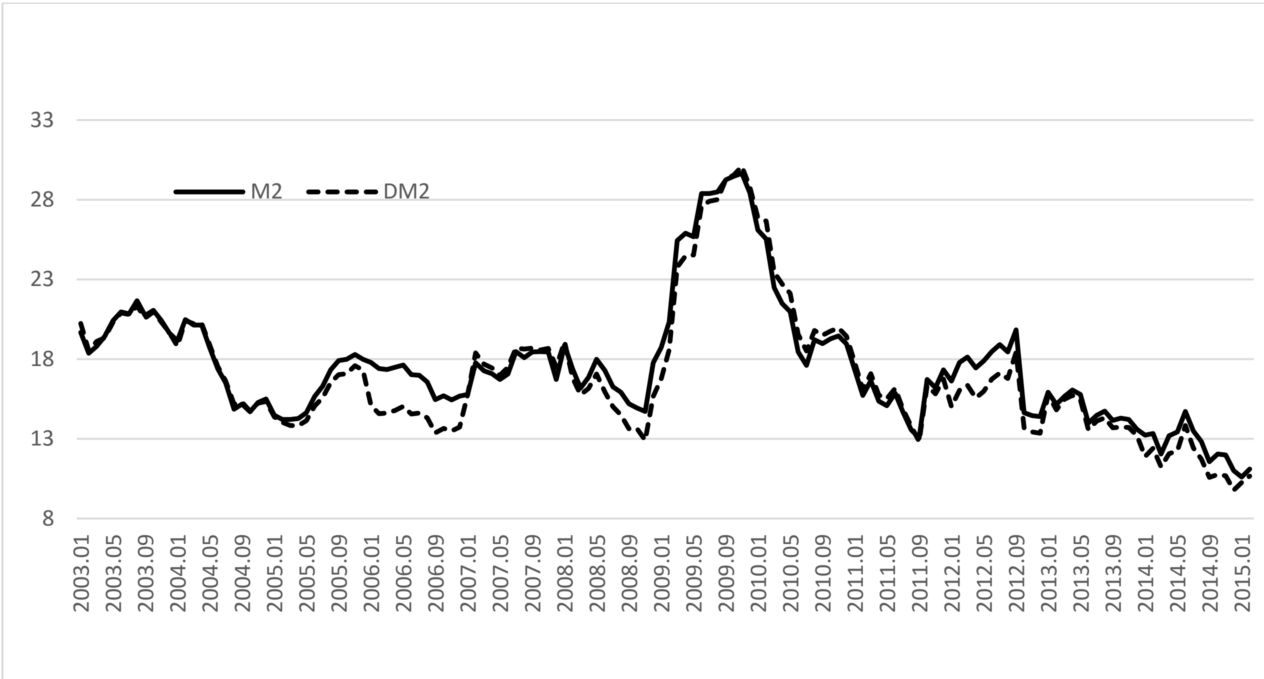

Figure 6: Divisia M2 and Simple Sum M2 Monthly Year-Over-Year Growth Rates (%) from January 2003 to February 2015

Figures 4, 5, and 6 show that the Chinese money supply growth rate increased rapidly around August or September 2008, and spiked around October 2009. This phenomenon can be explained by the Chinese government's 4 trillion Yuan's stimulus plan designed to offset the negative effects of the 2008 global financial crisis. After the stimulus plan, the money supply growth rate dropped sharply and has continued decreasing since early 2010.

Figure 7 displays the simple sum M0 monthly growth rate, showing a strong seasonal pattern, corresponding to demand for currency. For example, during the Chinese Spring Festival season, currency in circulation for retail purchases increases.

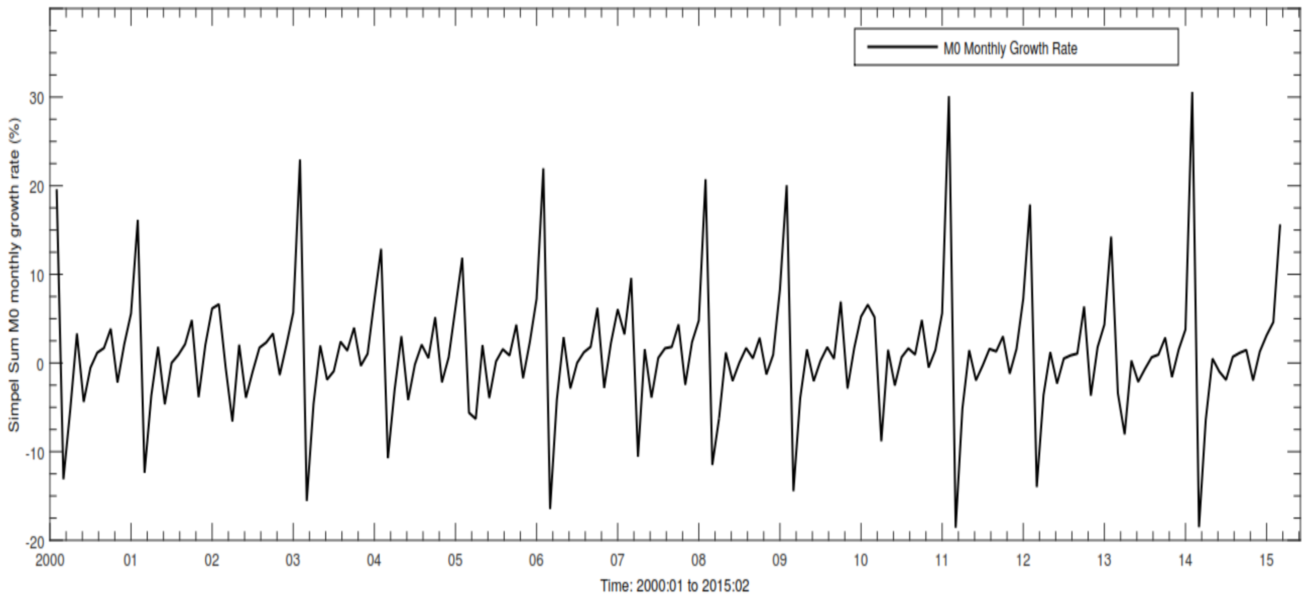

Figure 7: Chinese Simple Sum M0 Monthly Growth Rate (%)

Figures 8, 9, and 10 depict the broader indexes, Divisia M3 and M4, both in levels and annual growth rates.

