# Three Essays on Divisia Monetary Aggregates and GDP Nowcasting

By

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Submitted to the graduate degree program in Economics and the Graduate Faculty of the University of Kansas in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

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Abstract

GDP data are published quarterly with a substantial lag, while many other monetary and financial decisions are made at higher frequencies. GDP nowcasting can evaluate the current quarter'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. My dissertation explores nowcasting GDP growth rates, incorporating the Divisia monetary aggregate indexes as indicators, along with a large panel of economic data. This research contributes to the nowcasting literature by clarifying and summarizing existing work, and goes further, by introducing Divisia monetary aggregates into GDP nowcasting using a dynamic factor model. This new model produces better nowcasting results in the U.S. case than the Survey of Professional Forecasters at the Federal Reserve Bank of Philadelphia. Finally, the third chapter of my dissertation *Chinese Divisia Monetary Index and GDP Nowcasting* contributes to the literature by constructing Chinese Divisia monetary indexes, including M1, M2, and for the first time, M3 and M4. The two broader aggregates M3 and M4 were never published by the People's Bank of China. The third paper sheds lights on the increasing borrowing cost in China. The nowcasting results also show that the Chinese economy experienced a structural break in early 2012. Overall, the results demonstrate that Divisia indexes contain more information than simple sum aggregates, and thereby help to produce better results. My dissertation contain three chapters:

**Literature Review on GDP Nowcasting and US Quarterly GDP Nowcasting.** First I survey the literature on GDP nowcasting from the 1970s through to current research. This ranges from simple time series models to the current advanced econometric models, including dynamic factor models (DFM) with regime switching and structural changes. Then it moves on to

nowcasting US quarterly GDP growth with dynamic factor model and exploring information from a large and unbalanced panel of time series. It compares the nowcasting results from DFM to the results from other nowcasting models. DFM extracts a few common factors from a large number of monthly variables, regresses the GDP data on common factors which explain the bulk of the co-movement of the economy. The comparison demonstrates that DFM functions better nowcasting results than Survey of Professional Forecasters (SPF).

**Nowcasting US quarterly GDP with Divisia Monetary Index.** In this chapter, I investigate the nowcasting power of Divisia Monetary Index in U.S. economy. I briefly survey the development of the Divisia Monetary Index, the theory behind it, and the employment of the Divisia Index in related forecasting research literature. Using the Divisia index available from the Advances in Monetary and Financial Measurement (AMFM) program directed by Professor William A. Barnett with the Center for Financial Stability, I investigate the forecasting and nowcasting power of Divisia Monetary Aggregates Indexes, Divisia M1, M2, and M3 and evaluate the contributions of these monetary indexes to the accuracy of nowcasting. I also compare the nowcasting results from DFM with the traditional simple sum monetary aggregates M1, M2, and M3 to the model with weighted Divisia Index M1, M2, and M3. The comparison shows that Divisia monetary aggregates are superior to simple sum monetary aggregates by 9.1% in accurately nowcasting GDP.

**Chinese Divisia Monetary Index and GDP Nowcasting.** 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, 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. I conclude that different nowcasting models should be used during the two regimes.

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My brothers Xinshou Tang and Xinfu Tang for always being dependable and reliable.

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# Chapter 1: Nowcasting US Quarterly GDP

## 1.1 Literature Review on Nowcasting

Evaluating the current state of the economy is of great importance to policy makers, institutions, and economic agents. Decisions of central banks, fiscal authorities, private agents and commercial institutions in real time are based on assessments of current and future economic conditions using incomplete data. It is crucial to have accurate evaluation of the current state and future path of GDP to assess fiscal sustainability. Meanwhile most data are released with a lag and are subsequently revised, so both forecasting and assessing current-quarter conditions (nowcasting) are important tasks for central banks and other economic agents.

### 1.1.1 Non-Factor Model Nowcast

In 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 rate, such as naive model of four-quarter moving averaging of GDP, simple univariate autoregressive AR(1) model (Barhoumi et al., 2007) or naive constant model, the averaged bivariate vector autoregressive (VAR) models, and bridge equations (BEQ) (Arnostova, D. Havrlant, et al., 2011).

The bridge equation model combines qualitative judgments with ‘‘bridge equations’’ (Baffigi et al. 2004, Runstler and Sedillot 2003, Kitchen and Monoco 2003). Every monthly indicator is first forecasted based on AR (q) process, the lag length is selected by the criteria proposed by Bai and Ng (2002). Then the monthly series and its forecast are aggregated into quarterly frequency. The quarterly GDP data are paired with the quarterly indicators, at last, regress the GDP on the corresponding quarterly indicators through OLS model. The final GDP forecast is obtained as the arithmetic average of the forecasts from pairwise regression.

Any data of different frequency may contain potential economic information that will affect current-quarter estimate and its precision. Therefore, forecasters should not throw away any information, but rather use all the information available when the nowcasting is made. There are some challenges involved in using larger number of data series. The first 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 Domenico Giannone, Lucrezia Reichlin, David Small 2008, Matthew S. Yiu and Kenneth K. Chow 2011) which are released on different dates, with some data available in the current quarter and some data one or two months lag. The second challenge comes from designing a model that incorporates newly released data into nowcasting. With new release of data, it is crucial to incorporate the additional information into the forecast model to produce a more accurate GDP growth data. The third challenge is to measure the impact of new release on the accuracy of nowcasting and "bridges" monthly data releases with the nowcasting of quarterly GDP. Factor model or dynamic factor model meets these challenges. It is defined in a parsimonious manner, which can be achieved by summarizing the information of the many data releases with a few common factors. The nowcasting is then defined as the projection of quarterly GDP on the common factors estimated from the panel of monthly data.

### 1.1.2 Factor Model Nowcast

Factor model has been widely employed in forecasting and nowcasting GDP due to its ability to deal with the challenges involved with dealing with large unbalanced dataset. For a given size of the cross-section n, the literature has proposed frequency domain (Geweke, 1997; Sargent and Sims, 1977; Geweke and Singleton, 1980) and time Domain (Engle and Watson, 1981; Stock and Wastson, 1989; Quah and Sargent, 1992) methods. In econometric literature, factor analysis has been the main tool used in summarizing the large datasets. Stock and Watson (1999, 2002a, 2002b), Forni, Lippi, Hallin and Reichilin (2000, 2001, 2004, 2005), Doz, Giannone and Reichilin (2006, 2007) and Giannone, Reichilin and Small (2008) have carried out forecasting or nowcasting using factor model. Mariano and Murasawa (2003), Aruoba et al. (2009), and Boragan and Diebold (2010) incorporate data of different frequencies. Camacho and Perez-Quiros (2010) aim to estimate real GDP growth at the monthly frequency for the euro area by incorporating data on preliminary, advanced, and final GDP releases. Evans (2005) estimates real GDP at the daily frequency for the U.S. using different vintages of GDP but without using a dynamic factor model. William A. Barnett, the inventor of Divisia Monetary Aggregate, in his paper with Marcelle Chauvet and Danilo Leiva-Leon (2013), revolutionarily incorporates Divisia monetary aggregates into the nowcasting process and explore the predictive ability of several univariate and multivariate models. They conclude that a small scale dynamic factor model that contains information on real economic activity, inflation dynamics, and Divisia monetary aggregates produces the most accurate nowcasts of nominal GDP.

Runstler, Barhoumi, Senk and others compare the performance of dynamic factor model to other alternative nowcasing models, such as univariate time series model, vector autoregressive models(VAR), and Bridge Equations. They conclude that factor models outperform bridge equations and the quarterly models, and models that use monthly data tend to outperform those models that use purely quarterly data.

Matthew S. Yiu and Kenneth K. Chow's 2011's working paper, *Nowcasting Chinese GDP: Information content of Economic and Financial Data*, is the first paper that tries to nowcast Chinese quarterly GDP, it uses the Factor Model proposed by Giannone, Reichilin and Small (2008) to regress Chinese GDP on 189 times series. The paper utilizes Bai and Ng's (2002) criteria to determine the number of common factors. They find that the identified 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 block in estimating current-quarter GDP in China. Other important blocks are consumer and retail prices data and fixed asset investment indicators.

In Troy D. Matheson's 2009 paper: *An analysis of the informational content of New Zealand data releases: The importance of business opinion surveys*, he uses the same parametric factor model (that is used in Giannone, Rechlin and Small 2008) to estimate New Zealand's GDP growth with unbalanced real-time panels of quarterly data. The author uses approximately 2000 times series, and categories them into 21 blocks, which allows him to make 21 different factor model forecasts each quarter. For determining the number of common factors, he uses two methods: the first method is the Bai and Ng (2002) criteria to determine the number of statistically relevant (static) factors in the panel, and the second determines the number of (static) factors in an ad-hoc manner, following Giannone et al. (2005). The statistically optimal number of dynamic factors is found to be two using the Bai and Ng 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 Reserve Bank's forecasts. The authors find that survey data are important in determining factor model predictions, particularly for real GDP growth. However, the importance of the survey data was found to be mainly due to its timeliness; the relative importance of survey data diminished when estimates were made conditional on timeliness.

Angilini et al. in Short-term forecasts of euro area GDP growth (2010) evaluate models that exploit timely monthly releases to compute early estimates of current quarter GDP (now-casting) in the euro area. They compare traditional methods used at institutions to a new method proposed by Giannone et al. 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. They show that bridging via factors produces more accurate estimates than traditional bridge equations. They also show that survey data and other 'soft' information are valuable for nowcasting.

In William A. Barnett, Marcelle Chauvet and Danilo Levia-Leon 2013's paper: *Real-Time Nowcasting of Nominal GDP*, they incorporate Divisia monetary aggregates for the first time into the nowcasting model, compare the predictive ability of several univariate and multivariate nowcasting models. Their results show that a small-scale dynamic factor model that contains information of real economic activity, inflation dynamics and Divisia monetary aggregates, produces the most accurate nowcasts of Nominal GDP. In their dynamic factor model, the state variables or the common factors follow an AR (6) process, which is different from the common AR (1) used in the previous factor models of the literature. Meanwhile, the regression model of nominal GDP has time-varying parameters, which I think is revolutionary and can capture the real-time change more accurately. This paper set the direction for future research in nowcasting for two reasons. First, the incorporating of Divisia monetary aggregates data is innovative and indicative. Second, the small scale dynamic model makes the computation easier compared to the large scale factor model, therefore, the duplication of this paper will be easier for future research.

Marcelle Chauvet and Simon Potter in their paper Forecasting Output (2012), survey the recent literature on output forecasting, and examine the real time forecasting ability of nine different models for U.S. output growth. Their survey finds that there is a large difference in forecast performance across business cycle phases. Specifically, it is much harder to forecast output growth during recessions than during expansions. Simple linear and nonlinear autoregressive models have the best accuracy in forecasting output growth during expansions, although the dynamic stochastic general equilibrium model (DSGE) and the vector autoregressive model with financial variables do relatively well. They also find that most models do poorly in forecasting output growth during recessions. The autoregressive model based on the nonlinear dynamic factor model that takes into account asymmetries between expansions and recessions displays the best real time forecast accuracy during recessions. Compare to Blue Chip forecasts, the dynamic factor Markov Switching model has better accuracy, particularly with respect to the timing and depth of output fall during recessions in real time. The results suggest that there are large gains in considering separate forecasting models for normal times and models especially designed for periods of abrupt changes, such as during recessions and financial crisis.

Marta Banbura and Michele Modugno (2010) use maximum likelihood estimation for factor models on datasets with arbitrary pattern of missing data. The essential idea is to write the likelihood as if the data were complete and "fill in" the missing data in the expectation step. The approach handle datasets with an arbitrary pattern of data availability efficiently, therefore, this model can be particularly relevant for young economies for which many series have been compiled only since recently. Additionally, this paper shows how to extract a model based news from a statistical data release within the framework and the authors derive the relationship between the news and the resulting forecast revision. The model based news and its contribution to the revision allows researcher to determine the sign and size of a news as well as its contribution to the revision, especially in case of simultaneous data releases.

Bańbura, Marta and Rünstler, Gerhard (2011) derived forecast weights and uncertainty measure for assessing the roles of individual series in a dynamic factor model (DFM) for forecasting the euro area GDP from monthly indicators. They find that surveys and financial data contain important information for the GDP forecasts beyond the monthly real activity measures, only under the condition that their more timely publication is taken into account properly. Furthermore, their research finds that differences in publication lags play a very important role and should be considered in forecast evaluation. There is one question that is not been addressed is the role of subsequent revisions of the initial releases of real activity data.

Kajial Lahiri and George Monokroussos (2013) study the role of well-known diffusion indices produced by the Institute for Supply Management (ISM) in nowcasting current quarter US GDP growth. They investigate the marginal impact of the ISM surveys on nowcasts when large unbalanced macroeconomic data sets are used to generate them. They conclude that the ISM indices are helpful in improving the nowcasts when new ISM information becomes available at the beginning of the month, ahead of other monthly indicators. Furthermore, on the contrary to the existing literature that focuses almost exclusively on other monthly manufacturing information, their paper establish the increasingly significant role of the recently created non-manufacturing ISM diffusion indices in nowcasting contexts.

This paper use the dynamic factor model that is proposed by Giannone, Reichilin and Small 2008 to nowcast US GDP growth rate, and compare its result with the naive four-quarter moving average of GDP, and the result of Survey of Professional Forecast (SPF) from Federal Reserve of Philadelphia. This paper organized as following, Section 2 describes the model and competing models. Section 3 describes the data. Section 4 lists the result and section 5 concludes.

### 1.2 Dynamic Factor Model

The methodology of this paper is based on the dynamic factor model used in the paper of Giannone, Reichilin, and Small (2008). It assumes that every series of the large data panel has two orthogonal components: the co-movement component, which is a linear combination of a few common factors r<<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 autoregressive process of order one (AR (1) process) driven by a small number of macroeconomic shocks, such as the real and monetary shocks. Once the parameters of the model are estimated consistently from asymptotic principal components and regression, the Kalman filter is used to generate the more efficient estimates of the common factors and nowcasting are provided by simple regression projections.

Here I assume that every indicator of the n macroeconomic and finance time series, after certain transformation and standardization, is decomposed as a few common factors and an idiosyncratic component as follow:

$$x_{i,t} = \gamma_i F_t + \varepsilon_{i,t} \tag{1.1}$$

With i=1,…,n and t=1,...,T

Where $\gamma_i F_t \equiv \zeta_{it}$ and $\varepsilon_{i,t}$ are two orthogonal unobserved stochastic processes. In matrix notation, we have;

$$X_t = \Gamma F_t + E_t \tag{1.2}$$

Where $X_t = (x_{1t,} x_{2t,} \dots, x_{nt})'$ , $E_t = (\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{nt})'$ and $\Gamma = (\gamma_{1t}, \dots, \gamma_{nt})'$. The $n \times 1$ process $\zeta_{it}$ (the common component) is assumed to be a linear combination of a few unobserved common factors $F_t$ that reflect the bulk of the co-movements in the economy. Therefore, the common factors can summarize the fundamental state of the economy as the information is contained in all the indicators.

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

$$F_t = AF_{t-1} + Bu_t \tag{1.3}$$

With $u_t \sim WN(0, I_q)$r

Where $B$ is an $r \times q$ matrix of full rank q , A is an $r \times r$ matrix and all roots of $\det(I_r - Az)$ lie outside of the unit circle, and $u_t$ are the macroeconomic stochastic shocks to the common factors. The number of common factors r, is set to be large relative to the number of macroeconomic shocks, q.

**1.2.1 Estimation and Parameters Estimates**.

It is assumed that when the number of series in the panel data set is increasing, 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 confine to a particular group of series. Here, the common factors can be consistently estimated by asymptotic principal components.

Here, I 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 squared (OLS) on the r largest principal components of the panel data. The principal components come from the first r largest eigenvalues the sample correlation matrix of the series;

$$S = \frac{1}{T}\sum_{i=1}^{T} X_t X_t' \tag{1.4}$$

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

Denote D the $r \times r$ diagonal matrix with diagonal elements given the largest r eigenvalues of S and denote V the $n \times r$ matrix of the corresponding eigenvectors subject to the normalization $V'V = I_r$.

I approximate the common factors as following:

$$\widetilde{F}_t = V'X_t \tag{1.5}$$

With the common factors, $\widetilde{F}_t$, the factors loadings, $\Gamma$, and the covariance matrix of the idiosyncratic components, Π can be estimated by regressing the data series on the estimated common factors as the follows:

$$\hat{\Gamma} = \sum X_t \widetilde{F}_t{}' \, (\widetilde{F}_t \, \widetilde{F}_t{}')^{-1} = V \tag{1.6}$$

$$\widehat{\Pi} = diag(S - VDV) \tag{1.7}$$

The parameters of the factor dynamic equation, A and B can be estimated by running a VAR on the common factor $\widetilde{F}_t$.

These estimates, $\hat{\Gamma}$ , $\widehat{\Pi}$ , $\widehat{A}$ , $\widehat{B}$, are proven to be consistent as $n, T \to \infty$ by Forni et al.(2000) and, under different assumptions, Stock and Watson(2002), Bai and Ng(2003) and Giannone, Reichilin, and Sala(2004) prove the estimates are consistent.

Secondly, with these estimates being available, 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 using the principal component method because the filter uses all the information up to the estimation has been made. Then the nowcast is produced as a simple linear projection, i.e. the quarterly GDP growth is regressed on the common factors using OLS.

### 1.2.2 Determine the number of the common factors.

There are several methods of determining the number of the common factors. One standard approach is based on the degree of variance in the data set explained by the first few principal components. Usually, the number of factors is selected when the marginal explanation of the next consecutive factor is less than 10 percentage points. This approach seems practical, it has been criticized for not having a solid theoretical basis.

In this paper, I use the criteria developed by Bai and Ng (2002). In order to determine the optimal number of factors, Bai and Ng propose some penalty criteria under the assumption of large cross-section, n, and large time dimension, T. In the large data panel, the common factors are estimated by asymptotic principal components, and the optimal number of common factor, r, is estimated by minimizing the following loss function.

$$V\left(k, \widehat{F^k}\right) + kg(N, T) \tag{1.8}$$

$V\left(k, \widehat{F^k}\right)$ is the sum of squared residuals from time series regressions of the data on the k common factors and kg(N,T) penalized over-fitting. Bai and Ng propose the following three criteria to determine the “correct' number of common factors:

$$IC_{P1} = \ln\left(V\left(f, \widehat{F^k}\right)\right) + k\left(\frac{N+T}{NT}\right)\ln\left(\frac{NT}{N+T}\right) \tag{1.9}$$

$$IC_{P2} = \ln\left(V\left(f, \widehat{F^k}\right)\right) + k\left(\frac{N+T}{NT}\right)\ln C_{NT}^2 \tag{1.10}$$

$$IC_{P3} = \ln\left(V\left(f, \widehat{F^k}\right)\right) + k\left(\frac{\ln C_{NT}^2}{C_{NT}^2}\right) \tag{1.11}$$

Here, $C_{NT} = min\left\{\sqrt{N},\ \sqrt{T}\right\}$

The decision rule is to select K to minimize the above three criteria. However, since the criteria are constructed for the factor model in static form only, the “correct” number of common factors determined by the criteria here only indicates an upper bound of the true number of dynamic factors.

