Essays on Divisia Monetary Aggregates and Global Monetary Policies: Evidence from the United States and China

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Abstract

The Divisia Monetary Aggregate Index was based on aggregation theory in microeconomics and index theory in statistics. It has a solid theoretical foundation and is generally recognized by the academy as the monetary aggregation model that is superior to the simple sum aggregation. It has been gradually adopted by central banks of various countries. However, under the background of the continuous deepening of financial innovation, the existing index can no longer meet the requirements for the measurement of new monetary assets.

With the booming of e-commerce and online shopping, e-commerce consumption loans that includes the hottest buy-now-later service provided by non-banking financial institutions, are playing a more important role than ever. However, these transaction services have never been included in the measures of monetary aggregation. This paper derives a consumption loan augmented monetary aggregates that based on aggregation theory and discusses aggregates for even broader liquid assets. By applying the model with China's data, the consumption loan augmented Divisia Aggregation shows its unique correlation with the economy. A further spectrum analysis illustrates the periodic patterns between monetary aggregation and nominal GDP, which also verify the external validity of the model.

Money supply of the United States is the main intermediary target of macro-control which matters to both domestic and worldwide. Divisia Monetary Aggregates have proved to be preferable to the conventional simple sum aggregates in many ways. This paper empirically compared periodic characteristics of different monetary aggregates of the United States by solving the inherit measurement issues with analysis methods in frequency domain. In particular, I have reorganized and visualized related spectrum analysis results including their coherencies and phase differences

with major economic policy targets in the short term and long term, in order to suggest a potential optimal intermediary target for macroeconomic regulation with different control period requirements.

Chapter 3 compares the monetary aggregates of the two world's giants: The United States and China, with the spectrum analysis methods in frequency domain. By deriving the binary spectrum analysis results between monetary aggregates and nominal GDP for both countries, I analyze the periodic pattern in both short runs and long runs of the published simple sum monetary aggregates and the advanced Divisia Monetary Aggregates, including their coherencies and synchronization relationships with GDP of the two countries. Furthermore, we conclude the periodic patterns of all monetary aggregates for each country and provide the possible explanations of the difference in the in two countries' monetary policies. Our results also provide empirical evidence of classic monetary theories and views.

We evaluate the treatment effect of interest-rate liberalization in China with the difference-in-difference (DID) model. DID model has been used in econometrics to quantitatively evaluate the effect of public policy or project implementation by solving the non-random sample allocation for the policy implementation group and the control group. However, the unique interest rate liberalization in China makes it impossible to find related panel data. In Chapter 4, we will solve this problem by involves Divisia Monetary Aggregation and restate the time series data and evaluate policy reforms of China's recent Interest Rate Liberalization.

Keywords: Divisia Monetary Aggregates, Spectrum Analysis, Global Monetary Policies

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Chapter I: Consumption Loan Augmented Divisia Monetary Index and China Monetary Aggregation

1.1 Introduction

During the COVID-19 pandemic, many retailers closed physical stores while online customers were increasing. The Financial Review commented that the growth of Afterpay, a buy-now-pay-later service provider, was spurred by "investors are seeking exposure to e-commerce as the coronavirus crisis pushes more shopping online, and continuing government stimulus will keep bad debts low". Meantime, E-commerce consumption loan services has already stepped on its next stage in China. In October 2020, Ant Group, the world's largest mobile and online payments platform, the provider of e-commerce consumption loan Ant Check Later, was set to raise US$34.5 billion in the world's largest IPO at the time, valuing the company at US$313 billion.

Studies of e-commerce consumption loan services has indicated that, Millennials were their main customer demographic, accounting for 75% of all users. Another significant segment of e-commerce consumption loan customer base is university students, of which one third have been found to use short-term borrowing. With the booming of electronic business started from last decade, e-commerce consumption loans that includes the hottest buy-now-later service provided by non-banking financial institutions, are playing a more important role than ever.

However, as a new form of transaction service that different from other types of liquid assets, its measurement in monetary aggregation needs to be redefined. Unlike mortgage loan, this type of consumption loan does not require real estate as guaranty. Also, it is not the same as bank-issued credit card transaction. With independent credit evaluation system and its limit liquidity in markets, consumption loan in e-commerce should be considered as a unique part in monetary aggregation.

Barnett et al. (2016), extending the well-known Divisia monetary aggregates that originated by Barnett (1980) with liabilities for the first time. By including credit card transaction services on the demand side, Divisia Monetary Aggregates showed its applicability to debt basis monetary services. Based on the microeconomic theory of aggregation and results for liabilities in aggregation, it is possible to measure the non-banking consumption loan in e-commerce on the demand side and generalized the existing models.

To measure the joint services of e-commerce consumption loans and money, an important assumption would be the weak separability. A specific payment service or liquid asset must be able to pay for all consumption goods and services. Otherwise, it is not applicable when aggregate with cash or other money. More detail will discuss in the following models.

Huabei[1] consumption loan service that relied on world's largest mobile and online payments platform Alipay, has already been applied to all consumptions in China including groceries and utilities, while e-commerce consumption loans in other countries are still limited to fashion retailers or designer brands. In this paper, I would use the volume of Huabei services as the empirical data source and update results for China’s monetary aggregation.

The latest research for China’s Divisia Monetary Aggregation was Tang (2015). In late 2015, China had completed its process of interest rate marketization. An updated monetary aggregation may provide more information about China’s interest rate marketization process. Also, a longer

[1] Huabei were also referred as Ant Check Later services. See Xie et al. (2020). However, to avoid confusion from translating issues, we adopt its original product name in this paper.

data horizon would provide more information in frequency domain analysis. By applying spectrum analysis to China's monetary aggregates, the results show that in the short run, coherencies between monetary aggregates and nominal GDP decline, and monetary aggregates has serious lagging. This is just another evidence of Milton Friedman's conclusion, that the validity of targeting the quantity of money in the short run is questionable. In this paper, I will include related results to explain the statistic difference between short run and long run monetary aggregates.

1.2 The Model

Assume that the resource allocation of representative consumers has only three types: consumption, monetary assets (includes debts or loans), and benchmark assets, where the benchmark asset is represented by A_s. A benchmark asset refers to a pure investment product that does not have liquidity, that is, it does not provide any liquidity services other than expected returns. In other words, it has zero cashability, and it could be considered as the boundary asset of all monetary assets (includes debts or loans).

1.2.1 Consumer's Utility Maximization Problem

Let period t be the current period (or equivalent to the instant at the beginning of the period), and consumers will make decisions for all periods s$\{s : t, t+1\}$ at time t. First, we define the variables that are used in the consumer's utility maximization problem：

$\mathbf{c}_s$ = vector of per capita (planned) consumptions of goods and services (including those of durables) during period s.

$\mathbf{p}_s$ = vector of goods and service expected prices and of durable goods expected rental prices during period s.

p_s^* = true cost of living index, used to deflate nominal.

m_{is} = planned per capita real balance of monetary asset I during period s $(i = 1, ..., n)$.

r_{is} = the expected nominal holding period (including capital gains and losses) yield on monetary asset during period s $(i = 1, ..., n)$.

d_{js} = real expenditure volumes with consumption loan (including credit card services) type j for transactions during period s $(j = 1, ..., k)$.

e_{js} = expected interest rate on consumption loan d_{js} during period s $(j = 1, ..., k)$.

A_s = planned per capita real benchmark asset holding during period s.

R_s = the expected (one-period holding) yield on the benchmark asset during period s.

L_s = per capita labor supply during period s.

W_s = the wage rate during period s.

Then the consumer's intertemporal decision problem is to choose $(\mathbf{c}_t, \mathbf{c}_{t+1}; \mathbf{d}_t, \mathbf{d}_{t+1}; \mathbf{m}_t, \mathbf{m}_{t+1}; A_{t+1})$ at time t to

$$\max u(\mathbf{c}_t, \mathbf{c}_{t+1}; \mathbf{d}_t, \mathbf{d}_{t+1}; \mathbf{m}_t, \mathbf{m}_{t+1}; A_{t+1}) \qquad (1.1)$$

subject to

$$\mathbf{p}_t\mathbf{c}_t = W_tL_t + p_t^*\mathbf{d}_t - (1+\mathbf{e}_{t-1})p_{t-1}^*\mathbf{d}_{t-1} + (1+\mathbf{r}_{t-1})p_{t-1}^*\mathbf{m}_{t-1} - p_t^*\mathbf{m}_t + (1+R_{t-1})p_{t-1}^*A_{t-1} - p_t^*A_t$$

(1.2)

Here, only the benchmark asset of the last period will appear in the utility function, since the benchmark asset is defined as not being able to provide consumers with monetary services (except for the last period), and the role of the benchmark asset in other periods is only for intertemporal wealth transfer.

1.2.2 User Cost of Consumption Loan

The Lagrangian Function is

$$\begin{aligned}
L &= u(\mathbf{c}_t, \mathbf{c}_{t+1}; \mathbf{d}_t, \mathbf{d}_{t+1}; \mathbf{m}_t, \mathbf{m}_{t+1}; A_{t+1}) \\
&+\lambda_0[W_t L_t + p_t^* \mathbf{d}_t - (1+\mathbf{e}_{t-1}) p_{t-1}^* \mathbf{d}_{t-1} + (1+\mathbf{r}_{t-1}) p_{t-1}^* \mathbf{m}_{t-1} - p_t^* \mathbf{m}_t + (1+R_{t-1}) p_{t-1}^* A_{t-1} - p_t^* A_t - \mathbf{p}_t \mathbf{c}_t] \\
&+\lambda_1[W_{t+1} L_{t+1} + p_{t+1}^* \mathbf{d}_{t+1} - (1+\mathbf{e}_t) p_t^* \mathbf{d}_t + (1+\mathbf{r}_t) p_t^* \mathbf{m}_t - p_{t+1}^* \mathbf{m}_{t+1} + (1+R_t) p_t^* A_t - p_{t+1}^* A_{t+1} - \mathbf{p}_{t+1} \mathbf{c}_{t+1}]
\end{aligned}$$

(1.3)

First order conditions are

$$\frac{\partial L}{\partial \mathbf{c}_t} = \frac{\partial u}{\partial \mathbf{c}_t} - \lambda_0 \mathbf{p}_t = 0 \tag{1.4}$$

$$\frac{\partial L}{\partial \mathbf{m}_t} = \frac{\partial u}{\partial \mathbf{m}_t} - \lambda_0 p_t^* + \lambda_1 (1+\mathbf{r}_t) p_t^* = 0 \tag{1.5}$$

$$\frac{\partial L}{\partial \mathbf{d}_t} = \frac{\partial u}{\partial \mathbf{d}_t} + \lambda_0 p_t^* - \lambda_1 (1+\mathbf{e}_t) p_t^* = 0 \tag{1.6}$$

$$\frac{\partial L}{\partial A_t} = \frac{\partial u}{\partial A_t} - \lambda_0 p_t^* + \lambda_1 (1+R_t) p_t^* = 0 \tag{1.7}$$

From equation (1.4), (1.5), (1.6), (1.7) we have

$$\frac{\partial u}{\partial \mathbf{c}_t} = \lambda_0 \mathbf{p}_t \tag{1.8}$$

$$\frac{\partial u}{\partial \mathbf{m}_t} = \lambda_0 p_t^* - \lambda_1(1+\mathbf{r}_t)p_t^* \tag{1.9}$$

$$\frac{\partial u}{\partial \mathbf{d}_t} = -\lambda_0 p_t^* + \lambda_1(1+\mathbf{e}_t)p_t^* \tag{1.10}$$

$$\frac{\partial u}{\partial A_t} = \lambda_0 p_t^* - \lambda_1(1+R_t)p_t^* \tag{1.11}$$

Since we assume that only the last period of the benchmark asset is the control variable, and the rest of the periods do not enter the utility function, the partial derivative of the benchmark asset during t is equivalent to the partial derivative of a constant, that is $\frac{\partial u}{\partial A_t} = 0$. Hence

$$\lambda_1 = \frac{\lambda_0}{1+R_t} \tag{1.12}$$

Substitute (1.12) into (1.9) and (1.10) we have

$$\frac{\partial u}{\partial \mathbf{m}_t} = \lambda_0 p_t^* \frac{R_t - \mathbf{r}_t}{1+R_t} \tag{1.13}$$

$$\frac{\partial u}{\partial \mathbf{d}_t} = \lambda_0 p_t^* \frac{\mathbf{e}_t - R_t}{1+R_t} \tag{1.14}$$

Note that when $\lambda_0 = 1$, the marginal utility of current consumption is the price of consumer goods. As we assume that monetary assets and credit card services are regarded as durable goods or services, their rental or user costs are just the marginal utilities in this model:

$$\pi_{it} = \frac{p_t^*(R_t - r_{it})}{1+R_t} \tag{1.15}$$

$$\tilde{\pi}_{jt} = \frac{p_t^*(e_{jt} - R_t)}{1+R_t} \tag{1.16}$$

Here π_{it} is the nominal use cost price of monetary asset i at time t, $\boldsymbol{\pi_t} = (\pi_{1t}, \pi_{2t}, ..., \pi_{nt})'$ is the nominal user cost vector of monetary asset in period t; $\tilde{\pi}_{jt}$ is the nominal use cost of consumption loans j, $\tilde{\boldsymbol{\pi}}_{\boldsymbol{t}} = (\tilde{\pi}_{1t}, \tilde{\pi}_{2t}, ..., \tilde{\pi}_{kt})'$ is the nominal user cost vector consumption loans.

1.2.3 Consumption Loan Augmented Monetary Aggregation

Suppose previous utility function $u(\mathbf{c}_t, \mathbf{c}_{t+1}; \mathbf{d}_t, \mathbf{d}_{t+1}; \mathbf{m}_t, \mathbf{m}_{t+1}; A_{t+1})$ is weak separable.

To ensure the applicability of weak separability, the consumption loans we adopt here should not be limited in specific stores or specific good purchases. For example, gift cards that are only good for gasoline purchases or one store's goods, or part of the existing e-commerce consumption loan services that only available for limited retailers would not satisfies the assumption of weak separability.

Weak separability allows consumption loans to aggregate along with other payment mechanisms, such as cash and checking account balances, within the weakly separable block containing monetary assets that can be used to buy any of the goods in the vector of consumer goods in the utility function.

Let $(\mathbf{m}_\mathbf{t}^*, \mathbf{d}_\mathbf{t}^*) = (m_{1t}, m_{2t}, ..., m_{nt}, d_{1t}, d_{2t}, ..., d_{kt})'$ as part of the solution to the above maximization problem, Barnett (1980) and Barnett (1981) showed that $(\mathbf{m}_\mathbf{t}^*, \mathbf{d}_\mathbf{t}^*)$ is also the solution for the current period conditional decision problem

$$\max u(\mathbf{m}_t, \mathbf{d}_t) \tag{1.17}$$

subject to

$$\boldsymbol{\pi}_t' \cdot \mathbf{m}_t + \tilde{\boldsymbol{\pi}}_{\boldsymbol{t}}' \cdot \mathbf{d}_t = y_t \qquad (1.18)$$

where $y_t = \boldsymbol{\pi}_t' \cdot \mathbf{m}_t + \tilde{\boldsymbol{\pi}}_{\boldsymbol{t}}' \cdot \mathbf{d}_t$ is the total expenditure of the portfolio of (n+k) monetary assets and debt basis consumption loans.

Let the aggregation equation of monetary liquid assets be v (), then the exact aggregation of money M_t can be expressed as $M_t = v(\mathbf{m}_{\mathbf{t}}^*)$. The index theory in statistics provides theoretical basis to get M_t without estimation of the unknown equation v (). In a continuous time period, the new payment service augmented monetary aggregation, $M_t^c = u(\mathbf{m}_{\mathbf{t}}^*, \mathbf{d}_{\mathbf{t}}^*)$, can be accurately obtained by the Divisia index without error, and is also the solution of the following differential equation

$$\frac{d \log M_t^c}{dt} = \sum_{i=1}^{n} \omega_{it} \frac{d \log m_{it}^*}{dt} + \sum_{j=1}^{k} \tilde{\omega}_{jt} \frac{d \log d_{jt}^*}{dt} \qquad (1.19)$$

Here,

$$\omega_{it} = \frac{\pi_{it} m_{it}}{\boldsymbol{\pi}_t \cdot \mathbf{m}_t + \tilde{\boldsymbol{\pi}}_t \cdot \mathbf{d}_t} = \frac{\pi_{it} m_{it}}{\sum_{i=1}^{n} \pi_{it} m_{it} + \sum_{j=1}^{k} \tilde{\pi}_{jt} d_{jt}} \qquad (1.20)$$

$$\tilde{\omega}_{jt} = \frac{\tilde{\pi}_{jt} d_{jt}}{\boldsymbol{\pi}_t \cdot \mathbf{m}_t + \tilde{\boldsymbol{\pi}}_t \cdot \mathbf{d}_t} = \frac{\tilde{\pi}_{jt} d_{jt}}{\sum_{i=1}^{n} \pi_{it} m_{it} + \sum_{j=1}^{k} \tilde{\pi}_{jt} d_{jt}} \qquad (1.21)$$

Above growth rate weight ω_{it} is the share of monetary assets in the total consumption of the monetary liquid asset portfolio, and $\tilde{\omega}_{jt}$ is the share of new payment services such as credit card services or other small consumption loans, in the total consumption of the monetary liquid asset portfolio. Since economic data are mostly discrete-time data, it is necessary to perform a second-order $Törnqvist - Theil$ approximation (mostly called an $Törnqvist - Theil$ Index) to the above-mentioned continuous-time index, to obtain the discrete-time Divisia Index of monetary aggregation:

$$\log M_t^c - \log M_{t-1}^c = \sum_{i=1}^{n} \bar{\omega}_{it}(\log m_{it} - \log m_{i,t-1}) + \sum_{j=1}^{k} \bar{\tilde{\omega}}_{jt}(\log d_{jt} - \log d_{j,t-1}) \tag{1.22}$$

Where the discrete weights are approximated by

$$\bar{\omega}_{it} = \frac{1}{2}(\omega_{it} + \omega_{i,t-1}) \tag{1.23}$$

$$\bar{\tilde{\omega}}_{it} = \frac{1}{2}(\tilde{\omega}_{jt} + \tilde{\omega}_{j,t-1}) \tag{1.24}$$

1.3 China's Monetary Aggregation

1.3.1 Data Description and Pretreatments[2]

Currency: from 2000 January to 2020 December, M0 data revealed by PBC;

Demand deposit: from 2000 January to 2020 December, revealed by PBC;

Fixed deposits: data only available for all fixed deposits without clarify their maturities. Missing data for 09/2001 and 11/2001 were estimated by Linear Interpolation method; The interest rate data uses the one-year time deposit interest rate.

Saving deposit: from 2000 January to 2020 December; The interest rate data uses the one-year time deposit interest rate.

Interbank Lending: from 2000 January to 2020 December; Missing data for 02/2000 was estimated by Linear Interpolation method.

GDP: The quarterly GDP data comes from the China Statistical Yearbook, from first quarter of 2000 to last quarter of 2020. We convert quarterly data into monthly data using quadratic function interpolation.

Benchmark rate: LPR (Loan Prime Rate), from 2000 January to 2020 December, revealed by PBC.

[2] Treasury Bills, negotiable certificate of deposit and business paper had not been regular published by PBC, so they are not included in this paper.

1.3.2 Consumption Loan Augmented Divisia Aggregates

It is natural to consider that the consumption that made with credit card services should be counted as a specific type of consumption loan. Noted that the credit card cash withdrawal are not the services we are considering in this section.

The data available for the credit card is the quarterly data of the volume of credit card service from 2012 to 2020. Here we use spline interpolation to estimate the monthly data, and perform first order difference operation to obtain the monthly added value of the credit card's loan payable.

The cost of using credit card transaction services includes multiple parts. The cost here is different from the user cost of credit card services that we deduced in the previous sections, but the additional fees to be paid by credit card transactions. In addition to the annual fee of the credit card, there is no payment for the consumption of the card, so there is no capital cost, and it is not included in the credit balance; and when it is overdue, the bank will charge consumers repayment penalty of the amount excessing its minimum repayment amount, at an average rate of 5% per time. Since credit card services are mostly settled on a monthly basis, a credit card payable loan will be charged 12 times at most in a year, which annual interest rate is equivalent to $(1 + 5\%)^{12} - 1 = 0.795856 \approx 79.59\%$. Hence, based on the different overdue time, the average annual interest rate of the outstanding balance is 39.27%.

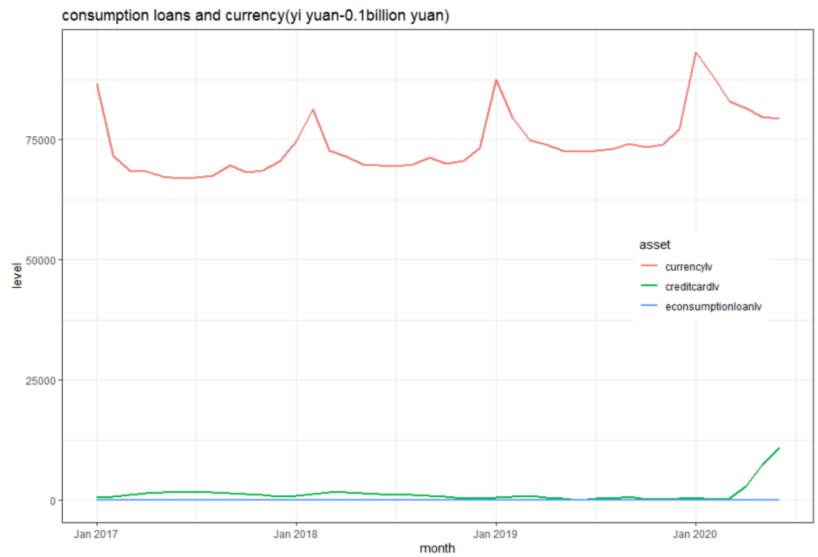

Figure 1.1: Comparison between consumption loans and currency level(2017-2020)

For e-commerce consumption loan, we adopt data for Huabei service provided by Alibaba China. Alibaba takes 12% share of consumption in China 2019 which is 2/3 of e-commerce business. Compared with Amazon's Gross Merchandise Volume 344 billion dollars, Alibaba's is 947 billion dollars in 2018, by Emarketer's data. Huabei consumption loan service are applicable for all purchase on Alibaba including not only groceries but also cars, luxuries, and even online courses or other services that are way integrated than Amazon. With fully functional as other monetary assets for consumption purpose, e-commerce consumption loans like Huabei could be considered within the weakly separable block containing monetary assets that can be used to buy any of the goods in the vector of consumer goods in the utility function.

However, as a new payment service, available data for Huabei and Jiebei is limited from first quarter of 2017 to the second quarter of 2020. We applied spline interpolation to estimate monthly data. Huabei and Jiebei balances are also payable loans balances, just as credit card balances. The repayment penalty of Huabei payable balances = balance* 0.05% * (days of repayment). With similar method, we could get the average annual interest rate of Huabei payable balances is 14.4%.

Considering the length of data, we will focus China's aggregation between 2017 Jan to 2020 June. And the goal is to figure out if consumption loan data could provide more information about total money supply or macro economy.