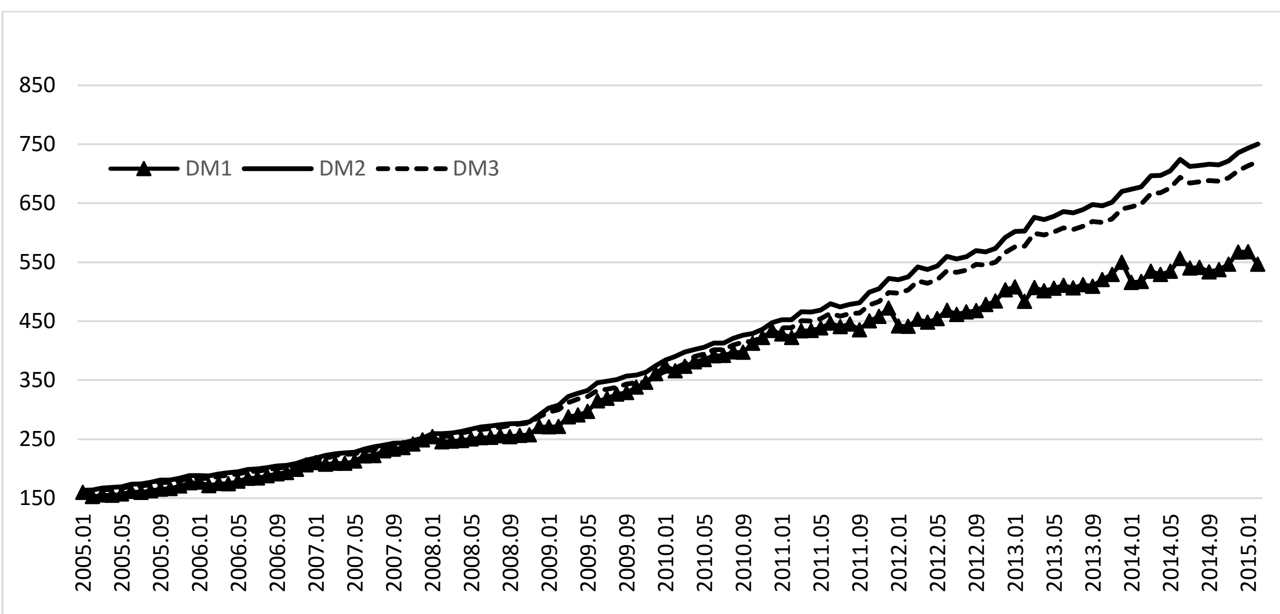

Figure 8: Chinese Divisia M1, M2, M3

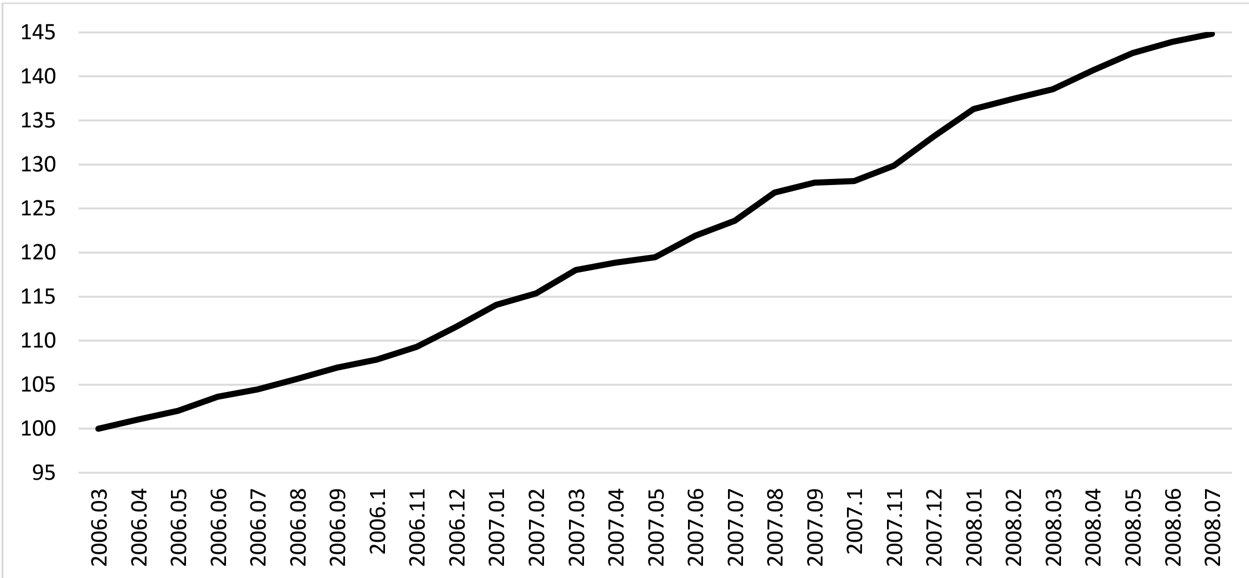

Figure 9: Chinese Broader Divisia M4

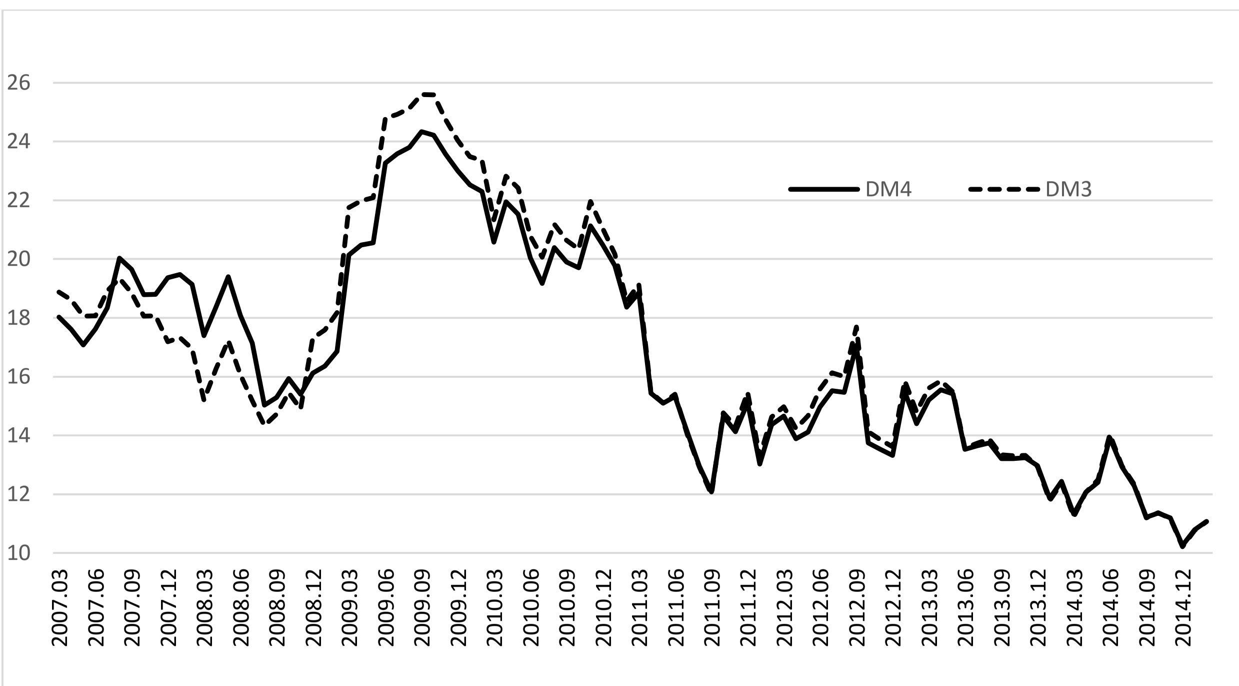

Figure 10: Divisia M3 and M4 Annual Growth Rates (%)

From Figure 10, we can see that the broader money supplies, M3 and M4, both start to fall around October 2009. The slower growth contributed to the complaints of corporations of more difficult borrowing environment and slowing of the economy. Meanwhile, the slowing of the money supply growth also may have influenced the subsequent loosening of the central bank's monetary policy. The central bank lowered the loan rate five times between December 2014 and August 2015 and decreased the required reserve ration 4 times between February 2015 and August 2015.