For this paper, I follow the general tradition on the number of common factors and factor shocks, and make them to be both 2. And many previous research show that, 2 is the optimal number for the common factors in dynamic factor models in the United States case.

### 1.3 Data

The data set of this paper consists of 193 macroeconomic series for US economy, including real variables such as (industrial production and employment), financial variables, prices, wages, money and credit aggregates, surveys from other sources.  The span of the data is from January 1982 to June 2013. The data from 2007 onwards is reserved for the evaluation of out-of-sample nowcasts.

The dataset is described in Appendix and most of the series are monthly, except GDP growth rate are quarterly. To make it simple, I use the quarterly data as monthly data, and in the same quarter, the one data is repeated three times. All the variables are transformed to be stationary and insure that the transformed variables correspond to a quarterly quantity when observed at the end of the quarter. The details on the data transformations for individual series are reported in Appendix.

Based on their release date, the data panel is aggregated into 15 blocks, namely interest rates, financial, housing, surveys1, surveys 2, PPI, CPI, GDP and Income, Initial claims industrial Production, Mixed 1, Mixed 2, mixed 3,labor and wages, money and credit. Generally, surveys have very short publishing lags and are often forecasts for future months or quarters; GDP has the longest delay, about 6 weeks after the previous quarter ends. Industrial production, prices, and other series are intermediate cases.

As in paper D. Giannone et al (2008), the first block is called “Survey 2”, consists of Chicago Report of the National Association of Purchasing Management, which is released on the first business day of the month. The next block-“Mixed 3” includes some miscellaneous releases, such as, construction spending and the advanced report on durable goods manufacturers. Money and Credit follows the “Mixed 3”, and so on. Table 1 describes the details of these 15 blocks.

As for the financial variables and the interest rate, they are available on daily basis in principal. Because most of the series of the panel are monthly, I take the monthly average of these variables and assume that they are available on the last day of the month, which will simplify the block structure in the model but possibly understate the importance of the financial variables.

Table 1: Variables Release Date of the Month

| **Block Name** | **Release** | **Date (approx.)** | **Publishing lag** | **Frequency of Data** |
|---|---|---|---|---|
| Survey 2 | PMGR-manufacturing | 1$^{st}$ business day of the month | 1 month | monthly |
| Mixed 3 | Commercial paper outstanding | 1$^{st}$ bus. Day | 1 month | monthly |
| Mixed 3 | Construction put in place | 1$^{st}$ bus. Day (appro) | 2 months | monthly |
| Mixed 3 | Advance report on durable goods manufactures shipments, inventories and orders | 24-28$^{th}$ (approx.) | 1-2 month | monthly |
| Mixed 3 | Full report on durable goods manufactures shipments, inventories and orders | 5 days after advance durables | 2 months | monthly |
| Money and credit | Consumer delinquency, bulletin | Quarterly(series is monthly) | 2 quarters | monthly |
| Money and credit | Aggregate reserves of depository institutions and the monetary base | 1$^{st}$ Thursday of month | 1 month | monthly |
| Money and credit | Money stock measures | 2$^{nd}$ Thursday of month | 1 month | monthly |

| | | | | |
|---|---|---|---|---|
| Money and credit | Assets and liabilities of commercial banks in the US | 1st Friday of month | 1 month | monthly |
| Labor and wages | Employment situation | 1st Friday of month | 1 month | monthly |
| Mixed 1 | Consumer credit | 5th business day of month | 2 months | monthly |
| Mixed 1 | Advance monthly sales for retail and food services | 11-15th of month | 1 month | monthly |
| Mixed 1 | Monthly treasury statement of receipts and outlays of the US government | Middle of month | 1 month | monthly |
| Mixed 1 | US international trade in goods and services(FT900 and FT920) | 2nd full week of month | 2 months | monthly |
| Ind. production | Industrial production and capacity utilization | 15-17th of month | 1 month | monthly |
| Mixed 2 | New residential construction | 16-20th of month | 1 month | monthly |
| Mixed 2 | Business outlook survey: Federal Reserve Bank of Philadelphia | 3rd Thursday of month | Current month | monthly |
| PPI | Producer prices | Middle of month | One month | monthly |
| CPI | Consumer prices | Middle of month | One month | monthly |
| GDP and income | GDP-detail: inventories and sales | Day after GDP-release | 2 months | monthly |
| GDP and income | GDP-release; GDP and GDP deflator | Last week of month | 1 quarter | quarterly |
| GDP and income | Personal income and outlays | Day after GDP-release | 1 month | monthly |
| Housing | Manufactured homes survey | 3rd to last business day of month | 2 months | monthly |
| Housing | New residential sales | Last week of month | 1 month | monthly |
| Surveys 1 | Chicago fed Midwest manufacturing index | Last week of month | 1-2 month | monthly |
| Surveys 1 | Consumer confidence index | Last Tuesday of month | Current month | monthly |

| | | | | |
|---|---|---|---|---|
| Surveys 1 | Michigan survey of consumers | Last Friday of month | Current month | monthly |
| Initial claims | Claims, unemployment insurance weekly claims reports | Last Thursday of month: monthly ave. | Current month | weekly |
| Interest rates | Freddie Mac primary mortgage survey | Last Monday of month; monthly ave. | Current month | weekly |
| Interest rates | Selected interest rates | Last day of month | Current month | daily |
| Financial | Foreign exchange rate | Last day of month: monthly ave. | Current month | daily |

### 1.4 Results

The nowcasting of current-quarter GDP growth is obtained as a projection on the common factors. The following graph shows the estimation result from the Naive estimation methods (namely the current quarterly GDP is the average of the last four quarterly GDP) and the Dynamic Factor Model which was used in Giannone and Rechilin and Small (2008)'s paper. And from the graph, we can see that the DFM methods estimation coordinate much better with the official GDP release.

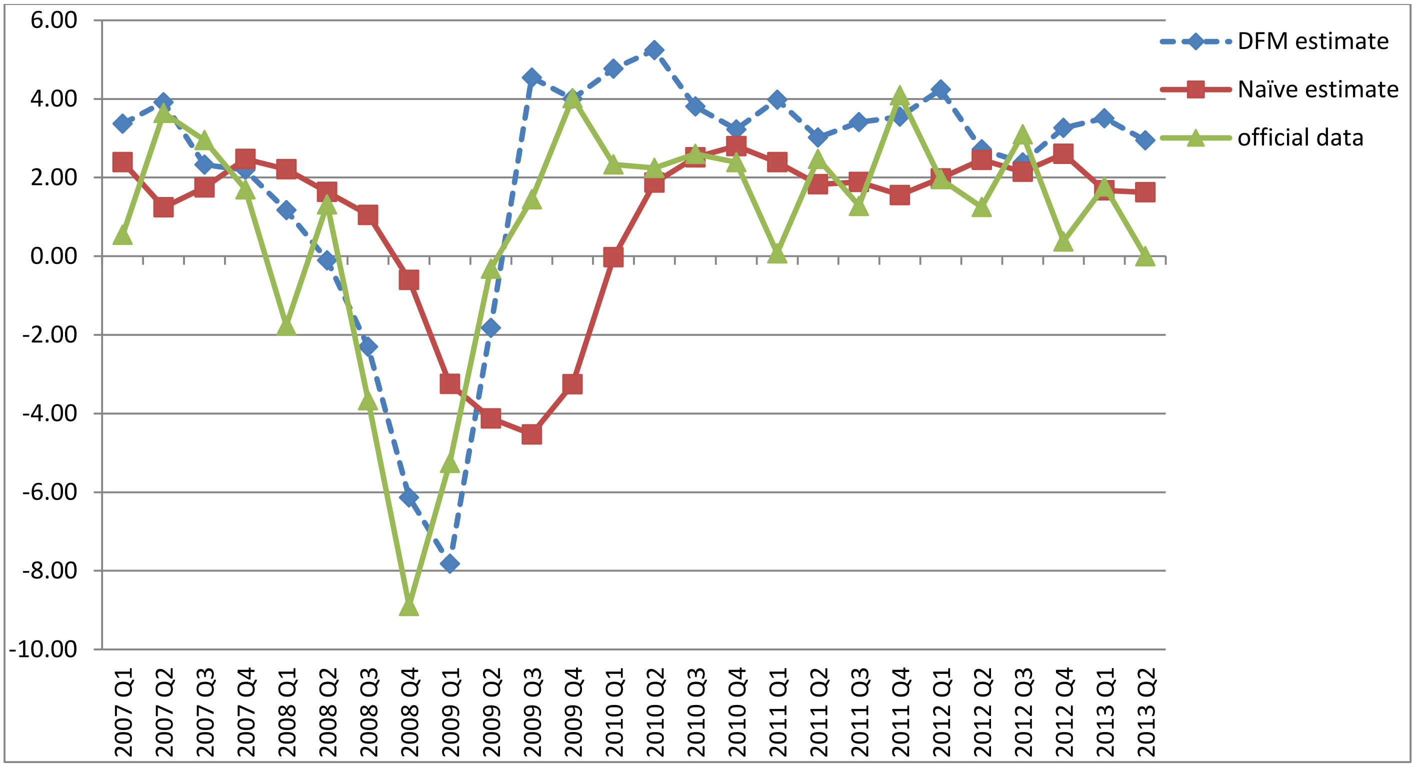


Figure 1: Comparison of Naïve Estimation and DFM estimation of US Quarterly GDP Growth Rate (2007 Q1 to 2013 Q2)

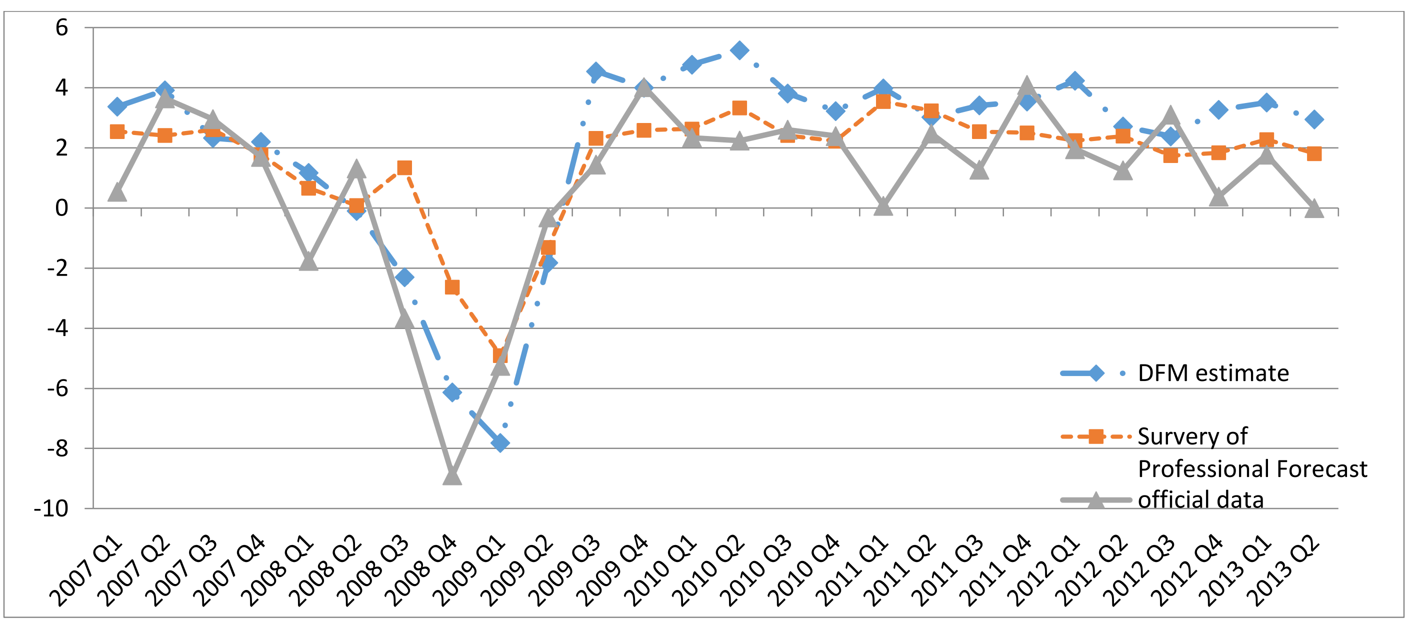


Figure 2: Realized US GDP Vs DFM estimation and SPF forecast (2007 Q1 to 2013 Q2)

Table 2: Nowcasts and forecasts of US GDP: out of sample evaluation

| Horizon | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| DFM | 4.155234622 | 5.924054526 | 10.6556682 | 16.38806623 |
| SPF | 4.191630676 | 5.383111081 | 8.246766694 | 10.30896 |
| Naïve | 10.0416887 | 9.129370093 | 8.311023 | 7.855832 |

Mean square forecast error of GDP growth for the Dynamic factor model (DFM) and Survey of Professional Forecasts (SPF), and Naïve forecast model of four quarters average for GDP. Evaluation period: 2007 Q1-2013 Q2.

From table 2, we can see that for nowcast, Factor Model works the best, then Survey of professional forecast works better than the Naïve forecast. As for the 1 quarter ahead forecast, SPF works the best, and for 2 and 3 quarters ahead, both SPF and Naïve forecasting model results in more accurate forecast than DFM.

**1.5 Conclusion**

This study evaluates the out-of-sample GDP nowcasting performance of 3 models; (1) dynamic factor model, (2) naïve estimation of four quarter average, and (3) the near-term forecast from Survey of Professional Forecasters (SPF) made by Federal Reserve Bank of Philadelphia.

From section 4, it is clear that the Factor Model performs best for the current quarter, or nowcasts best compared to the SPF and naïve forecast model. The MSFE for current quarter is approximate 4.15 from DFM result and 4.2 from SPF result, with Naïve estimation having the highest MSFE of 9.13.  For forecast, the SPF performs the best for 1 and 2 quarters ahead, with the MSFE 5.38 and 8.24 for 1 and 2 quarters respectively. For 3 quarters ahead forecast, the Naïve forecast model produces the most accurate result among these three models.

Overall, the results show consistence with the previous research in nowcasting, which is dynamic factor model can produce the most accurate nowcast for current quarter, with the horizons increase, its accuracy decreases. For the longer horizons, for 2 quarters and 3 quarters ahead forecast, SPF and Naïve forecast does better than DFM. The SPF has the same pattern as DFM, performs better with shorter horizons, and its forecast quality declines as the horizons increase. On the contrary, the Naïve forecast of four-quarter average performs better with horizon increases.

# Chapter 2: Divisia Monetary Aggregates and US GDP Nowcasting

## 2.1 Introduction

In the last three decades, a set of influential studies have placed short-term interest rate at the heart of monetary policy, for example, the New Keynesian model and central banks use interest rate as its main policy tools. Meanwhile these studies have downplayed the monetary aggregates' role. The new Keynesian model assumes the neutrality of the long term effect of the money supply on the output of the economy, therefore, the model excludes the money supply from equations. Taylor rules only assumes the relationship between interest rate, inflation and output gap and pays no attention to the money supply. This can be demonstrated by the US Federal Reserve's recent adoption of quantitative easing with its goal of affecting the supply of liquid assets, as a break from its standard practices.

Barnett (2008) writes “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.”

Central banks around the world normally publish their economies' monetary aggregates or money supply, such as M1, M2, M3, or broader monetary aggregates time series. We call these monetary aggregates simple-sum aggregates. These aggregates are simply the sum of the nominal value of the all monetary assets in circulation, ignoring the fact that different asset components yield different flow of liquidity services, bear different level interest rates, and thus different opportunity costs, or user costs when they were demanded for their monetary services. This simple sum monetary aggregation implicitly assumes that all the component assets are perfect substitutes for each other, which is unrealistic and theoretically flawed. The currency and demand deposits are of higher liquidity than the time deposits, saving accounts, or repurchase agreements etc., therefore, they are not perfect substitutes for each other and their user costs or opportunity costs vary accordingly.

Barnett (1978, 1980) was the first economist that pointed out the unrealistic assumption for the perfect substitution of the components of the monetary aggregates. Based on the microeconomic aggregation theory and index number theory, Barnett (1980) originated and developed the nonparametric and theoretically correct monetary aggregates. These aggregates were named after Divisia index which serves to apply different weights to different assets in accordance with the degree of their contribution to the flow of the monetary services in economy.

Many empirical studies such as Barnett and Serletis (2000), Barnett, Jones and Nesmith(2008), Istiak and Gogas(2012), Belongia and Ireland (2012) find that the Superlative (Divisia) monetary aggregates help in forecasting movements in the key macroeconomic variables, and outperform the simple-sum monetary aggregates. Barnett and Chauvet(2014) conclude that the Divisia monetary aggregates outperform the simple-sum aggregates in the US nominal GDP nowcating.

### 2.2 Literature on Nowcasting

Evaluating the current state of the economy is of great importance to policy makers, institutions, and economic agents. Decisions of central banks, fiscal authorities, private agents, and commercial institutions in real time are based on assessments of current and future economic conditions using incomplete data. It is crucial to have an accurate evaluation of the current state and future path of GDP to assess fiscal sustainability. Meanwhile most data are released with a lag and are subsequently revised, so both forecasting and assessing current-quarter conditions (nowcasting) are important tasks for central banks and other economic agents.

In 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 rate, such as naive model of four-quarter moving averaging of GDP, simple univariate autoregressive AR(1) model (Barhoumi et al., 2007) or naive constant model, the averaged bivariate vector autoregressive (VAR) models, and bridge equations (BEQ) (Arnostova, D. Havrlant, et al., 2011).

The bridge equation model combines qualitative judgments with "bridge equations" (Baffigi et al. 2004, Runstler and Sedillot 2003, Kitchen and Monoco 2003). Every monthly indicator is first forecasted based on AR (q) process, the lag length is selected by the criteria proposed by Bai and Ng (2002). Then the monthly series and its forecast are aggregated into quarterly frequency. The quarterly GDP data are paired with the quarterly indicators, at last, regress the GDP on the corresponding quarterly indicators through OLS model. The final GDP forecast is obtained as the arithmetic average of the forecasts from pairwise regression.

Any data may contain potential economic information that will affect current-quarter estimation, therefore, forecasters should use all the available information when the nowcasting is made. There are some challenges involved in using larger numbers of data series. The first 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 Domenico Giannone, Lucrezia Reichlin, David Small 2008, Matthew S. Yiu and Kenneth K. Chow 2011) which are released on different dates, with some data available in the current quarter and some data one or two months lag. The second challenge comes from designing a model that incorporates newly released data into nowcasting.

With new release of data, it is crucial to incorporate the additional information into the forecast model to produce a more accurate GDP growth data. The third challenge is to measure the impact of new release on the accuracy of nowcasting and "bridges" monthly data releases with the nowcasting of quarterly GDP. Factor model or dynamic factor model meets these challenges. It is defined in a parsimonious manner, which can be achieved by summarizing the information of the many data releases with a few common factors. The nowcasting is then defined as the projection of quarterly GDP on the common factors estimated from the panel of monthly data.