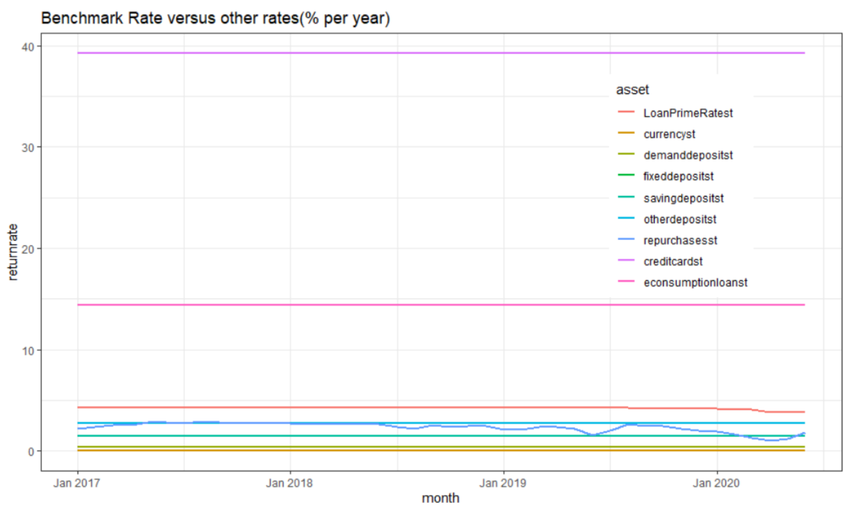

Figure 1.2: Benchmark rate and other rates(2017-2020)

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For a better knowledge of the exact monetary aggregation level, I adopt the corresponding simple sum data as initial level for the China's Divisia aggregates.

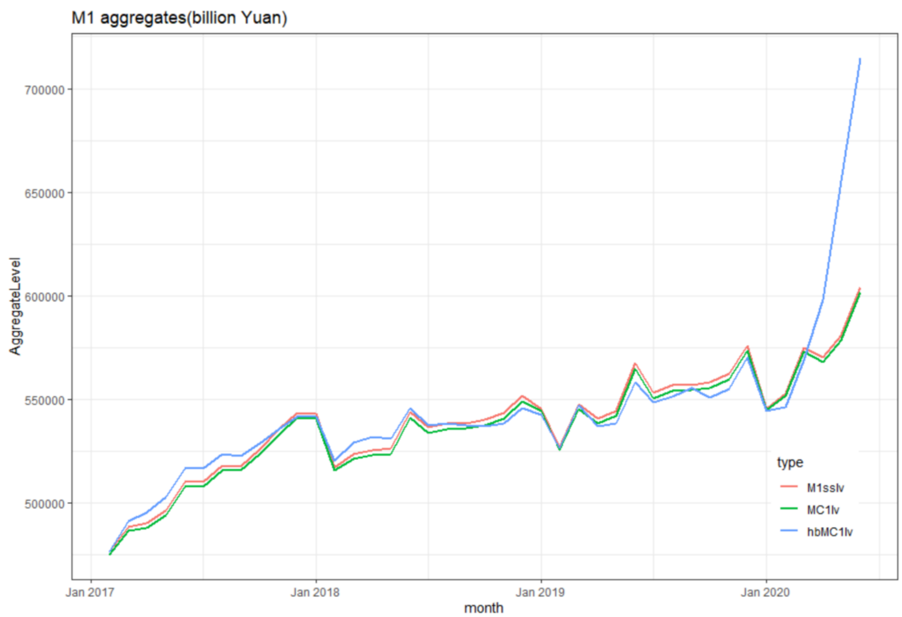

Figure 1.3: Divisia M1, Consumption Loan Augmented M1 and simple sum M1

For aggregates of most liquid monetary assets or services, results doesn't show much difference in most times (Jan 2017 - Jan 2020). However, aggregates that augmented with consumption loans shows a significant booming after Jan 2020, which is exactly the period when Covid-19 virus broke out. During the quarantine period in China, most employees were asked to stay at home and keep away from their working site. Without regular income, there were significant amount of people turns to consumption loans including credit card services and Huabei, to cover their daily expenses and housing mortgage. Only the consumption augmented Divisia M1 shows the abnormality caused by pandemic.

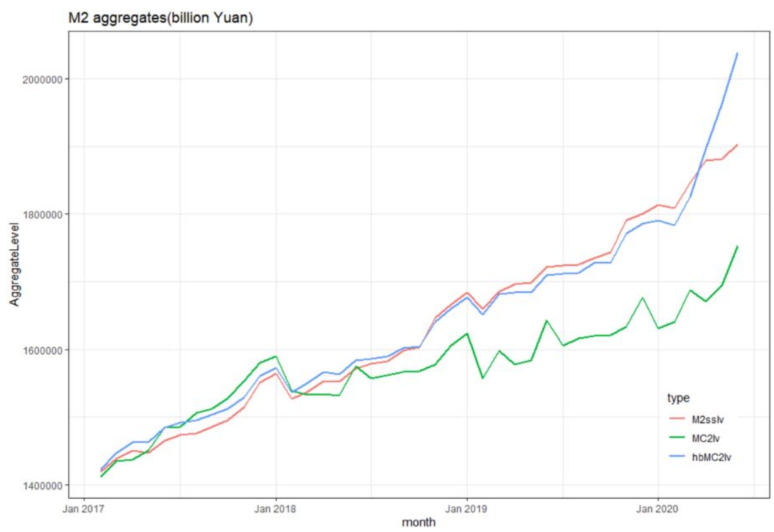

Figure 1.4: Divisia M2, Consumption Loan Augmented M2 and simple sum M2

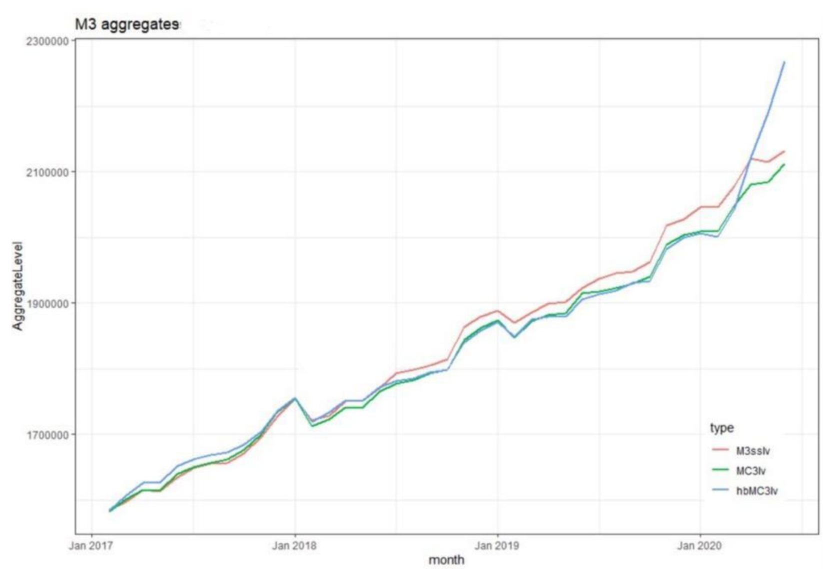

Figure 1.5: Divisia M3, Consumption Loan Augmented M3 and simple sum M3

Table 1.1 shows basic statistics for different consumption loan augmented monetary aggregates. The results show that the difference between Consumption Augmented Divisia monetary aggregation and simple sum aggregation are decreasing as more monetary assets are involved. However, when aggregations getting broader, correlation coefficients with monthly GDP are getting smaller. This result is way different from related research for money quantity and monetary aggregates. In the following sections, I will compare the results with stats for long time horizon data and try to explain this anomaly with spectrum analysis method.

Despite low correlation with nominal GDP, Consumption Augmented Divisia Aggregates are still showing more obvious advantage over simple sum. Also, with smaller standard deviations, Divisia aggregates shows better stability compared to simple sum aggregates.

Table 1.1: basic statistics for different consumption loan augmented monetary aggregates

	Min.	Max.	Range	Mean	Std.Dev	Cor(,GDP)
Simple sum M1	476527.6	604318	127790.4	539213.9	26187.87	0.7015354
M_1^c	475117.9	601579.3	126461.4	540912	26056.11	0.6933125
M_1^c+	476410.8	714589.9	238179.2	543895.5	29402.44	0.7253561
Simple sum M2	1419188	1903308	484120	1633972	137898.9	0.5599771
M_2^c	1420778	1892873	471094.6	1631437	129664.6	0.5720135
M_2^c+	1422516	2038599	616083.3	1640332	131172.1	0.5797076
Simple sum M3	1584969	2131711	546741.4	1836080	158963.4	0.5681474
M_3^c	1582517	2112359	529842.6	1823183	147460	0.5759296
M_3^c+	1584319	2268600	684270.9	1832586	149378.5	0.5759484

1.3.3 China's Money Supply in Long time horizon (01/2000-12/2020)

By applying the Divisia Monetary Aggregation in section 2, we derive the DM1, DM2 and DM3 for China from 2000 January to 2020 December. Figure 1.6 shows the Benchmark rate and other return rates in long time horizon.

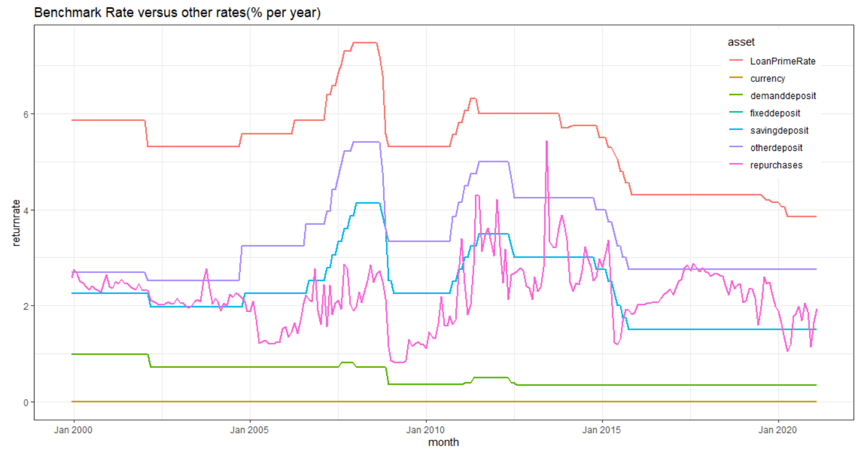

Figure 1.6: Benchmark rate and other return rates in long time horizon (2000-2020)

Table 1.2 shows basic statistics for different monetary aggregations. The results show that the difference between Divisia monetary aggregation and simple sum aggregation are increasing as more monetary assets are involved. As aggregations getting broader, correlation coefficients with monthly GDP are getting greater, and Divisia aggregates are showing more obvious advantage over simple sum. Also, with smaller standard deviations, Divisia aggregates shows better stability compared to simple sum aggregates.

Noted that, not like United State or some other developed countries with zero demand deposit interest rate, China's bank are still paying interest for demand deposits. So DM1 and simple sum M1 shows difference in our results.

Table 1.2: the data summary for different monetary aggregation (2000-2020)

	Min.	Max.	Range	Mean	Std.Dev	Cor(,GDP)
Simple sum M1	44679	625581	580902	259632.2	176712.4	0.9872589
M_1^c	44848.81	614508.2	569659.4	255626.5	173407.6	0.9872337
Simple sum M2	116293.4	1989887	1873594	780288.2	562083.5	0.9881089
M_2^c	116091.1	1839876	1723785	733839.6	515714.4	0.9886445
Simple SumM3	121220	2234298	2113078	850844.1	637900.8	0.9863492
M_3^c	120593.4	1945297	1825704	767073.1	546655.6	0.9880806

Trends comparison between Divisia aggregates and simple sums were showed in Figure 1.7.

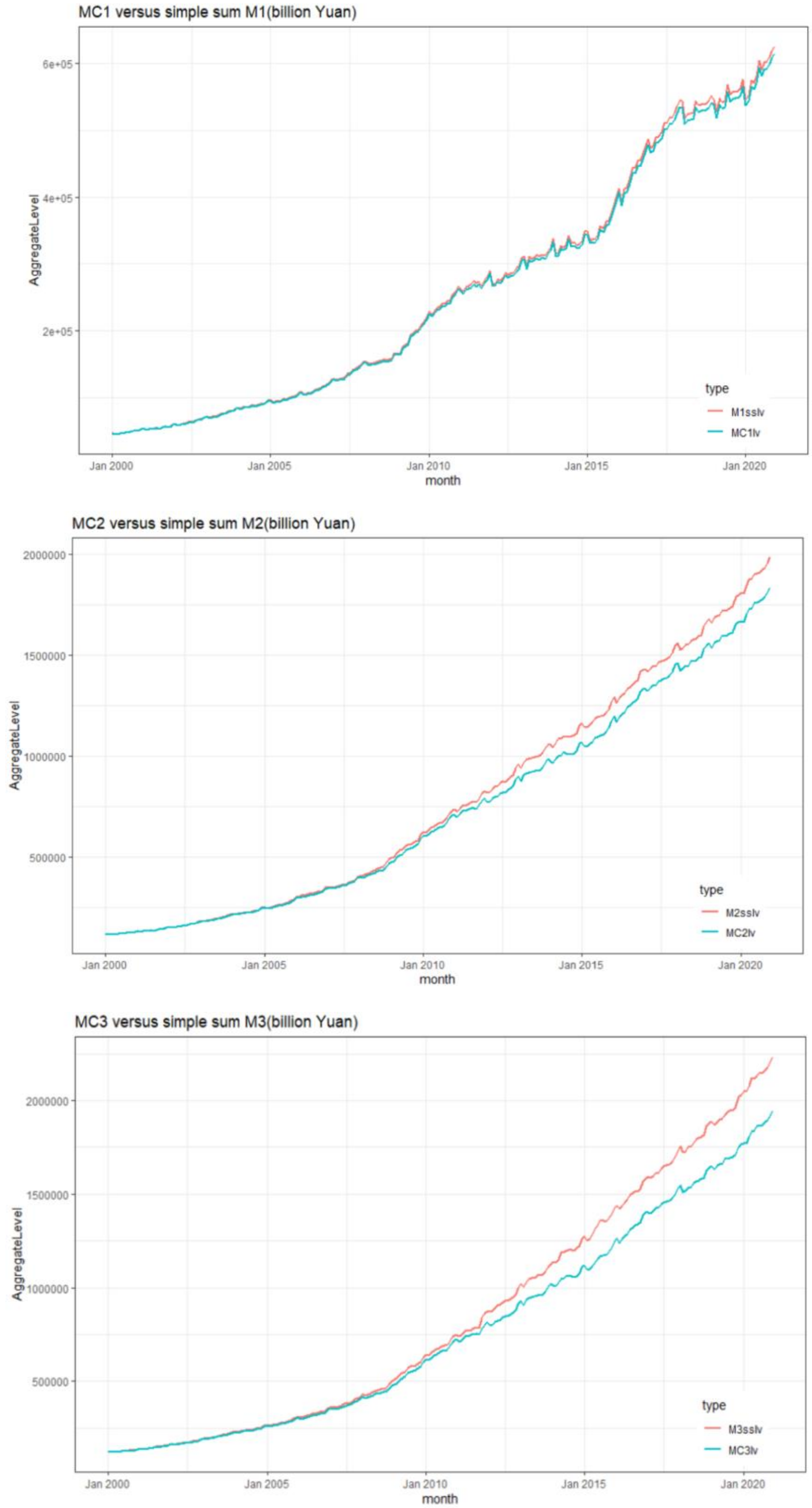

Figure 1.7: Divisia monetary aggregates and simple sum (billion Yuan)

1.3.4 China Monetary Aggregation and Macroeconomic cycle

To Explain the low correlation between Consumption Loan Augmented Divisia Aggregates in short run, I apply the spectrum analysis method to previous data. More details and related results could be found in Barnet and He (2022) paper.

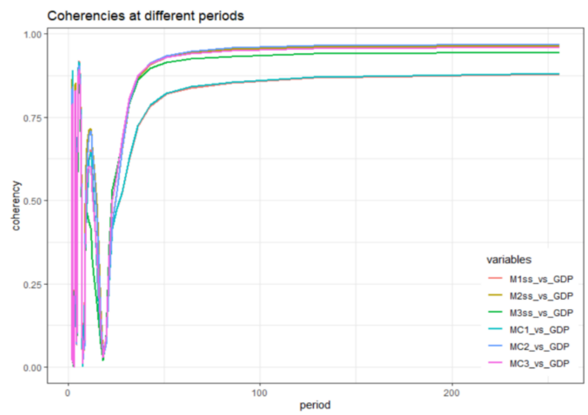

Figure 1.8: Coherencies under with all periods

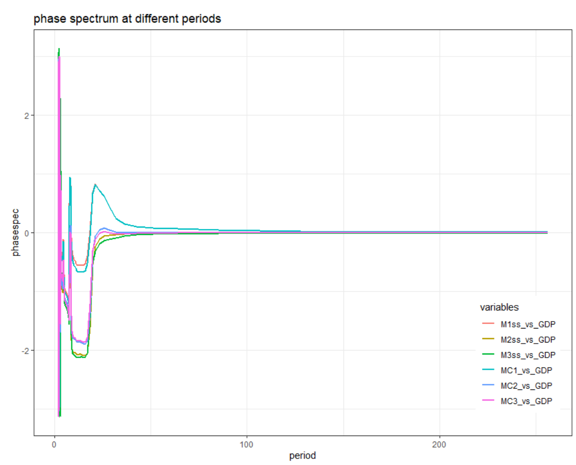

Figure 1.9: Phase differences under with all periods

Figure 1.8 and Figure 1.10 all depict the coherencies between all different monetary aggregates and nominal GDP. By zooming in the coherencies with short periods, Figure 10 provides more accurate numeric results for short term coherencies.

Figure 1.8 shows the coherencies between monetary aggregates and nominal GDP with all periods. In the long run (period > 5 year), all coherencies tend to be converge to a certain level: coherencies for (DM2, nominal GDP) and (DM3, nominal GDP) are around 0.95, coherencies for (simple sum M3, nominal GDP) are around 0.92, coherencies for (simple sum M2, nominal GDP), (simple sum M1, nominal GDP) and (DM1, nominal GDP) are around 0.875. So, we can conclude that all monetary aggregates maintain a high correlation with nominal GDP in the long run, especially for broader Divisia Monetary Aggregates.

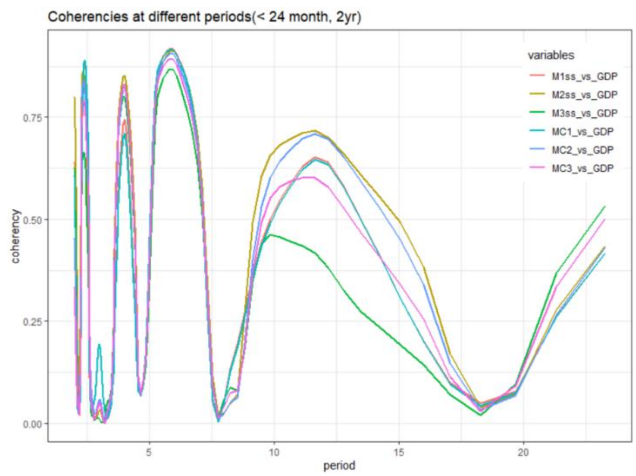

Figure 1.10: Coherencies with short periods

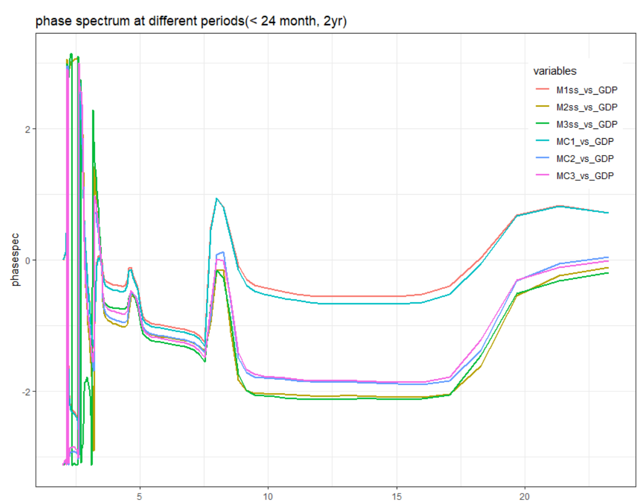

Figure1.11: Phase differences with short periods

Figure 1.10 shows the coherencies between monetary aggregates and nominal GDP with short periods. In the short run (period < 2 year), all coherencies tend are dramatically vibrate around 0.5, which is almost half of the coherencies in the long run. This result shows the limit and unstable correlation between all monetary aggregates and nominal GDP in the short run, which also explain the statistic results for consumption loan augmented Divisia Monetary Aggregates in section 3.2.

Figure 1.9 and Figure 1.11 all depict the phase differences between all different monetary aggregates and nominal GDP. By zooming in the phase differences with short periods, Figure 1.11 provides more accurate numeric results for short term phase differences.

Compare the phase differences results in short run and long run, we can conclude that in the long run, there is no lag between monetary aggregates and nominal GDP; while in the short run (period < 2 year), phase differences are negative for most times, which means an obvious lag between all monetary aggregates and nominal GDP. This is just another evidence of Milton Friedman's conclusion, that the validity of targeting the quantity of money in the short run is questionable.

1.4 Augmented Divisia Monetary Aggregation and New Monetary Assets

By concluding debt basis consumption loan in the framework of Divisia Monetary Aggregation, we could generalize the Divisia Monetary Aggregates with other types of cashable currencies:

Central Bank Digital Money has been adopted and developed by central bank in many countries. Related program includes Jasper Canada, Ubin Singapore, Stella Japan, Inthanon Thailand, LionRock Hongkong China, and PBC Digital China. These paperless currencies that issued by central banks would serve as cash once published.

Table 1.3: Components for New Currency Augmented Divisia Monetary Aggregation

<table>
<tr><th colspan="5">Divisia Monetary Aggregates</th><th>Type</th></tr>
<tr><td rowspan="14">M_4^c</td><td rowspan="11">M_3^c</td><td rowspan="9">M_2^c</td><td rowspan="6">M_1^c</td><td rowspan="2">M_0^c</td><td>Cash</td></tr>
<tr><td>Central Bank Digital money</td></tr>
<tr><td rowspan="4"></td><td>Credit Card Services</td></tr>
<tr><td>(E-commerce) Consumption Loans</td></tr>
<tr><td>Virtual currency</td></tr>
<tr><td>Demand Deposits</td></tr>
<tr><td colspan="2" rowspan="3"></td><td>Fixed Deposits in Commercial Banks</td></tr>
<tr><td>negotiable certificate of deposit</td></tr>
<tr><td>Saving Deposits in Commercial Banks</td></tr>
<tr><td colspan="3" rowspan="2"></td><td>Fixed Deposits in Finance Companies</td></tr>
<tr><td>Saving Deposits in Finance Companies</td></tr>
<tr><td colspan="4" rowspan="3"></td><td>Overnight and Term Repurchases</td></tr>
<tr><td>Business Paper and Bills</td></tr>
<tr><td>Treasury Bills</td></tr>
</table>

Virtual Currency is currency held within the blockchain network that is not controlled by a centralized banking authority. Virtual currency is different than digital currency since digital currency is simply currency issued by a bank in digital form. The most well-known virtual currency is the Bitcoin Cash, which is available on Paypal and other online payment systems. With limit cashability in transaction it could may consider to enjoy the similar liquidity with demand deposit balances.