3.4 User-Cost of the Divisia Aggregates

The following figures provide the user-cost index for Divisia M0, M1, M2, M3, and M4.

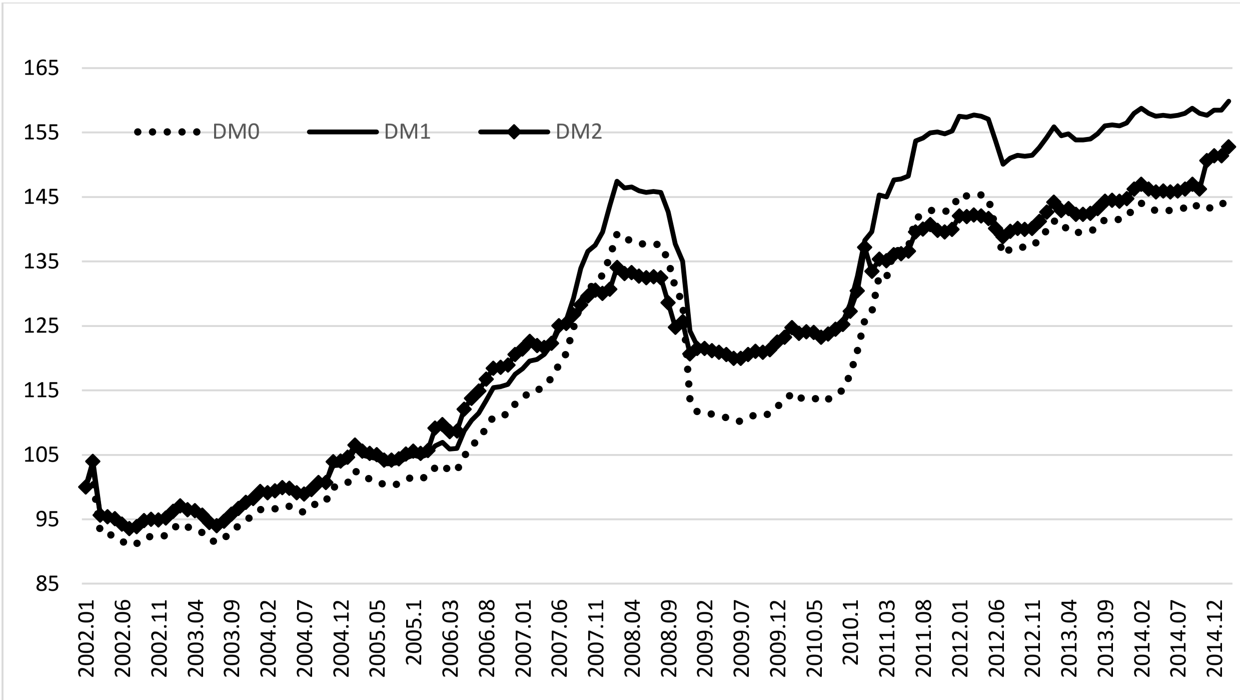

Figure 11: User Cost for Divisia M0, M1, and M2

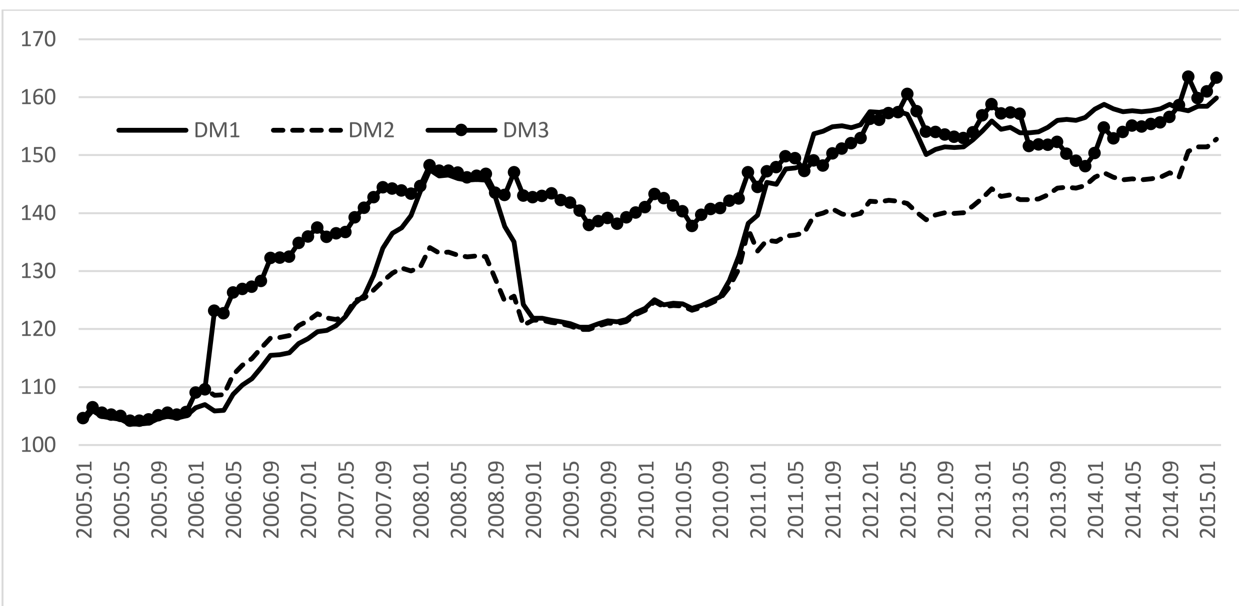

Figure 12: User Costs for Divisia M1, M2, and M3

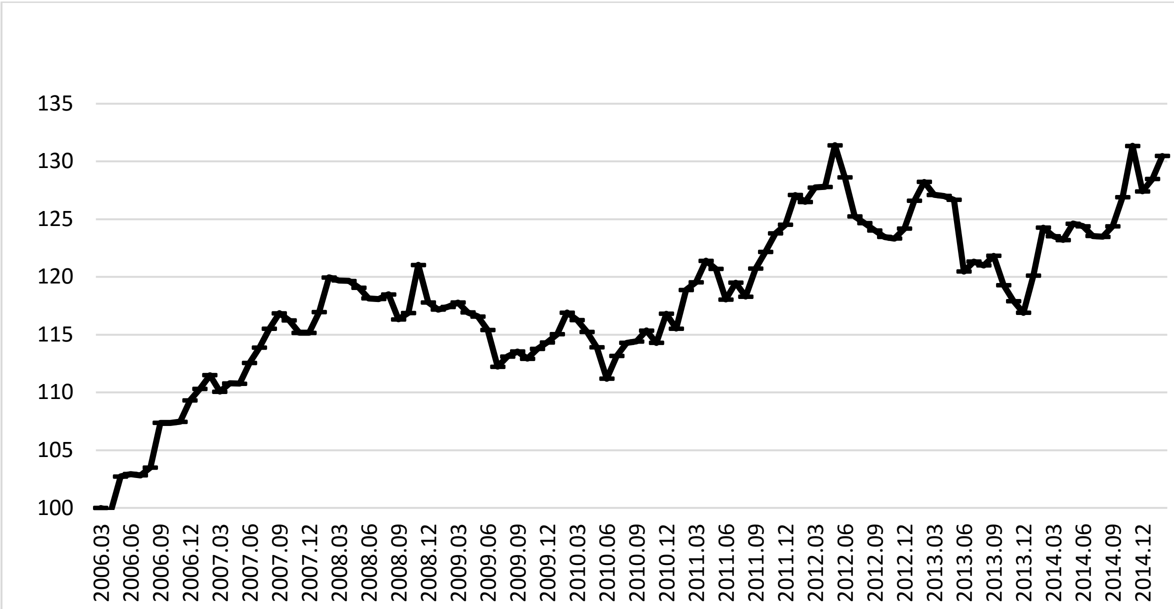

Figure 13: User Cost for Divisia M4

Figure 11 contains the user-costs for Divisia M0, M1, and M2 from December 1999 to February 2015. From that figure we can see that the user-cost for all of the monetary aggregates have been increasing. These results confirm Chinese corporations' complaints of higher financing costs. Both figures 12 and 13 reflect the fact that the opportunity cost of holding money has been increasing over time for all of the four money supply aggregates, M1, M2, M3, and M4. The borrowing cost's decrease from the middle of 2008 corresponds to the Chinese stimulus policy from 2008 to the beginning of 2011. Since then, the borrowing costs have been increasing steadily, contributing to the slowing of the economy.

4. Nowcasting Chinese Real GDP with Divisia Index

For many policy purposes, it is crucial to have an accurate evaluation of the current state and future path of GDP. Since GDP data are available quarterly but not monthly, nowcasting can be used to interpolate the quarterly data monthly and assess the current month's value prior to publication of the current quarter's value. Both forecasting and assessing current-quarter conditions (nowcasting) are important tasks for central banks and other economic agents.

Many empirical studies, such as Barnett and Serletis (2000), Barnett et al. (2008), Gogas et al. (2012), and Belongia and Ireland (2014), find that the Divisia monetary aggregates help in forecasting movements in the key macroeconomic variables and outperform the simple-sum monetary aggregates in that role. More recently, Barnett et al. (2015) have found that the Divisia monetary aggregates outperform the simple-sum aggregates as an indicator in US nominal GDP nowcasting. We investigate nowcasting of GDP for China.

4.1. Non-Factor Model Nowcasting

In the GDP nowcasting literature, there are both non-factor models and factor models. For non-factor models, simple time series models have been employed to evaluate current quarter's GDP growth rates. Examples include the "naive model" using a four-quarter moving averaging of GDP, the simple univariate autoregressive AR(1) model, the "naive constant model," the averaged bivariate vector autoregressive (VAR) models, and the bridge equations (BEQ) (Arnostova, D. Havrlant, et al. (2011)).