Factor model has been widely employed in forecasting and nowcasting GDP due to its ability to deal with the challenges involved with dealing with large unbalanced dataset. For a given size of the cross-section $n$, the literature has proposed frequency domain (Geweke, 1997; Sargent and Sims, 1977; Geweke and Singleton, 1980) and time Domain (Engle and Watson, 1981; Stock and Wastson, 1989; Quah and Sargent, 1992) methods. In econometric literature, factor analysis has been the main tool used in summarizing the large datasets. Stock and Watson (1999, 2002a, 2002b), Forni, Lippi, Hallin and Reichilin (2000, 2001, 2004, 2005), Doz, Giannone and Reichilin (2006, 2007) and Giannone, Reichilin and Small (2008) have carried out forecasting or nowcasting using factor model. Mariano and Murasawa (2003), Aruoba et al. (2009), and Boragan and Diebold (2010) incorporate data of different frequencies. Camacho and Perez-Quiros (2010) aim to estimate real GDP growth at the monthly frequency for the euro area by incorporating data on preliminary, advanced, and final GDP releases. Evans (2005) estimates real GDP at the daily frequency for the U.S. using different vintages of GDP but without using a dynamic factor model. William A. Barnett, in his paper with Marcelle Chauvet and Danilo Leiva-Leon (2015), incorporates Divisia monetary aggregates into the nominal GDP nowcasting process and explore the predictive ability of several univariate and multivariate models.

This chapter uses the dynamic factor model proposed by Giannone, Reichilin and Small (2008) to nowcast US real GDP growth rate, and compare its result with the naive four-quarter moving average of GDP,and Survey of Professional Forecast report. This paper is organized as follows: Section 3 describes the Divisia monetary aggregates index theory and derivation procedure, section 4 describes the dynamic factor model and competing models, section 5 describes the data, section 6 lists the results, and section 7 concludes.

### 2.3 Divisia Monetary Aggregates

Solid and sound economics decisions must be made based on an accurate assessment and understanding of the state of the economy. From the perspective of monetary aggregation, evaluating the economy by means of simple-sum aggregations, having no theoretical foundations whatsoever, can lead to erroneous judgments. As Barnett (2008) wrote "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."

By linking microeconomic theory and statistical index number theory, Barnett (1978, 1980) created Divisia monetary aggregates. Divisa monetary aggregates measure money supply in an economy, by assigning weights to different components (such as, currency, demand deposits, saving and time deposits, repurchasing agreement, etc) according to their separate proportion on the whole monetary expenditure within an aggregate, or their contributions to the monetary services flow within the aggregate they are part of. The index depends on the price, user cost or opportunity cost as well as quantities of the monetary assets. The price of a monetary asset is the interest forgone to consumer the services of the assets. The interest forgone depends upon the interest paid by the asset and the higher expected benchmark rate, defined to be the rate of the return on pure investment capital, providing no monetary services.

According to Barnett (2008), the theoretical foundations of the Divisia monetary index are laid upon the exact aggregates of microeconomic aggregation theory and index number theory. The former depends on unknown functions, such as utility, production, and cost functions, which must be econometrically estimated. Due to the dependency of unknown functions on estimator and specification, this way of aggregation is often viewed as a research tool rather than a practical data construction procedure. Statistical index-number theory, on the contrary, can directly compute indexes from quantity and price data without estimating unknown parameters. Statistical index numbers rely on no unknown parameters, but instead are calculated based on prices and quantities, such index numbers are Laspeyres, Paasche,Divisia, Fisher Ideal and Tornqvist Index. Diewert(1976) Defined class of second-order "superlative" index numbers, linked index number theory and aggregation theory. Barnett (1978 and 1980, 1987) derived the user cost formula for the demanded monetary services and the supplied monetary services. The index number theory is connected to the monetary economics, and the Divisia monetary index created by Barnett (1980) is a superlative index endowed with a solid theoretical foundation capable of tracing the exact theoretical monetary aggregate of aggregation theory.

The user cost of monetary assets is the interest users forgo to consume the services of the assets; it is the difference between the interest return from holding the asset and the higher expected benchmark rate, defined as the rate of the return on pure investment capital providing no monetary services. It is derived from a rigorous Fisherine intertemporal consumption expenditure allocation model, and the representative consumer aims to maximize intertemporal utility function with money included and weak separability among groups of consumption good. See Barnett (1978, 1980, 1987) and Anderson, Jones and Nesmith (1997) for the detailed model description and procedure of the user cost derivation.

The user cost of monetary assets is derived from the following economic decision problem: Let Vector $m_t^{'} = (m_{1t}, m_{2t}, ..., m_{nt})^{'}$ is the nominal balance of monetary assets during period $t$, the vector $\pi = (\pi_{1t}, \pi_{2t}, ..., \pi_{nt})^{'}$ is the vector of use-cost for monetary assets $m_t$, $y_t$ is the total expenditure budget on the monetary services during period $t$, and $p_t^*$ is the true cost-of-living index at time $t$, the real monetary assets quantities vector is $m_t^* = m_t / p_t^*$.

The optimal monetary portfolio allocation decision is:

$$\max u(m_t) \tag{2.1}$$

subject to $\pi_t^{'} m_t = y_t$

Here, $u$ is the decision maker's utility function, assumed to monotonically increasing and strictly concave. Barnett (1978, 1980) derived the nominal user cost of monetary asset $i$, having quantity $m_{it}$ during period during period $t$ is as following:

$$\pi_{it} = p_t^* \frac{R_t - r_{it}}{1 + R_t} \tag{2.2}$$

Where:

$R_t$ is the benchmark rate at time $t$

$r_{it}$ is the rate of return on asset $i$ during $t$

$p_t^*$ is the true cost-of-living index price at time $t$

The user cost of formula (2.2) measures the forgone interest rate or opportunity cost of holding a unit of monetary asset $i$.

Assume $m_t$ is the solution to decision problem (2.1) With the necessary assumption of $u$ to be weakly separable within the consumer's complete utility function over all goods and services, and the linearly homogeneity and monotonically increasing, the exact monetary aggregate of economic theory is the utility level associated with holding the portfolio, and therefore is the maximized value of the decision's objective function(Barnett, 2008).

$$M_t = u(m_t^*) \tag{2.3}$$

Equation (2.3) is the exact monetary aggregate function, however, it depends on the unknown utility function $u$. Statistical index-theory can tract the $M_t$ exactly, without estimating the unknown function.

In continuous time, the Divisia price and quantity index can be used to tract the aggregate, which solves the following dual differential equations for the price aggregate, $\Pi_t = \Pi(\pi_t)$, and the monetary aggregates, $M_t = M(m_t)$, respectively:

$$\frac{dlog\Pi_t}{dt} = \sum_i s_{it} \frac{dlog\pi_{it}}{dt} = \sum_i \frac{\pi_{it} m_{it}}{y_{it}} \frac{dlog\pi_{it}}{dt} \tag{2.4}$$

$$\frac{dlogM_t}{dt} = \sum_i s_{it} \frac{dlogm_{it}}{dt} = \sum_i \frac{\pi_{it} m_{it}}{y_{it}} \frac{dlogm_{it}}{dt} \tag{2.5}$$

Where $y_t = \pi_t^{'} m_t$ is the total expenditure on the whole portfolio's monetary assets, and

$s_{it} = \frac{\pi_{it} m_{it}}{y_t}$ is the $i^{th}$ asset's expenditure share during period $t$.

The user cost dual satisfies Fisher's factor reversal in continuous time:

$$\Pi_t M_t = \pi_t^{'} m_t \tag{2.6}$$

In the empirical research field, the discrete time representation of the Divisia index is needed, since economic data are measured in discrete time. Theil (see Toquivist 1936 and Theil 1967) approximation is a second order approximation to the continuous time Divisia index. At time $t$ , the discrete time representation of the Divisia price index $\Pi_t$ over the user-cost prices, and Divisia quantity index $M_t$, over the monetary components respectively are:

$$log\Pi_t - log\Pi_{t-1} = \sum_{i=1}^{N} S_{it}^{*}(log\pi_{it} - log\pi_{i,t-1}) \tag{2.7}$$

$$logM_t - logM_{t-1} = \sum_{i=1}^{N} S_{it}^{*}(logm_{it} - logm_{i,t-1}) \tag{2.8}$$

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 $s_{i,t-1}$.

Therefore, equations (2.7), (2.8) are the weighted average growth of the $\Pi_t$ and $M_t$ over the user-costs and monetary components respectively. From equation (2.8), the Divisia monetary index in level, $M_t$ is:

$$\frac{M_t}{M_{t-1}} = \prod_{i=1}^{n}\left(\frac{m_{it}}{m_{i,t-1}}\right)^{s_{it}^{*}} \tag{2.9}$$

The above equation (2.9) is known as the Tornqvist-Theil Divisia monetary quantity index. Dual to the aggregates quantity index, the aggregate user-cost index can be directly computed from equation (2.7), the Fisher's factor reversal test.

$$\Pi_t = \frac{\pi_t^{'} m_t}{M_t} = \frac{\sum_{i=1}^{N} \pi_{it} m_{it}}{M_t} \tag{2.10}$$

Barnett(1980) showed that the Divisia index growth rate, equation (19), is accurate to within three decimal places, with the weekly or monthly monetary data. Meanwhile, the price aggregates produced form equation (17) and the discrete Divisia price growth rate produced from equation (18) are not exactly the same price aggregate. However, the difference are third order and comparably small, typically is smaller than the round-off in the component data[1].

The US Divisia monetary aggregates are available on the Center for Financial Stability website in the CFS program Advances in Monetary and Financial Measurement (AMFM)[2] , they are freely available to the public. These Divisia monetary aggregates data on the CFS website are very comprehensive and date back to 1967 January, they range from the narrower level aggregates M1, M2, M2M, MZM, and All, to the broader ones, M3, M4, M4- are published on a monthly basis, normally on the 16th-22nd of the month, with one month lag. For the five narrow level monetary aggregates, St. Louis Federal Reserve also provides, which they call monetary services index (MSI). The differences between Divisia monetary aggregate from CFS and St. Louis Fed are in their benchmark rate their dual user-cost aggregates behave differently.

The following graphs show us the Simple-Sum M1, M2 and Divisia M1, M2.

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

[2] http://www.centerforfinancialstability.org/amfm_data.php

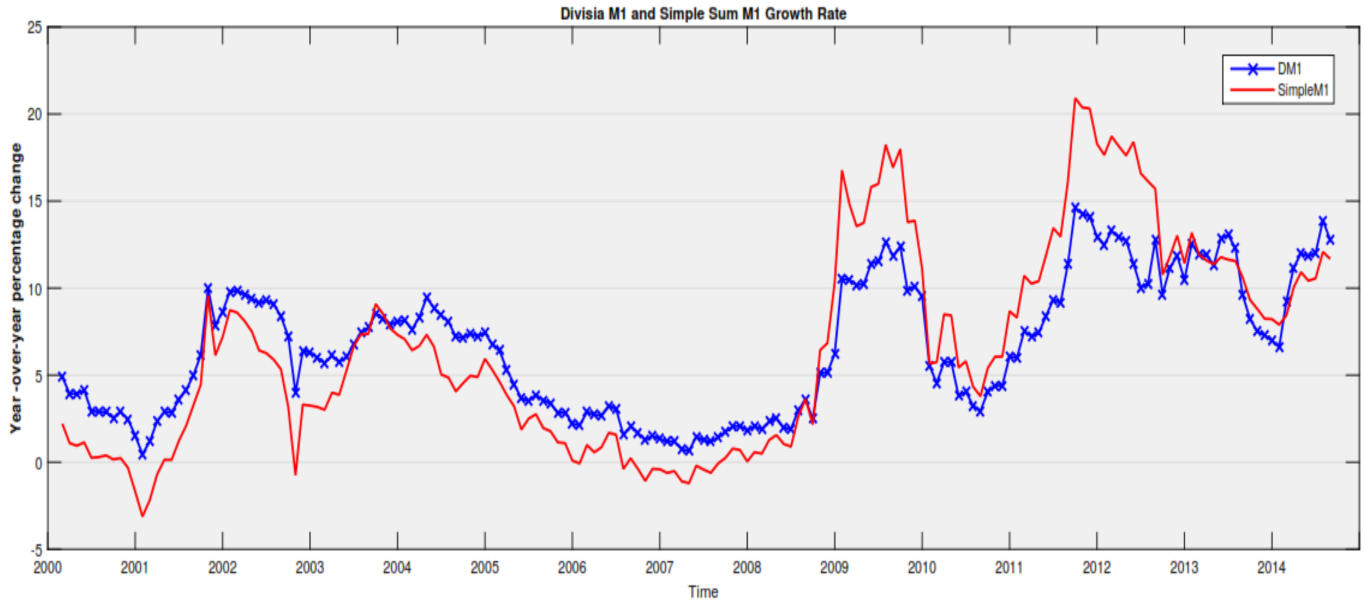


Figure 3 Simple Sum M1 and Divisia M1 Monthly Growth Rate

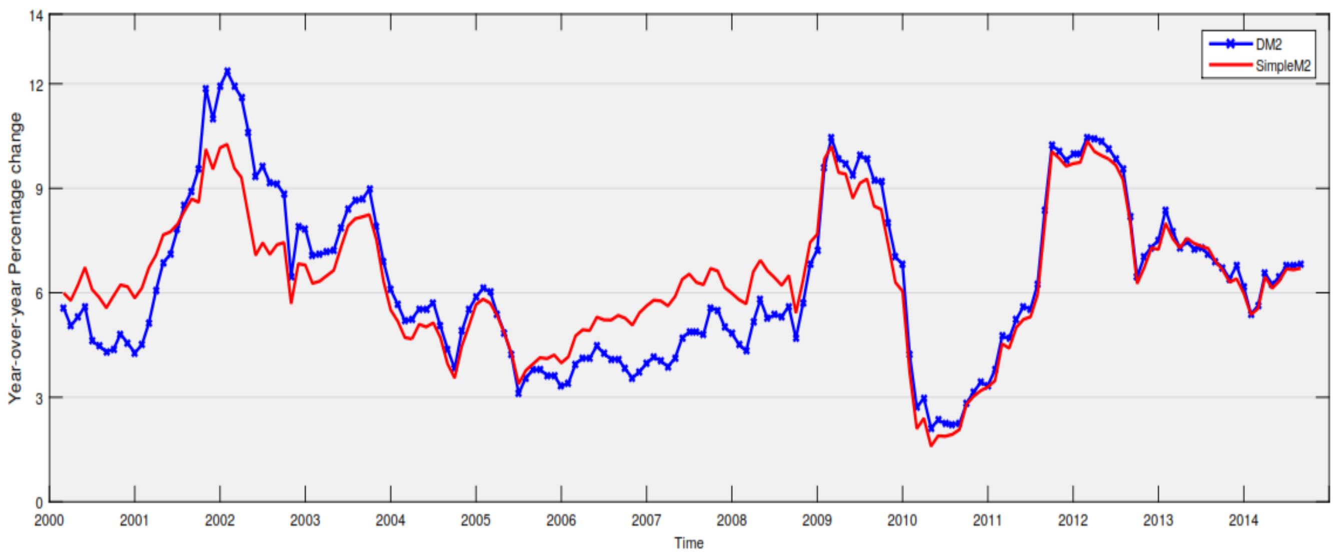


Figure 4: Simple Sum M2 and Divisia M2 Monthly Growth Rate

Figure 3, 4 are the comparison of simple sum monetary aggregates and Divisia monetary aggregates growth rate of the corresponding level of aggregates. Below, Figure 5 shows the growth rate of the broader Divisia monetary aggregates, M3, M4 and M4-. These aggregates are meant to substitute for the now discontinued Federal-Reserve simple-sum M3 and L aggregate, M4-exclude the T-bills.

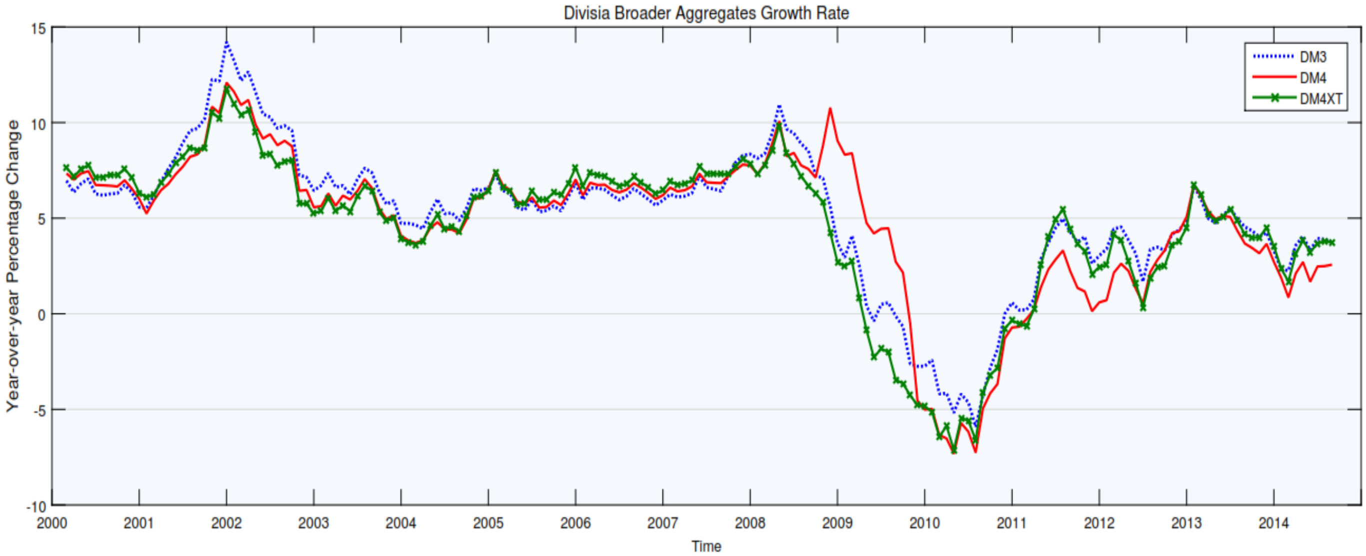


Figure 5: Divisia M3, M4 and M4XT Growth Rate

Figure 6, is the MSI M1 and Divisia M1 growth rates; from the graph, we can see they behave very similarly.