Based on the discussion of various types of new currencies, we can incorporate various types of new currencies into the monetary aggregate based on the Divisia Monetary Aggregation Theory, and establish augmented monetary aggregates of new currencies. Components for augmented Divisia Monetary Aggregation are re-summarized in Table 1.3.

1.5 Conclusion

Divisia Aggregation is the most advanced measurement of all liquid asset so far. E-commerce Consumption Loan Divisia Aggregates shows its unique correlation with the macroeconomic environment. With a longer time horizon, Divisia Monetary aggregates shows higher coherency with nominal GDP, compared with simple sum aggregates. In conclusion, the Divisia Monetary Aggregates would be an ideal long-term control intermediate target.

Chapter II: Monetary Aggregation and Macroeconomics Regulation Periods

2.1 Introduction

Money supply is one of the main intermediary targets of macroeconomic regulation and control. There are plenty of researches indicate that Divisia Monetary Aggregates are preferable over simple-sum monetary aggregates as a measurement in the implementation of monetary policy (Darrat, Chopin, Lobo 2005). For the regulation plan with different cycle lengths, how to choose its intermediate target is the proposition of this paper. For the two-year and five-year control plans, is the Divisia Monetary Aggregate still a better intermediate target choice than the simple summed money supply? If so, which liquidity is more suitable for short-term regulatory objectives and which is more suitable for long-term regulatory objectives?

In order to answer previous questions, this paper applied the spectral analysis method on the monetary aggregates of the United States, based on the Fourier transformation of the discrete time series and Spectrum Analysis methods. By deriving periodic features in frequency domain of economic time series data, the data trimming issues when compare indexes with different normalization method and initial values could be simplified after Fourier Decomposition.

We also construct a binary coherence spectral estimator to calculate the degree of correlation between two time series at different frequencies or periods. In addition, we also use the binary phase difference spectral estimator to measure the lagging or leading relationship of two time series. By summarizing the estimated results of coherencies and phase differences for monetary aggregates and nominal GDP, we initially concluded the correlation between the monetary aggregate and main economic policy goals under different control periods, which helps in selecting a suitable intermediary target for a given control cycle.

2.2 Methodology

Spectral analysis methods were first used in macroeconomic research in the mid-1960s. The original relevant literature was on seasonal adjustment (Nerlove, 1964) and the general spectral structure of economic data (Granger, 1966). From previous studies, Economists have found that the coherence spectrum method is particularly useful and irreplaceable in discovering and explaining the relationship of economic variables (Lee, 1995).

In the following decades, the scope of application of spectral analysis was extended to the study of other econometric problems, including the problem of trend cycle separation, the extraction and measurement of economic cycles, and the linkage between some variable series in international business cycle research. The latest economic research with spectrum analysis application is about the comparison between supply side and demand side Divisia monetary aggregation (Barnett, He, 2020). Spectrum analysis was also applied in DSGE model simulations and have proved to be more accurate with related toolbox.

It should be noted that spectral analysis is a purely descriptive analysis and cannot be directly used to predict economic problems[3]; nonetheless, it is still a powerful tool for studying cyclical phenomena and synchronous linkages. Among them, coherency spectral analysis in spectral analysis has irreplaceable advantages for studying the correlation between variables, and can provide more specific and accurate periodic correlation analysis.

[3] A further study with wavelet analysis method would be updated for the related topic, which could have the time domain information reserved and avoiding further issues with data stationarity.

2.2.1 Discrete Fourier Transform of Time Series and Its Smooth Spectral Estimator

In general, the characteristic behavior of time series can be decomposed into three main categories: long-term, medium-term, and short-term behavior. These three categories of behaviors or characteristics are respectively associated with slowly evolving trends, shorter oscillating business cycles, as well as fast and irregular seasonal changes. Empirical macroeconomists have been using a variety of methods to linearly correct and smooth data, such as using moving averages to remove random fluctuations, first-order differences to remove long-term trends, and subtracting linear trends to remove offset terms.

Although these methods are conceptually correct and valid when applied to data processing, none of the above methods will lead to a formal analytical decomposition of time series and cannot give accurate conclusions about business cycles based on mathematical results. The Fourier decomposition can separate the signal into different pure periodic components. When perform discrete Fourier decomposition on the time series, the frequency domain features with mathematical basis can be obtained. This is the reason why we employ the spectral analysis model for this problem.

For a finite series $u(j)$ with length $T = N\Delta t$, the discrete Fourier transform (DFT) $U(k)$ of $u(j)$ and its inverse (IDFT) for finite series are (Barnett and He, 2020)

$$U(k) = \frac{1}{N}\sum_{j=0}^{N-1} u(j)e^{-i2\pi jk/N} \tag{2.1}$$

$$u(j) = \sum_{k=-\lfloor N/2 \rfloor}^{\lfloor (N-1)/2 \rfloor} U(k)e^{i2\pi jk/N} \tag{2.2}$$

where N refers to the sample size and Δt refers to the sampling periodicity. For the k-th term in the series $\{U(k)\}$, its frequency is denoted as $v_k = \frac{k}{N\Delta t}$; and $t_j = j\Delta t$ denotes the time for j-th term in the corresponding time series $\{u(j)\}$ in time domain.

$\{U(k)\}$'s power spectrum or power spectral density function is given by

$$P_u(k) = |U(k)|^2 \tag{2.3}$$

which is the square of the amplitude for Fourier Series $\{U(k)\}$ in (2.2). The power spectrum describes the distribution of signal power in the frequency domain. According to the Baševal's theorem, energy is conserved whether in the time domain or frequency domain: for a signal, power reflects the amplitude of its signal strength at a certain frequency; for the time series economic variables considered in this paper, its power can be interpreted as the relative change of the value of the economic variable at a certain frequency, and its absolute value has no economic intuition to have further discussion in this paper.

An estimator for the power spectrum is given by the Schuster's Periodogram (Iacobucci,2003):

$$\mathrm{P}_u(k) = \Delta t \sum_{J=-(N-1)}^{N-1} \gamma_{uu}(J) \cos\frac{2\pi Jk}{N} \tag{2.4}$$

where $\gamma_{uu}(J) = \gamma_{uu}(-J) = N^{-1}\sum_{j=-(N-J)}^{N-J}(u(j)-\bar{u})(u(j+J)-\bar{u})$ is the standard sample estimation at lag J of the autocovariance function for time series$\{u(j)\}$.

To build a more stable spectral estimator – i.e. has a smaller variance – than $P_u(k)$, we turn to the technique of windowing. This technique is employed both in time and in frequency domain to smoothen all abrupt variations and to minimize the spurious fluctuations generated every time a series is truncated. The Smoothed Spectrum is given by

$$\hat{S}_u(k) = \Delta t \sum_{J=-(N-1)}^{N-1} \omega_M(J)\gamma_{uu}(J)\cos\frac{2\pi Jk}{N} \tag{2.5}$$

where the autocovariance function is weighted by the lag window $\omega(j)$ of width M. It is clear that windowing with width M is equivalent to splitting the series in N/M sub-series of length$M$, then computing their mean power spectrum.

2.2.2 Coherency Spectrum Analysis: Binary Expansion

Univariate spectral analysis can be used to explore the changes within a single series, while bivariate spectral analysis can describe the correlation characteristics of the pair of time series in the frequency domain by decomposing the covariance between the two different frequency components. In other words, coherent spectrum analysis in frequency domain analysis can be analogous to correlation analysis in time domain. And estimator of a (smoothed) coherency spectrum could be obtained by replacing the auto-covariance function in equations (4) and (5) with the cross-covariance function of the time series pair.

For two time series $\{u_1(j_1)\}$ and $\{u_2(j_2)\}$ with cross-covariance $\gamma_{12}(J) = \gamma_{12}(-J)$, thier cross spectrum is

$$\hat{S}_{12}(k) = \Delta t \sum_{J=-(N-1)}^{N-1} \omega(J)\gamma_{12}(J)e^{-i2\pi Jk/N} = \hat{C}_{12}(k) - i\hat{Q}_{12}(k) \quad (2.6)$$

Here, the real part $\hat{C}_{12}(k)$ is the coincident spectrum and the imaginary part $\hat{Q}_{12}(k)$ the quadrature spectrum.

The Coherency Spectrum is

$$\hat{K}_{12}(k) = \frac{|\hat{S}_{12}(k)|}{\sqrt{\hat{S}_1(k)\hat{S}_1(k)}} = \frac{\sqrt{\hat{C}_{12}(k)^2+\hat{Q}_{12}(k)^2}}{\sqrt{\hat{S}_1(k)\hat{S}_1(k)}} \quad (2.7)$$

which measures the correlation between two series in frequency domain, similar to the correlation coefficient in time domain analysis.

The Phase Spectrum (time-lag) is

$$\hat{\Phi}_{12}(k) = \arctan(-\frac{\hat{Q}_{12}(k)}{\hat{C}_{12}(k)}) \quad (2.8)$$

which measures the phase differences between the frequency components of the two series $\{u_1(j_1)\}$ and $\{u_2(j_2)\}$: for any given frequency v_k, if the corresponding $\Phi_{12}(k) > 0$,then $u_1(k)$ is ahead of $u_2(k)$; if the corresponding $\Phi_{12}(k) < 0$,then $u_1(k)$ is lag behind of $u_2(k)$. The degree of lead or lag is measured by the standardized phase:

$$(2\pi v_k)^{-1}\Phi_{12}(k) \quad (2.9)$$

2.3 Data Description and Model Setting

2.3.1 Data Description

Simple sum M1 data are seasonal adjusted monthly obtained from the Federal Reserve Bank website[4] data in billions of dollars. Simple sum M1 consists of (1) currency outside the U.S. Treasury, Federal Reserve Banks, and the vaults of depository institutions; (2) demand deposits at commercial banks (excluding those amounts held by depository institutions, the U.S. government, and foreign banks and official institutions) less cash items in the process of

[4] Board of Governors of the Federal Reserve System (US), M1 [M1SL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/M1SL.

collection and Federal Reserve float; and (3) other checkable deposits (OCDs), consisting of negotiable order of withdrawal, or NOW, and automatic transfer service, or ATS, accounts at depository institutions, share draft accounts at credit unions, and demand deposits at thrift institutions.

Simple sum M2 data are seasonal adjusted monthly obtained from the Federal Reserve Bank website[5] data in billions of dollars. Simple sum M2 consists of M1 plus (1) savings deposits (including money market deposit accounts); (2) small-denomination time deposits (time deposits in amounts of less than $100,000) less individual retirement account (IRA) and Keogh balances at depository institutions; and (3) balances in retail money market funds (MMFs) less IRA and Keogh balances at MMFs.

Simple sum M3 data are seasonal adjusted monthly obtained from the Federal Reserve Bank website[6] data in billions of dollars. Components of Simple sum M3 could be found from the Federal Reserve Bank website listed in the footnote 3.

Divisia Monetary Aggregates M1, M2 and M3 level of the United States were published by Center for Financial Stability (CFS) website[7]. The components of Divisia Monetary aggregates are the same as the corresponding simple-summed monetary aggregates published by Federal Reserve Bank. The CFS published US Divisia M1, M2, M3 level was normalized to equal 100 in Jan. 1967.

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[5]Board of Governors of the Federal Reserve System (US), M2 [M2SL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/M2SL.

[6]Organization for Economic Co-operation and Development, M3 for the United States [MABMM301USM189S], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MABMM301USM189S.

[7] https://centerforfinancialstability.org/amfm_data.php#xl

For a more comparable analysis with Divisia Aggregates, we are applying the same normalization to the simple sum aggregates. All simple sum M1, M2, M3 level that published by Federal Reserve Bank was normalized to equal 100 in Jan. 1967. However, the results are remaining unchanged when comparing with results before normalization, which reflects the feature of spectrum analysis.

Noted that the power spectrums of all-time series have no economic intuition themselves, and we are focusing on the periodic features for bivariant analysis, so the data adopted for all monetary aggregates are those which preserve as much raw information as possible that without further trimming. The components of DM1 and DM2 are the same as in the Federal Reserve Board's official aggregates, but demand deposits are sweep adjusted.

The quarterly GDP data comes from the Federal Reserve Bank website[8]. Here, quarterly data was converted into monthly data with quadratic function interpolation.

In order to derive periodic features for both short-term and long-term controls, we are working with data that available in a long-time horizon. The data time span is from January 2000 to December 2020.

2.3.2 Model Settings

The previous section mentioned the pretreatment method of time series data in time domain analysis to eliminate drift items or trend items. However, when using the spectral analysis method, the trend of all the time series in the time domain does not affect the results of the

[8] https://fred.stlouisfed.org/series/GDP

frequency domain analysis, so there is no need of over-trimming or further normalization of all monetary aggregate data and the nominal GDP data. The convenience of frequency domain analysis in data pretreatment or multi-variant comparison has been proved when normalizing the simple sum data in Section 2.3.1.

Since all data are monthly sampled, so the sampling period Δt corresponding to the model in Section 2.1 is one month. The sample size could be calculated by N=21x12=252, which counts all the monthly data of 21 years from 2000 to 2020.

Here, we select the Modified Daniell Smoother as the smoothing function. After the sample size N is determined, we tried multiple smoothing window widths to tradeoff between the estimation bias and stationarity. By the spectral analysis model used in this paper, the larger the value of the smoothing window width M, the smaller the variance of the estimated spectrum at a given frequency, but the larger the estimated deviation. In order to obtain a smooth estimated spectrum without losing too much information, we take M = 8 in the following analysis.

2.4 Bivariate Frequency Domain Analysis of Monetary Aggregates

This section will compare the Divisia and simple sum monetary aggregates of the United States at each liquidity level. The specific steps include: First, derive the power spectrum of each monetary aggregates in the frequency domain with method in Section 2.2.1, as well as their binary squared coherence spectrum; the second is to perform binary spectrum analysis on different monetary aggregates and nominal GDP, and the results are displayed as the binary squared coherence spectrum and binary phase difference.

2.4.1 FED Simple Sum M1 and CFS Divisia M1

The components for the two monetary aggregates are the same, so we are figuring out the difference in aggregation methodology. In the time domain analysis, the correlation between the simple aggregate M1 and Divisia M1 can be expressed by the correlation coefficient:

> cor(usm1ss,usdm1) [1] 0.7799325

However, in a bivariate frequency domain analysis, we can conclude more information by their power spectrum and coherencies of two monetary aggregates at different frequencies.

Figure 2.1 plots the Power Spectrums of simple sum M1 and Divisia M1 of the United States. The black curve is the simple sum M1, and the red dotted line is the Divisia M1. It can be seen that the powers of the two monetary aggregates are quite different, which different from the correlation coefficient result that calculated before. The difference between the two power spectrum is relatively obvious with most frequencies, and get closer when the frequencie are smaller than 0.05, corresponding to the periods that greater than 2 years. The results indicate that in a short period, the two monetary aggregates will have a relatively obvious difference, and as the period increases, the total amount of the two currencies tends to be consistent. It should be noted that the absolute value of power has no economic intuition in this case as stated in previous sections.

The frequencies v_k indicated by the frequency axis are 0.0, 0.1, 0.2, 0.3, 0.4, 0.5; in fact, the time series data of the two monetary aggregates are decomposed into 128 waves with different frequencies after Fourier Transformation, therefore k =1, 2, … ,128. The range of all the 128 frequencies are (0.00390625, 0.50000000). Multiplying the $1/v_k$ by the sampling period we have the corresponding periods are 10, 5, 3.3, 2.5, 2 months from the frequency axis, and the range of the corresponding 128 periods is (2, 256) months.

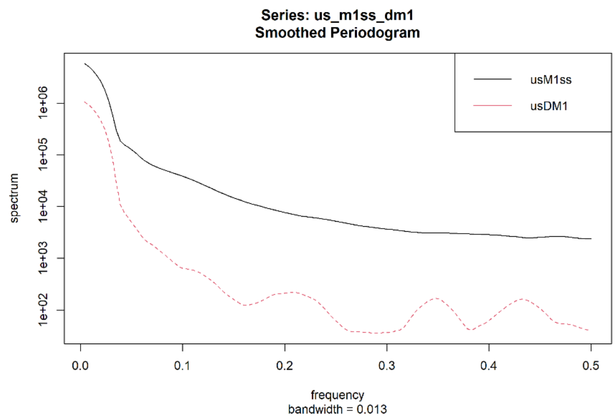


Figure 2.1 Power Spectrums of simple sum M1 and Divisia M1 - the United States

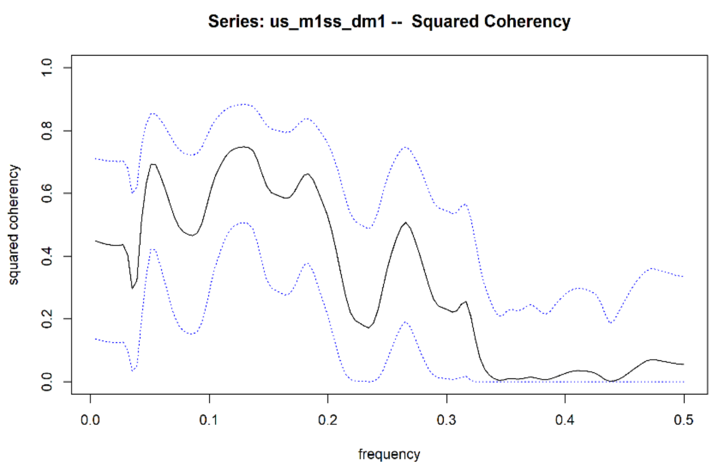
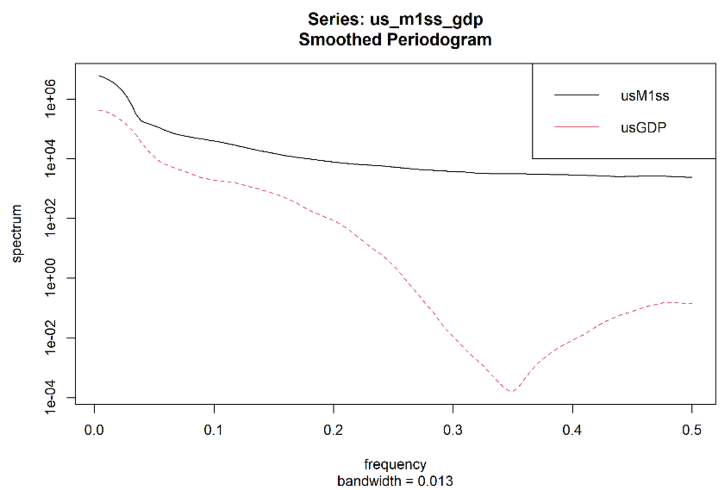


Figure 2.2 Squared Coherency of simple sum M1 and Divisia M1 - the United States

Figure 2.2 plots the squared coherency spectrum of the simple aggregate M1 and Divisia M1. It shows that the coherency at higher frequencies is closed to zero but fluctuates around 0.5 at lower frequencies, or say when the frequencies are smaller than 0.3. Accordingly, the coherencies between the two monetary aggregates is higher when the period is longer than about 3 months. Noted that the blue dashed line in the squared coherency spectrum is the 95% confidence interval band, the blue dashed line of other squared coherency spectrums in the later of the chapter are served as the same purpose.

Figures of Phase Spectrums included in the Appendix part. We are not digging into them in this section considering their limited intuition in Economics.

The following part is the bivariate frequency domain analysis of the two monetary aggregates and the main macroeconomic indicators, nominal GDP of the United States.



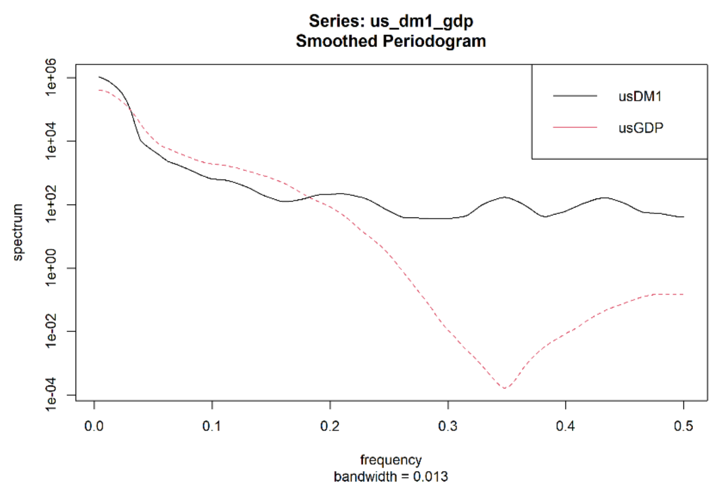


Figure 2.3 Power Spectrum of the two monetary aggregates and nominal GDP – the United States (top: simple sum M1; bottom: Divisia M1)

Figure 2.3 plots the power spectrums of the two monetary aggregates(top: simple sum M1; bottom: Divisia M1) and nominal GDP. The power spectrum of nominal GDP decreases with the shortening of the period, its power decreases to a minimum at a frequency of about 0.3, which corresponds to The period is three months. It can be seen that the power spectrum of Divisia M1 is closer to the power spectrum of the United States nominal GDP in general, expecially when the frequencies are lower than 0.3 that corresponding to the period around 3 months.

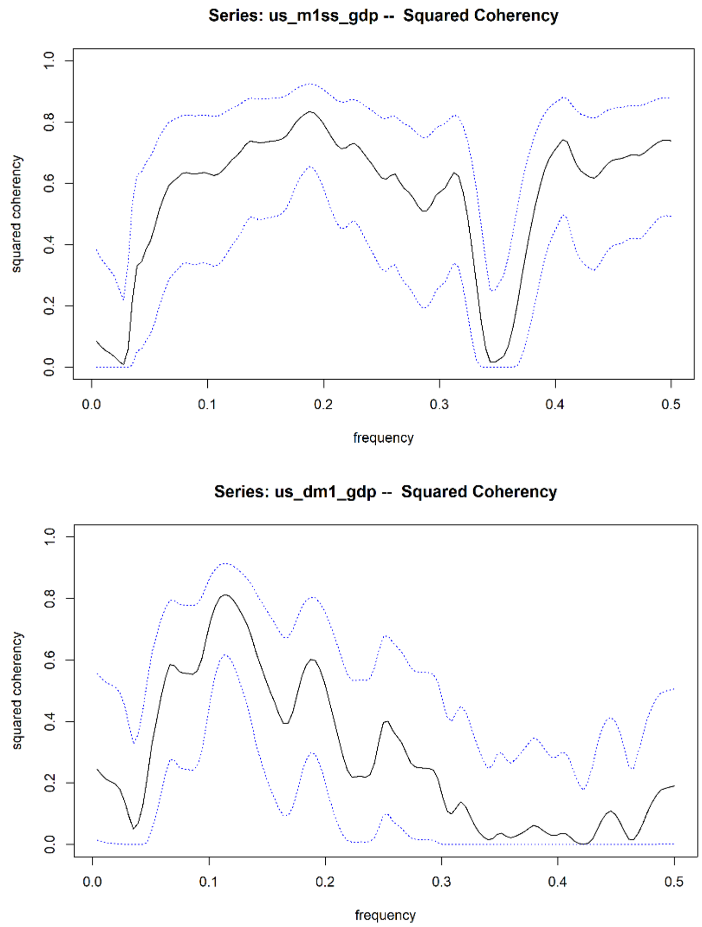


Figure 2.4 Squared Coherency between the two monetary aggregates and nominal GDP – the United States (top: simple sum M1; bottom: Divisia M1)

Figure 2.4 plots the squared coherencies between the two monetary aggregates(top: simple sum M1; bottom: Divisia M1) and nominal GDP. It can be seen that the squared coherencie between simple sum M1 and States nominal GDP is generally higher when the frequencies are greater than 0.1 that corresponding to the period around 10 months or 1 year. However, the squared coherencies between Divisia M1 and nominal GDP are higher when frequencies are smaller than 0.1 that corresponding to periods that greater than 1 year. Considering that most macroeconomic policies are implemented more than a year, so the features for long term are required for further analysis. Empiracal results and figures for long periods will be reintroduced in the later chapters.