The bridge equation model combines qualitative judgments with "bridge equations." See, Baffigi et al. (2004). Each monthly indicator is first forecasted using an AR (q) process, with the lag length being selected by the criteria proposed by Bai and Ng (2002). Then the monthly series and their forecasts are aggregated into quarterly frequency. The quarterly GDP data are paired with the quarterly indicators, with GDP then regressed on each of the corresponding quarterly indicators through ordinary least squares. The final GDP forecast is obtained as the arithmetic average of the forecasts from the pairwise regressions.

Although many series can be useful as indicators of GDP, challenges are involved in using larger numbers of data series. One difficulty comes from dealing with large and unbalanced or "jagged edge" datasets. Normally, forecasters condition their estimates of GDP on a large number of time series, such as Giannone et al. (2008) and Yiu and Chow (2011). These related indicator series are often released on different dates, with some data available in the current quarter and other data with one or two months lags. Another difficultly comes from designing a model that incorporates newly released data. It is crucial to incorporate the additional newly released information into the forecast model to produce more accurate GDP growth data. A third difficulty is to measure the impact of new monthly data releases on the accuracy of nowcasting and to "bridge" those monthly data releases with the GDP nowcasting.

Factor models meet these challenges. The approach is defined in a parsimonious manner by summarizing the information of the many data releases with a few common factors. Nowcasting then projects quarterly GDP onto the common factors, estimated from the panel of monthly data.

4.2. Factor Model Nowcasting

Factor models have been widely employed in forecasting and nowcasting GDP to deal with the challenges involved in using large unbalanced datasets.[11] Stock and Watson (2002a, 2002b), Forni, et al. (2000, 2002), and Giannone et al. 2008) have carried out forecasting or nowcasting using factor models. Aruoba et al. (2009) incorporate data of different frequencies. Evans (2005) estimates daily real GDP for the U.S. using different vintages of GDP, but without using a dynamic factor model. Barnett et al. (2015) incorporate Divisia monetary aggregates into nominal GDP nowcasting and explore the predictive ability of univariate and multivariate models.

Yiu and Chow (2011) nowcast Chinese quarterly GDP by using the factor model proposed by Giannone et al. (2008) to regress Chinese GDP on 189 times series. They find the model generates out-of-sample nowcasts for China's GDP with smaller mean squared forecast errors than those of the random walk benchmark. They also find that interest rate is the single most important related variable in estimating current-quarter GDP in China. Other important related values include consumer and retail prices and fixed asset investment indicators.