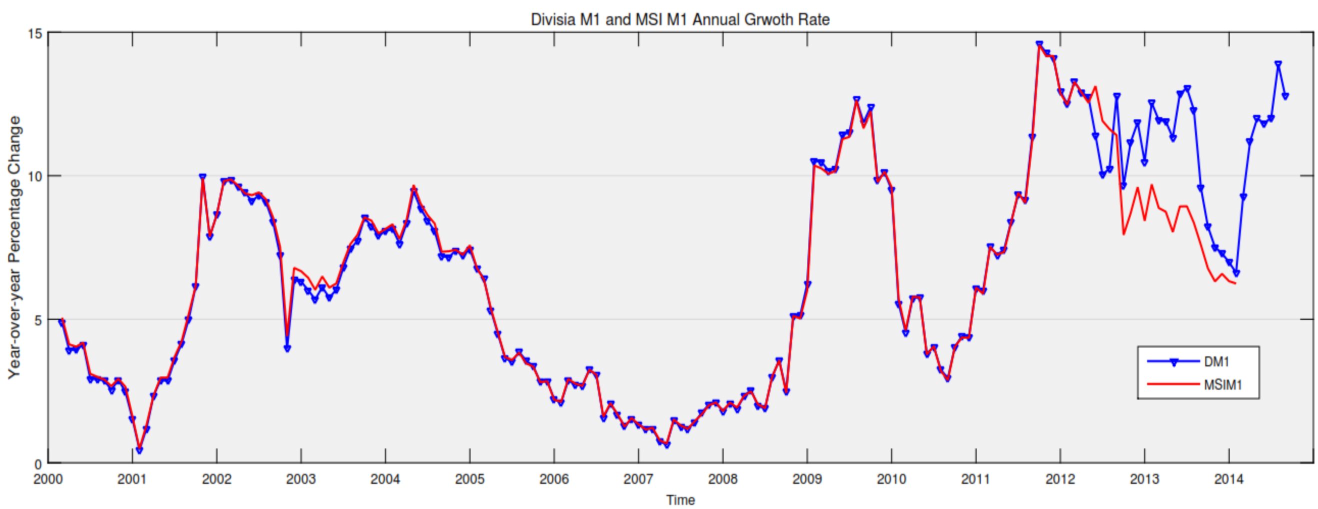


Figure 6: MSI M1 and, Divisia M1 Growth Rate

### 2.4 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:

$$\chi_{i,t} = \boldsymbol{\gamma}_i'\mathbf{F}_t + \epsilon_{i,t} \tag{2.11}$$

with $i = 1,...,n$ and $t = 1,...,T$, 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:

$$\mathbf{X}_t = \boldsymbol{\Gamma}\mathbf{F}_t + \mathbf{E}_t \tag{2.12}$$

where $\mathbf{X}_t = (\chi_{1t}, \chi_{2t}, ..., \chi_{nt})'$ and $\mathbf{E}_t = (\epsilon_{1t}, \epsilon_{2t}, ..., \epsilon_{nt})'$ are vectors and $\boldsymbol{\Gamma} = \left[\boldsymbol{\gamma}_1, ..., \boldsymbol{\gamma}_n\right]'$ is a matrix. The common component, $\zeta_{it}$, 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:

$$\mathbf{F}_t = \mathbf{A}\mathbf{F}_{t-1} + \mathbf{B}\mathbf{u}_t \tag{2.13}$$

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 outside the unit circle $\det(\mathbf{I}_r - \mathbf{A})$. The number of common factors, *r*, is set to be large relative to the number of macroeconomic shocks, *q*.

### 2.4.1 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,

$$\mathbf{S} = \frac{1}{T}\sum_{i=1}^{T}\mathbf{X}_t\mathbf{X}_t' \tag{2.14}$$

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

$$\tilde{\mathbf{F}}_\mathbf{t} = \mathbf{V}'\mathbf{X}_\mathbf{t} \tag{2.15}$$

With the common factors, $\tilde{\mathbf{F}}_t$, 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:

$$\hat{\mathbf{\Gamma}} = \sum_t \mathbf{X}_t \tilde{\mathbf{F}}_t^{'} (\tilde{\mathbf{F}}_t \tilde{\mathbf{F}}_t^{'})^{-1} = \mathbf{V} \quad (2.16)$$

$$\hat{\mathbf{\Pi}} = diag(\mathbf{S} - \mathbf{VDV}) \quad (2.17)$$

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

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.

### 2.4.2 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:

$$V(r, \mathbf{F}^r) + rg(n, T) \tag{2.18}$$

where $V(r, \mathbf{F}^r)$ 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).

**2.5 Data**

This paper's dataset consists of 193 macroeconomic series for US economy, including real variables such as (industrial production and employment), financial variables, prices, wages, money and credit aggregates, surveys from other sources. The span of the data is from January 1982 to July 2014. The data from 2007 onwards is reserved for the evaluation of out-of-sample nowcasts.

The dataset is described detailed in appendix and most of the series are monthly, except real GDP growth rate are quarterly. To make it simple, the quarterly data is repeated three times in the quarter to make it monthly. All the variables are transformed to be stationary and insure that the transformed variables correspond to a quarterly quantity when observed at the end of the quarter. The details on the data transformations for individual series are reported in Appendix.

Based on the release date, the data panel is aggregated into 15 blocks, namely interest rates, financial, housing, surveys 1, surveys 2, PPI, CPI, GDP and Income, Initial claims industrial Production, Mixed 1, Mixed 2, mixed 3, labor and wages, money and credit. Generally, surveys have very short publishing lags and are often forecasts for future months or quarters; GDP has the longest delay, about 6 weeks after the previous quarter ends. Industrial production, prices, and other series are intermediate cases.

As in paper D. Giannone et al (2008), the first block is called "Survey 2", consists of Chicago Report of the National Association of Purchasing Management, which is released on the first business day of the month. The next block "Mixed 3" includes some miscellaneous releases, such as, construction spending and the advanced report on durable goods manufacturers. Money and Credit follows the "Mixed 3", and so on, see the appendix[3] for the detailed description.

For some daily financial variables, because most of the series of the panel are monthly, I take the monthly average of these variables and assume that they are available on the last day of the month, which will simplify the block structure in the model but possibly understate the importance of the financial variables.

The Divisia monetary aggregates are available on the Center for Financial Stability (CFS) website, within the CFS program Advances in Monetary and Financial Measurement (AMFM). They are available on monthly basis, and are published between 16th and 22nd of the month with a one month lag. Meanwhile, St. Louis Fed Reserve also provides Divisia monetary aggregates,

[3] The two tables of data description in appendix are similar to the one in Giannone Reichilin, Small 2008 paper.

which they call monetary services index (MSI). For the first five narrower level of monetary aggregates, M1, M2, M2M, MZM, and ALL, they are both available on CFS website and the St. Louis Federal Reserve FRED program, and they are composed of currency, deposit accounts, and money market accounts. The liquid asset extensions to M3, M4-, and M4 resemble in spirit the now discontinued M3 and L aggregates, including repurchase agreements, large denomination time deposits, commercial paper, and Treasury bills. See Barnett, Mattson, Liu(2013)[4] for the detailed description of the monetary components and their data resources. The St. Louis Federal Reserve initiated and maintains the five narrow Divisia monetary aggregates for the US and calls them MSI[5] in accordance with the theory and formulas derived by Barnett (1980).

For the broader monetary aggregates, since the Federal Reserve no longer provides its former broad aggregates, M3 and L, the CFS is now maintaining the broad aggregates, Divisia M3 and Divisia M4[6] where M4 is similar to the Fed's former broadest aggregate, L. The primary distinction between the CFS's and St. Louis Fed's narrow Divisia aggregates is the measurement of the rate of return on capital (the benchmark rate), used within the Divisia formula. The CFS's and the St. Louis Fed's narrow Divisia quantity aggregates can be expected usually to behave similarly, though their dual user-cost price aggregates behave differently.

**2.6 Results**

The nowcasting and forecast performance of all the models are demonstrated by the following graphs.

The following is a graph of the GDP quarterly growth rate.

[4] https://server1.tepper.cmu.edu/barnett/divisia_data_sources.pdf
[5] http://research.stlouisfed.org/msi
[6] http://www.centerforfinancialstability.org/amfm_data.php

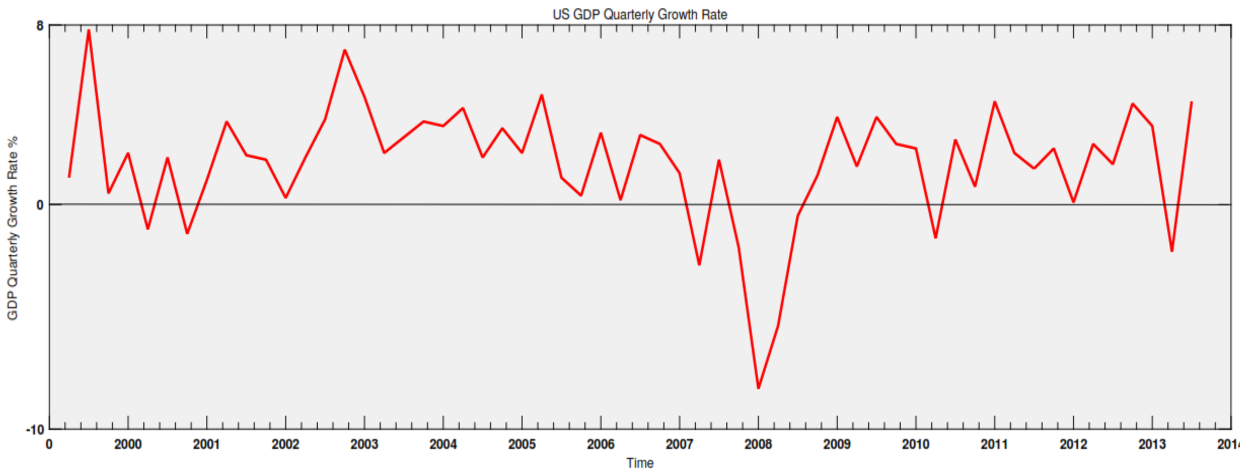


Figure 7: US GDP Growth Rate

In Appendix, the 5 tables are the detailed forecasting results for dynamic factor models with only monetary aggregates, the Naive model, and SPF[7].Please see the appendix for the detailed data, the following table only showed the nowcast result of DFM with only Divisia monetary aggregates.

Table 3: Nowcasting Result of Dynamic Factor Model with only Divisia Monetary Aggregates Index

| Quarters | Nowcasting | 1 Quarter Ahead | 2 Quarter Ahead | 3 Quarter Ahead | 4 Quarter Ahead |
|---|---|---|---|---|---|
| 2007:Q1 | 2.4772 | 2.9963 | 2.6364 | 3.3372 | 3.311 |
| 2007:Q2 | 3.4474 | 2.8523 | 3.386 | 2.8637 | 3.3279 |
| 2007:Q3 | 3.4714 | 3.3675 | 3.2285 | 3.6512 | 3.14 |
| 2007:Q4 | 2.3529 | 3.5669 | 3.3213 | 3.5227 | 3.7793 |
| 2008:Q1 | 1.4595 | 2.7666 | 3.5921 | 3.3073 | 3.6981 |
| 2008:Q2 | 0.9756 | 1.5846 | 3.1731 | 3.5657 | 3.3175 |
| 2008:Q3 | 0.9889 | 1.8977 | 2.0336 | 3.4871 | 3.511 |
| 2008:Q4 | -1.6325 | 1.7371 | 2.793 | 2.6041 | 3.6726 |
| 2009:Q1 | -6.6236 | 0.1149 | 2.5357 | 3.4873 | 3.1378 |
| 2009:Q2 | -2.3623 | -2.6612 | 1.8211 | 3.2128 | 3.9077 |
| 2009:Q3 | 5.5295 | -0.2987 | 1.6326 | 3.2286 | 3.678 |
| 2009:Q4 | 4.8647 | 7.6319 | 1.7811 | 5.4074 | 4.2068 |
| 2010:Q1 | 4.6012 | 6.6279 | 8.4556 | 3.5842 | 8.0666 |
| 2010:Q2 | 3.3667 | 5.4764 | 7.5023 | 8.1612 | 4.9206 |
| 2010:Q3 | 3.1066 | 3.7192 | 5.8975 | 7.4517 | 7.0617 |

[7] http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters

| | | | | | |
|---|---|---|---|---|---|
| 2010:Q4 | 3.1771 | 2.8777 | 3.9382 | 5.8807 | 6.6102 |
| 2011:Q1 | 4.8278 | 3.1211 | 2.7077 | 4.0284 | 5.4957 |
| 2011:Q2 | 4.6121 | 4.9608 | 3.0647 | 2.6003 | 4.0056 |
| 2011:Q3 | 1.8761 | 4.5524 | 4.8696 | 3.0134 | 2.5527 |
| 2011:Q4 | 2.9758 | 1.4312 | 4.3444 | 4.6108 | 2.971 |
| 2012:Q1 | 3.533 | 2.848 | 1.2396 | 4.0401 | 4.2459 |
| 2012:Q2 | 3.3553 | 3.3263 | 2.7561 | 1.2669 | 3.69 |
| 2012:Q3 | 2.0051 | 2.9851 | 3.1237 | 2.702 | 1.4634 |
| 2012:Q4 | 3.4878 | 1.7879 | 2.6895 | 2.9456 | 2.6834 |
| 2013:Q1 | 3.1805 | 3.4813 | 1.7366 | 2.4831 | 2.8055 |
| 2013:Q2 | 3.3735 | 3.005 | 3.4185 | 1.8208 | 2.4831 |
| 2013:Q3 | 4.3057 | 2.8805 | 2.8565 | 3.318 | 2.0025 |
| 2013:Q4 | 3.6927 | 4.4154 | 2.4795 | 2.7446 | 3.1985 |
| 2014:Q1 | 2.9378 | 3.71 | 4.355 | 2.1885 | 2.6731 |
| 2014:Q2 | 3.5522 | 2.6647 | 3.6475 | 4.1741 | 2.0127 |
| 2014:Q3 | 4.8322 | 3.4548 | 2.4806 | 3.5318 | 3.9206 |
| 2014:Q4 | NA | 4.7088 | 3.3245 | 2.3815 | 3.3874 |
| 2015:Q1 | NA | NA | 4.4409 | 3.1816 | 2.3559 |
| 2015:Q2 | NA | NA | NA | 4.0886 | 3.0426 |
| 2015:Q3 | NA | NA | NA | NA | 3.7055 |

The following figure is the nowcast results from DFM with Divisia aggregates and SPF report, compared to the official real GDP growth rate from 2006:Q1-2014:Q3.

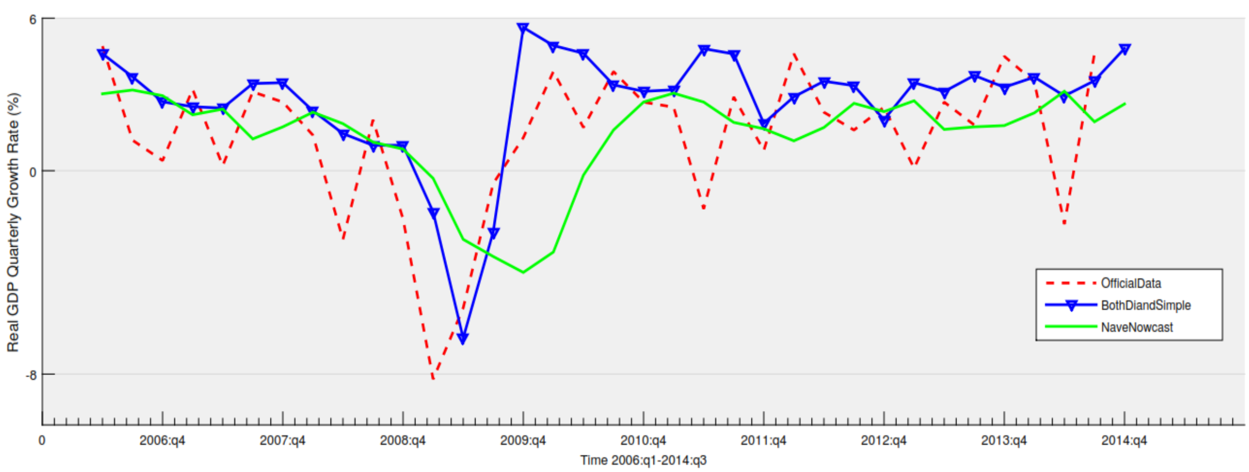


Figure 8: Comparison of US GDP Nowcasting Results from DFM and Naive Models, to Official GDP Data

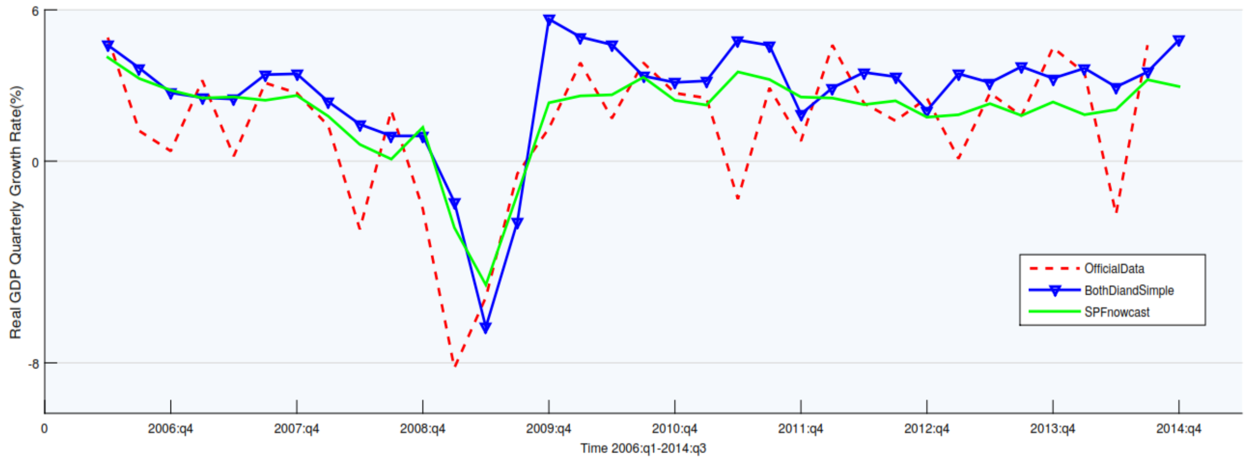


Figure 9: Comparison of US GDP Nowcasting Results of DFM and SPF, Official GDP Data

Figure 8, 9 show us that the DFM models nowcast results move more closely to the official GDP growth rate than the SPF result and the Naive model nowcast result. Both the SPF and Naive model results fluctuate less and move more smoothly, which is different from the highly fluctuated official real GDP data.