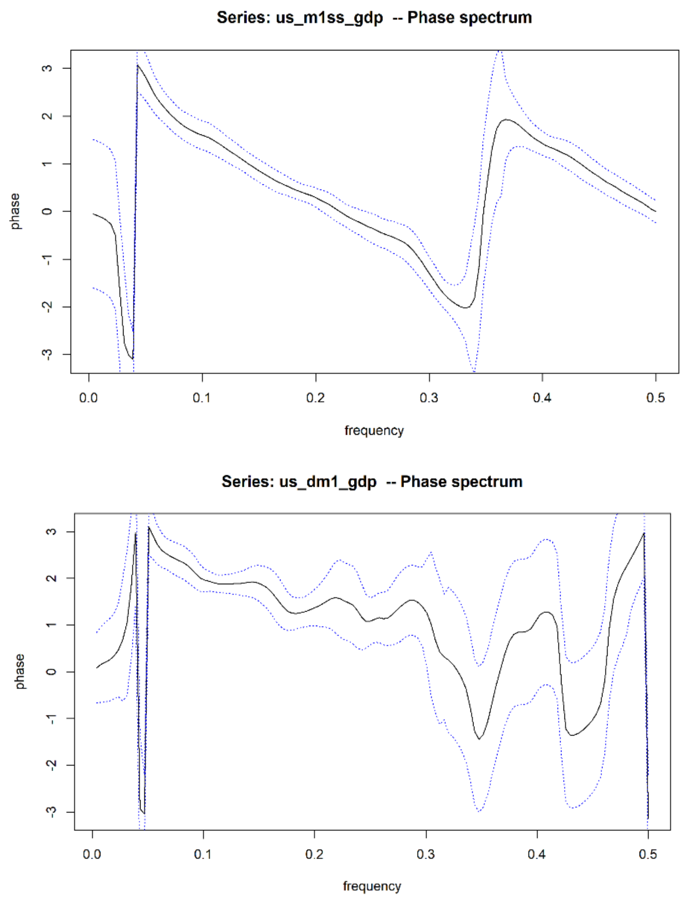


Figure 2.5 Phase differences between the two monetary aggregates and nominal GDP – the United States (top: simple sum M1; bottom: Divisia M1)

Figure 2.5 plots the phase differences spectrum between the two monetary aggregates(top: simple sum M1; bottom: Divisia M1) and nominal GDP. The phase spectrum describes the leading or lagging relationship between monetary aggregates and nominal GDP: at most frequencies/periods, the phase difference is oscillating around zero; but the Divisia M1 shows higher phase differences with GDP at most most frequencies. Especially when the frequencies are smaller than 0.05, which corresponding to periods that greater than 2 years, the simple sum

M1 shows obvious hysteresis while Divisia M1 shows leading to the nominal GDP in the long run.

This result is consistent with the of the power spectrums and the squared coherence spectrums, which further indicates the superiority of Divisia M1 over the conventional simple sum M1, especially in the long run.

2.4.2 FED Simple Sum M2 and CFS Divisia M2

In the time domain analysis, the correlation between the simple aggregate M2 and Divisia M2 can be expressed by the correlation coefficient:

> cor(usm2ss,usdm2) [1] 0.9998007

Figure 2.6 plots the Power Spectrums of simple sum M2 and Divisia M2 of the United States. It can be seen that the powers of the two monetary aggregates are close, which are consistent to the correlation coefficient result that calculated before. The power spectrum of the two monetary aggregates are getting even closer when the frequencie are smaller than 0.05, corresponding to the periods that greater than 2 years.

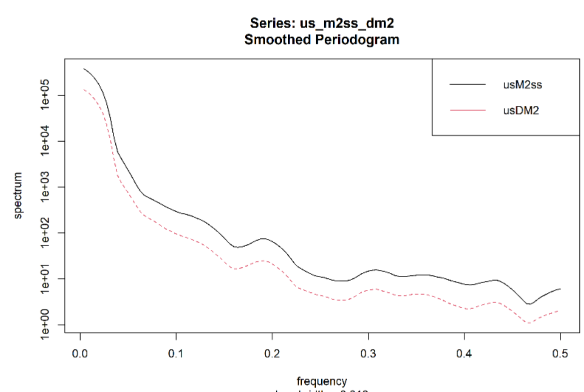


Figure 2.6 Power Spectrums of simple sum M2 and Divisia M2 - the United States

Figure 2.7 plots the squared coherency spectrum of the simple aggregate M2 and Divisia M2. The squared coherence spectrum shows that for all frequency values, the squared coherence of both is about 1, which is also consistent with the results of the correlation coefficient and the power spectrum results.

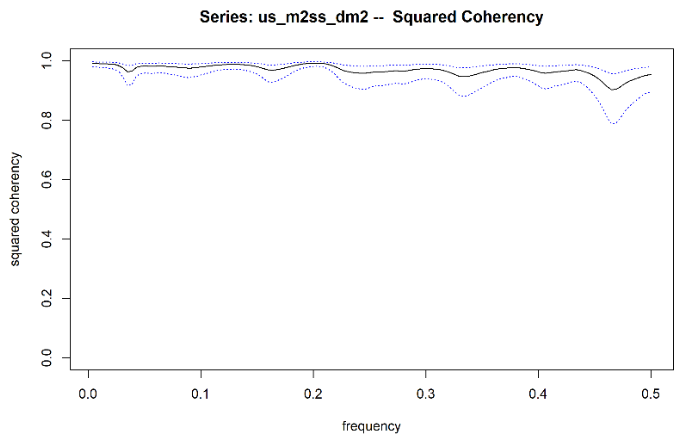


Figure 2.7 Squared Coherency of simple sum M2 and Divisia M2 - the United States

The following part is the bivariate frequency domain analysis of the two monetary aggregates and the main macroeconomic indicators, nominal GDP of the United States.

Figure 2.8 plots the power spectrums of the two monetary aggregates(top: simple sum M2; bottom: Divisia M2) and nominal GDP. As the frequency increases and the period shortens, the power spectrum of the two monetary aggregates gradually decreases. Although it can be seen that the power spectrum of Divisia M2 is closer to the power spectrum of the United States nominal GDP in general, the difference is insignificant from the power spectrums. This is consistent with the previous results.

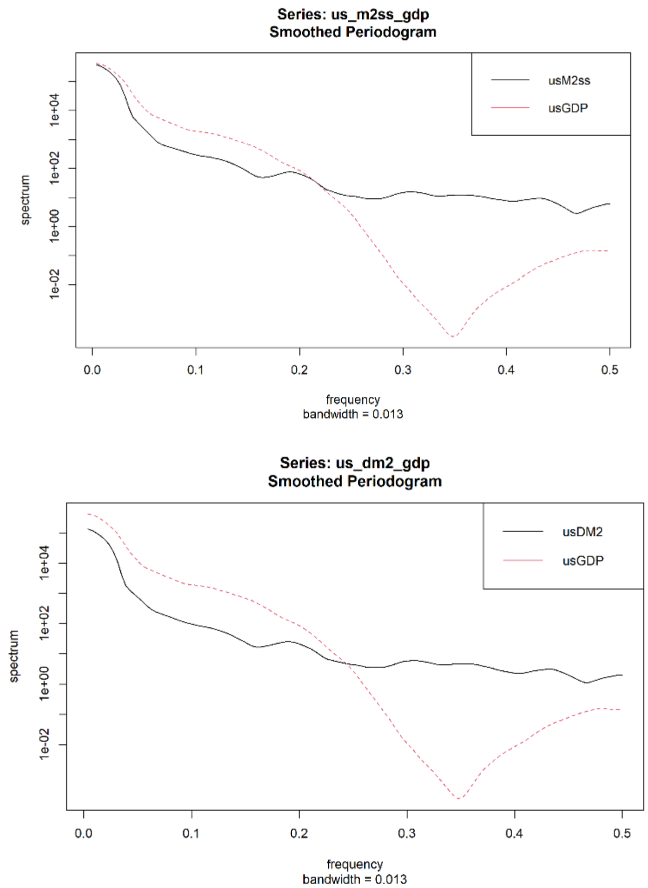
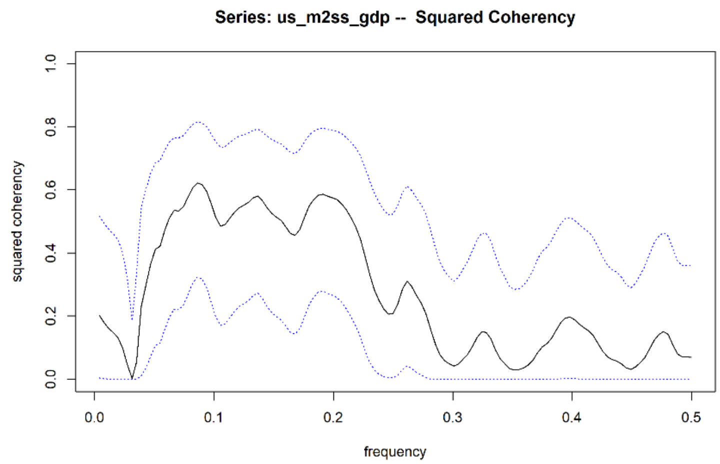


Figure 2.8 Power Spectrum of the two monetary aggregates and nominal GDP – the United States (top: simple sum M2; bottom: Divisia M2)

Figure 2.9 plots the squared coherencies between the two monetary aggregates(top: simple sum M2; bottom: Divisia M2) and nominal GDP. It can be seen that the squared coherencie between the two monetary aggregates and nominal GDP is still similar. However, Divisia M2 shows more advantages when the frequencies are around 0.1 that corresponding to the period around 10 months or 1 year.



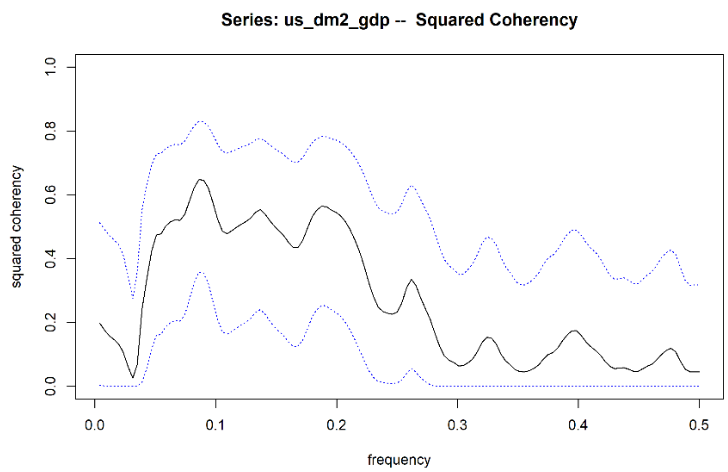


Figure 2.9 Squared Coherency between the two monetary aggregates and nominal GDP – the United States (top: simple sum M2; bottom: Divisia M2)

Figure 2.10 plots the phase differences spectrum between the two monetary aggregates(top: simple sum M2; bottom: Divisia M2) and nominal GDP. The two phase spectrums are almost identical at most frequencies/periods, but the Divisia M2 shows higher phase differences with GDP at frequencies that around 0.05, which corresponding to periods around two years.

This result is consistent with the of the power spectrums and the squared coherence spectrums, which further indicates the superiority of Divisia M2 over the conventional simple sum M2.

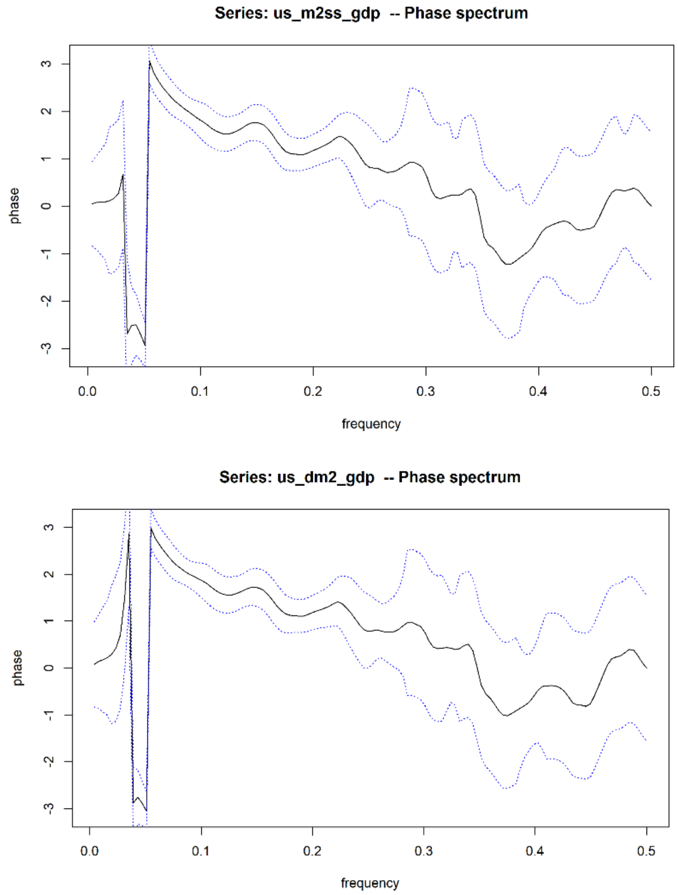


Figure 2.10 Phase differences between the two monetary aggregates and nominal GDP – the United States (top: simple sum M2; bottom: Divisia M2)

2.4.3 FED Simple Sum M3 and CFS Divisia M3

In the time domain analysis, the correlation between the simple aggregate M3 and Divisia M3 can be expressed by the correlation coefficient:

> cor(usm3ss,usdm3) [1] 0.9831248

Figure 11 plots the Power Spectrums of simple sum M3 and Divisia M3 of the United States. It can be seen that the powers of the two monetary aggregates are showing different patterns when the frequencies are high, which indicate that the two monetary aggregates have different power when periods are small.

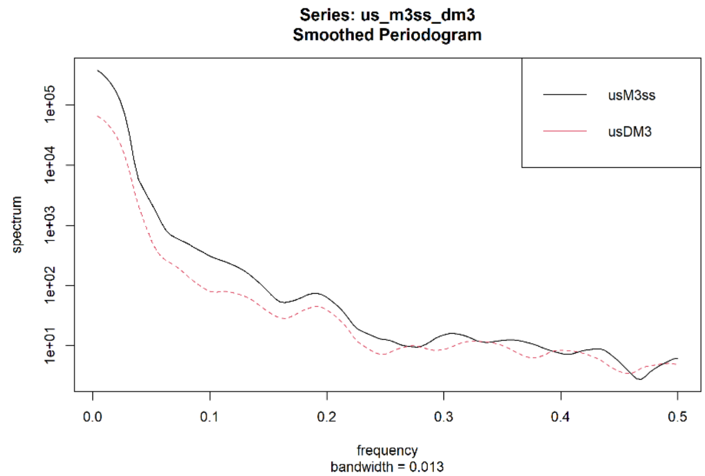


Figure 2.11 Power Spectrums of simple sum M3 and Divisia M3 - the United States

Figure 2.12 plots the squared coherency spectrum of the simple aggregate M3 and Divisia M3. It shows that the coherency at higher frequencies are fluctuating around 0.2 and at lower frequencies are fluctuating around 0.4. Both results from the Figure 11 and Figure 12 are showing that the simple sum M3 and Divisia M3 are quite different when analyzing in the frequency domain, which is the conclusion that hard to derive from the simple correlation coefficient of the two series or other analysis method in time domain.

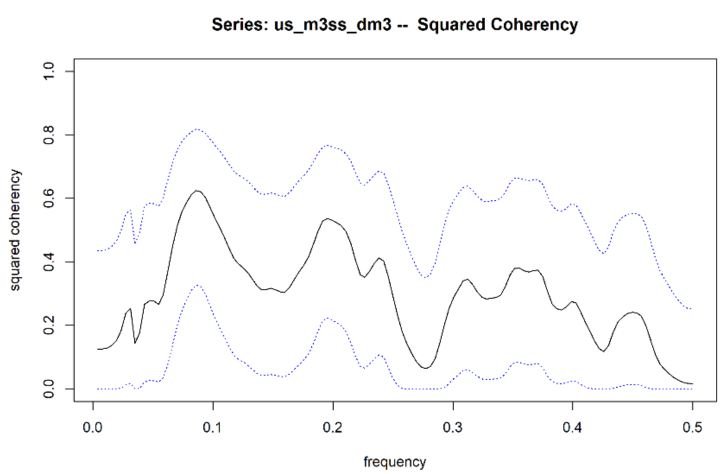
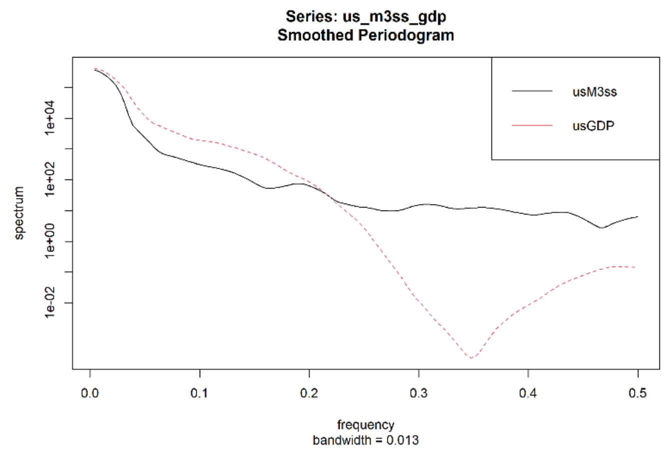


Figure 2.12 Squared Coherency of simple sum M3 and Divisia M3 - the United States

The following part is the bivariate frequency domain analysis of the two monetary aggregates and the main macroeconomic indicators, nominal GDP of the United States.



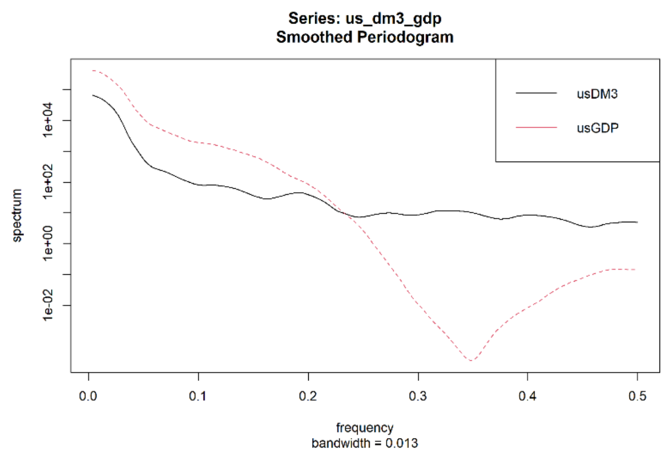


Figure 2.13 Power Spectrum of the two monetary aggregates and nominal GDP – the United States (top: simple sum M3; bottom: Divisia M3)

Figure 2.13 plots the power spectrums of the two monetary aggregates(top: simple sum M3; bottom: Divisia M3) and nominal GDP. It can be seen that the power spectrum of Divisia M3 is closer to the power spectrum of the United States nominal GDP in general, but the difference is insignificant from the power spectrums.

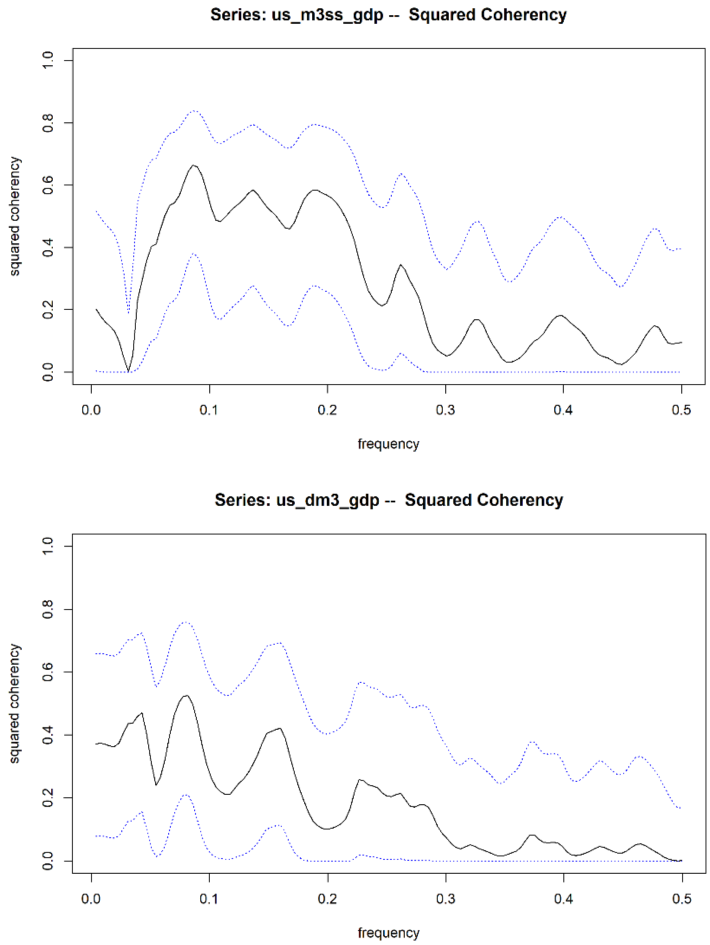


Figure 2.14 Squared Coherency between the two monetary aggregates and nominal GDP – the United States (top: simple sum M3; bottom: Divisia M3)

Figure 2.14 plots the squared coherencies between the two monetary aggregates(top: simple sum M3; bottom: Divisia M3) and nominal GDP. It can be seen that the squared coherencie between simple sum M1 and States nominal GDP is generally higher when the frequencies are greater than 0.05 that corresponding to the period around 20 months or 2 years. However, the squared coherencies between Divisia M1 and nominal GDP are higher when frequencies are smaller than 0.05 that corresponding to periods that greater than 2 years. In order to have a clearer look of the long term features, I will reintroduced the related results in the next chapter.