Matheson (2009) uses the parametric factor model proposed by Giannone et al. (2008) to estimate New Zealand's GDP growth with unbalanced real-time panels of quarterly data. He uses approximately 2000 times series grouped into 21 blocks. He applies both the Bai and Ng (2002) criteria and the Giannone et al. (2008) *ad hoc* approach to determine the number of statistically relevant static factors in the panel. The statistically optimal number of dynamic factors is found to be two, using the Bai and Ng (2002) criteria and four using the *ad hoc* criterion. The results show that at some horizons the factor model produces forecasts of similar accuracy to the New Zealand Reserve Bank's forecasts. The author finds that survey data are important in determining factor model predictions, particularly for real GDP growth. However, the importance of survey data was

[11] The literature also has proposed frequency domain methods (Geweke (1997), Sargent and Sims (1977), Geweke and Singleton (1980)) and time domain methods (Engle and Watson (1981), Stock and Watson (1989), Quah and Sargent (1993).

found to be mainly from their timeliness. The relative importance of survey data diminished when estimates were made conditional on timeliness.

Angelini et al. (2011) evaluate models that exploit timely monthly releases to nowcast current quarter GDP in the euro area. They compare traditional methods used at institutions to the newer method proposed by Giannone et al. (2008). The method consists of bridging quarterly GDP with monthly data via a regression on factors extracted from a large panel of monthly series with different publication lags. Bridging via factors produces more accurate estimates than traditional bridge equations.

Barnett et al. (2015) incorporate Divisia monetary aggregates into the nowcasting model for the US, compare the predictive ability of univariate and multivariate nowcasting models, and incorporate structural breaks and time varying parameters. They find that a small-scale dynamic factor model, containing information on real economic activity, inflation dynamics, and Divisia monetary aggregates, produces the most accurate nowcasts of US nominal GDP.

Our research uses the dynamic factor model proposed by Giannone et al. (2008) to nowcast Chinese real GDP growth rate, and compares its results with those of the naive four-quarter moving average and time series forecasting models.

4.3. Dynamic Factor Nowcasting Model

The methodology of this paper is based on the Giannone et al. (2008) dynamic factor model. It assumes that every series in a large data panel has two orthogonal components: the co-movement component, which is a linear combination of a few common factors, $r \ll n$, and the idiosyncratic component that is specific to the series. The dynamics of the common factors are further assumed to be represented by an AR (1) process driven by a small number of macroeconomic shocks. Once the parameters of the model are estimated consistently from asymptotic principal components and regression, a Kalman filter is used to generate more efficient estimates of the common factors, and nowcasting is completed by simple regression projections.

Here we assume that every indicator, $\chi_{i,t}$, of the n macroeconomic time series, after certain transformations and standardization, is decomposed into a vector of r common factors, $\mathbf{F}_t$, and an idiosyncratic component, $\epsilon_{i,t}$, as follow:

$$\chi_{i,t} = \boldsymbol{\gamma}_i'\mathbf{F}_t + \epsilon_{i,t} \tag{9}$$

with $i = 1,\ldots,n$ and $t = 1,\ldots,T$, where the r dimensional vector $\boldsymbol{\gamma}_i$ does not vary over time and where $\zeta_{it} \equiv \boldsymbol{\gamma}_i'\mathbf{F}_t$ and $\epsilon_{i,t}$ are two orthogonal unobserved stochastic processes. In matrix notation, we have

$$\mathbf{X}_t = \boldsymbol{\Gamma}\mathbf{F}_t + \mathbf{E}_t \ , \tag{10}$$

where $\mathbf{X}_t = (\chi_{1t}, \chi_{2t}, \ldots, \chi_{nt})'$ and $\mathbf{E}_t = (\epsilon_{1t}, \epsilon_{2t}, \ldots, \epsilon_{nt})'$ are vectors and $\boldsymbol{\Gamma} = \left[\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_n\right]'$ is a matrix. The common component, ζ_{it}, is assumed to be a linear combination of the *r* unobserved common factors, $\mathbf{F}_t$, reflecting the bulk of the co-movements in the economy. Therefore, the vector of common factors can summarize the fundamental state of the economy from the information contained in all the indicators.

Furthermore, the common factors are assumed to follow a vector autoregressive (VAR) process:

$$\mathbf{F}_t = \mathbf{A}\mathbf{F}_{t-1} + \mathbf{B}\mathbf{u}_t \ , \tag{11}$$

with the macroeconomic stochastic shocks to the common factors, $\mathbf{u}_t$, being white noise with zero mean and covariance matrix , $\mathbf{I}_q$, where $\mathbf{B}$ is an $r \times q$ matrix of full rank q, and $\mathbf{A}$ is an $r \times r$ matrix with all roots of $\det\left(\mathbf{I}_r \ - \mathbf{A}\right)$ outside the unit circle. The number of common factors, *r*, is set to be large relative to the number of macroeconomic shocks, *q*.

4.4. Estimation

It is assumed that when the number of series in the panel data set increases, the common factors remain as the main source of variation and the effects of the idiosyncratic factors will not propagate to the whole data set but only be confined to a particular group of series. Then the common factors can be consistently estimated by asymptotic principal components.

We use the two-step procedure developed by Doz et al. (2007) to estimate the parameters of the factor model and the common factors. The first step is to estimate the model parameters from an ordinary least squares regression on the *r* largest principal components of the panel data. The principal components come from the largest eigenvalues of the sample correlation matrix of the series,

$$\mathbf{S} = \frac{1}{T}\sum_{i=1}^{T}\mathbf{X}_t\mathbf{X}_t{}' . \tag{12}$$

The r largest principal components are extracted from the sample correlation matrix.

Denote by $\mathbf{D}$ the $r \times r$ diagonal matrix with diagonal elements given by the largest r eigenvalues of $\mathbf{S}$, and denote by $\mathbf{V}$ the $n \times r$ matrix of corresponding eigenvectors subject to the normalization $\mathbf{V}'\mathbf{V} = \mathbf{I}_r$.

The approximation of the common factors is the following:

$$\tilde{\mathbf{F}}_{\mathbf{t}} = \mathbf{V}'\mathbf{X}_{\mathbf{t}} . \tag{13}$$

With the common factors, $\tilde{\mathbf{F}}_{\mathbf{t}}$, we can estimate the factor loadings, $\mathbf{\Gamma}$, and the covariance matrix of the idiosyncratic components, $\mathbf{\Pi}$, by regressing the data series on the estimated common factors, as follows:

$$\hat{\mathbf{\Gamma}} = \sum_t \mathbf{X}_t\tilde{\mathbf{F}}_t^{'}(\tilde{\mathbf{F}}_t\tilde{\mathbf{F}}_t^{'})^{-1} = \mathbf{V} , \tag{14}$$

$$\hat{\mathbf{\Pi}} = diag(\mathbf{S} - \mathbf{VDV}) . \tag{15}$$

The dynamic factor equation parameters, $\mathbf{A}$ and $\mathbf{B}$, can be estimated from a VAR on the common factors, $\tilde{\mathbf{F}}_{\mathbf{t}}$.

These estimates, $\hat{\mathbf{\Gamma}}$, $\hat{\mathbf{\Pi}}$, $\hat{\mathbf{A}}$, $\hat{\mathbf{B}}$, have been proven to be consistent as $n, T \to \infty$ by Forni et. al. (2000). Under different assumptions, Stock and Watson (2002), Bai and Ng (2002), and Giannone et al. (2004) have also shown the estimates to be consistent.