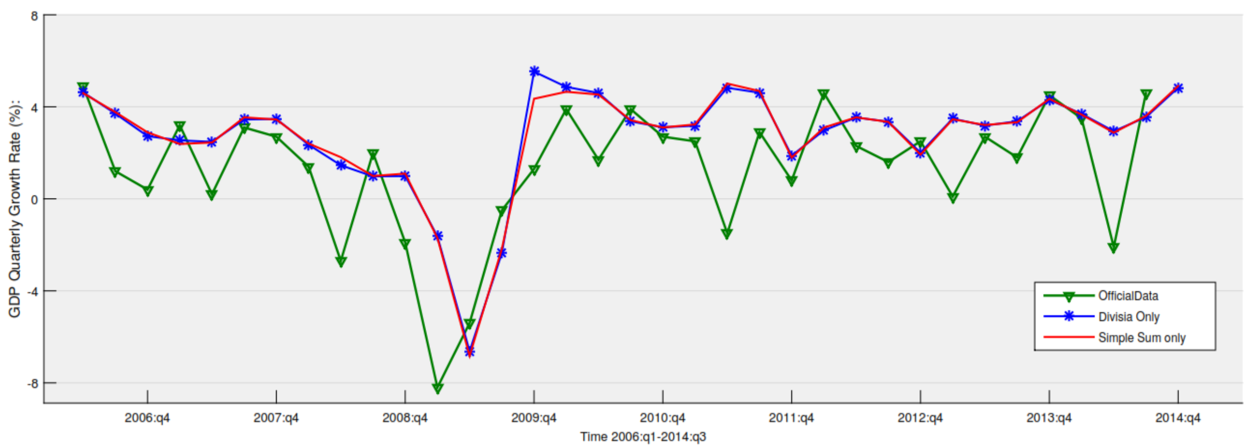


Figure 10: With Divisia and Without Divisia Nowcasting Results from DFM

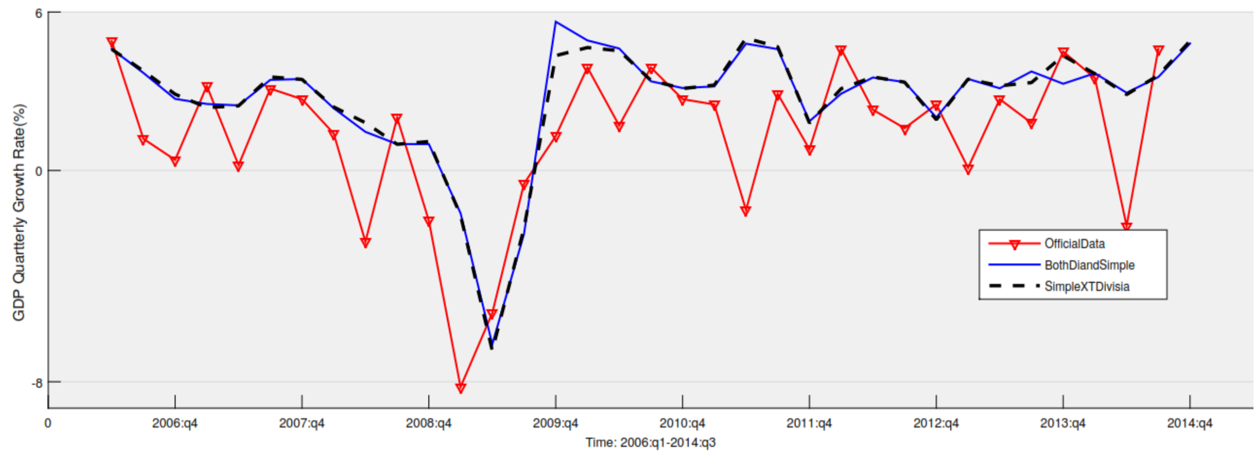


Figure 11: The US GDP Nowcasting Results of DFM with both Divisia and Simple-Sum Monetary aggregates, and results of with only Simple Sum Monetary Aggregates

Figure 10, 11 both show us that DFM with both the Divisia and simple sum monetary aggregates traces the official GDP data more closely than that of the simple sum monetary aggregates including factor model.

Table 4: The Mean Squared Forecast Errors From all the Models at five horizons

| **Horizon** | **Nowcasting** | **1 Quarter** | **2Quarter** | **3 Quarter** | **4 Quarter** |
|---|---|---|---|---|---|
| DFM With Divisia | 2.3342 | 3.088 | 2.9303 | 3.572 | 3.6836 |
| DFM With Both | 2.4496 | 3.5134 | 4.024 | 4.1762 | 4.2526 |
| DFM with Simple-Sum | 2.5671 | 3.8868 | 3.4057 | 3.5569 | 3.6163 |
| SPF | 2.6795 | 2.5577 | 1.9823 | 2.4156 | 2.7462 |
| Benchmark(AR) | 4.0257 | 4.5375 | 4.3773 | 3.8877 | 3.8052 |
| Naive | 8.9235 | 4.0645 | 3.3867 | 4.4036 | 7.7659 |

Table 4 is the measurement of the accuracy of the six models across the five horizons of nowcasting, 1,2,3,4 quarters ahead forecast. To measure the accuracy of the forecasting models, we take the usual way of calculating of their Mean Squared forecast errors (MSFE). To make the MSFE reflect the accuracy more, I get rid of the MSFE outliers, by doing this, the results will be less affected by the extreme cases, and can reflect the true forecasting power more comprehensively.

Table 5: The percentage (%) of gained accuracy by including Divisia into DFM

| Model compared to | DFM with Simple | SPF | Benchmark | Naïve |
|---|---|---|---|---|
| DFM with Divisia | 9.10% | 12.90% | 42% | 73.80% |
| DFM BOTH | 4.60% | 8.60% | 39.20% | 72.50% |

Table 5 is the percentage of gained accuracy for nowcasting by including Divisia monetary aggregates into the model upon the models that do not contain Divisia monetary aggregates, such as SPF and benchmark model and Naive model.

The table 5 demonstrate us that DFM with Divisia improves the nowcasting result by 9.1 % upon the DFM with only simple sum monetary aggregates. And the DFM with both the Divisia and simple sum monetary aggregates improved 4.6% in nowcasting accuracy compared to that of DFM with simple sum aggregates.

**2.7 Conclusions**

From the Above results, we can conclude that the Dynamic Factor Model works the best for Nowcasting performance. Among the DFM, the nowcasting results with Divisia Monetary aggregates included works the best; the lowest Mean Squared Forecast Error of being 2.3342, then the DFM with both the simple sum and the Divisia monetary aggregates. The Survey of Professional Forecast (SPF) from the Federal Reserve Bank of Philadelphia's Real-Time Research Data program, with an MSFE of 2.6795.SPF, is followed by the Benchmark model of AR, with MSFE of 4.0257. The Naive model of four quarter moving average performs the worst for the nowcasting.

Among the different models, for the 1st, 2nd, and 3rd quarter forecasts, the SPF outperforms the other models in this paper. Then the DFM with only Divisia Monetary aggregates follows, then the Benchmark model, and lastly the Naive model, being the least accurate models.

Across the different horizons, the DFM models' nowcasting power outperforms its forecasting power, which gradually decreases with the increase of horizon. The SPF model works the best for the 3 quarters ahead forecast, then forecasting power declines over the horizons. The benchmark model's forecast power is more consistent, and its forecasting power becomes better when the horizons increase, which is the opposite of the SPF. Naive model's forecasting power is the highest at the 2 quarter ahead, with nowcast and 4 quarters ahead forecast being the least accurate horizon.

Most importantly, the DFM model's nowcasting accuracy is consistent with the data construction. DFM model with the Divisia monetary aggregates only outperforms any other factor models with the simple sum monetary aggregates, which means that simple sum aggregates can hurt the nowcast power of DFM with its not so theoretically sound foundations, and can sometimes be misleading to agencies who rely on it for decisions making.

Overall, the DFM model nowcasts the strongest predictor, and the factor models with the Divisia monetary index works the best. DFM with Divisia monetary aggregates only and with both Divisia and simple sum aggregates improve the nowcast results of GDP by 9.1% and 4.6 % respectively compared to the factor model with only simple sum aggregates. So we can conclude that Divisia monetary aggregates contains more information than the simple sum monetary aggregates and can track the money supply better. The SPF works better in the longer horizons, and the Naive model is the least accurate among all these models.

## Chapter 3: Chinese Divisia Monetary Index and GDP Nowcasting

### 3.1 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[8]. 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.[9] 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.[10] Barnett (1978, 1980)

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[8] 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.

[9] 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."

[10] 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."

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.

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.

### 3.2 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

$$\pi_{it} = p_t^* \frac{R_t - r_{it}}{1 + R_t} \tag{3.1}$$

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, $\pi_{it}$, for $i = 1,\ldots,N$.

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

$$\frac{d\log \Pi_t}{dt} = \sum_i s_{it}\frac{d\log \pi_{it}}{dt} = \sum_i \frac{\pi_{it}m_{it}}{y_t}\frac{d\log \pi_{it}}{dt} \tag{3.2}$$

$$\frac{d\log M_t}{dt} = \sum_i s_{it}\frac{d\log m_{it}}{dt} = \sum_i \frac{\pi_{it}m_{it}}{y_t}\frac{d\log m_{it}}{dt} \tag{3.3}$$

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.

$$\Pi_t M_t = \boldsymbol{\pi}_t^{'}\mathbf{m}_t \tag{3.4}$$

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

$$\log \Pi_t - \log \Pi_{t-1} = \sum_{i=1}^{N} s_{it}^{*}(\log \pi_{it} - \log \pi_{i,t-1}) \tag{3.5}$$

$$\log M_t - \log M_{t-1} = \sum_{i=1}^{N} s_{it}^{*}(\log m_{it} - \log m_{i,t-1}) \tag{3.6}$$

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 (3.5) and (3.6) can be interpreted as share-weighted averages of user-cost and quantity growth rates respectively. From equation (3.6), the Tornqvist-Theil discrete time Divisia monetary index, $M_t$ , can alternatively be written as:

$$\frac{M_t}{M_{t-1}} = \prod_{i=1}^{n} \left(\frac{m_{it}}{m_{i,t-1}}\right)^{s_{it}^{*}} \tag{3.7}$$

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

$$\Pi_t = \frac{\pi_t^{'} m_t}{M_t} = \frac{\sum_{i=1}^{N} \pi_{it} m_{it}}{M_t} \tag{3.8}$$

The price aggregates produced from equation (3.5) and (3.8) 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.[11]

### 3.3 The Chinese Divisia Index

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

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

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.[12]

Limited initial work has appeared on the construction of Divisia monetary aggregates for China.[13] 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.

**3.3.1 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)[14], (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

[12] 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).

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

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

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 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.[15]

### 3.3.2 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

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

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.[16] Hence, our benchmark rate always exceeds the rates of return on monetary assets.

### 3.3.3 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.

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 12-14 provide levels of the Chinese Divisia monetary aggregates, M0, M1, M2, and the corresponding simple sum aggregates. Figures 15, 16, and 17 display growth rate paths.

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

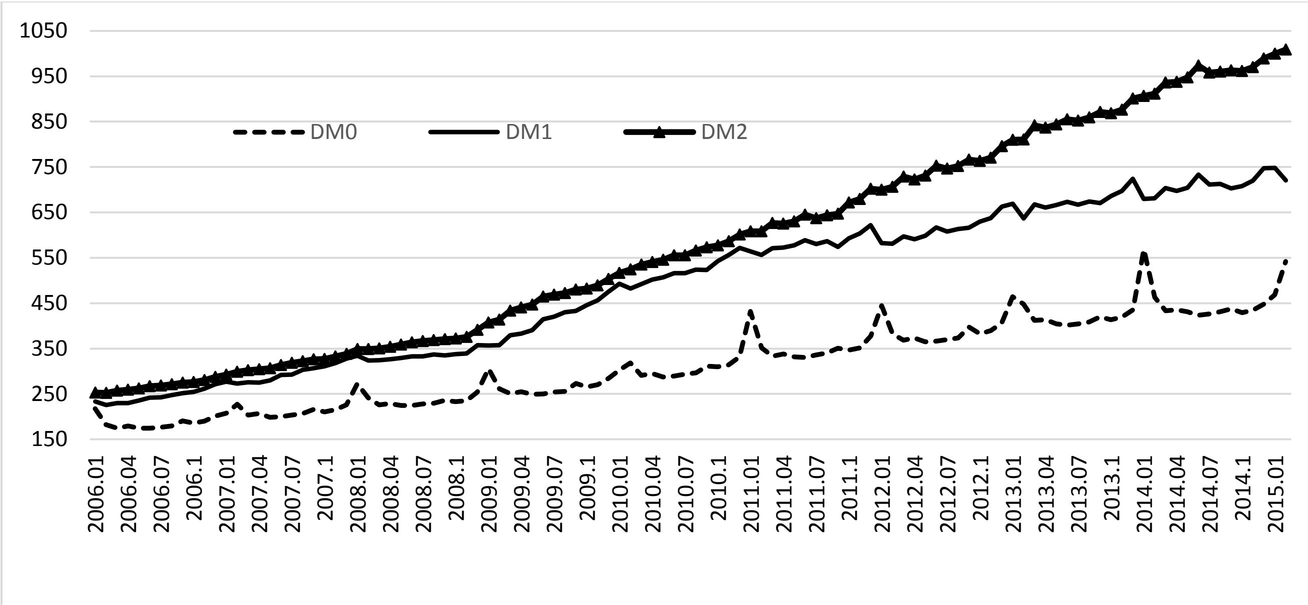


Figure 12: Chinese Divisia Index Level for M0, M1, M2 with December 1999 Set at 100.

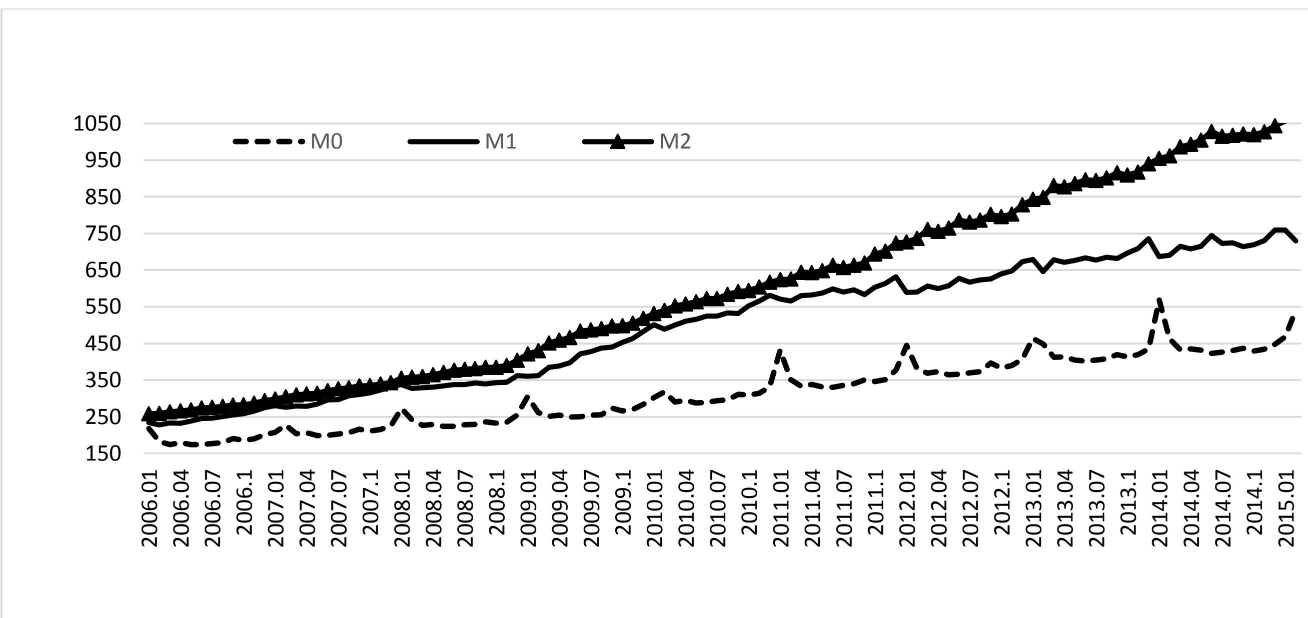


Figure 13: Chinese Simple Sum M0, M1, M2 Level with December 1999 Set at 100.

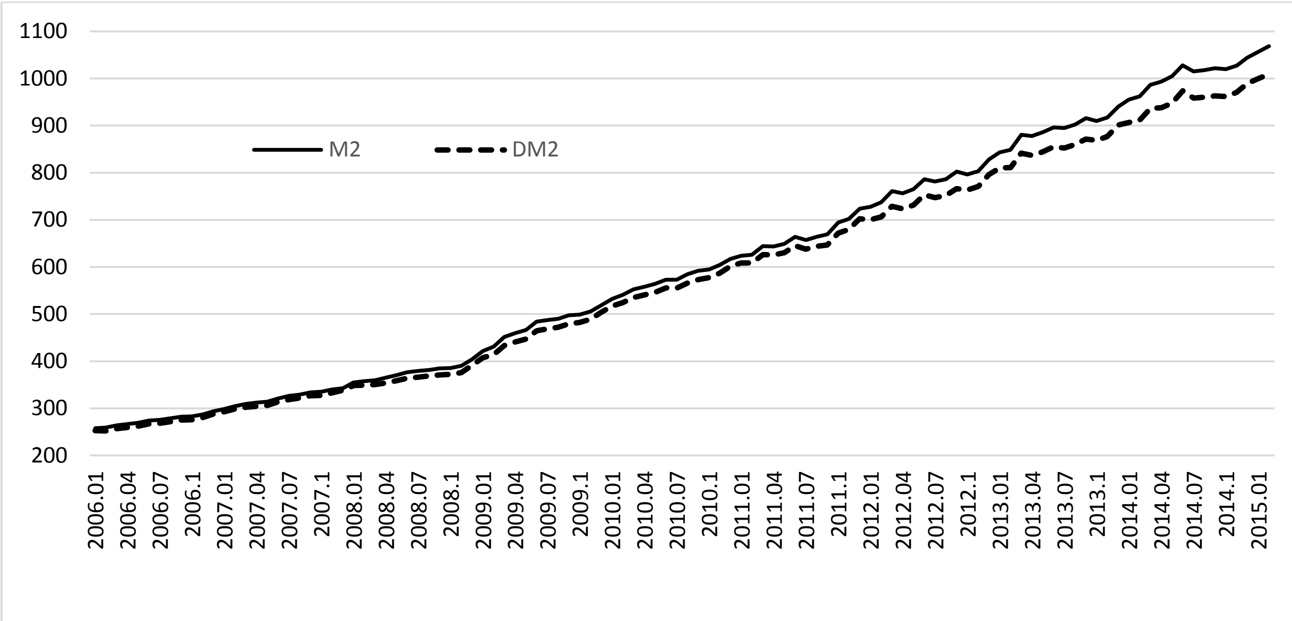


Figure 14: Chinese Divisia M2 and Simple Sum M2 with December 1999 Set at 100.