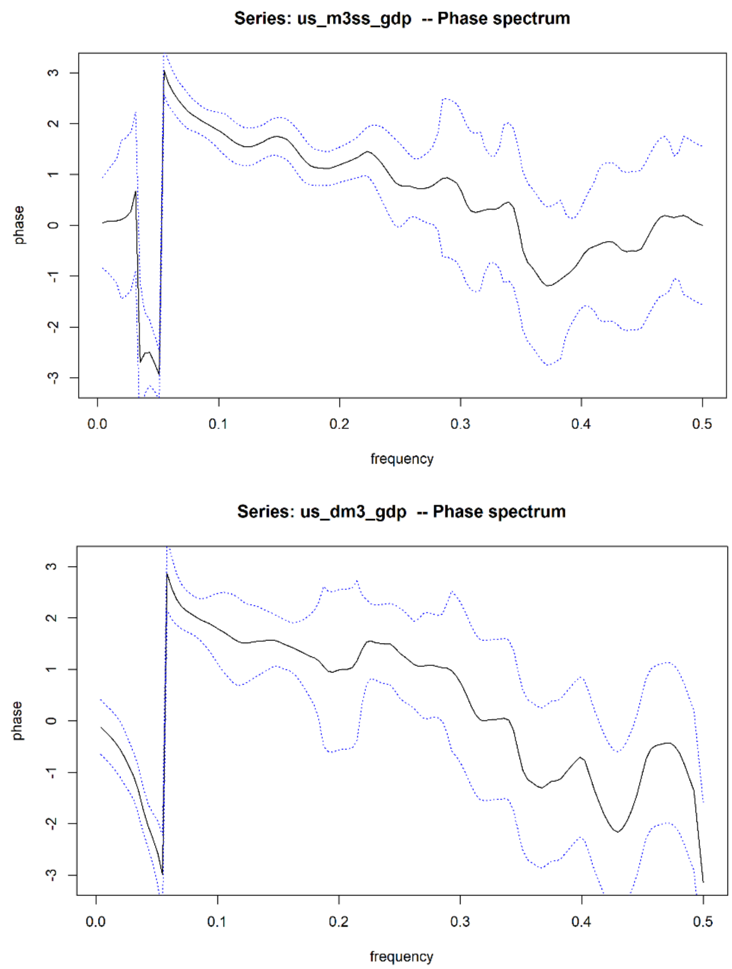


Figure 2.15 Phase differences between the two monetary aggregates and nominal GDP – the United States (top: simple sum M3; bottom: Divisia M3)

Figure 2.15 plots the phase differences spectrum between the two monetary aggregates(top: simple sum M3; bottom: Divisia M3) and nominal GDP. The two phase spectrums are almost identical at most frequencies/periods, but the Divisia M3 shows higher phase differences with GDP at frequencies that around 0.05, which corresponding to periods around two years.

The binary spectrum analysis results for simple sum M3 and Divisia M3 are not solid enough for a conclusion of the better intermediary targe of economic. A further analysis is applied in the next chapter.

2.5 Bivariate Frequency Domain Analysis: Periodic Features in the Long Run

In the previous sections, we conducts the frequency domain analysis of the two published monetary aggregates of the United States according to the classification of liquidity, and compares their coherencies with monthly nominal GDP. For any given liquidity, the corresponding Divisia Monetary Aggregates were proved to be more preferrable than the corresponding simple sum aggregates, especially in a time period that greater than 1 year. Considering its higher coherencies and smaller hysteresis with GDP in the long run, it is reasonable to conclude that Divisia Monetary Aggregates are the more suitable intermediary target of the macroeconomic plans.

However, a direct binary spectrum is not clear enough to reveal periodic features for monetary aggregates in the long run. Also, the binary spectrum analysis method could not apply a thorough comparision among all monetary aggregates.

To resolve the inherit defects of applying binary spectrum analysis to economic time series, we are reintroducing the results of all monetary aggregates by period: The ranges of all the 128 frequencies $\{v_k\}$ are (0.00390625, 0.50000000), multiplying them by the sampling period we have the corresponding periods with a range of (2, 256) months. Therefore, the most accurate intermediary target of monetary aggregate can be selected more intuitively according to the periodic requirements of macro-control.

2.5.1 All Periods Results: 2-256 Months

Figure 16 plots the squared coherencies between all monetary aggregates of the United States and nominal GDP under all periods ranging from 2 months to 256 months (twenty-one years).

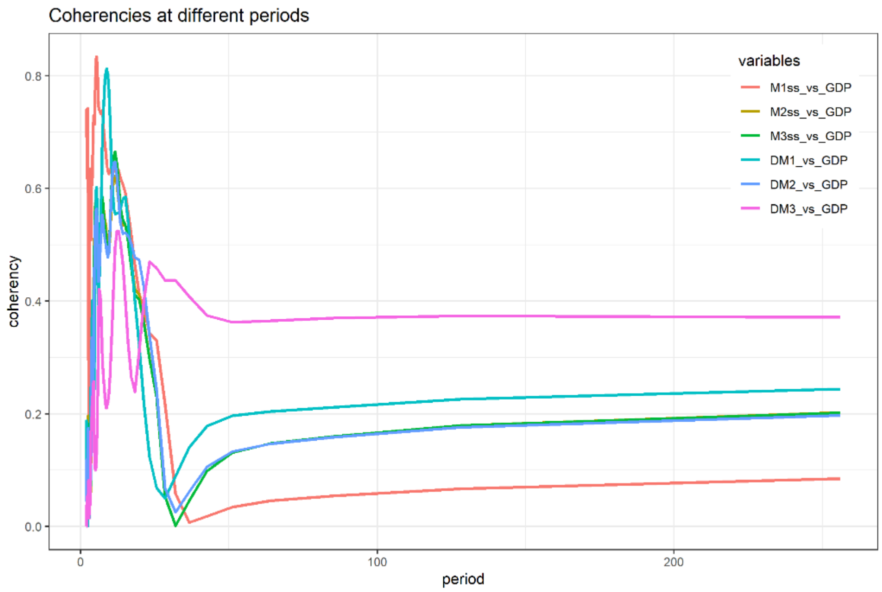


Figure 2.16 Squared coherencies between monetary aggregates and nominal GDP: 2-256 months

The squared coherency spectrum of each monetary aggregate and nominal GDP tends to stabilize after the period is greater than 60 months (or 5 years): the purple curve represents the Divisia M3 whose squared coherencies with nominal GDP are greater than 0.35 in the long run; the light blue curve represents the Divisia M1 whose squared coherencies with nominal GDP are greater than 0.2 in the long run; the orange curve represents the simple sum M1 whose squared coherencies with nominal GDP are the lowest that ranging from 0.05 to 0.1; while the three curves in between are showing the similar results in the long run whose squared coherencies with nominal GDP are around 0.1 in the long run.

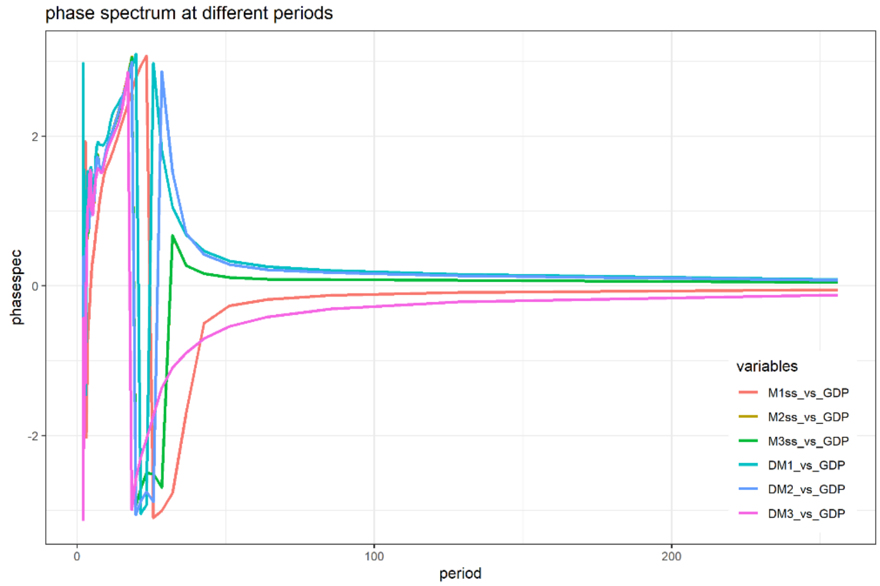


Figure 2.17 Phase differences between monetary aggregates and nominal GDP: 2-256 months

Figure 2.17 plots the phase differences between all monetary aggregates of the United States and nominal GDP under all periods ranging from 2 months to 256 months (twenty-one years). The phase differences each monetary aggregate and nominal GDP tends to stabilize around zero after the period is greater than 60 months (or 5 years). However, Divisia M2, Divisia M1, simple sum M2 and simple sum M3 are showing leading to the nominal GDP, where Divisia M2 and Divisia M1 are showing more leadings ahead of the nominal GDP of the United States in the long run; while the simple sum M1 and Divisia M3 are slightly lag behind the nominal GDP in the long run. The hysteresis of Divisia M3 could be explained by its components with lower liqudity.

Based on the information obtained from Figure 2.16 and Figure 2.17, it is reasonable to conclude that when the monetary aggregate is taken as the intermediate target of macro-control, a longer control cycle can eliminate its lag, and a reasonable selection of the monetary aggregate can help to ensure that the monetary aggregates are in line with the macro-control.

Results from Figure 2.16 and Figure 2.17 once again proves the superiority of Divisia monetary aggregates as an intermediary target for macro-control in the long run: Divisia M3 has the highest coherencies with nominal GDP among all monetary aggregates while Divisia M2 and Divisia M1 are showing a slight perspectiveness to the nominal GDP of the United States.

Due to the large span of period lengths after sorting, Figure 16 and Figure 17 cannot clearly show the spectral analysis results when the period is less than 60 months. In the following subsections, we will zoom in the previous figures to have a better look of shorter common regulation cycle, and make further analysis.

2.5.2 2-5 Year Results: 24-60 months

Figure 2.18 plots the squared coherencies between all monetary aggregates of the United States and nominal GDP under periods ranging from 2 months to 60 months. In this subsection, we are focus on period from 24 to 60 months.

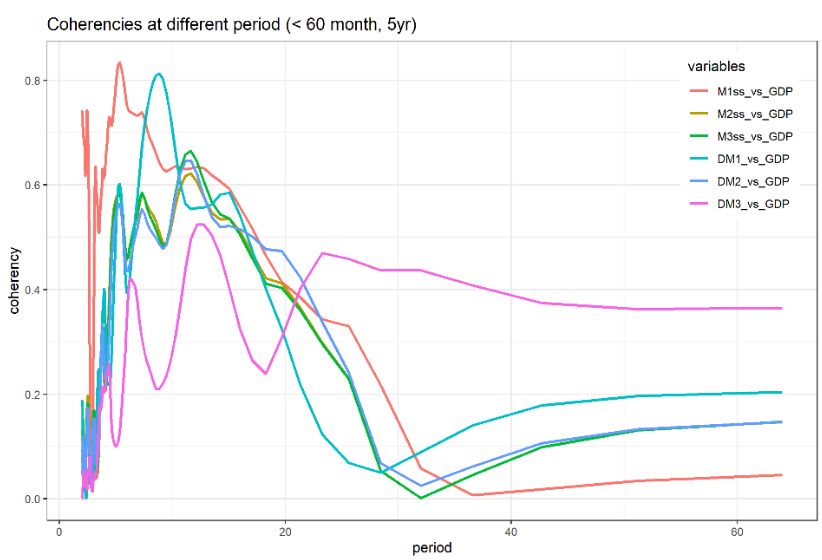


Figure 2.18 Squared coherencies between monetary aggregates and nominal GDP: <60 months

It can be seen from the Figure 18 that Divisia M3 has the highest coherency around 0.45 with the nominal GDP when the period is around 24 months/ 2 years, and gradually decreases to 0.35. However, coherencies of other monetary aggregates are stablizing after around 36 months/ 3 years at lower levels from 0.05(simple sum M1) to 0.2 (Divisia M1).

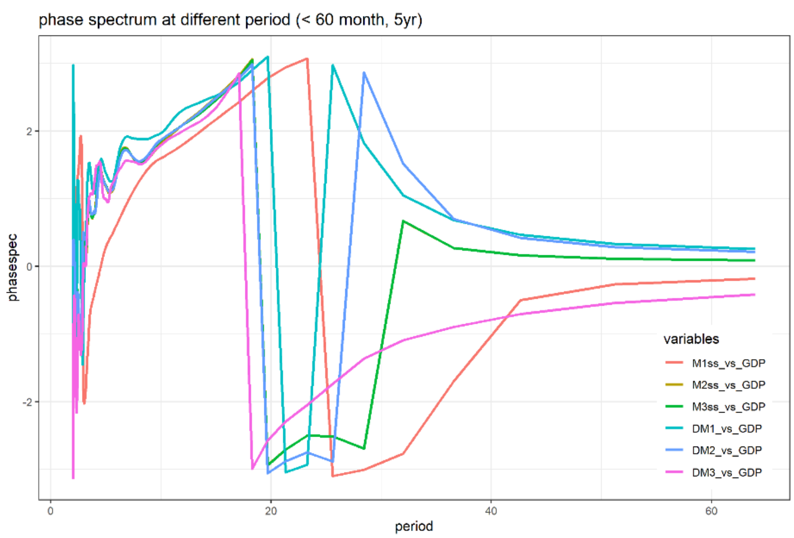


Figure 2.19 Phase differences between monetary aggregates and nominal GDP: <60 months

Figure 2.19 plots the phase differences between all monetary aggregates of the United States and nominal GDP under periods ranging from 2 months to 60 months. Divisia M1 and Divisia M2 are showing the highest leading features ahaed of the nominal GDP when periods are around 24 months and 30 months and then gradually decreasing to its steady level in the long run. However, phase differences of other monetary aggregates are stablizing after around 36 months/ 3 years. Noted that the phase differences of simple sum M1 drop from its maximum to its minimum when periods are around 24 months.

Based on the information obtained from Figure 2.18 and Figure 2.19, it is reasonable to conclude that when the monetary aggregate is taken as the intermediate target of macro-control, a longer control cycle can eliminate its lag, and a reasonable selection of the monetary aggregate can help to ensure that the monetary aggregates are in line with the macro-control.

Results from Figure 2.18 and Figure 2.19 are similar to the results for periods that greater than 5 years. So we could extent the previous conclusion as: Divisia M3 has the highest coherencies with nominal GDP among all monetary aggregates while Divisia M2 and Divisia M1 are showing a slight perspectiveness to the nominal GDP of the United States when periods are greater than 2 years, which further proves the superiority of Divisia monetary aggregates as an intermediary target for macro-control.

2.5.3 Short-term Results: < 24 months

Figure 20 plots the squared coherencies between all monetary aggregates of the United States and nominal GDP under periods ranging from 2 months to 24 months.

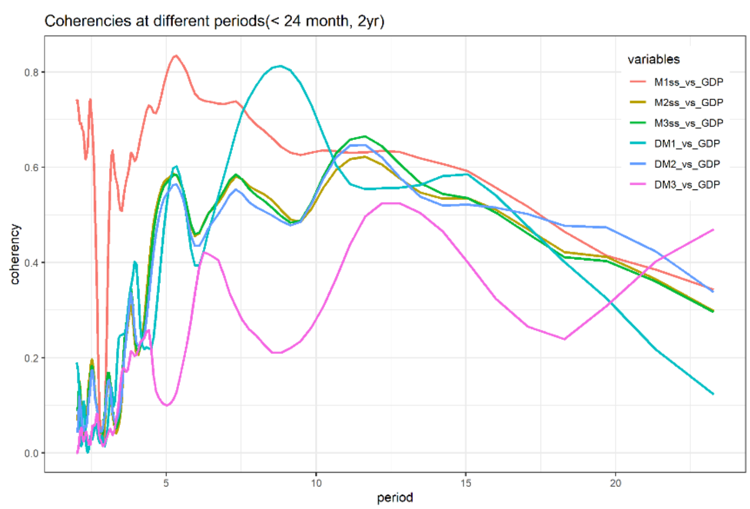


Figure 2.20 Squared coherencies between monetary aggregates and nominal GDP: <24 months

It can be seen from the Figure 2.20 that the coherencies of all monetary aggregates with nominal GDP are ever-changing when the periods are between 2 months to 24 months. Coherencies of simple sum M2/M3, Divisia M1/M2 with GDP are growing from 0 to 0.5 in volatility with the increasing of periods that smaller 6 months, while the simple sum M1 has the coherencies drop from 0.75 to 0 when periods are around 3 months. When periods are between 6 months to 24 months, coherencies of simple sum M1/M2/M3 and Divisia M1/M2 are decreasing to its steady level in the long run, while the Divisia M3 are increasing with volatilies as the periods are increasing. Noted that the simple sum M2 are distinguishable from simple sum M3 for the first time in Figure 2.20.

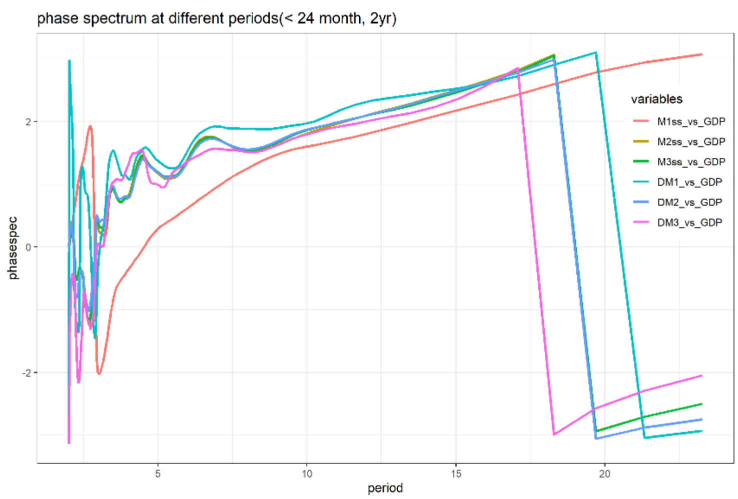


Figure 2.21 Phase differences between monetary aggregates and nominal GDP: <24 months

Figure 2.21 plots the phase differences between all monetary aggregates of the United States and nominal GDP under periods ranging from 2 months to 24 months. The phase differences are changing dramaticly from -3 to 3 when periods are smaller than 3 months, and maintain positive when periods are between 3 months to 18 months. However, phase differences of Divisia M3, Divisia M2, simple sum M3, simple sum M2 and Divisia M1 are droping from their maximum to its minimum when periods are around 18 months, 20 months and 24 months, which are similar to the pattern of simple sum M1 with periods around 24 months(See Figure 2.19).

A possible explanation of the sudden droping of phase differences for all aggregates is the transmission mechanism between monetary policy and macroeconomics in the short run.

2.6 Conclusion

In order to propose the most suitable monetary aggregate as the intermediary target for macro-control plans with different periods, we apply the spectral analysis method to the monetary aggregate data. By introducing the binary spectrum analysis of time series, unnecessary data trimming could be avoid and more original information could be maintained. The unique advantages of frequency domain analysis make it possible to compare among different monetary aggregates with different liquidity level.

Based on the binary spectrum analysis results of different liquidity monetary aggregates of the United States, we believes that when the regulation period is less than 12 months, monetary aggregates should not be used as the intermediary target of macroeconomic regulation. Because whether it is simple sum monetary aggregates or Divisia, their coherencies with nominal GDP are not stable in a short period, and the chances are high that a hysteresis occurs in a short period.

For the a relative long run that more than 12 months, or even a long-term regulation plan with a period of five to twenty years, our results have proved the superiority of Divisia Monetary Aggregates through spectral analysis methods, including its higher coherencies with nominal GDP stability and lower hysteresis. Therefore, we believes that the corresonding Divisia monetary aggregates should be selected as the intermediary target of macro-control when the liqudity is pre-selectd; and in the case that the monetary aggregate has no liquidity restrictions, a broader Divisia monetary aggregates is the most accurate intermediary target of macro-control.

Chapter III: Comparative Periodic Analysis of Global Monetary Aggregates - Evidence of the United States and China

3.1 Introduction

In the "post-pandemic period" of the global economic downturn, the macroeconomic stimulus policies implemented by various countries seem to be stretched: long-term quantitative easing policies have made interest rates continue to fall until their zero lower limits. Many economists believe that expansionary monetary policy is the only solution to the above-mentioned liquidity trap problem, which further emphasize the effect of controls of money supplies and monetary aggregates.

Monetary policies of the world's two giants, the United States and China, have long been interests of both researchers and policymakers all around world. Several existing studies have documented strong international effects of U.S. monetary policy. For example, Kim (2001) and Canova (2005) provide evidence on the transmission of U.S. monetary policy to non-U.S. G6 and Latin American countries, respectively. Rey (2013) finds that U.S. monetary policy is an important driver of global financial cycles.

Not like the US Dollar who plays the unique role in the international financial markets and trades, China Yuan will have smaller international effects relatively, and it has been concluded by several publications. For example, Yang, Xu and Wang (2020) compares the asymmetric spill-over effects of both countries and finds that the U.S. monetary policy has effects on China that are even stronger than its domestic economic factors.

However, comparative analysis about the domestic effects of their monetary policies are limited. One reason is the inherit differences between the related data or indexes that published by the

United States and China. Different initial values, publication frequencies, normalization method are all tricky data treatment issues that may lead failure in further cross-country analysis.

In this paper, we are trying to figure out the difference between monetary policies of the United States and China, with spectrum analysis methods in frequency domain. And answer the following questions: will the two countries' control of monetary aggregates have the same effects on their productions and markets? If not, what could be the possible explanations of the differences? Will the effect be undermined in the long run or not?

By summarizing the estimated results of coherencies and phase differences for monetary aggregates and nominal GDP, we initially concluded the correlation between the monetary aggregate and main economic policy goals under different control periods, which helps in selecting a suitable intermediary target for a given control cycle.

3.2 Methodology: Binary Spectrum Analysis

Barnett and Tang (2015) found that China's monetary aggregate and its growth rate show a certain cyclicality, and believe that the reason for its cyclical characteristics is that China's legal annual holidays will affect money demand and money supply. Figure 1 plots the monthly growth rate of China's Divisia Monetary Aggregates and simple-sum aggregates M1 from January 2000 to December 2020. For the most liquid monetary aggregate M1, no matter whether it is simply aggregated empirical data, it shows a fluctuation law with an annual cycle, in which the growth rate of the monetary aggregate falls to a trough in December or January every year. The cyclical characteristics of China's monetary aggregates have not been fully empirically tested, and as the intermediary target of macroeconomic regulation, the cyclical relationship between monetary aggregates and macroeconomic indicators will have be an important reference for economic goal of regulation and control.