With these available estimates, the Kalman filter can re-estimate the underlying common factors. The re-estimates of the common factors from the Kalman filter are more efficient than from the principal components method, because the filter uses all the information up to the time of the estimation. Then the nowcast is produced as a simple linear projection; i.e., the quarterly GDP growth is regressed on the common factors using ordinary least squares.

4.5. Determining the Number of Common Factors

There are several methods of determining the number of the common factors. One standard approach is based on the amount of the variation in the data explained by the first few principal components. The number of factors is selected, when the marginal explanation of the next consecutive factor is less than 10 percentage points. Although practical, this approach has been criticized for lacking a solid theoretical basis.

To determine the optimal number of factors, Bai and Ng (2002) propose penalty criteria for large cross-sections, n, and large time dimensions, T. The common factors are estimated by asymptotic principal components, with the optimal number of common factor, r, estimated by minimizing the following loss function:

$$V(r, \widehat{\mathbf{F}^r}) + rg(n,T) \ , \tag{16}$$

where $V(r, \widehat{\mathbf{F}^r})$ is the sum of squared residuals from time series regressions of the data on the r common factors. The function $rg(n,T)$ penalizes over-fitting with $\mathbf{F}^r$ being the estimated common factors, when there are r of them. However, since the criteria are constructed for the factor model in static form only, the "correct" number of common factors determined by the criteria provide only an upper bound on the optimal number of dynamic factors.

We follow the general tradition on selection of the number of common factors and of factor shocks by setting both to 2. Many previous studies in the United States case have shown that 2 is the optimal number of common factors for dynamic factor models. See, e.g., Quah. and Sargent (1993) and Giannone et al. (2008))

5. Data

We use 193 macroeconomic series for the Chinese economy, including real variables, such as industrial production and international trade along with financial variables, such as prices, money, and credit aggregates. The data spans from December 1999 to June 2015. The data from 2007 quarter 4 onwards is reserved for the evaluation of out-of-sample nowcasts.

The dataset is described in detail in the appendix, and most of the series are monthly, except real GDP growth rates, which are quarterly. For simplicity, the quarterly data are repeated three times in the quarter to provide data consistency with "monthly" frequency. All the variables are transformed to be stationarity with the transformed variables corresponding to a quarterly value, observed at the end of the quarter. The details on the data transformations for individual series are available upon request.

Based on the release dates and contents, the data panel is aggregated into 13 blocks, consisting of CPI, PPI, retail price index, money supply, retail sales, international trade, industrial production, postal and telecommunication, real estate, investment, interest rate, exchange rate, Divisia monetary index, and GDP. The GDP data have the longest delay, about 4 weeks after the previous quarter ends. Industrial production, prices, and other series are intermediate cases. For some daily financial variables, we compute the monthly average and assume availability on the last day of the month.

6. Results

Table 1 provides the nowcasting results of the dynamic factor model (DFM) with both simple sum and Divisia monetary aggregates jointly included and DFM with only Divisia monetary aggregates included. The following graph is Chinese GDP growth rate from 2003 first quarter to 2015 second quarter.

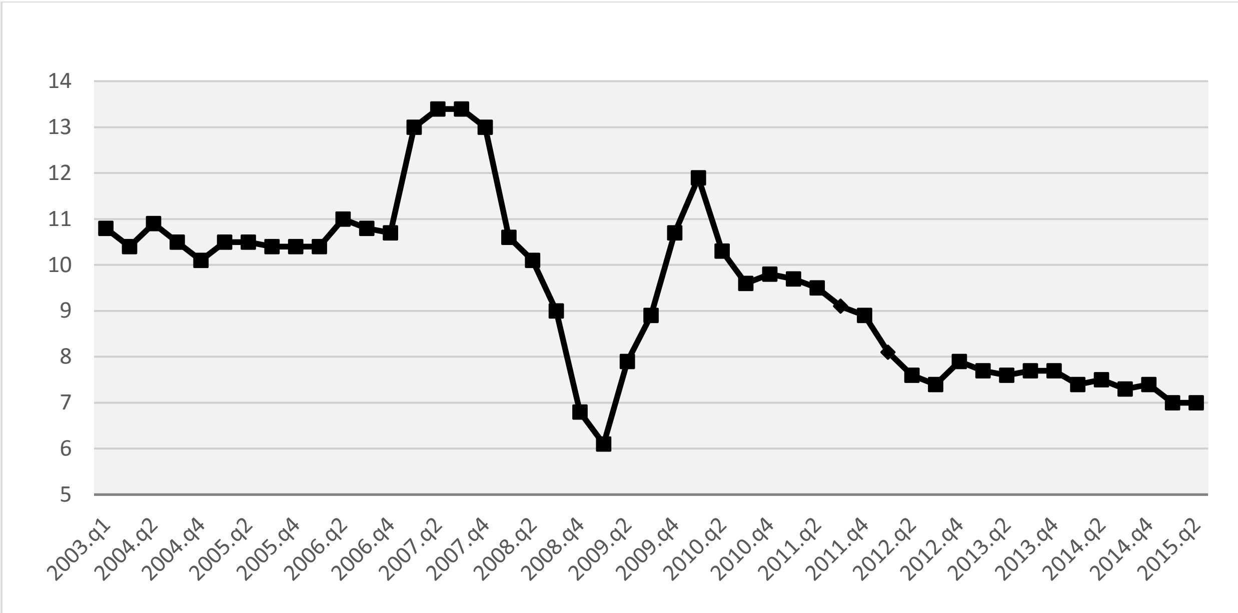

Figure 16: Real GDP Quarterly Growth Rate 2003Q1 to 2015Q2

From the figure 16, we can see that before 2007, the average GDP growth rate is within a range of 10% to 11%. But after 2012 the GDP growth rate is between 7% and 8%, implying that the Chinese economy had settled into a new lower and steady growth pattern.