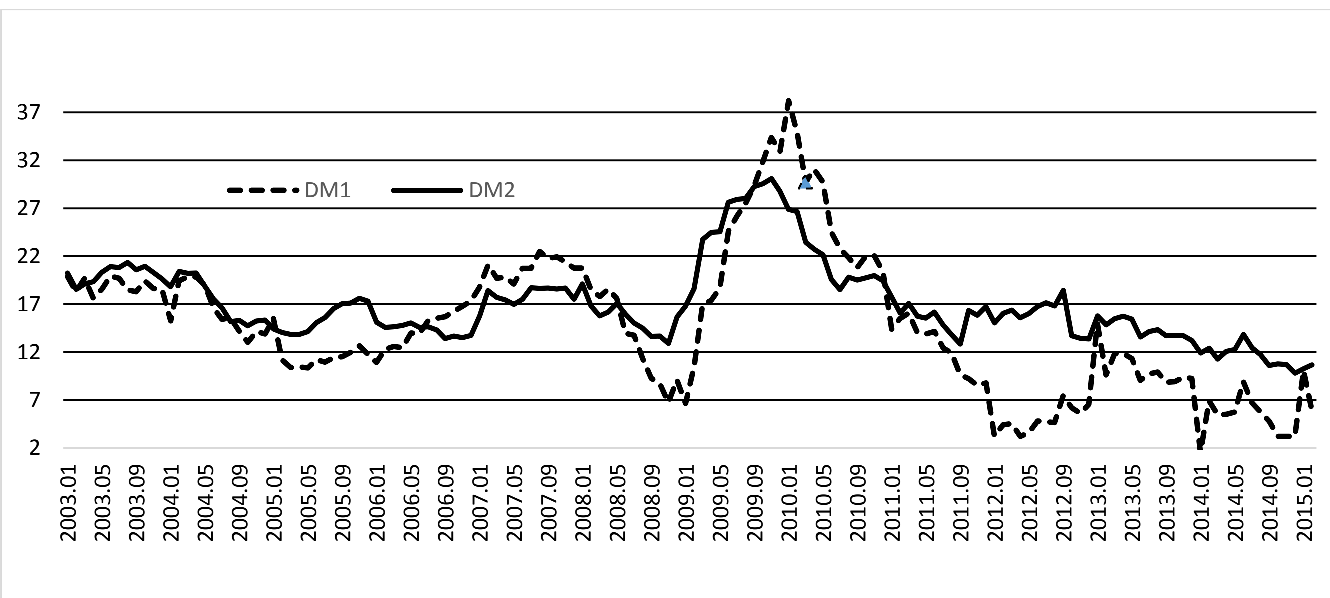


Figure 15: Chinese Divisia M1, M2 Monthly Year-Over-Year Growth Rate (%) from January 2003 to February 2015

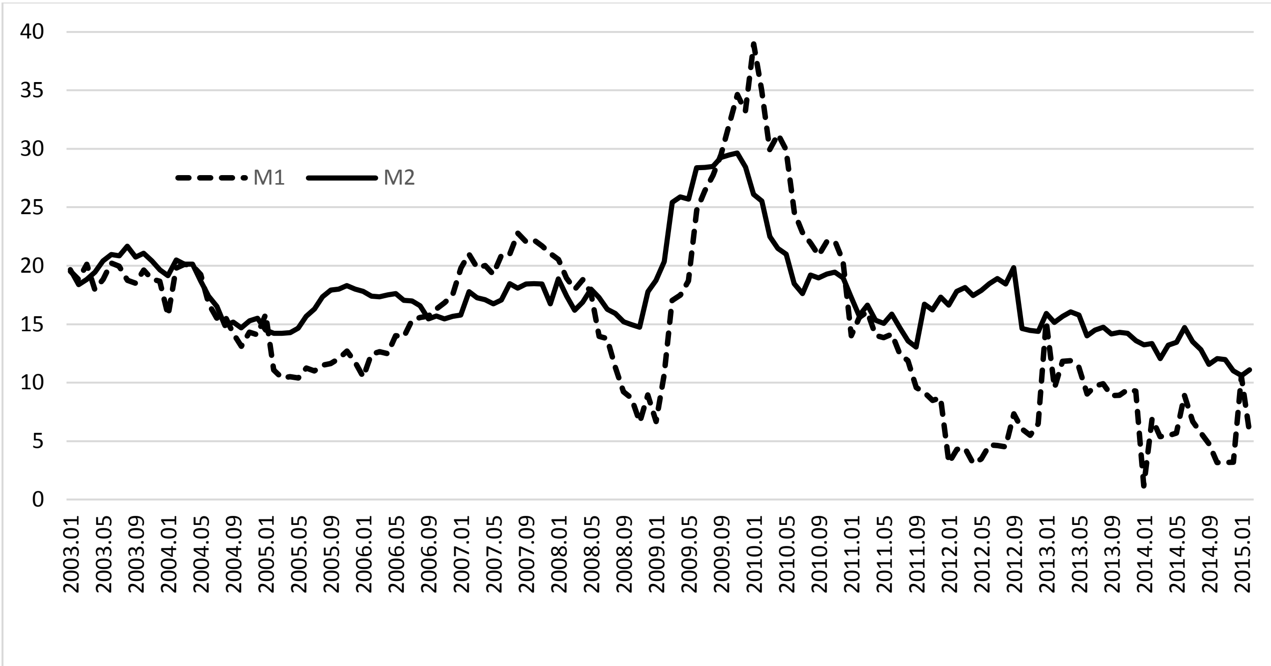


Figure 16: Chinese Simple Sum Monetary Aggregates M1, M2 Monthly Year-Over-Year Growth Rates (%) from January 2003 to February 2015

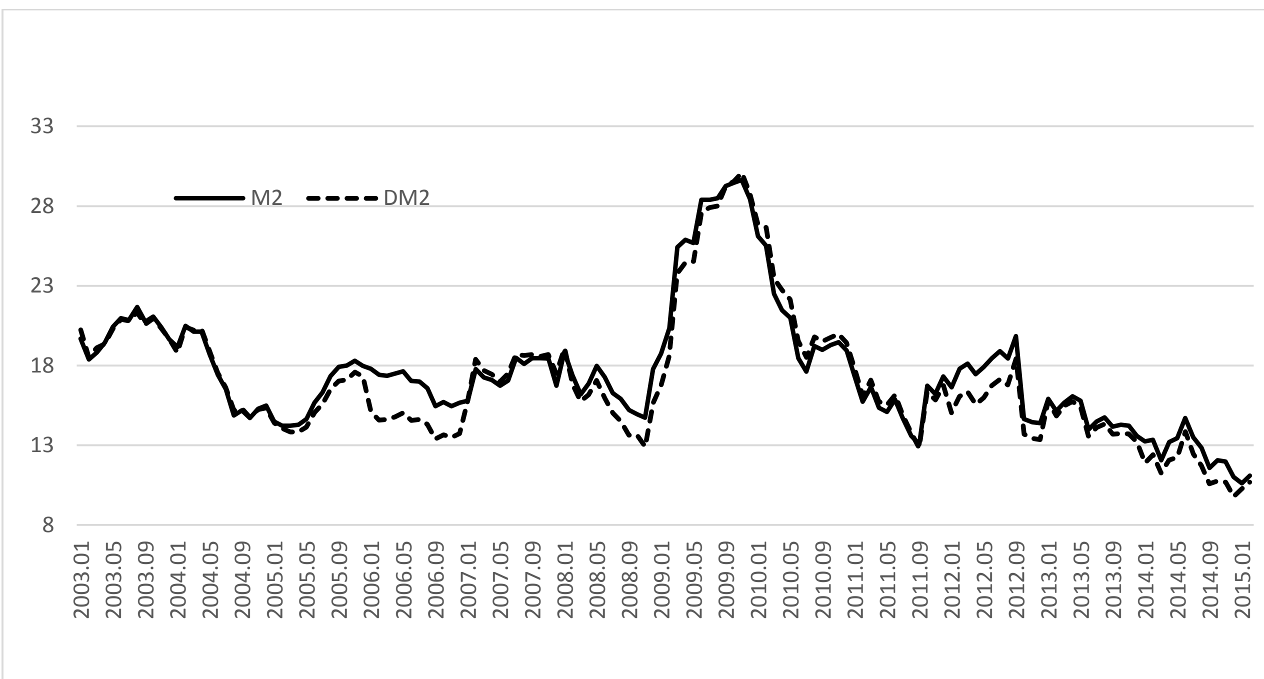


Figure 17: Chinese Divisia M2 and Simple Sum M2 Monthly Year-Over-Year Growth Rates (%) from January 2003 to February 2015

Figures 15, 16, and 17 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 18 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.

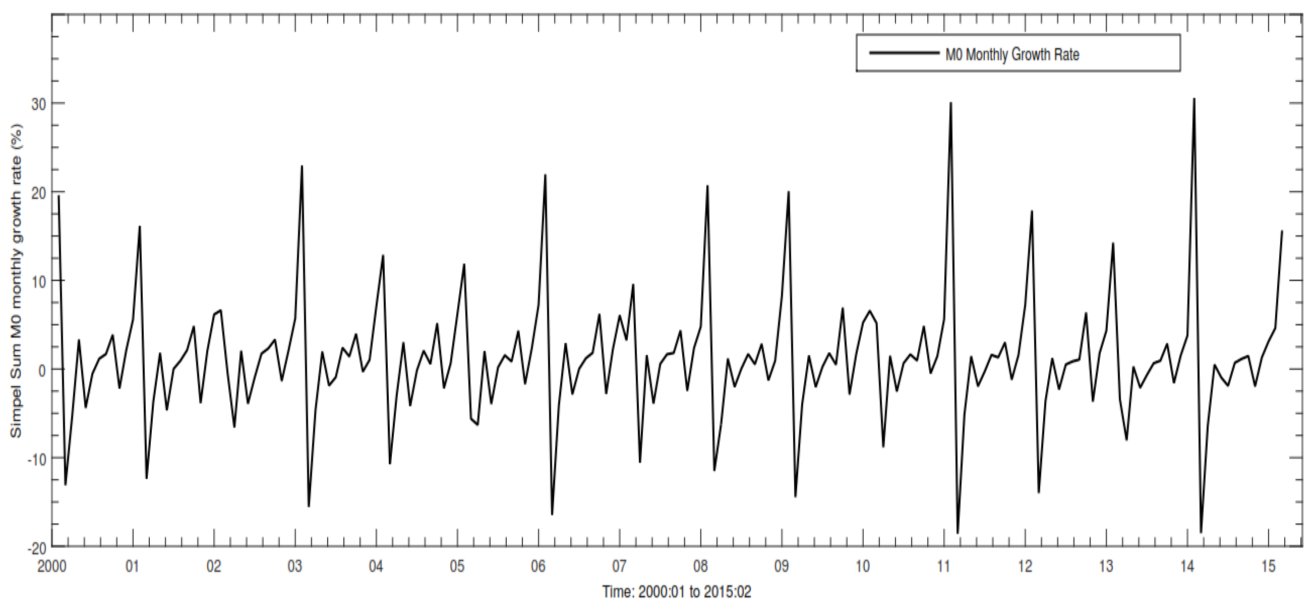


Figure 18: Chinese Simple Sum M0 Monthly Growth Rate (%)

Figures 19, 20, and 21 depict the broader indexes, Divisia M3 and M4, both in levels and annual growth rates.

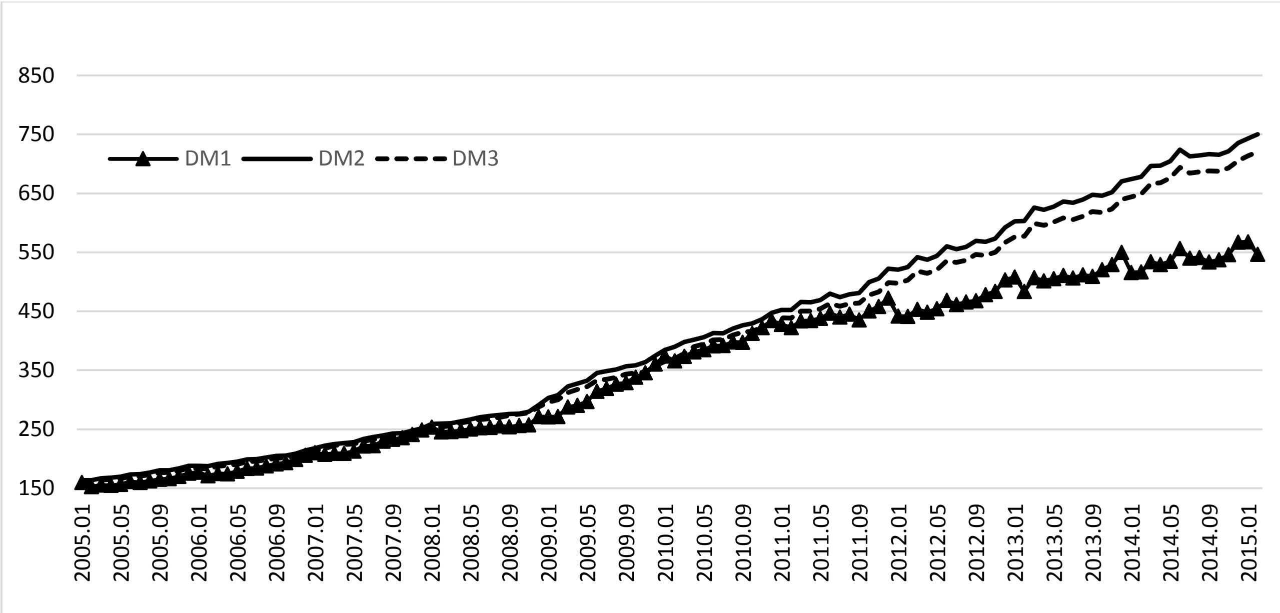


Figure 19:Chinese Divisia M1, M2, M3

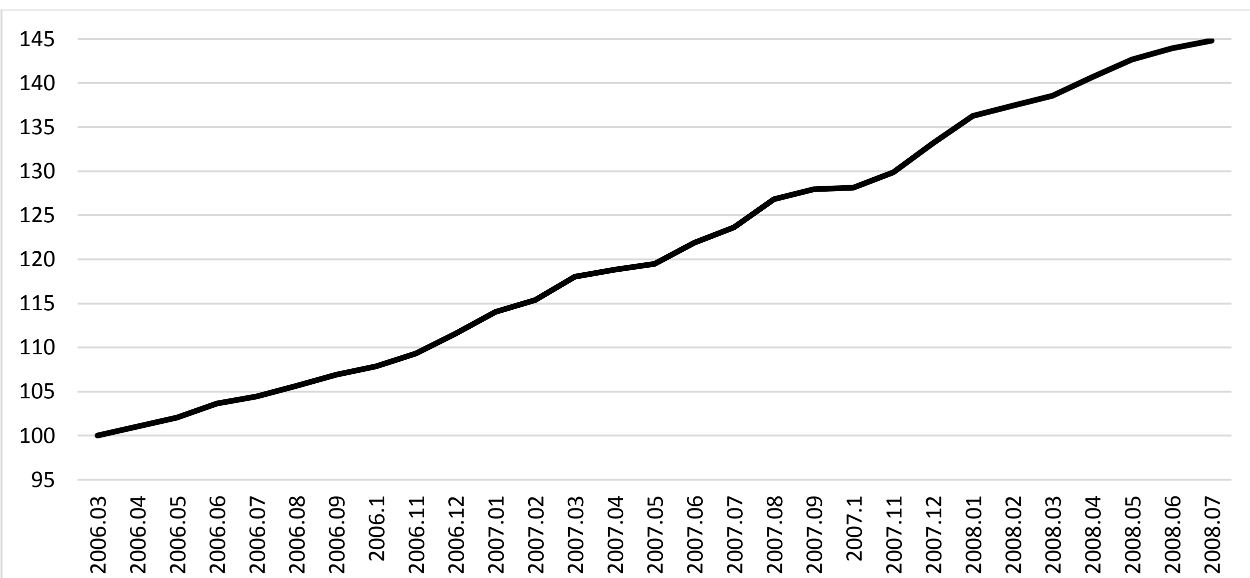


Figure 20: Chinese Broader Divisia M4

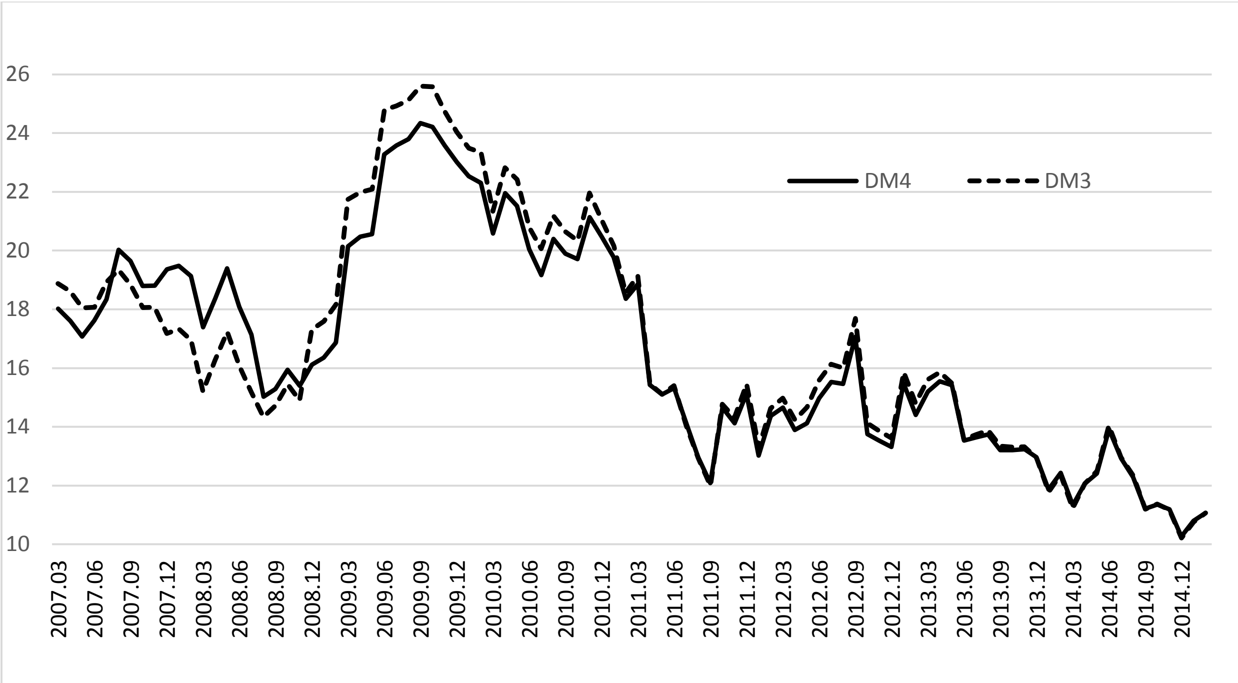


Figure 21: Chinese Divisia M3 and M4 Annual Growth Rates (%)

From Figure 21, 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.