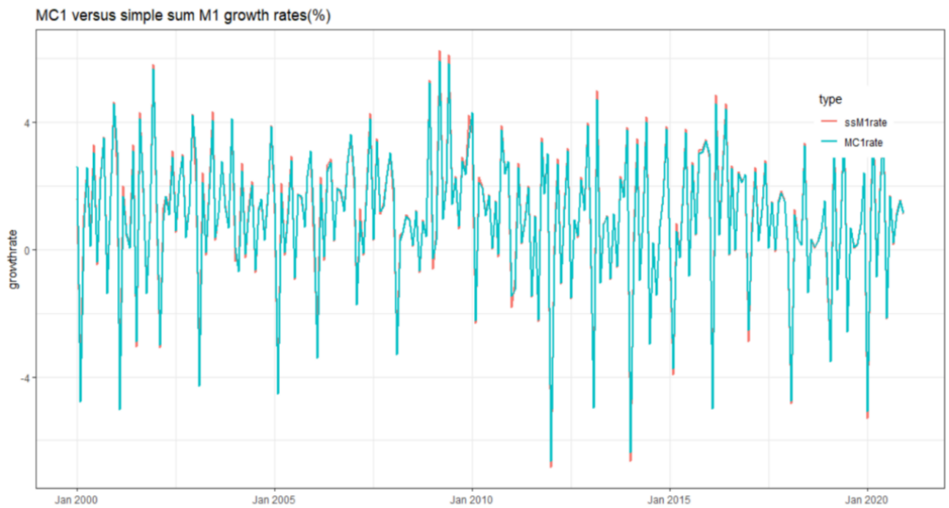


Figure 3.1 Growth Rate of China's Divisia Aggregates and Simple-sum Aggregates M1

In this chapter, we are applying the similar spectrum analysis procedures to China's Divisia Monetary Aggregates, and focus on the results of the coherencies with nominal GDP for both the United States and China, in order to compare the monetary policies of the two countries.

Here we reintroduce the key estimator that will be involved in the following sections:

For a finite series $u(j)$ with length $T = N\Delta t$, the discrete Fourier transform (DFT) $U(k)$ of $u(j)$ and its inverse (IDFT) for finite series are (Barnett and He, 2020)

$$U(k) = \frac{1}{N}\sum_{j=0}^{N-1} u(j)e^{-i2\pi jk/N} \qquad (3.1)$$

$$u(j) = \sum_{k=-\lfloor N/2\rfloor}^{\lfloor (N-1)/2\rfloor} U(k)e^{i2\pi jk/N} \qquad (3.2)$$

where N refers to the sample size and Δt refers to the sampling periodicity. For the k-th term in the series $\{U(k)\}$, its frequency is denoted as $v_k = \frac{k}{N\Delta t}$; and $t_j = j\Delta t$ denotes the time for j-th term in the corresponding time series $\{u(j)\}$ in time domain.

$\{U(k)\}$'s power spectrum or power spectral density function is given by

$$P_u(k) = |U(k)|^2 \quad (3.3)$$

An estimator for the power spectrum is given by the Schuster's Periodogram (Iacobucci,2003):

$$\mathrm{P}_u(k) = \Delta t \sum_{J=-(N-1)}^{N-1} \gamma_{uu}(J) \cos \frac{2\pi Jk}{N} \quad (3.4)$$

The Smoothed Spectrum is given by

$$\hat{S}_u(k) = \Delta t \sum_{J=-(N-1)}^{N-1} \omega_M(J)\gamma_{uu}(J) \cos \frac{2\pi Jk}{N} \quad (3.5)$$

For two time series $\{u_1(j_1)\}$ and $\{u_2(j_2)\}$ with cross-covariance $\gamma_{12}(J) = \gamma_{12}(-J)$, thier cross spectrum is

$$\hat{S}_{12}(k) = \Delta t \sum_{J=-(N-1)}^{N-1} \omega(J)\gamma_{12}(J)e^{-i2\pi Jk/N} = \hat{C}_{12}(k) - i\hat{Q}_{12}(k) \quad (3.6)$$

Here, the real part $\hat{C}_{12}(k)$ is the coincident spectrum and the imaginary part $\hat{Q}_{12}(k)$ the quadrature spectrum.

The Coherency Spectrum is

$$\hat{K}_{12}(k) = \frac{|\hat{S}_{12}(k)|}{\sqrt{\hat{S}_1(k)\hat{S}_1(k)}} = \frac{\sqrt{\hat{C}_{12}(k)^2+\hat{Q}_{12}(k)^2}}{\sqrt{\hat{S}_1(k)\hat{S}_1(k)}} \quad (3.7)$$

which measures the correlation between two series in frequency domain, similar to the correlation coefficient in time domain analysis.

The Phase Spectrum (time-lag) is

$$\hat{\Phi}_{12}(k) = \arctan(-\frac{\hat{Q}_{12}(k)}{\hat{C}_{12}(k)}) \quad (3.8)$$

which measures the phase differences between the frequency components of the two series $\{u_1(j_1)\}$ and $\{u_2(j_2)\}$: for any given frequency v_k, if the corresponding $\Phi_{12}(k) > 0$,then $u_1(k)$ is ahead of $u_2(k)$; if the corresponding $\Phi_{12}(k) < 0$,then $u_1(k)$ is lag behind of $u_2(k)$. The degree of lead or lag is measured by the standardized phase:

$$(2\pi v_k)^{-1}\Phi_{12}(k) \quad (3.9)$$

3.3 Data Description and Model Settings

3.3.1 Data Description

Simple sum M1, M2 and M3 data of the United States was obtained from the Federal Reserve Bank website, measured in billions of dollars. Divisia Monetary Aggregates M1, M2 and M3 level of the United States were published by Center for Financial Stability (CFS) website[9]. The components of Divisia Monetary aggregates are the same as the corresponding simple-summed monetary aggregates published by Federal Reserve Bank. The CFS published US Divisia M1, M2, M3 level was normalized to equal 100 in Jan. 1967. The quarterly GDP data comes from the Federal Reserve Bank website. Here, quarterly data was converted into monthly data with quadratic function interpolation.

China's monetary aggregate data used in this article include China's monetary aggregate(Barnett, He and He, 2022), denoted as M_1^c,M_2^c and M_3^c; and the simple sum monetary aggregates M1 (denoted as m1ss), M2 (denoted as m2ss) and M3 (denoted as m3ss) published by the PBC(People's Bank of China) for comparison. There is no further normalization needed since the initial value of China's Divisia Aggregates was set as the same as the simple sum M1, M2, M3 that published by PBC. The quarterly GDP data comes from the China Statistical Yearbook. Here, quarterly data was converted into monthly data with quadratic function interpolation. The data time span is from January 2000 to December 2020; the unit is 100 million yuan (Yi yuan).

[9] https://centerforfinancialstability.org/amfm_data.php#xl

In order to derive periodic features for both short-term and long-term controls, we are working with data that available in a long-time horizon. The data time span is from January 2000 to December 2020.

3.3.2 Model Settings

All data are monthly data, so the sampling period Δt corresponding to the model in Section 2.1 is one month. The sample size could be calculated by N=21x12=252, which counts all the monthly data of 21 years from 2000 to 2020. Here, we select the Modified Daniell Smoother as the smoothing function.

After the sample size N is determined, we tried multiple smoothing window widths to tradeoff between the estimation bias and stationarity. In the spectral analysis model used in this chapter, the larger the value of the smoothing window width M, the smaller the variance of the estimated spectrum at a given frequency, but the larger the estimated deviation. In order to obtain a smooth estimated spectrum without losing too much information, we take M = 8 in the following analysis.

3.4 Bivariate Frequency Domain Analysis of China’s Monetary Aggregates

In this section, we are applying the similar spectrum analysis procedures to China’s Divisia Monetary Aggregates, and focus on the results of the coherencies with nominal GDP of China.

3.4.1 PBC Simple Sum M1 and China's Divisia M1

The correlation between the PBC's simple aggregate M1 and China's DM1 derived by the consumption loan augmented Divisia is

> cor(m1ss,mc1) [1] 0.9999972

Figure 3.2 plots the squared coherency spectrum of the simple aggregate M1 and Divisia M1. The squared coherence spectrum shows that for all frequency values, the squared coherence of both is about 1, which is also consistent with the results of the correlation coefficient.

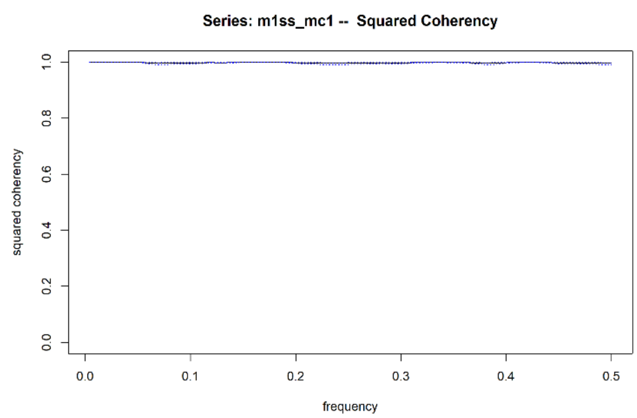


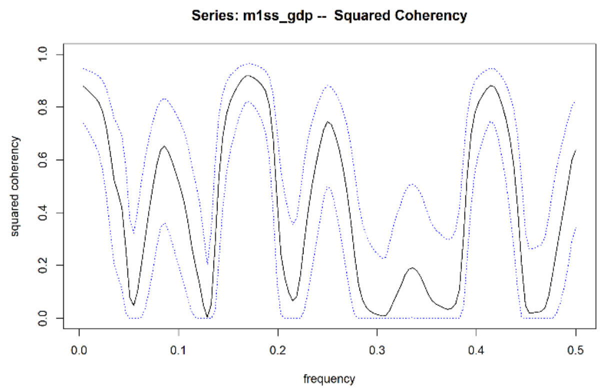
Figure 3.2 Squared Coherency of simple sum M1 and Divisia M1 – China

Combining the analysis results in both the time domain and frequency domain, it can be concluded that when considering China's monetary aggregate with high liquidity and a rate of return close to zero, different aggregation methods will not affect the monetary aggregate level and its cyclical characteristics too much.

Figures 3.3 plots the binary squared coherency spectrum between the two monetary aggregates (top: simple sum M1; bottom: Divisia M1) and nominal GDP. We have analyzes that the difference between different monetary aggregates at the M1 level is not large for China's data.

The statistics also verify once again that under different regulatory periods or frequency requirements, the two most liquid monetary aggregates have the same effect as the intermediary target of regulation.

Noted that the coherency spectrum for both monetary aggregates drops to a minimum at a frequency of around 0.33, which corresponds to a three-month period. Power Spectrums of the two monetary aggregates and nominal are also showing the similar results(see Appendix).



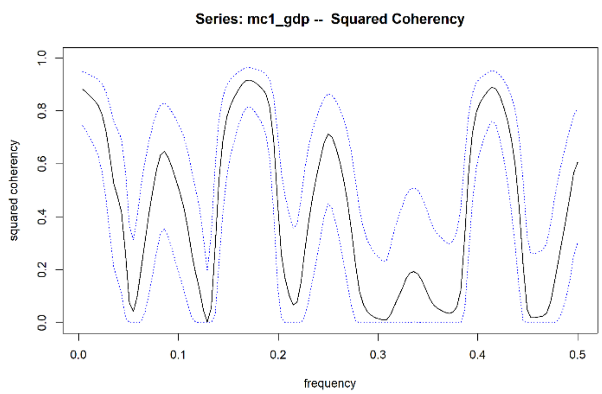


Figure 3.3 Squared Coherency of the two monetary aggregates and nominal GDP – China
(top: simple sum M1; bottom: Divisia M1)

Figure 3.4 plots the phase differences spectrum between the two monetary aggregates(top: simple sum M1; bottom: Divisia M1) and nominal GDP. The phase spectrum shows: at most frequencies/periods, the phase difference is zero or oscillating around zero; but when the frequency is between 0.3 and 0.4, the phase differences are more volatile. This result is consistent with the results of the power spectrum and the squared coherence spectrum. Correspondingly, it is resonable to concludes that when the cycle is about three months or one quarter, there may be a relatively obvious lag or delay when taking Divisia M1 or the simple aggregate M1 as the intermediary target of macro-control.

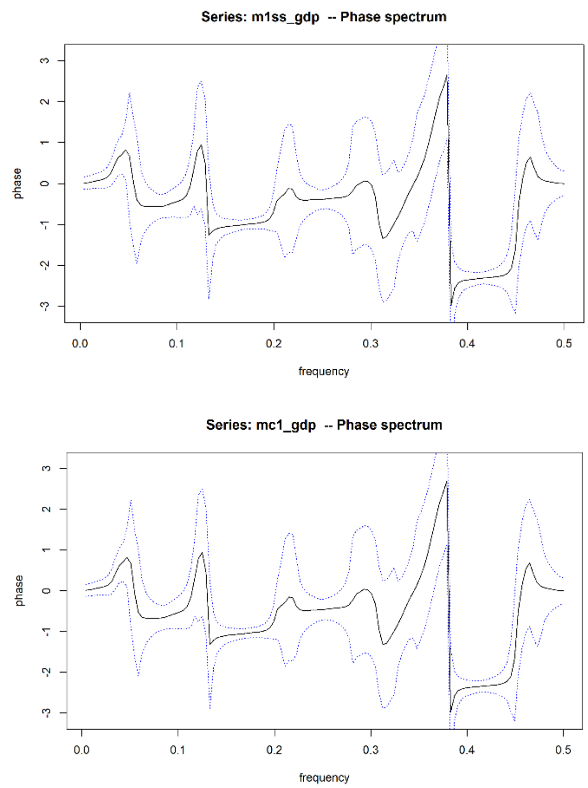


Figure 3.4 Phase Spectrum of the two monetary aggregates and nominal GDP – China
(top: simple sum M1; bottom: Divisia M1)

3.4.2 PBC Simple Sum M2 and China's Divisia M2

The correlation between the PBC's simple aggregate M2 and China's DM2 derived by the consumption loan augmented Divisia is

> cor(m2ss,mc2): [1] 0.9998776

Figure 3.5 plots the squared coherency spectrum of the simple aggregate M2 and Divisia M2. It shows that the squared coherencies between the two monetary aggregates is smaller when the frequency is the largest, that is, in a short period, the two currency aggregates will have relatively obvious differences, and as the period increases, the two currency aggregates tend to be consistent.

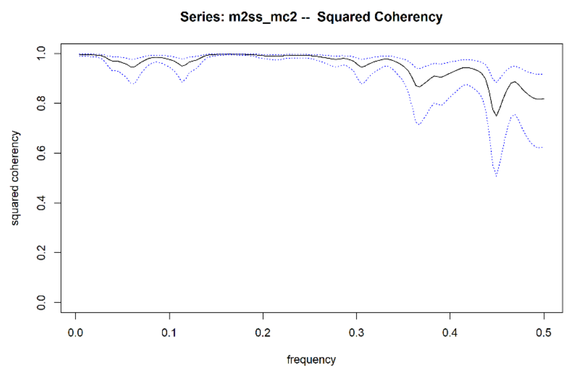


Figure 3.5 Squared Coherency of simple sum M2 and Divisia M2 – China

The above results show that there will be some differences between the two monetary aggregates in a short period: when choosing the intermediary target of macroeconomic control between the two monetary aggregates, if the period is longer, the two aggregates are almost indifferent; if the is short, more information needs to be further considered.

Figures 3.6 plots the binary squared coherency spectrum between the two monetary aggregates (top: simple sum M2; bottom: Divisia M2) and nominal GDP. As the liquidity of monetary aggregates decreases, the types of aggregated currency-based liquid assets increase, and the return on assets increases, the difference between monetary aggregates and simply aggregated M2 gradually emerges, especially when the period is shortIt can be seen from the statistical results that compared with simple sum M2, the correlation between nominal GDP and Divisia

M2 is generally higher; when the regulation period is short, the Divisia M2 should be selected as the intermediate target of macro-control; In the long run, there is little difference between the aggregates of the two currencies.

Power Spectrums of the two monetary aggregates and nominal are also similar(see Appendix).

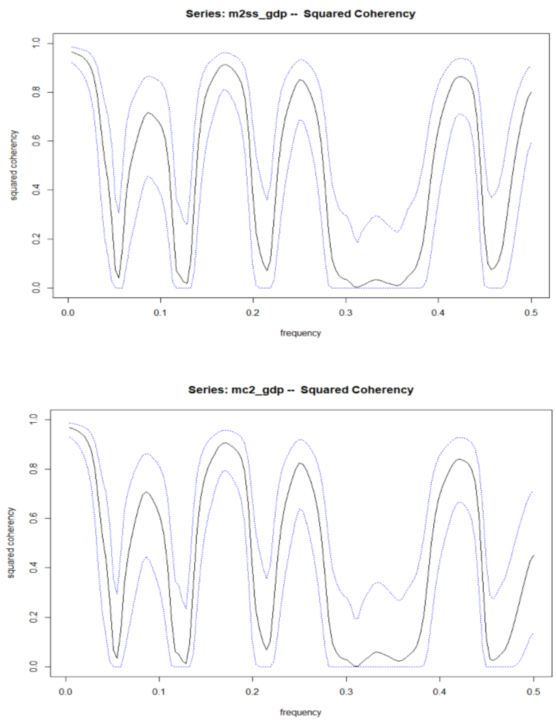


Figure 3.6 Squared Coherency of the two monetary aggregates and nominal GDP – China
(top: simple sum M2; bottom: Divisia M2)

Figure 3.7 plots the phase differences spectrum between the two monetary aggregates(top: simple sum M2; bottom: Divisia M2) and nominal GDP. In most frequencies / cycles, the phase difference is negative, indicating that the both monetary aggregates is lagging behind Nominal GDP. But when the frequency is greater than 0.3, the phase difference between the simple sum M2 and the nominal GDP shows greater fluctuations: when the regulation cycle is short, there may be more serious lags for simple sum M2 as a mediation target. All in all, there is sufficient evidence to conclude that when the regulation cycle is less than three months or a quarter, both monetary aggregates may have obvious lag or delay as a macro-regulated intermediary target.

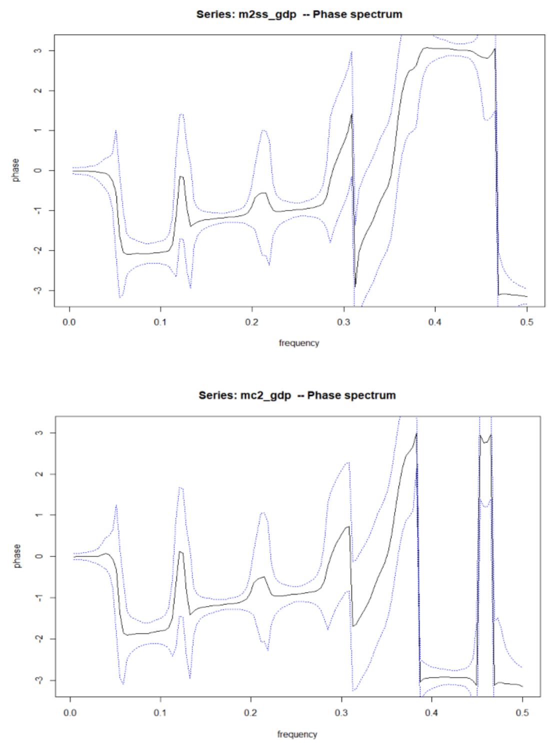


Figure 3.7 Phase Spectrum of the two monetary aggregates and nominal GDP – China
(top: simple sum M2; bottom: Divisia M2)

3.4.3 PBC Simple Sum M3 and China's Divisia M3

The correlation between the PBC's simple aggregate M3 and China's DM3 derived by the consumption loan augmented Divisia is

> cor(m3ss,mc3): [1] 0.9995356

Figure 3.8 plots the squared coherency spectrum of the simple aggregate M3 and Divisia M3. It shows that the coherencies of the two monetary aggregates reach the highest when the frequency is around 0.15, whose corresponding period is 6 months. As the period increases, the difference between the two monetary aggregates is gradually greater. When the period is less than 6 months, the fluctuations of the coherence spectrum are more intense. Generally, the coherency of the two monetary aggregates are greater in the long run, so more information needs to be further considered when taking simple sum M3 or Divisia M3 as intermediary targets for economic regulation with different control periods.

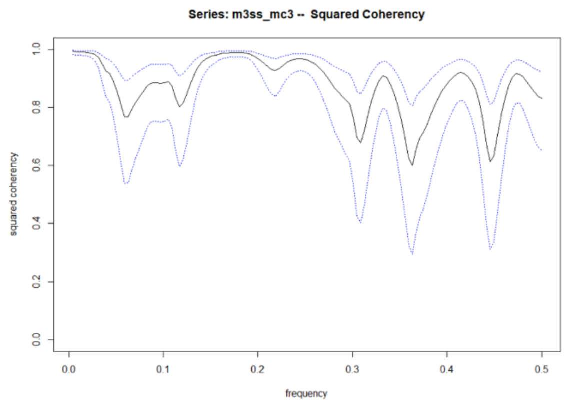


Figure 3.8 Squared Coherency of simple sum M3 and Divisia M3 – China

Figures 3.9 plots the binary squared coherency spectrum between the two monetary aggregates (top: simple sum M3; bottom: Divisia M3) and nominal GDP. In order to quantitatively compare the two with the binary spectrum analysis results. It can be seen from the statistical results that compared with simple sum M2, the correlation between nominal GDP and Divisia M2 is higher. The Divisia M2 should be suggested as the intermediate target of macro-control.

Power Spectrums of the two monetary aggregates and nominal are also similar(see Appendix).

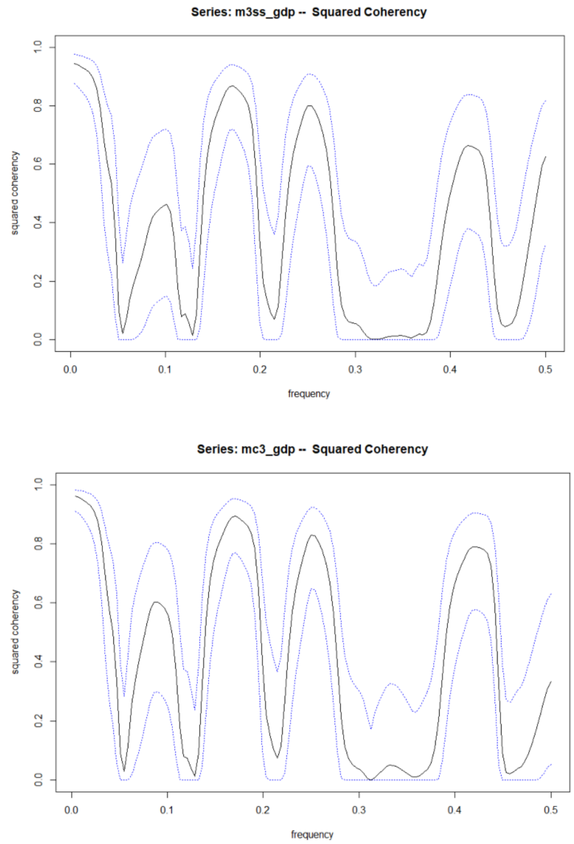
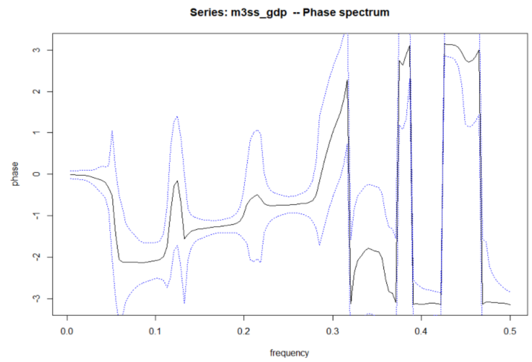


Figure 3.9 Squared Coherency of the two monetary aggregates and nominal GDP – China
(top: simple sum M3; bottom: Divisia M3)

Figure 3.10 plots the phase differences spectrum between the two monetary aggregates(top: simple sum M3; bottom: Divisia M3) and nominal GDP. In most frequencies / cycles, the phase difference is negative, indicating that the both monetary aggregates is lagging behind Nominal GDP. But when the frequency is greater than 0.3, the simple sum M3 shows greater lag to the nominal GDP. All in all, there is sufficient evidence to conclude that when the regulation cycle is less than three months or a quarter, both monetary aggregates may have obvious lag or delay as a macro-regulated intermediary target.