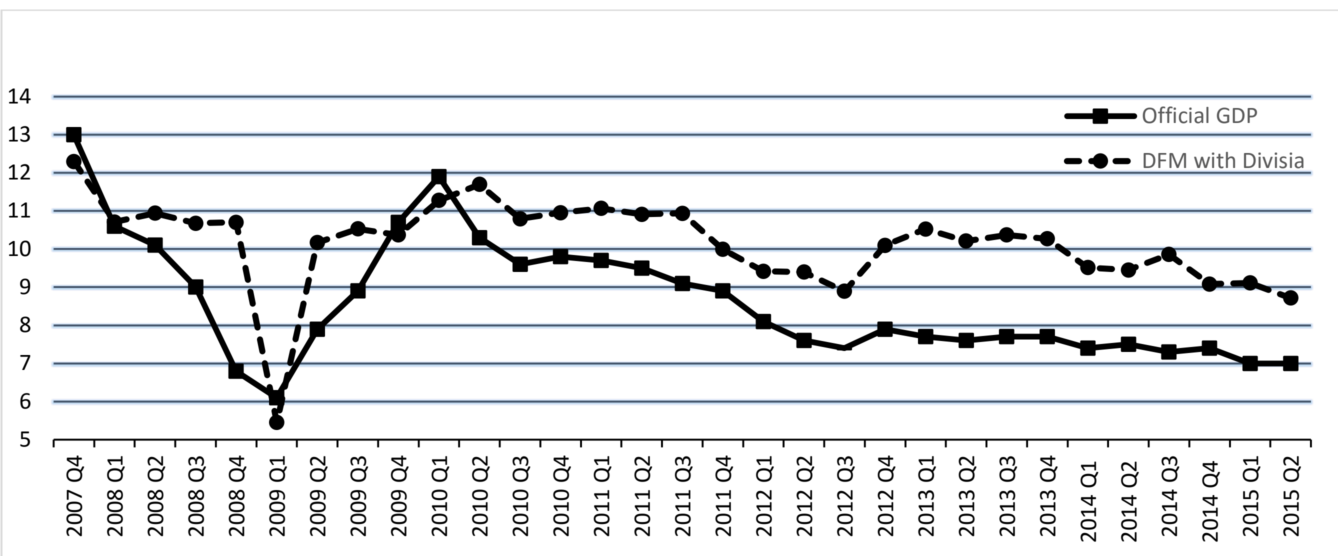

Figure 17: Real GDP and Nowcasting result from Dynamic Factor Model (DFM) with Divisia index, 2007Q4 to 2015Q2.

Table1: Nowcasting Result of Dynamic Factor Models with Different Monetary Data

Time	Official GDP	DFM with Both	DFM with Divisia
2007Q4	13	12.0713	12.2976
2008Q1	10.6	10.4453	10.7102
2008Q2	10.1	11.1118	10.9418
2008Q3	9	10.6678	10.6755
2008Q4	6.8	10.8765	10.7003
2009Q1	6.1	6.9934	5.4536
2009Q2	7.9	10.1528	10.167
2009Q3	8.9	10.4348	10.5309
2009Q4	10.7	10.3736	10.3701
2010Q1	11.9	11.6659	11.2741
2010Q2	10.3	11.7382	11.694
2010Q3	9.6	10.8142	10.7947
2010Q4	9.8	10.9605	10.9516
2011Q1	9.7	11.04	11.0645
2011Q2	9.5	10.8647	10.9092
2011Q3	9.1	10.9327	10.9348
2011Q4	8.9	9.9939	9.9921
2012Q1	8.1	9.3866	9.4164
2012Q2	7.6	9.3842	9.3984
2012Q3	7.4	8.8774	8.8922
2012Q4	7.9	10.1025	10.0989
2013Q1	7.7	10.5654	10.5245
2013Q2	7.6	10.2269	10.2091
2013Q3	7.7	10.3744	10.3706
2013Q4	7.7	10.2668	10.2698
2014Q1	7.4	9.5109	9.512
2014Q2	7.5	9.4491	9.4505
2014Q3	7.3	9.8561	9.8572
2014Q4	7.4	9.0805	9.0807
2015Q1	7	9.1176	9.1093
2015Q2	7	8.7162	8.7147

From table 1, we can see that the dynamic factor model with only Divisia monetary aggregates performs better than DFM with both simple sum and Divisia monetary aggregates jointly. We can conclude that the Divisia index contains more information or more accurate information than the simple sum aggregates about the economy. In fact the marginal contribution of inclusion of simple sum, when Divisia money is already included, is negative.

We next compare the factor models' nowcasting results with other models' results, including the "Naïve model" using a four quarter moving average and an AR(1) model. The comparisons are in terms of mean squared forecast errors.

Table 2: Mean Squared Forecast Error for Different Models at Different Time Period

Time Period	DFM with both	DFM with only Divisia	Naïve Model
2007Q4 to 2015 Q2	3.50224	3.43947	2.50427
2007Q4 to 2011Q4	2.51780	2.51693	4.29511
2012Q1 to 2015Q2	4.69762	4.55969	0.32969

Compared to the "Naïve Model," the factor models perform better until the first quarter of 2012. After 2012 the four quarter moving average models performs better in terms of mean squared forecast errors. A possible explanation could be that at 2012, an economic structural break or regime change occurred in the Chinese economy. At 2012 quarter 1, GDP growth rate decreased to 8.1%. From then on, the growth rate has been around 7% to 8%, compared with the average 10% growth rate during the prior three decades. In addition, it is widely believed that the Chinese government is targeting structural change and lower steady growth levels to produce a "greener" or "steady" growth path.

Following the first quarter of 2012, time series models have produced better nowcasting results than the large panel data factor model. If there has been a regime change, the factor model could benefit from changing the estimation period.

Using only Divisia monetary aggregates from the first quarter of 2012 to the second quarter of 2015, table 3 contains the nowcasting results from the AR (1) model, the "Naïve Model," and the dynamic factor model.

Table 3: The Nowcasting Results of Different Models from 2012Q1 to 2015Q2

Time	Official GDP	DFM with Divisia	AR(1) Model	Naïve Model
2012Q1	8.1	9.4164	8.989	9.3
2012Q2	7.6	9.3984	8.2358	8.9
2012Q3	7.4	8.8922	7.7651	8.425
2012Q4	7.9	10.0989	7.5768	8
2013Q1	7.7	10.5245	8.0475	7.75
2013Q2	7.6	10.2091	7.8592	7.65
2013Q3	7.7	10.3706	7.765	7.65
2013Q4	7.7	10.2698	7.8592	7.725
2014Q1	7.4	9.512	7.8292	7.675
2014Q2	7.5	9.4505	7.5768	7.6
2014Q3	7.3	9.8572	7.6701	7.575
2014Q4	7.4	9.0807	7.4826	7.475
2015Q1	7	9.1093	7.5768	7.4
2015Q2	7	8.7147	7.200	7.3
MSFE	N/A	4.55969	0.17028	0.32968

Table 3 shows that between the period of 2012 first quarter and 2015 second quarter, both the simple time series AR (1) model and the "Naïve" model outperform the dynamic factor model in terms of the Mean Squared Forecast Error (MSFE). Among the three models, AR(1) performs the best with a MSFE of 0.17028, followed by the naïve model with MSFE of 0.32968. The least accurate model is the dynamic factor model with the highest MSFE of 4.55969. This results could be a sign of a regime switch of the Chinese economy after 2012. Before 2012, the factor model is the most effective in nowcasting. After 2012, the time series models works better than the factor model.

7. Conclusion

We construct for China the Divisia monetary aggregates, M1, M2, M3, and M4. With these Divisia indexes and a large panel dataset, we apply a dynamic factor model to nowcast the monthly Chinese real GDP growth rates.