### 3.3.4 User-Cost of the Divisia Aggregates

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

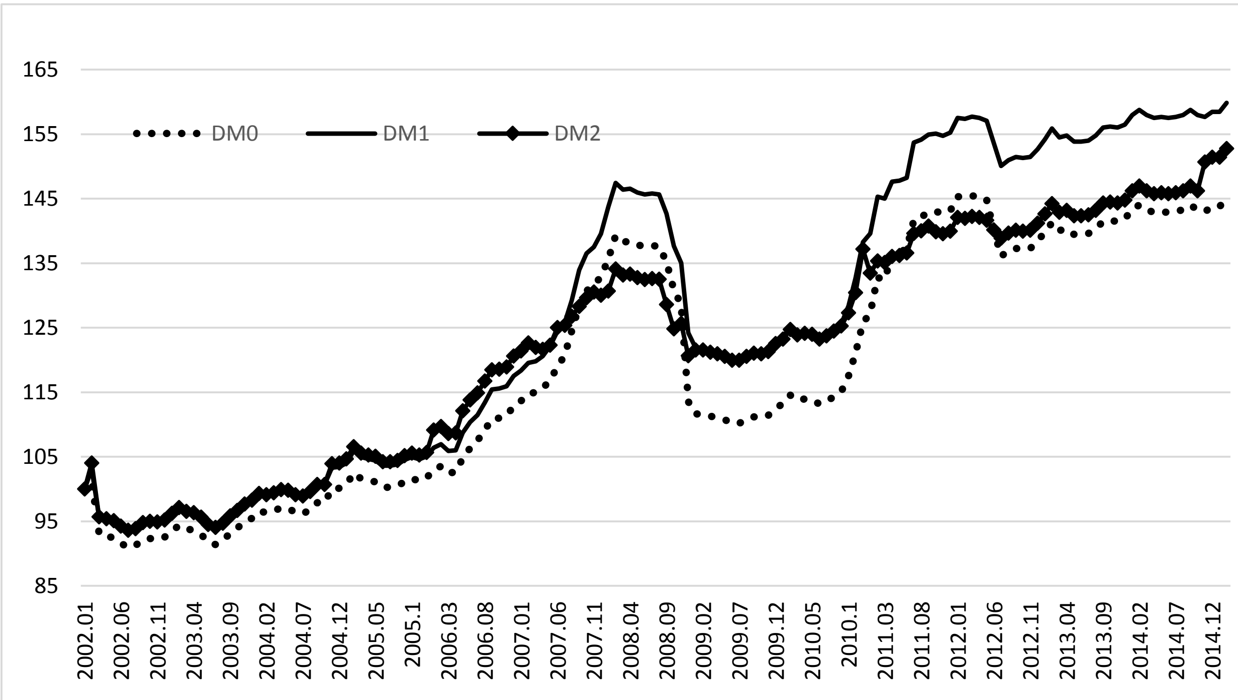


Figure 22: User Cost for Chinese Divisia M0, M1, and M2

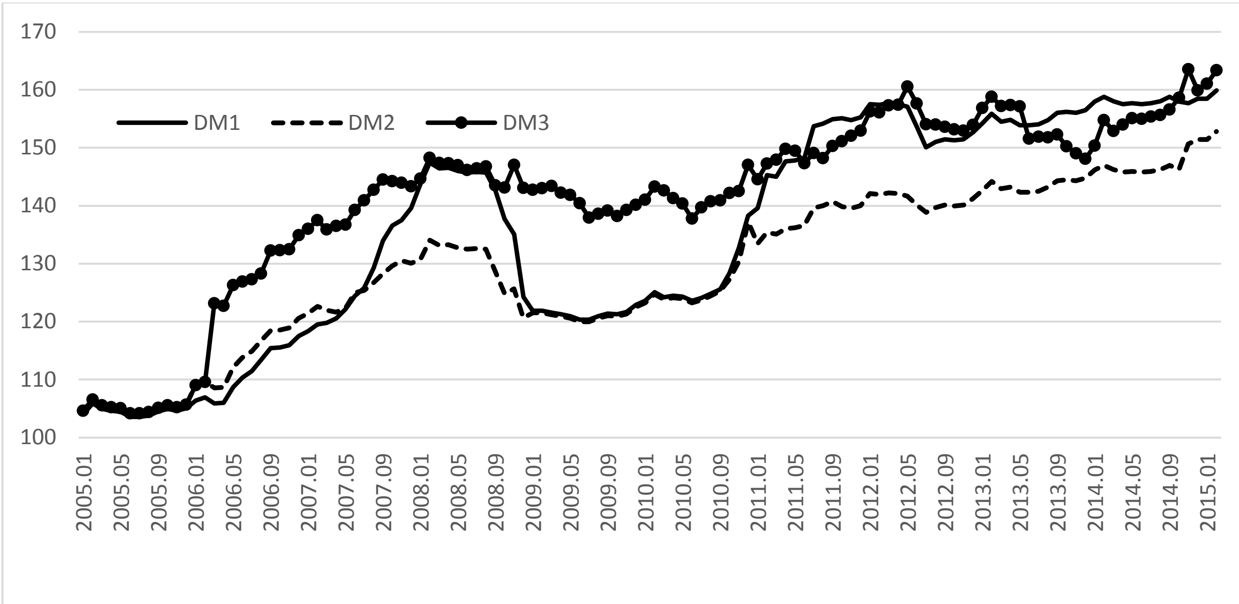


Figure 23: User Costs for Chinese Divisia M1, M2, and M3

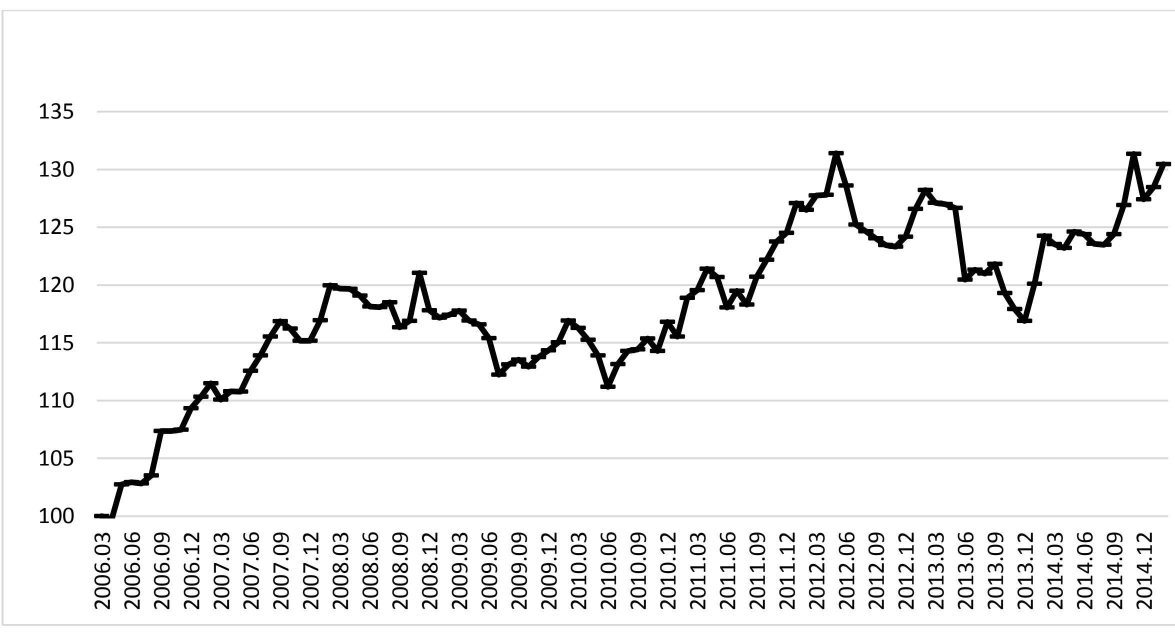


Figure 24: User Cost for Chinese Divisia M4

Figure 22 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 23 and 24 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.

### 3.4 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.

#### 3.4.1 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.

### 3.4.2 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.[17] 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

[17] 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).

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 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.

### 3.4.3 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:

$$\chi_{i,t} = \boldsymbol{\gamma}_i'\mathbf{F}_t + \epsilon_{i,t} \tag{3.9}$$

with $i = 1,...,n$ and $t = 1,...,T$, 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

$$\mathbf{X}_t = \boldsymbol{\Gamma}\mathbf{F}_t + \mathbf{E}_t \tag{3.10}$$

where $\mathbf{X}_t = (\chi_{1t}, \chi_{2t}, ..., \chi_{nt})'$ and $\mathbf{E}_t = (\epsilon_{1t}, \epsilon_{2t}, ..., \epsilon_{nt})'$ are vectors and $\boldsymbol{\Gamma} = \left[\boldsymbol{\gamma}_1, ..., \boldsymbol{\gamma}_n\right]'$ is a matrix. The common component, $\zeta_{it}$, 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:

$$\mathbf{F}_t = \mathbf{A}\mathbf{F}_{t-1} + \mathbf{B}\mathbf{u}_t \tag{3.11}$$

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 $\det(\mathbf{I}_r - \mathbf{A})$ outside the unit circle. The number of common factors, *r*, is set to be large relative to the number of macroeconomic shocks, *q*.

### 3.4.4 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,

$$\mathbf{S} = \frac{1}{T}\sum_{i=1}^{T} \mathbf{X}_t \mathbf{X}_t' \tag{3.12}$$

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

Denote by D the $r \times r$ diagonal matrix with diagonal elements given by the largest r eigenvalues of $\mathbf{S}$, and denote by 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:

$$\tilde{\mathbf{F}}_t = \mathbf{V}'\mathbf{X}_t \tag{3.13}$$

With the common factors, $\tilde{\mathbf{F}}_t$, 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:

$$\hat{\mathbf{\Gamma}} = \sum_t \mathbf{X}_t \tilde{\mathbf{F}}_t' (\tilde{\mathbf{F}}_t \tilde{\mathbf{F}}_t')^{-1} = \mathbf{V} \tag{3.14}$$

$$\hat{\mathbf{\Pi}} = diag(\mathbf{S} - \mathbf{VDV}) \tag{3.15}$$

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.

### 3.4.5 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:

$$V(r, \mathbf{F}^r) + rg(n, T) \qquad (3.16)$$

where $V(r, \mathbf{F}^r)$ 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)

**3.5 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.

**3.6 Results**

Table 6 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.

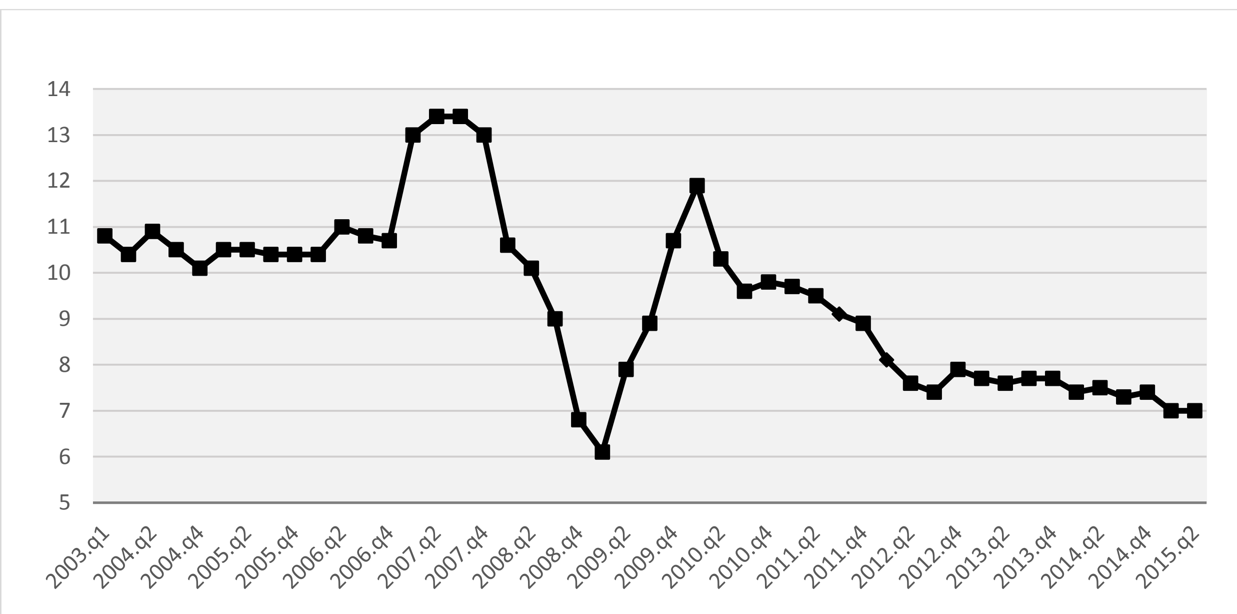


Figure 25: Chinese Real GDP Quarterly Growth Rate 2003Q1 to 2015Q2

From the figure 25, 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.

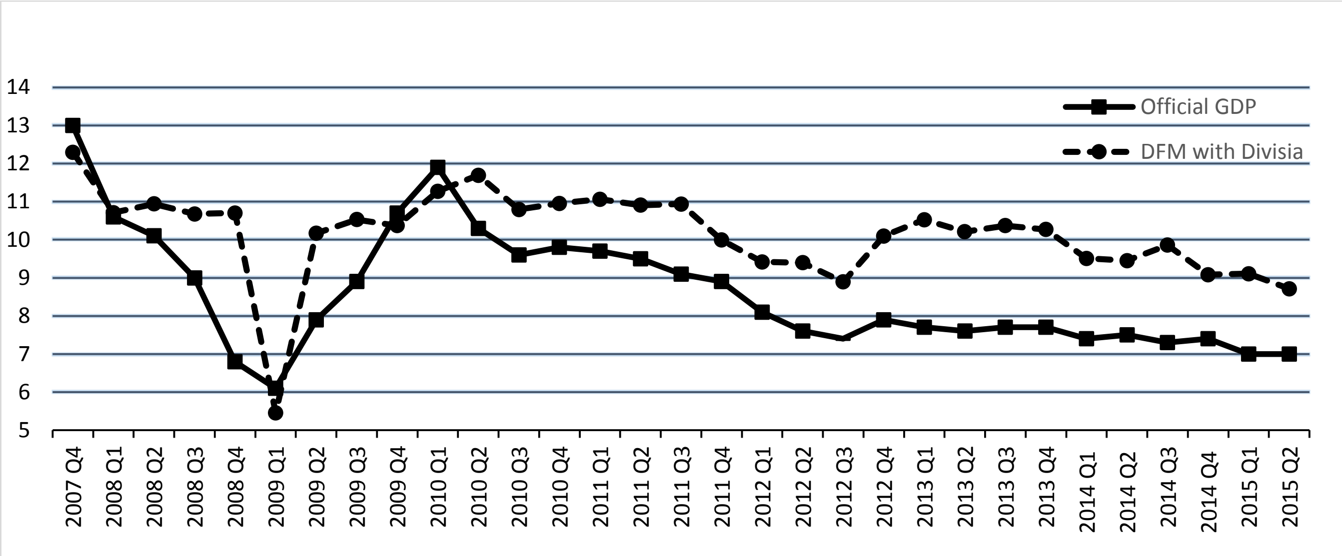


Figure 26: Real Chinese GDP and Nowcasting result from Dynamic Factor Model (DFM) with Divisia index, 2007Q4 to 2015Q2

Table 6: Chinese GDP 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 6, 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 7: Mean Squared Forecast Error of Chinese GDP 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 8 contains the nowcasting results from the AR (1) model, the "Naïve Model," and the dynamic factor model.

Table 8: Chinese GDP 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 8 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.

### 3.7 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.[18]

[18] 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

Table A: Nowcasting Result of US GDP from 2007 Q1 to 2013 Q2 (First Chapter)

| **Time** | **official data** | **DFM estimate** | **Naïve estimate** |
|---|---|---|---|
| 2007 Q1 | 0.543500358 | 3.3699 | 2.394770415 |
| 2007 Q2 | 3.646592045 | 3.9194 | 1.243959714 |
| 2007 Q3 | 2.955421461 | 2.3276 | 1.747342816 |
| 2007 Q4 | 1.702907574 | 2.1966 | 2.472889183 |
| 2008 Q1 | -1.763043649 | 1.1697 | 2.212105359 |
| 2008 Q2 | 1.322055519 | -0.1008 | 1.635469358 |
| 2008 Q3 | -3.661257655 | -2.3026 | 1.054335226 |
| 2008 Q4 | -8.890118354 | -6.1329 | -0.599834553 |
| 2009 Q1 | -5.250679433 | -7.8184 | -3.248091035 |
| 2009 Q2 | -0.313972129 | -1.8201 | -4.119999981 |
| 2009 Q3 | 1.447872458 | 4.5456 | -4.529006893 |
| 2009 Q4 | 4.023899011 | 4.0044 | -3.251724365 |
| 2010 Q1 | 2.335339512 | 4.7685 | -0.023220023 |
| 2010 Q2 | 2.244016936 | 5.2454 | 1.873284713 |
| 2010 Q3 | 2.602896117 | 3.8097 | 2.512781979 |
| 2010 Q4 | 2.39334545 | 3.228 | 2.801537894 |
| 2011 Q1 | 0.078042987 | 3.9841 | 2.393899504 |
| 2011 Q2 | 2.47666029 | 3.0205 | 1.829575373 |
| 2011 Q3 | 1.280466371 | 3.4099 | 1.887736211 |
| 2011 Q4 | 4.093133736 | 3.546 | 1.557128774 |
| 2012 Q1 | 1.959954193 | 4.2388 | 1.982075846 |
| 2012 Q2 | 1.252984138 | 2.7165 | 2.452553647 |
| 2012 Q3 | 3.105341967 | 2.3855 | 2.146634609 |
| 2012 Q4 | 0.379222793 | 3.2638 | 2.602853509 |
| 2013 Q1 | 1.775833469 | 3.5096 | 1.674375773 |
| 2013 Q2 | . | 2.9456 | 1.628345592 |

Table B: The Nowcasting Result of Naive Model for US GDP (Second Chapter)

| Quarter | Nowcasting | 1 Quarter ahead | 2 Quarter ahead | 3 Quarter ahead | 4 Quarter ahead |
|---|---|---|---|---|---|
| 2007:Q1 | 2.425 | 2.175 | 2.971 | 3.743 | 2.828 |
| 2007:Q2 | 1.25 | 1.806 | 1.494 | 2.49 | 3.454 |
| 2007:Q3 | 1.725 | 1.26 | 1.958 | 1.567 | 2.812 |
| 2007:Q4 | 2.3 | 2.056 | 1.478 | 2.347 | 1.859 |
| 2008:Q1 | 1.85 | 2.075 | 1.77 | 1.047 | 2.134 |
| 2008:Q2 | 1.125 | 2.263 | 2.544 | 2.163 | 1.259 |
| 2008:Q3 | 0.85 | 0.631 | 2.053 | 2.405 | 1.929 |
| 2008:Q4 | -0.3 | 0.3875 | 0.114 | 1.891 | 2.331 |
| 2009:Q1 | -2.7 | -0.725 | -0.134 | -0.207 | 2.014 |
| 2009:Q2 | -3.375 | -2.7 | -0.23125 | 0.843 | 0.416 |
| 2009:Q3 | -4 | -4.718 | -3.875 | -0.789 | 0.554 |
| 2009:Q4 | -3.2 | -4.525 | -5.423 | -4.369 | -0.511 |
| 2010:Q1 | -0.175 | -1.95 | -3.606 | -4.729 | -3.411 |
| 2010:Q2 | 1.6 | 1.131 | -1.087 | -3.158 | -4.562 |
| 2010:Q3 | 2.7 | 2.215 | 1.539 | -1.234 | -3.822 |
| 2010:Q4 | 3.05 | 3.05 | 2.331 | 1.599 | -1.868 |
| 2011:Q1 | 2.7 | 2.838 | 2.838 | 1.939 | 1.024 |
| 2011:Q2 | 1.9 | 2.95 | 3.122 | 3.122 | 1.99 |
| 2011:Q3 | 1.65 | 1.4 | 2.713 | 2.927 | 2.927 |
| 2011:Q4 | 1.175 | 1.386 | 1.075 | 2.716 | 2.984 |
| 2012:Q1 | 1.7 | 0.844 | 1.109 | 0.719 | 2.769 |
| 2012:Q2 | 2.65 | 2.5 | 1.429 | 1.762 | 1.273 |
| 2012:Q3 | 2.325 | 2.586 | 2.4 | 1.062 | 1.477 |
| 2012:Q4 | 2.75 | 2.706 | 3.034 | 2.8 | 1.128 |
| 2013:Q1 | 1.625 | 2.288 | 2.233 | 2.643 | 2.35 |
| 2013:Q2 | 1.725 | 1.456 | 2.284 | 2.216 | 2.729 |
| 2013:Q3 | 1.775 | 1.756 | 1.42 | 2.455 | 2.37 |
| 2013:Q4 | 2.275 | 1.593 | 1.57 | 1.15 | 2.444 |
| 2014:Q1 | 3.125 | 2.819 | 1.967 | 1.938 | 1.413 |
| 2014:Q2 | 1.925 | 3.231 | 2.848 | 1.784 | 1.747 |
| 2014:Q3 | 2.625 | 1.956 | 3.589 | 3.11 | 1.78 |
| 2014:Q4 | NA | 2.156 | 1.32 | 3.361 | 2.763 |
| 2015:Q1 | NA | NA | 1.82 | 0.775 | 3.327 |
| 2015:Q2 | NA | NA | NA | 2.8 | 1.484 |
| 2015:Q3 | NA | NA | NA | NA | 2.35 |