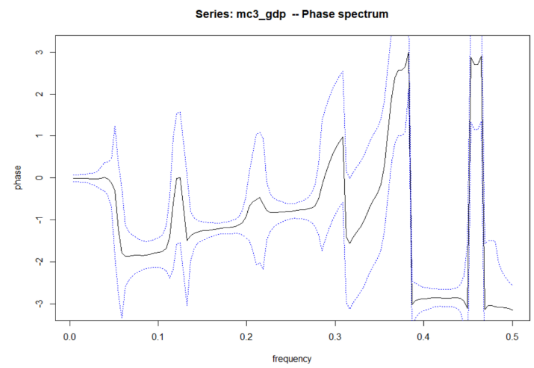


Figure 3.10 Phase Spectrum of the two monetary aggregates and nominal GDP – China (top: simple sum M3; bottom: Divisia M3)

3.5 Comparative Periodic Analysis

In the previous section, I applied the binary spectrum analysis method to the monetary aggregates with same liquidity classifications, and compared their coherencies with nominal GDP. Results of both countries are indicating that the correlations between monetary aggregates and nominal GDP are unclear in the short run, but stabilized in a long run. We also conclude that at any given liquidity level, Divisia Monetary Aggregates are always preferable than the corresponding simple sum aggregates, especially in the long run.

However, the results from the direct binary spectrum analysis for the United States are still showing obvious diffrences with the corresponding results for China. The binary spectrum analysis method could not apply a thorough comparision among all monetary aggregates and multiple economies, which makes it hard to compare the results for the two countries. Also, we noticed that the results for lower frequencies or higher periods are not clear enough to reveal periodic features for monetary aggregates.

To resolve the concerns above, we are reintroducing the results of all monetary aggregates by period in this chapter: The ranges of all the 128 frequencies $\{v_k\}$ are (0.00390625, 0.50000000), multiplying them by the sampling period we have the corresponding periods with a range of (2, 256) months. Then the related results from frequency domain analysis were converted into results under different time periods, and were visualized in one figure. The summarized figure will make it easier to apply a comparative analysis between the monetary policies of the United States and China. Relative statistic results were also provided for further analysis purposes.

3.5.1 Comparative Analysis with Long Periods: 60-256 Months

Figure 3.11 plots the squared coherencies between all monetary aggregates and nominal GDP under all periods ranging from 2 months to 256 months (top: The United States; bottom: China). The results of the two countries are showing great difference, which are consistent with the results of the previous sections. Since the analysis for the United States results is available in Chapter 2, we are only having a further look of China’s results in this section.

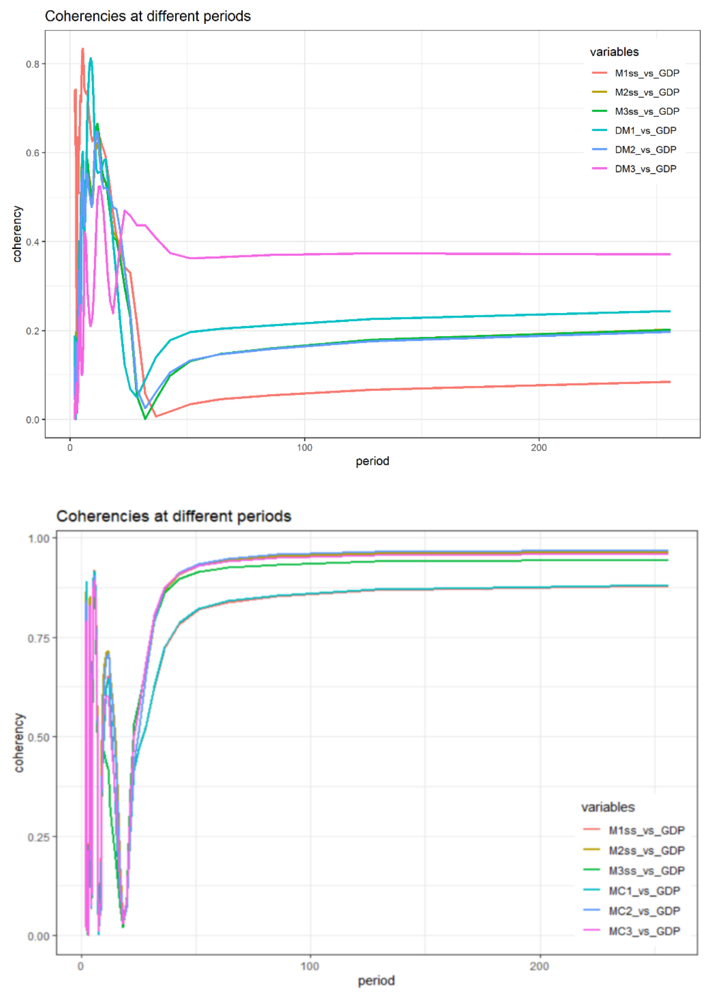


Figure 3.11 Squared Coherency between monetary aggregates and nominal GDP – 2-256 months (top: The United States; bottom: China)

The bottom part of Figure 3.11 plots the squared coherencies between all monetary aggregates of China and nominal GDP under all periods ranging from 2 months to 256 months (twenty-one years). The squared coherency spectrum of each monetary aggregate and nominal GDP tends to stabilize after the period is greater than 60 months (or 5 years): the dark blue curve represents the China's Divisia M2 and the pink curve represents the China's Divisia M3, their squared coherencies with nominal GDP are all greater than 0.92 in the long run; the squared coherencies between the simple sum M3 represented by the green curve and nominal GDP is slightly lower, about 0.91. The three other monetary aggregates with lower correlation with nominal GDP are the simple sum M1 represented by the red curve, the simple sum M2 represented by the yellow curve, and the Divisia M1 represented by the light blue curve: when periods are between 50 and 120 months, their coherencies with nominal GDP is between 0.85 and 0.875, and when the period is greater than 120 months, their coherencies with nominal GDP remains around 0.875.

Table 3.1 Statistics of Squared Coherencies[10] – The United States, 5-21 yr

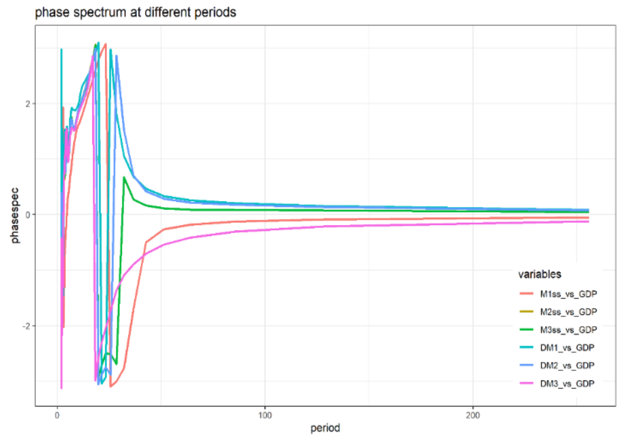
Vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
1	24	.19	.1	.18	.19	.05	.05	.37	.33	.57	-.41	.02

Table 3.2 Statistics of Squared Coherencies – China, 5-21 yr

Vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
1	24	.92	.05	.94	.92	.03	.84	.97	.13	-.64	-1.33	.01

It is easy to conclude that the coherencies between all monetary aggregates and nominal GDP are convergent to a certain level in the long run(greater than 5 years). However, the United States and China are showing great difference in coherency levels of their monetary aggregates with nominal GDP: monetary aggregates of China are having higher coherencies with its domestic production whose average is 0.92; while monetary aggregates of the United States are having way lower coherencies with its domestic production whose average is only 0.19.

[10] The statistics of spectral analysis results were calculated with the 'describe' function in the psych package in R, and the obtained statistics include mean, sd (standard deviation), median, trimmed (trimmed mean), mad (median absolute deviation), skew (skewness), kurtosis and se (standard error).



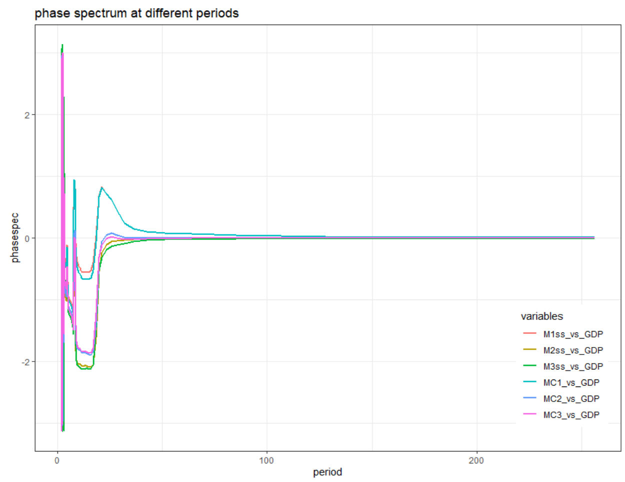


Figure 3.12 Phase Differences between monetary aggregates and nominal GDP - 2-256 months (top: The United States; bottom: China)

Figure 3.12 plots the phase differences between all monetary aggregates and nominal GDP under all periods ranging from 2 months to 256 months (top: The United States; bottom: China). Although the phase diffences of all monetary aggregates are converging to a level the closed to zero with any periods that greater than 60 months, the results for the United States are showing greater diversity among all its monetary aggregates. Since the analysis for the United States results is available in Chapter 2, we are only having a further look of China's results in this section.

The bottom part of Figure 3.12 plots the phase differences specturm between monetary aggregates and nominal GDP of China for periods ranging from 2 months to 256 months (twenty-one years). As period increases, the lags between the nominal GDP and all monetary aggregates are stabilized aroung zero. In a long-term macro-control with monetary aggregates as the intermediary target, the regulation hysteresis will gradually decrease to no hysteresis with the increase of the regulation periods. This conclusion applies to all monetary aggregates when the period is greater than 120 months or ten years.

Based on the information obtained from Figure 3.11 and Figure 3.12, it is convincible to conclude that when the monetary aggregate is taken as the intermediate target of macroeconomic regulation, a longer control cycle can eliminate its lag, and a reasonable selection of the monetary aggregate can ensure that it is in line with the macro-control target. Moreover, this section once again proves the superiority Divisia Monetary Aggregates in all aspects.

Due to the large span of period lengths after sorting, Figure 3.11 and Figure 3.12 cannot clearly show the spectral analysis results when the period is less than 60 months. In the following subsections, I will interception and redepict the Squared Coherency Spectrum and Phase Differeny Spectrum with common regulation periods, and make further analysis.

3.5.2 Comparative Analysis with Long Periods: 24-60 Months

Figure 3.13 plots the squared coherencies between all monetary aggregates and nominal GDP under all periods ranging from 2 months to 60 months (top: The United States; bottom: China). The results of the two countries are showing great difference. However, the specturms for both countries' monetary aggregates are showing obvious trend when periods are greater than 24 months/ 2 years. In this section, we are focus on the spectrum analysis results with periods between 2 years to 5 years.

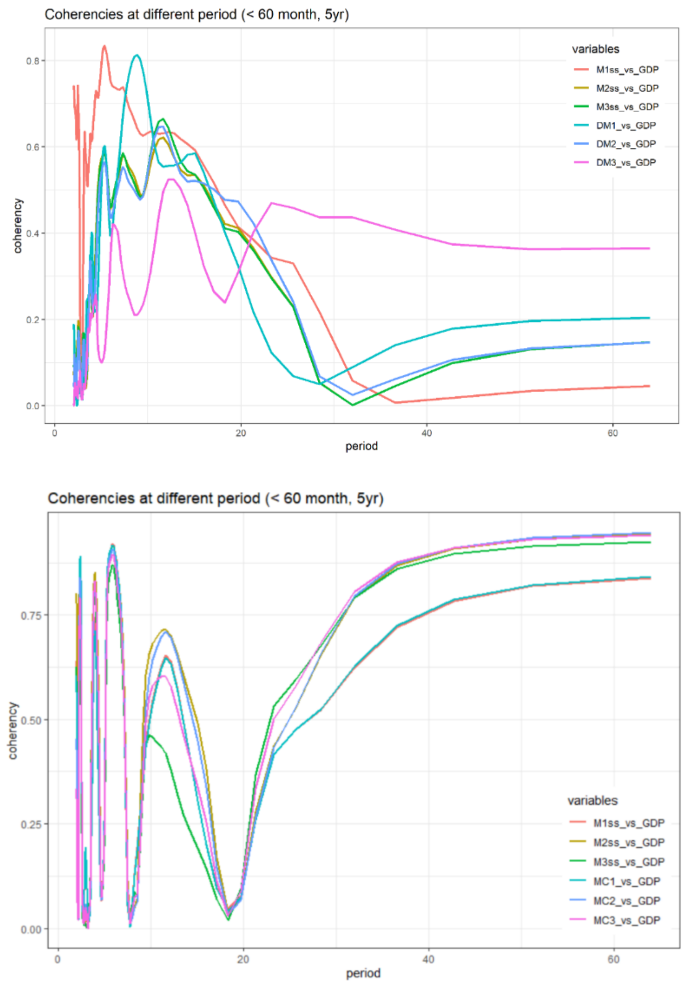


Figure 3.13 Squared Coherency between monetary aggregates and nominal GDP - 2-60 months (top: The United States; bottom: China)

The bottom part of Figure 3.13 plots the squared coherencies between all monetary aggregates of China and nominal GDP under all periods ranging from 2 months to 60 months. The squared coherency spectrum of each monetary aggregate and nominal GDP are showing obvious trend after the period is greater than 24 months (or 2 years): China's Divisia M3, Divisia M2, and simple sum M3 have squared coherencies with nominal that gradually increase to a level around 0.9 after 48 months/ 4 years; while the Divisia M1, simple sum M1 and simple sum M2 are reaching to a level around 0.83.

However, when the periods are between 24 months to 48 months, the coherences between monetary aggregates and nominal GDP are increasing from 0.42 to their maximum around 0.9 with the increase of periods. This pattern is just opposite to the pattern of the U.S. monetary aggregates, whose coherences with GDP are decreasing as the periods are decreasing and reach to their minimum when periods are around 3 year.

Table 3.3 Statistics of Squared Coherencies – The United States, 2-5 yr

Vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
1	48	.18	.14	.14	.17	.14	0	.47	.47	.62	-.94	.02

Table 3.4 Statistics of Squared Coherencies – China, 2-5 yr

Vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
1	48	.73	.17	.79	.74	.19	.42	.95	.53	-.38	-1.33	.03

Figure 3.14 plots the phase differences between all monetary aggregates and nominal GDP under all periods ranging from 2 months to 60 months (top: The United States; bottom: China). The phase differences of the U.S. monetary aggregates are showing great uncertainty when the periods are smaller than 48 month; while phase differences of China's monetary aggregates are converge to zero when periods are greater than 36 month. Another difference in the two figures is that China's monetary aggregates are showing obvious lags to GDP in short run. This delay could be concluded as the inherit hysteresis between intermediate control target-monetary policies and GDP.

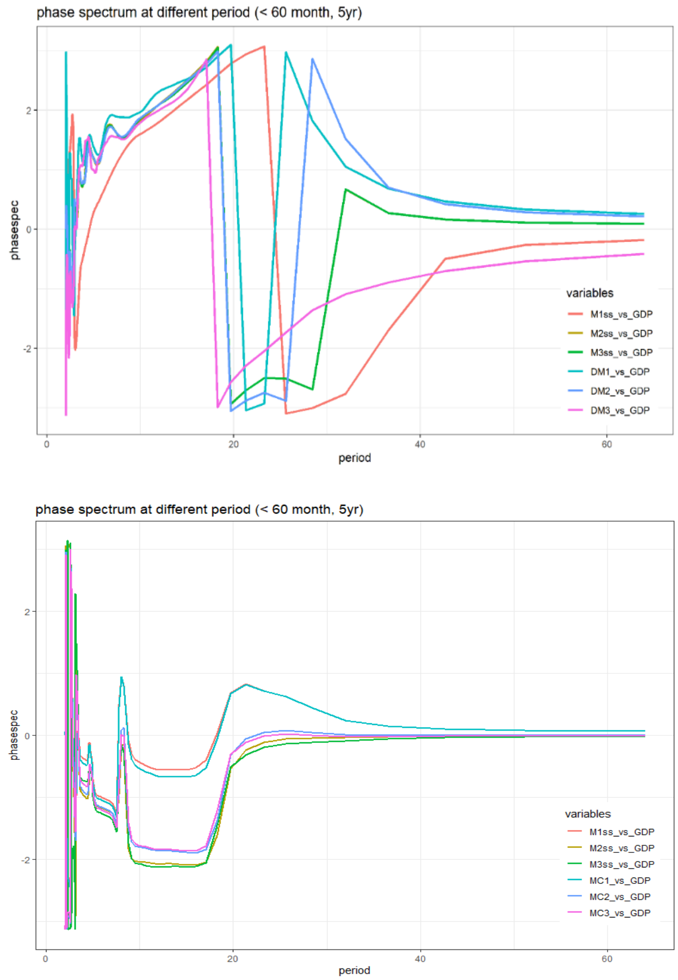


Figure 3.14 Phase Differences between monetary aggregates and nominal GDP - 2-60 months
(top: The United States; bottom: China)

Based on the information obtained from Figure 3.13 and Figure 3.14, it is convincible to conclude that when the monetary aggregate is taken as the intermediate target of macroeconomic regulation, a longer control cycle can eliminate its lag, and a reasonable selection of the monetary aggregate can ensure that it is in line with the macro-control target. Moreover, this section once again proves the superiority Divisia Monetary Aggregates in all aspects.

Due to the large span of period lengths after sorting, Figure 3.11 and Figure 3.12 cannot clearly show the spectral analysis results when the period is less than 60 months. In the following subsections, I will interception and redepict the Squared Coherency Spectrum and Phase Differeny Spectrum with common regulation periods, and make further analysis.

3.5.3 Possible Explanations and Solutions

Since the spectrum analysis result are not convergent for monetary aggregates of both the United States and China, we are not over-interpretating the results of periods that shorter than 24 months.

Combining the comparative results in this section, it is easy to conclude that the correlations between monetary aggregates and its domestic production may showing great differences between different countries.

The difference in spectrum analysis results between the United States and China could be explained by the following differences in their monetary policies:

In terms of policy transmission mechanism, China's monetary policy transmission is mainly based on the "central bank-commercial bank" transmission system under the modern credit currency system, while the US monetary policy transmission mechanism is based on interest rate channels, wealth effect channels, bank credit channels, and balance sheet channels. In the transmission of China's monetary policy, the People's Bank of China uses monetary policy tools to adjust the liquidity of the banking system and the total amount of money supply. Commercial banks inject liquidity into the real economy through loan issuance and bond investment to achieve the ultimate goal of monetary policy. In the transmission of U.S. monetary policy, the

Federal Reserve affects the short-term interest rate of the market by adjusting the target rate of the federal funds, and affects the medium and long-term interest rates of mortgage loans and corporate bonds through the effect of the term premium. The effect affects the investment and consumption activities of the real sector.

Second, the inflation environment of the two countries affects the monetary policy orientation in a specific period, resulting in policy differentiation. For example, in the first differentiation stage (2010), the quantitative easing monetary policy of the United States did not effectively stimulate real consumption and capital expenditure, the broad money M2 did not expand significantly, the real inflation level remained low, and the Fed’s monetary policy did not adjust; Stimulated by fiscal and monetary policies, the domestic economy has formed demand-driven inflationary pressures. In order to stabilize price levels and manage inflation expectations, the People's Bank of China has chosen to tighten monetary policy.

Third, the target of monetary policies are different between the two countries. China's monetary policy continues to emphasize "self-centeredness", with increasing autonomy. Since 2017, China has actively promoted the reform of the exchange rate market, liberalized cross-border capital flows in an orderly manner, the flexibility of the RMB exchange rate has gradually increased, and the implementation space of monetary policy has gradually expanded. At present, China's monetary policy pays more attention to the balance between internal and external equilibrium, and mainly adjusts the strength and pace of the policy according to the domestic economic growth and inflation. The autonomy of monetary policy operation is increasing day by day.

Fourth, the spill-over effect are different between US Dollar and CN Yuan. The U.S. dolloar is more internationalized with highest spill-over effect among all other currencies; it's the main foreign exchange reserves of most countries, so the coherencies with its domestic production are lower than a more closed economy. For countries with less openness, its Money Quantity Equation are more reliable which leads to higher coherencies between its monetary aggregates and GDP.

3.6 Conclusion

The comparative results shows that the correlations between monetary aggregates and its domestic production may showing great differences between different countries.

Further analysis would help to check the conclusion that we claimed in this chapter.

It is possible that the results of the United States will get closer to the results of China, if productions of more Dollar-dominated markets were considered. For countries with less openness, its Money Quantity Equation are more reliable which leads to higher coherencies between its monetary aggregates and GDP.

Chapter IV: The Influence of China's Interest Rate Marketization Process on GDP

We evaluate the treatment effect of interest-rate liberalization in China with the difference-in-difference (DID) model. DID model has been used in econometrics to quantitatively evaluate the effect of public policy or project implementation by solving the non-random sample allocation for the policy implementation group and the control group. However, the unique interest rate liberalization in China makes it impossible to find related panel data. In this paper, we will solve this problem by involves Divisia Monetary Aggregation and restate the time series data and evaluate policy reforms of China's recent Interest Rate Liberalization.

4.1 Introduction

The Chinese government has maintained tight controls over domestic interest rates. The People's Bank of China (PBC), the country's central bank, sets the benchmark lending and deposit rates for all financial institutions in China. The PBC has permitted banks to offer a range of deposit and lending rates within a relatively narrow band, and it has adjusted the bands occasionally. Interest rate controls create a wedge between the two types of interest rates (see Figure 4.1).

However, as the market elements of the economy expanded, it became increasingly clear that central allocations of financial resources resulted in serious inefficiencies. For instance, thriving financial institutions and private companies found it difficult to acquire enough financial resources, while inefficient companies with better political connections usually had easy access to loans.

Since planned financial resource allocations were incompatible with the market-oriented shift in China's economic structure, China commenced its interest rate liberalization in mid-1990s as part of the process for developing a market-based allocation mechanism for financial resources.

The interest rate liberalization includes a series of supplementary reform measures, such as enabling financial markets and financial institutions to conduct market-based pricing, introducing market-based interest rate products, establishing the monetary policy framework under which policy rates can be adjusted to influence market interest rates, and improving the transmission mechanism of interest rates.