The Divisia monetary aggregates prove to be revealing about the Chinese economy. Of particular importance is our construction of the broad money supply measures, M3 and M4, never before constructed for China. We find that the Chinese money supply declined at the beginning of 2010, after which the growth rates of Divisia M1, M2, M3, and M4 all steadily decreased, reflecting the tightened borrowing conditions in Chinese money.

In terms of nowcasting results, the dynamic factor model performs better with only Divisia monetary aggregates included than with both the simple sum and Divisia monetary aggregates jointly. With inclusion of the Divisia monetary aggregates in the model, the further inclusion of simple sum monetary aggregates provides no further information and in fact harms the abilities of the dynamic factor model.

Compared to the other models, factor models produced better nowcasting result before 2012, while the other time series models performed better after 2012. This phenomenon reflects a regime change or structural break in 2012. This regime change requires a different estimation period for the factor model to be effective in nowcasting. The possible economic regime change is evident in both the Divisia monetary aggregates, the user-cost of the money supply, and the real GDP growth rate. The growth rates of the Divisia monetary aggregates, M1, M2, and M3, began to decrease, while the user-costs of all the Divisia aggregates started to increase rapidly in 2012. Since 2012, the Chinese real annual GDP growth rate settled into a lower steady growth range of within 7% to 8%, which is lower than the previous average of 10% to 11% during the past decade. These results reflect the fact that the Chinese economy experienced a structural break or regime change in 2012. Chow tests confirm that in the first quarter of 2012, a structural change in China's economy occurred. The Chow test results are provided in Appendix 3.[12]

[12] In Appendix 3, real Chinese GDP growth rates are tested for structural change with both the Chow test and the multiple breakpoints test. The results from both tests show that there is structural change in GDP growth rates and hence structural change in the Chinese economy. The Chow breakpoint test's F-statistic is 30.73554 with p-value of 0,0000, which is highly significant. We reject the null hypothesis that no breaks at 2012 quarter 1 exist and accept the alternative hypothesis that there is structural change in 2012 first quarter. Similarly, the Bai-Perron multiple breakpoint test demonstrates that at 2012 first quarter, there is a structural break in Chinese GDP.

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Appendix 1:

GDP Nowcasting Results from Different Models

Time	Official GDP	DFM with Both	DFM with Divisia	Naïve Model
2007Q4	13	12.0713	12.2976	12.625
2008Q1	10.6	10.4453	10.7102	13.2
2008Q2	10.1	11.1118	10.9418	12.6
2008Q3	9	10.6678	10.6755	11.775
2008Q4	6.8	10.8765	10.7003	10.675
2009Q1	6.1	6.9934	5.4536	9.125
2009Q2	7.9	10.1528	10.167	8
2009Q3	8.9	10.4348	10.5309	7.45
2009Q4	10.7	10.3736	10.3701	7.425
2010Q1	11.9	11.6659	11.2741	8.4
2010Q2	10.3	11.7382	11.694	9.85
2010Q3	9.6	10.8142	10.7947	10.45
2010Q4	9.8	10.9605	10.9516	10.625
2011Q1	9.7	11.04	11.0645	10.4
2011Q2	9.5	10.8647	10.9092	9.85
2011Q3	9.1	10.9327	10.9348	9.65
2011Q4	8.9	9.9939	9.9921	9.525
2012Q1	8.1	9.3866	9.4164	9.3
2012Q2	7.6	9.3842	9.3984	8.9
2012Q3	7.4	8.8774	8.8922	8.425
2012Q4	7.9	10.1025	10.0989	8
2013Q1	7.7	10.5654	10.5245	7.75
2013Q2	7.6	10.2269	10.2091	7.65
2013Q3	7.7	10.3744	10.3706	7.65
2013Q4	7.7	10.2668	10.2698	7.725
2014Q1	7.4	9.5109	9.512	7.675
2014Q2	7.5	9.4491	9.4505	7.6
2014Q3	7.3	9.8561	9.8572	7.575
2014Q4	7.4	9.0805	9.0807	7.475
2015Q1	7	9.1176	9.1093	7.4
2015Q2	7	8.7162	8.7147	7.3

Appendix 2:

Data Description

Block Name	Release	Date (approximate)	Publish ing lag	Data Frequenc y
CPI	Consumer Price	9th to 10th of the month	m-1	Monthly
PPI	Producer Price	9th to 10th of the month	m-1	Monthly
Retail price Index	Commodity Retail Price Index	9th to 10th of the month	m-1	monthly
Money and Credit	Money Supply	15th of the month	m-1	monthly
Sales	GDP retail sales	11th to 15th	m-1	monthly
International Trade	Export and Import	9th to 14th	m-1	monthly
Industrial Production	Industrial Production	11th to 15th	m-1	monthly
Post and telecommunicatio n	Post and Telcom Services	5th of the month	m-2	monthly
Real Estate	Real estate	11th to 15th	m-1	monthly
Fixed asset investment	Investment	11th to 15th	m-1	monthly
Interest Rate	Interest Rate	Last day of the month	m	monthly
Exchange Rate	Exchange Rate	Last day of the month	m	monthly
Divisia Index	Divisia Monetary Index	Depends on the money components availability	m-1	monthly

Appendix 3

Structure Break Test Results

Chow Breakpoint Test: 2012Q1
Null Hypothesis: No breaks at specified breakpoints

Equation Sample: 1999Q4 2015Q2

F-statistic	30.73554	Prob. F(1,61)	0.0000
Log likelihood ratio	25.70627	Prob. Chi-Square(1)	0.0000

Multiple breakpoint tests
Bai-Perron tests of 1 to M globally determined breaks
Date: 10/16/15 Time: 02:56
Sample: 1999Q4 2015Q2
Included observations: 63
Breaking variables: C
Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05
Test statistics employ HAC covariances (Prewhitening with lags = 1,
Quadratic-Spectral kernel, Andrews bandwidth)
Allow heterogeneous error distributions across breaks

Sequential F-statistic determined breaks:	0
Significant F-statistic largest breaks:	5
UDmax determined breaks:	4
WDmax determined breaks:	4

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1	7.644957	7.644957	7.644957	8.58
2	4.126766	4.126766	4.904107	7.22
3 *	11.09370	11.09370	15.97046	5.96
4 *	67.36879	67.36879	115.8365	4.99
5 *	27.05719	27.05719	59.37357	3.91

UDMax statistic*	67.36879	UDMax critical value**	8.88
WDMax statistic*	115.8365	WDMax critical value**	9.91

* Significant at the 0.05 level.
** Bai-Perron (Econometric Journal, 2003) critical values.

Estimated break dates:
1: 2012Q1
2: 2003Q1, 2008Q3
3: 2003Q1, 2008Q3, 2012Q1
4: 2003Q1, 2006Q1, 2008Q2, 2012Q1
5: 2003Q1, 2006Q1, 2008Q2, 2011Q1, 2013Q2