Table c: The US GDP nowcasting result from Survey of Professional Forecast (Second Chapter)

| **Quarter** | **Nowcasting** | **1 Quarter ahead** | **2 Quarter ahead** | **3 Quarter ahead** | **4 Quarter ahead** |
|---|---|---|---|---|---|
| 2007:Q1 | 2.546 | 2.644 | 2.911 | 3.027 | 3.029 |
| 2007:Q2 | 2.414 | 2.484 | 2.861 | 3.061 | 2.838 |
| 2007:Q3 | 2.604 | 2.603 | 2.592 | 2.72 | 2.65 |
| 2007:Q4 | 1.78 | 1.998 | 2.365 | 2.599 | 2.755 |
| 2008:Q1 | 0.661 | 1.278 | 2.496 | 2.653 | 3.242 |
| 2008:Q2 | 0.079 | 2.17 | 1.447 | 2.01 | 2.639 |
| 2008:Q3 | 1.343 | 0.673 | 1.329 | 2.074 | 2.447 |
| 2008:Q4 | -2.635 | -1.119 | 0.575 | 1.638 | 2.163 |
| 2009:Q1 | -4.908 | -1.522 | 0.666 | 1.876 | 2.394 |
| 2009:Q2 | -1.311 | 0.559 | 1.663 | 2.052 | 2.725 |
| 2009:Q3 | 2.314 | 2.307 | 2.47 | 2.769 | 2.813 |
| 2009:Q4 | 2.588 | 2.587 | 2.826 | 2.847 | 2.923 |
| 2010:Q1 | 2.631 | 2.887 | 2.935 | 3.096 | 2.687 |
| 2010:Q2 | 3.328 | 3.103 | 3.102 | 2.972 | 3.006 |
| 2010:Q3 | 2.413 | 2.742 | 2.752 | 3.019 | 2.957 |
| 2010:Q4 | 2.225 | 2.461 | 2.764 | 3.029 | 3.199 |
| 2011:Q1 | 3.538 | 3.473 | 3.404 | 3.458 | 3.047 |
| 2011:Q2 | 3.238 | 3.36 | 3.335 | 2.989 | 3.124 |
| 2011:Q3 | 2.542 | 2.384 | 2.261 | 2.524 | 2.758 |
| 2011:Q4 | 2.501 | 2.337 | 2.398 | 2.564 | 2.702 |
| 2012:Q1 | 2.242 | 2.408 | 2.61 | 2.769 | 2.69 |
| 2012:Q2 | 2.391 | 2.551 | 2.729 | 2.473 | 2.658 |
| 2012:Q3 | 1.744 | 2.307 | 1.69 | 1.754 | 2.336 |
| 2012:Q4 | 1.839 | 1.642 | 2.148 | 2.672 | 2.868 |
| 2013:Q1 | 2.279 | 2.554 | 2.617 | 2.587 | 2.969 |
| 2013:Q2 | 1.809 | 2.365 | 2.777 | 2.875 | 2.988 |
| 2013:Q3 | 2.345 | 2.574 | 2.599 | 2.8 | 2.898 |
| 2013:Q4 | 1.842 | 2.533 | 2.743 | 2.824 | 2.911 |
| 2014:Q1 | 2.043 | 2.704 | 2.901 | 3.01 | 3.13 |
| 2014:Q2 | 3.229 | 2.989 | 3.019 | 3.05 | 2.954 |
| 2014:Q3 | 2.959 | 3.051 | 3.036 | 3.024 | 2.947 |
| 2014:Q4 | NA | 3.065 | 3.239 | 2.711 | 2.926 |
| 2015:Q1 | NA | NA | 3.126 | 3.118 | 2.234 |
| 2015:Q2 | NA | NA | NA | 3.109 | 3.137 |
| 2015:Q3 | NA | NA | NA | NA | 2.962 |

Table D: Nowcasting Result of US GDP from Dynamic Factor Model With Divisia Index Only (Second Chapter)

| Quarter | Nowcasting | 1 Quarter ahead | 2 Quarter ahead | 3 Quarter ahead | 4 Quarter ahead |
|---|---|---|---|---|---|
| 2007:Q1 | 2.4772 | 2.9963 | 2.6364 | 3.3372 | 3.311 |
| 2007:Q2 | 3.4474 | 2.8523 | 3.386 | 2.8637 | 3.3279 |
| 2007:Q3 | 3.4714 | 3.3675 | 3.2285 | 3.6512 | 3.14 |
| 2007:Q4 | 2.3529 | 3.5669 | 3.3213 | 3.5227 | 3.7793 |
| 2008:Q1 | 1.4595 | 2.7666 | 3.5921 | 3.3073 | 3.6981 |
| 2008:Q2 | 0.9756 | 1.5846 | 3.1731 | 3.5657 | 3.3175 |
| 2008:Q3 | 0.9889 | 1.8977 | 2.0336 | 3.4871 | 3.511 |
| 2008:Q4 | -1.6325 | 1.7371 | 2.793 | 2.6041 | 3.6726 |
| 2009:Q1 | -6.6236 | 0.1149 | 2.5357 | 3.4873 | 3.1378 |
| 2009:Q2 | -2.3623 | -2.6612 | 1.8211 | 3.2128 | 3.9077 |
| 2009:Q3 | 5.5295 | -0.2987 | 1.6326 | 3.2286 | 3.678 |
| 2009:Q4 | 4.8647 | 7.6319 | 1.7811 | 5.4074 | 4.2068 |
| 2010:Q1 | 4.6012 | 6.6279 | 8.4556 | 3.5842 | 8.0666 |
| 2010:Q2 | 3.3667 | 5.4764 | 7.5023 | 8.1612 | 4.9206 |
| 2010:Q3 | 3.1066 | 3.7192 | 5.8975 | 7.4517 | 7.0617 |
| 2010:Q4 | 3.1771 | 2.8777 | 3.9382 | 5.8807 | 6.6102 |
| 2011:Q1 | 4.8278 | 3.1211 | 2.7077 | 4.0284 | 5.4957 |
| 2011:Q2 | 4.6121 | 4.9608 | 3.0647 | 2.6003 | 4.0056 |
| 2011:Q3 | 1.8761 | 4.5524 | 4.8696 | 3.0134 | 2.5527 |
| 2011:Q4 | 2.9758 | 1.4312 | 4.3444 | 4.6108 | 2.971 |
| 2012:Q1 | 3.533 | 2.848 | 1.2396 | 4.0401 | 4.2459 |
| 2012:Q2 | 3.3553 | 3.3263 | 2.7561 | 1.2669 | 3.69 |
| 2012:Q3 | 2.0051 | 2.9851 | 3.1237 | 2.702 | 1.4634 |
| 2012:Q4 | 3.4878 | 1.7879 | 2.6895 | 2.9456 | 2.6834 |
| 2013:Q1 | 3.1805 | 3.4813 | 1.7366 | 2.4831 | 2.8055 |
| 2013:Q2 | 3.3735 | 3.005 | 3.4185 | 1.8208 | 2.4831 |
| 2013:Q3 | 4.3057 | 2.8805 | 2.8565 | 3.318 | 2.0025 |
| 2013:Q4 | 3.6927 | 4.4154 | 2.4795 | 2.7446 | 3.1985 |
| 2014:Q1 | 2.9378 | 3.71 | 4.355 | 2.1885 | 2.6731 |
| 2014:Q2 | 3.5522 | 2.6647 | 3.6475 | 4.1741 | 2.0127 |
| 2014:Q3 | 4.8322 | 3.4548 | 2.4806 | 3.5318 | 3.9206 |
| 2014:Q4 | NA | 4.7088 | 3.3245 | 2.3815 | 3.3874 |
| 2015:Q1 | NA | NA | 4.4409 | 3.1816 | 2.3559 |
| 2015:Q2 | NA | NA | NA | 4.0886 | 3.0426 |
| 2015:Q3 | NA | NA | NA | NA | 3.7055 |

Table E: Nowcasting Result of US GDP from Dynamic Factor Model Without Divisia Index /Only simple sum aggregates (Second Chapter)

| Quarter | Nowcasting | 1 Quarter ahead | 2 Quarter ahead | 3 Quarter ahead | 4 Quarter ahead |
|---|---|---|---|---|---|
| 2007:Q1 | 2.4472 | 2.8145 | 2.7325 | 3.336 | 3.4156 |
| 2007:Q2 | 3.5415 | 2.763 | 3.211 | 2.8749 | 3.3062 |
| 2007:Q3 | 3.4476 | 3.4729 | 3.0978 | 3.5134 | 3.0748 |
| 2007:Q4 | 2.4026 | 3.5579 | 3.413 | 3.384 | 3.699 |
| 2008:Q1 | 1.8079 | 2.7602 | 3.6013 | 3.3698 | 3.5851 |
| 2008:Q2 | 0.9915 | 1.8451 | 3.1115 | 3.5923 | 3.3457 |
| 2008:Q3 | 1.0961 | 1.7679 | 2.1359 | 3.3952 | 3.5501 |
| 2008:Q4 | -1.7007 | 1.8047 | 2.5515 | 2.544 | 3.5828 |
| 2009:Q1 | -6.8275 | -0.0592 | 2.5297 | 3.2005 | 2.9588 |
| 2009:Q2 | -2.1796 | -3.0783 | 1.5389 | 3.1403 | 3.6461 |
| 2009:Q3 | 4.3488 | -0.177 | 0.9716 | 2.8753 | 3.5704 |
| 2009:Q4 | 4.6542 | 6.8951 | 1.7742 | 4.5971 | 3.8397 |
| 2010:Q1 | 4.5333 | 6.4468 | 8.3604 | 3.4467 | 7.2836 |
| 2010:Q2 | 3.4166 | 5.3304 | 7.4071 | 8.7244 | 4.6982 |
| 2010:Q3 | 3.1015 | 3.7528 | 5.6664 | 7.4825 | 8.1405 |
| 2010:Q4 | 3.2332 | 2.8548 | 3.9373 | 5.5721 | 6.7789 |
| 2011:Q1 | 5.0096 | 3.205 | 2.6753 | 3.9779 | 5.1336 |
| 2011:Q2 | 4.684 | 5.1501 | 3.1575 | 2.5705 | 3.8974 |
| 2011:Q3 | 1.7957 | 4.6221 | 5.0035 | 3.1003 | 2.5373 |
| 2011:Q4 | 3.0972 | 1.3528 | 4.3757 | 4.6471 | 3.0424 |
| 2012:Q1 | 3.5421 | 2.9389 | 1.1916 | 4.0117 | 4.1678 |
| 2012:Q2 | 3.3429 | 3.3315 | 2.8131 | 1.2704 | 3.5972 |
| 2012:Q3 | 1.9228 | 2.964 | 3.1201 | 2.7279 | 1.5287 |
| 2012:Q4 | 3.4579 | 1.6979 | 2.6633 | 2.9331 | 2.6847 |
| 2013:Q1 | 3.2073 | 3.4618 | 1.6657 | 2.4594 | 2.7872 |
| 2013:Q2 | 3.3288 | 3.0497 | 3.4025 | 1.7887 | 2.3554 |
| 2013:Q3 | 4.3451 | 2.7903 | 2.9086 | 3.3006 | 2.0191 |
| 2013:Q4 | 3.6622 | 4.4553 | 2.3619 | 2.797 | 3.1772 |
| 2014:Q1 | 2.8762 | 3.6789 | 4.37 | 2.0675 | 2.7214 |
| 2014:Q2 | 3.6034 | 2.5618 | 3.6084 | 4.1493 | 1.9127 |
| 2014:Q3 | 4.9058 | 3.4937 | 2.3612 | 3.4808 | 3.8519 |
| 2014:Q4 | NA | 4.7643 | 3.3413 | 2.2686 | 3.3247 |
| 2015:Q1 | NA | NA | 4.4496 | 3.173 | 2.2678 |
| 2015:Q2 | NA | NA | NA | 4.0377 | 3.0111 |
| 2015:Q3 | NA | NA | NA | NA | 3.5971 |

Table F: US GDP Nowcasting Results from Dynamic Factor Model Forecast with both Divisia and Simple sum monetary aggregates (Second Chapter)

| Quarter | Nowcasting | 1 Quarter ahead | 2 Quarter ahead | 3 Quarter ahead | 4 Quarter ahead |
|---|---|---|---|---|---|
| 2007:Q1 | 2.4639 | 2.9707 | 2.627 | 3.3284 | 3.2921 |
| 2007:Q2 | 3.4301 | 2.8429 | 3.3664 | 2.8604 | 3.3233 |
| 2007:Q3 | 3.4628 | 3.3457 | 3.2255 | 3.6407 | 3.143 |
| 2007:Q4 | 2.3574 | 3.5602 | 3.3012 | 3.5258 | 3.7771 |
| 2008:Q1 | 1.4615 | 2.7774 | 3.588 | 3.2927 | 3.7049 |
| 2008:Q2 | 0.9996 | 1.5971 | 3.1878 | 3.5639 | 3.31 |
| 2008:Q3 | 0.999 | 1.9419 | 2.0541 | 3.5025 | 3.5109 |
| 2008:Q4 | -1.6182 | 1.7508 | 2.8468 | 2.6294 | 3.6855 |
| 2009:Q1 | -6.585 | 0.1506 | 2.5546 | 3.5398 | 3.1637 |
| 2009:Q2 | -2.4047 | -2.568 | 1.8789 | 3.2353 | 3.9499 |
| 2009:Q3 | 5.6331 | -0.393 | 1.7768 | 3.3005 | 3.7008 |
| 2009:Q4 | 4.9237 | 7.5686 | 1.6496 | 5.5831 | 4.2804 |
| 2010:Q1 | 4.6187 | 6.6837 | 8.2655 | 3.4352 | 8.2433 |
| 2010:Q2 | 3.3768 | 5.4941 | 7.5443 | 7.9125 | 4.7752 |
| 2010:Q3 | 3.1214 | 3.7321 | 5.9155 | 7.4722 | 6.8278 |
| 2010:Q4 | 3.1833 | 2.8927 | 3.9534 | 5.8984 | 6.6057 |
| 2011:Q1 | 4.8008 | 3.1258 | 2.7209 | 4.0454 | 5.5122 |
| 2011:Q2 | 4.5935 | 4.9347 | 3.0677 | 2.6104 | 4.0236 |
| 2011:Q3 | 1.8644 | 4.5391 | 4.8489 | 3.0148 | 2.5588 |
| 2011:Q4 | 2.9069 | 1.4208 | 4.3375 | 4.5985 | 2.9709 |
| 2012:Q1 | 3.5203 | 2.7822 | 1.2296 | 4.0393 | 4.2431 |
| 2012:Q2 | 3.3478 | 3.3179 | 2.6992 | 1.257 | 3.6943 |
| 2012:Q3 | 2.0055 | 2.9812 | 3.1197 | 2.658 | 1.4537 |
| 2012:Q4 | 3.4655 | 1.7906 | 2.6884 | 2.9453 | 2.6538 |
| 2013:Q1 | 3.1122 | 3.4606 | 1.7396 | 2.4838 | 2.8078 |
| 2013:Q2 | 3.7481 | 3.2513 | 3.4017 | 1.8226 | 2.3696 |
| 2013:Q3 | 3.2835 | 3.1929 | 3.1425 | 3.3063 | 2.0023 |
| 2013:Q4 | 3.683 | 3.2337 | 2.714 | 3.0324 | 3.1923 |
| 2014:Q1 | 2.9418 | 3.7063 | 3.164 | 2.3383 | 2.9325 |
| 2014:Q2 | 3.5392 | 2.6734 | 3.6501 | 3.0857 | 2.079 |
| 2014:Q3 | 4.8099 | 3.4417 | 2.4903 | 3.5385 | 3.0082 |
| 2014:Q4 | NA | 4.6905 | 3.3127 | 2.3892 | 3.395 |
| 2015:Q1 | NA | NA | 4.4302 | 3.1719 | 2.3598 |
| 2015:Q2 | NA | NA | NA | 4.087 | 3.0354 |
| 2015:Q3 | NA | NA | NA | NA | 3.7126 |

Table G: Data Description for US GDP Nowcasting (Chapter 2)

| Block Name | Release | Date(approx.) | Publishing lag | Data Frequency |
|---|---|---|---|---|
| Survey 2 | PMGR-manufacturing | 1st business day of the month | 1 month | monthly |
| Mixed 3 | Commercial paper | 1st business day | month | monthly |
| Mixed 3 | Construction put in place | 1st bus. Day(appro) | 2 month | monthly |
| Mixed 3 | Advance report on durable goods manufactures shipments,inventories and orders | 24-28th | 1-2 month | monthly |
| Mixed 3 | Full report on durable goods manufactures shipments,inventories and orders | 5 days after advance durables | 2 month | monthly |
| Money and credit | Aggregates reserves of depository institution and the monetary base | 1st Thursday of month | 1 month | monthly |
| Money and credit | Money stock measures | 2nd Thursday of month | 1 month | monthly |
| Money and credit | Assets and liabilities of commercial banks in the US | 1st Friday of month | 1 month | monthly |
| labor and wages | Employment situation | 1st Friday of month | 1 month | monthly |
| Mixed 1 | Consumer credit | 5th business day of month | 2 months | monthly |
| Mixed 1 | Advance monthly sales for retail and food services | 11-15th of month | 1 month | monthly |
| Mixed 1 | Monthly treasury statement of receipts and outlays of the US government | Middle of month | 1 month | monthly |
| Mixed 1 | US international trade in goods and services (FT900 and FT920) | 2nd full week of month | 2 months | monthly |
| Ind. production | Industrial production and capacity utilization | 15-17th of month | 1 month | monthly |
| Mixed 2 | New residential construction | 16-20th of month | 1 month | monthly |
| Mixed 2 | Business outlook survey:Federal Reserve Bank of Philadelphia | 3rd Thursday of month | current month | monthly |

| | | | | |
|---|---|---|---|---|
| PPI | Producer prices | Middle of month | 1 month | monthly |
| CPI | Consumer prices | Middle of month | 1 month | monthly |
| GDP and income | GDP-detail:inventories and sales | Day after GDP-release | 2 months | Monthly |
| GDP and income | GDP-release:GDP and GDP deflator | Last week of moneh | 1 quarter | Quarterly |
| GDP and income | Personal income and outlays | Day after GDP release | 1 month | Monthly |
| Housing | Manufacturing homes survey | 3rd to last business day of month | 2 month | Monthly |
| Housing | New residential sales | Last week of month | 1 month | Monthly |
| Surveys 1 | Chicago Fed Midwest manufacturing index | Last week of month | 1-2 month | Monthly |
| Surveys 1 | Consumer confident Index | Last Tuesday of month | Current month | Monthly |
| Surveys | Michigan surveys of consumers | Last Friday of month | Current month | Monthly |
| Initial claims | Claims,unemployment insurance weekly claims reports | Last Thursday of month | Current month | Weekly |
| Interest rate | Freddie Mac primary mortgage survey | Last Monday of month,monthly ave. | current month | weekly |
| Interest rates | Selected interest rates | Last day of month | current month | Daily |
| Financial | Foreign exchange rate | Last of month: monthly ave. | current month | Daily |

Table H: Chinese GDP Nowcasting Results from Different Models (Chapter 3)

| 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 |

Table I: Data Description (Third Paper)

| Block Name | Release | Date (approximate) | Publishing lag | Data Frequency |
|---|---|---|---|---|
| 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 telecommunication | 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 |

Figure A: Structure Break Test Results (Chapter 3)

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