During the 20 years between the mid-1990s and 2015, the PBC took many "mini" steps in liberalizing interest rates, starting with rates in the fixed income market, followed by rates for bank lending and finally deposits. In 2013, the PBC liberalized controls over bank lending rates. In 2015, the PBC further widened the range of deposit rates that banks can offer. By 2015, most administrative restrictions (ceilings and floors) on deposit and lending rates had been lifted. By then, China had completed its "narrowly defined" interest rate liberalization. The gradual process of that liberalization was a smooth one and did not cause either financial instability or macro-economic instability.

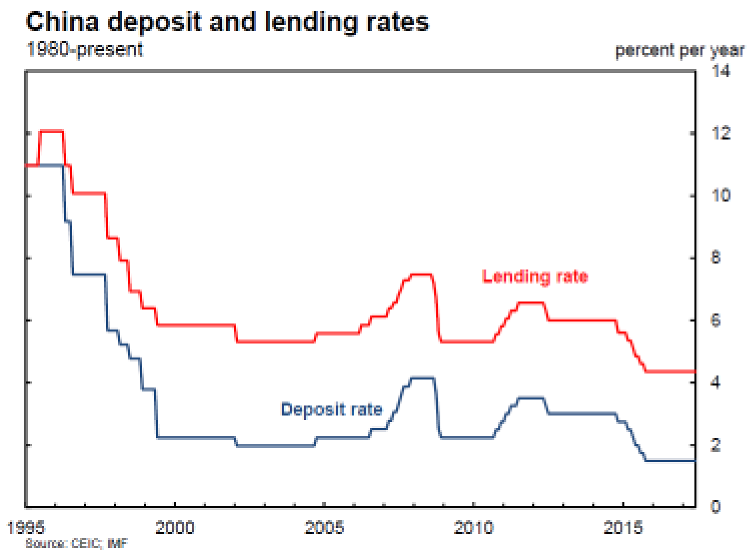


Figure 4.1: China's Deposit and Lending Rates (1980-2018)

As a unique Interest Rate Liberalization process, measurement of its effect has been a problem for macroeconomists in many ways. First, there are several stages in the Interest Rate Liberalization process, so it will be necessary to show its effect numerically to distinguish the differences in stages. The latest paper for Interest Rate Liberalization (Liu Z, Wang P, Xu Z, 2021), shows that the liberalization policy can have negative influence on productivity but failed to provide numerically results or distinguish policies at different stage during the liberalization process.

Second, there is no available data to use for variable controlling purpose since China is the only country that adopt the liberalization process. In this paper, we use a new difference-in-difference (DID) model to evaluate treatment effect of the interest rate liberalization policies in China. The difference-in-difference (DID) model has been used in econometrics to quantitatively evaluate the effect of public policy or project implementation in recent years. Generally, large-scale public policies are different from ordinary scientific research, and it is difficult to ensure that the sample allocation for the policy implementation group and the control group is completely random. The experiment that assigns the policy implementation group and the control group non-randomly is called a natural trial. This type of experiment has a more significant feature, that is, there may be pre-existing differences in samples between different groups before the implementation of the policy, and only through a single before-and-after comparison or a horizontal comparison. The method of analysis will ignore this difference, leading to biased estimates of the effect of policy implementation. The DID model is based on the data obtained from natural experiments, through modeling to effectively control the ex-ante differences between the research objects, and effectively separate the real results of the policy impact.

Recent DID model for macroeconomic policies include Johnson (2002) and Ball and Sheridan (2003). Johnson (2002) examines the effect of inflation targeting on the behavior of expected inflation in a panel of 11 industrial countries. Ball and Sheridan (2003) investigate the influence of inflation targeting on economic performance in 20 industrial countries. Using cross-section regressions, they show that the beneficial effect of inflation targeting is insignificant.

4.2 Methodology

4.2.1 Estimation of China's Theoretical GDP

The quantity theory of money claims that, regardless of interest rates, the amount of money people hold is proportional to the total transaction volume or total output, or GDP.

The LM curve of the money market is

$$\bar{M}/\bar{P} = kY - hi \qquad (4.1)$$

Where $\bar{M}$ is the nominal monetary aggregation (level), $\bar{P}$ is the price level, and k and h are the sensitivity of the real money balance to income and interest rates, respectively.

Considering to the background that the interest rate is tends to be around zero in this paper, we have $i \to 0$;

Under the liquidity trap background of low interest rates, if $h \to 0$, there is only one level of income that corresponding to a given real money supply M/P, which means that at that income level, the LM curve tends to be vertical.

The vertical LM is called the Classical Case. Under this condition, rewriting equation (4.1) we have

$$\bar{M} = k(\bar{P} \times Y) \qquad (4.2)$$

The money demand model based on the sum of money:

Here, we use the China's Divisia Monetary Aggregates M^c that derived in Chapter 1 to measure the nominal monetary level $\bar{M}$, and use GDP to measure the nominal total output Y, then the theoretical production could be estimated by

$$\tilde{Y} = \tilde{Y}(M^c, k) \qquad (4.3)$$

It should be noted that the reason why that we are using the Divisia monetary aggregates rather than simple sum is not only based on the empirical conclusions in Chapter 2, that is, the outstanding stability of China's Divisia monetary aggregates and its high coherencies with nominal GDP, especially the M_3^c. The other reason is that M^c Divisia monetary aggregates are based on monetary aggregate theory and index theory, which lays a theoretical foundation for the further derivation of related models.

4.2.2 The Difference-in-Difference Model

We set the upper and lower limits of the deposit and loan interest rates completely liberalized in August, 2015. Here are definitions for variables used in the model:

Y_{it} denotes the nominal GDP at time t and i denotes the type;

i describes the type of nominal GDP data, i = empirical GDP or estimated GDP.

D is targeting dummy of i:

If GDP data type i was affected by marketization, then the GDP data should be empirical data with i denoted as empirical GDP that belongs to the treated group, corresponding to D=1;

If GDP data type i was not affected by marketization, then the GDP data should be estimated data with i denoted as estimated GDP belongs to the control group, corresponding to D=0;

T is the implementation dummy for marketization:

If time t is before marketization (t < August 2015), then the corresponding data was considered as policy implemented, corresponding to T=0;

If time t is after marketization (t $\geq$ August 2015), then the corresponding data was considered as policy non-implemented, corresponding to T=1.

The initial idea is that we derive the difference between treated group GDP with Di=1, and control group with Di=0. That is,

$$E(Y_{it} \mid D_{it} = 1) - E(Y_{it} \mid D_{it} = 0), \qquad (4.4)$$

Which could be describe as the inherit difference between the empirical GDP and estimated GDP for all time: before and after interest rate marketization.

To check if the inherit differences is influenced by interest rate marketization, we could apply a Chow Test to see if the inherit differences (4.4) are following the same distribution before and after the interest rate marketization.

In fact, previous analysis could be concluded as the following DID model:

$$Y_{it} = \alpha_0 + \alpha_1 D + \alpha_2 T + \alpha_3 (D \times T) + u_{it} \qquad (4.5)$$

Take derivative with respect to T for equation (4.5), we have

$$\Delta Y_i = Y_{i,implemented} - Y_{i,non-implemented} = \alpha_2 + \alpha_3 D_i + u_{it}$$

(4.6)

Then take derivative with respect to Di for equation (4.6), we have

$$ATT = E(\Delta Y_i | D_i = 1) - E(\Delta Y_i | D_i = 0) = \alpha_3 \qquad (4.7)$$

Table 4.1 Average Treatment Effect

	Not Implemented (T=0)	Implemented (T=1)	Difference
Treated group (Di=1)	$\alpha_0 + \alpha_1$	$\alpha_0 + \alpha_1 + \alpha_2 + \alpha_3$	$\alpha_2 + \alpha_3$
Control Group (Di=0)	α_0	$\alpha_0 + \alpha_2$	α_2
Difference	α_1	$\alpha_1 + \alpha_3$	α_3 (D-in-D)

where the Average Treatment Effect on the Treated (ATT) is the cross-term coefficient of dummy variables.

4.3 Regression Results

4.3.1 Estimation of Theoretical GDP

Equation (4.3) describes the relationship between China's Divisia monetary aggregates M^c and nominal GDP; a (simplified) regression estimation function could be

$$M_3^c = k(GDP) + \epsilon \tag{4.8}$$

Using the monthly M_3^c and nominal GDP from January 2000 to December 2020, the statistics of the regression model (4.8) are shown in Table 4.2.

It can be seen from the regression model statistics that the approximate simplified linear model in this paper is more accurate: the goodness of fit multiple R-squared and the revised goodness of fit Adjusted R-squared are both close to 1. After the regression equation is observed for the sample the degree of fitting is relatively high; the F statistic in the significant F test of the regression equation, its P value is <2.2e-16<0.05, indicating that there is a significant linear relationship with nominal GDP (monthly estimated value), and the regression equation as a whole is significant of. According to the regression results, the author estimates that the sensitivity k of real money balance to income is about 20. The estimation of GDP will take as the control group in the following analysis.

Table 4.1 Regression Statistics of LM^cModel

Call: lm(formula = mc3 ~ -1 + gdp)						
Residuals	Min	1Q	Median	3Q	Max	Residual Std Error
	-183711	-65818	-33263	5357	443949	90480
Coefficients	Estimate	Std. Error	t value	Pr(>|t|)		
gdp	20.1063	0.1223	164.4.879	<2e-16 ***		
R-squared: 0.9908			Adjusted R-squared: 0.9908			
F-statistic: 2.702e+04 on 1 and 251 DF			p-value: < 2.2e-16			

4.3.2 Chow Test of Inherit Differences

Before applying the Difference-in-Difference model, we could exam the inherit difference of the empirical GDP and estimated GDP with Chow Test:

```
> sctest(inh_data$inh_diff ~ inh_data$monthlb, type = "Chow", point = 199)

        Chow test

data:  inh_data$inh_diff ~ inh_data$monthlb

F = 10.67, p-value = 3.588e-05
```

Here, ‘inh_diff’ is the difference between the empirical GDP and estimated GDP; and the 199 is the order of the month that the policy we discussed was issued.

The Chow Test results showing that the before and after policy distributions of the GDP difference are different, which allow us to explore the specific effect of interest rate marketization with DID model in the next part.

4.3.3 The Influence of China's Interest Rate Marketization – the DID model

Applying both the empirical and estimated nominal GDP from January 2000 to December 2020, the statistics of the regression model (4.5) are shown in Table 4.2.

Here R^2 is 0.6281, and the regression fitting result is valid; the estimated value of ATT is 5200. Combine with the GDP level after issuing the Interest Rate Marketization policy, the effect of its last act is to increase nominal GDP by about 0.6119% on average.

Table 4.3 Interest Rate Marketization Treatment Effect DID Regression Statistics

Call: lm(formula = Y_m1 ~ 1 + D_m1 + T_m1+ D_m1 * T_m1)						
Residuals	Min	1Q	Median	3Q	Max	Std Error
	-21966	-14027	-3432	12245	38628	16150

Coefficients	Estimate Std	Error	t value	Pr(>|t|)
(Intercept)	28710	1148	25.018	<2e-16
D_m1	48260	2479	19.468	<2e-16
T_m1	-1812	1623	-1.117	0.265
D_m1:T_m1	5200	3506	1.483	0.139

R-squared: 0.6281	Adjusted R-squared: 0.6258
F-statistic: 281.4	p-value: < 2.2e-16

4.4 Conclusion

In this Chapter, we evaluate the treatment effect of interest-rate liberalization in China with the difference-in-difference (DID) model. DID model has been used in econometrics to quantitatively evaluate the effect of public policy or project implementation by solving the non-random sample allocation for the policy implementation group and the control group. However, the unique interest rate liberalization in China makes it impossible to find related panel data. In this paper, we will solve this problem by involves Divisia Monetary Aggregation and restate the time series data and evaluate policy reforms of China's recent Interest Rate Liberalization.

By involving China's Divisia Monetary Aggregates, we have developed the control group data for nominal GDP of China based on the quantity theory of money. The theoretical GDP was proved to be significant and the price-taker of interest rates, which could be served as the perfect control group in this case.

The Average Treatment Effect that derived from the Difference-in-Difference model claimed that the last action of Interest Rate Marketization process has improved China's GDP by 0.6119% on average, which is the first numeric estimation of the effect of China's Interest Rate Marketization Process.

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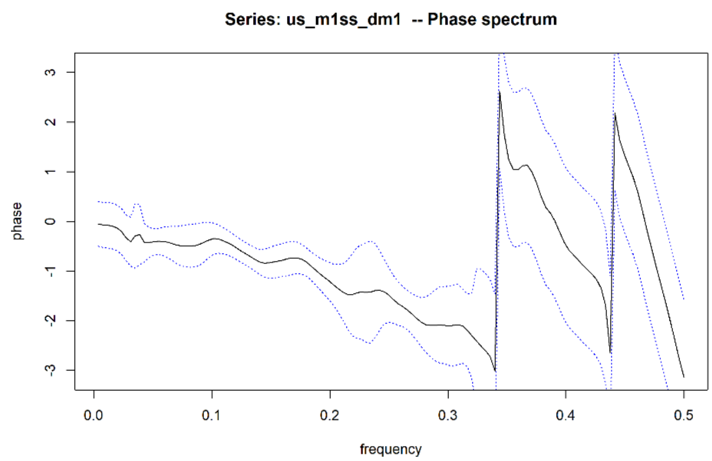
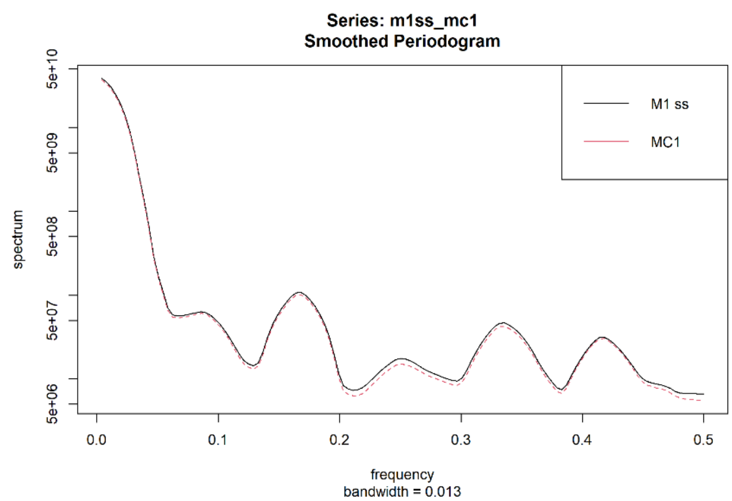
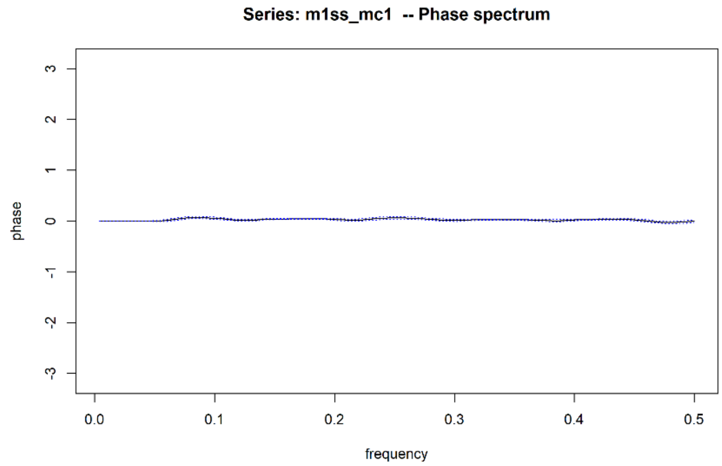
Appendices



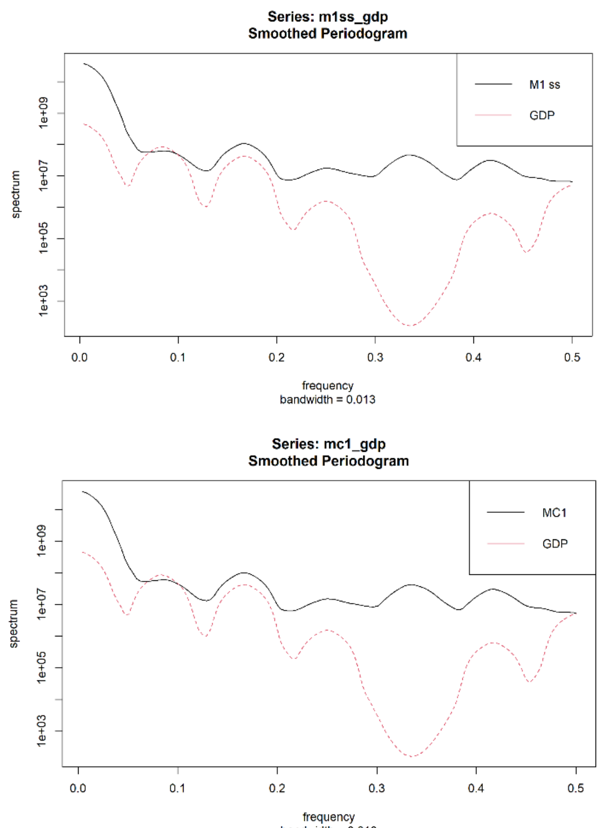
Phase spectrum for simple sum M1 and Divisia M1 - the United States



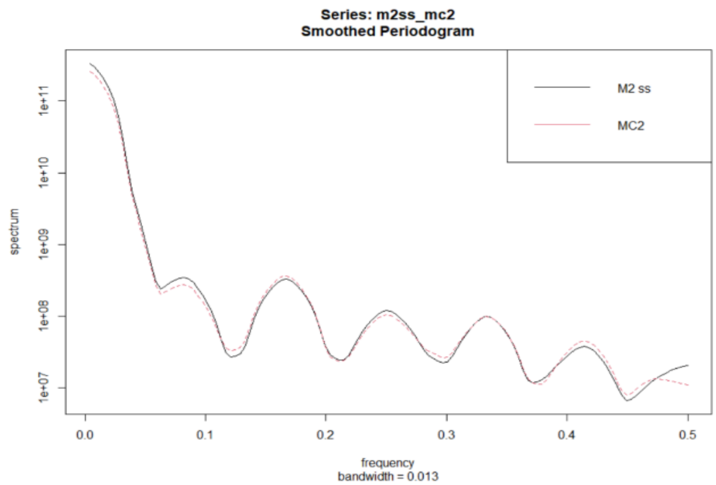
Power Spectrums of simple sum M1 and Divisia M1 – China



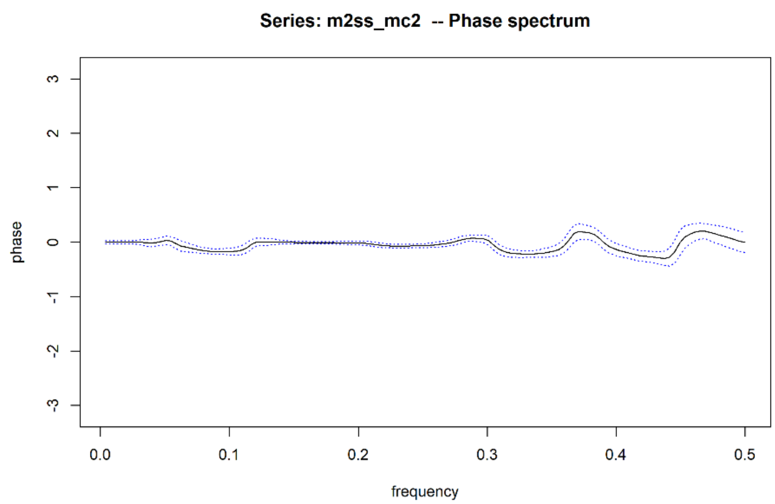
Phase spectrum for simple sum M1 and Divisia M1 – China



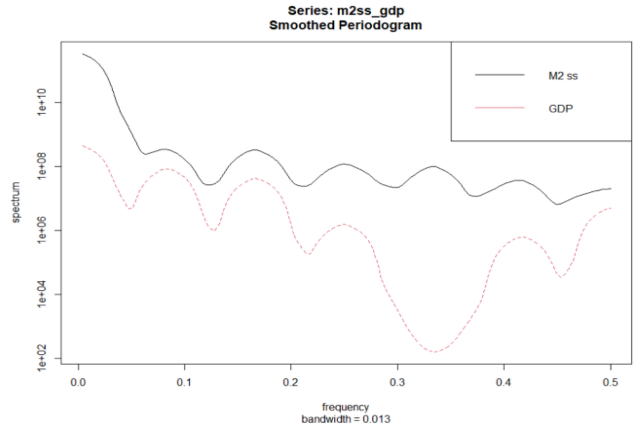
Power Spectrums of the two monetary aggregates and nominal GDP – China
(top: simple sum M1; bottom: Divisia M1)

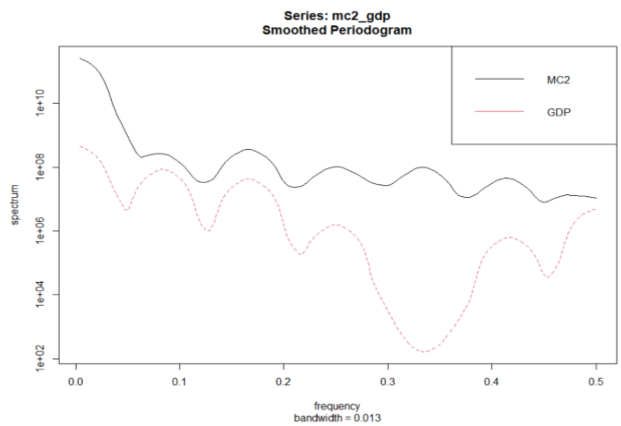


Power Spectrums of simple sum M2 and Divisia M2 – China



Phase spectrum for simple sum M2 and Divisia M2 – China





Power Spectrums of the two monetary aggregates and nominal GDP – China
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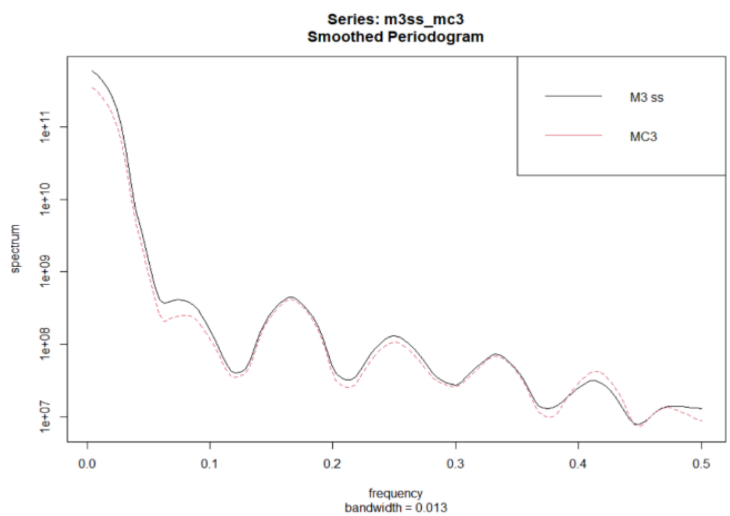
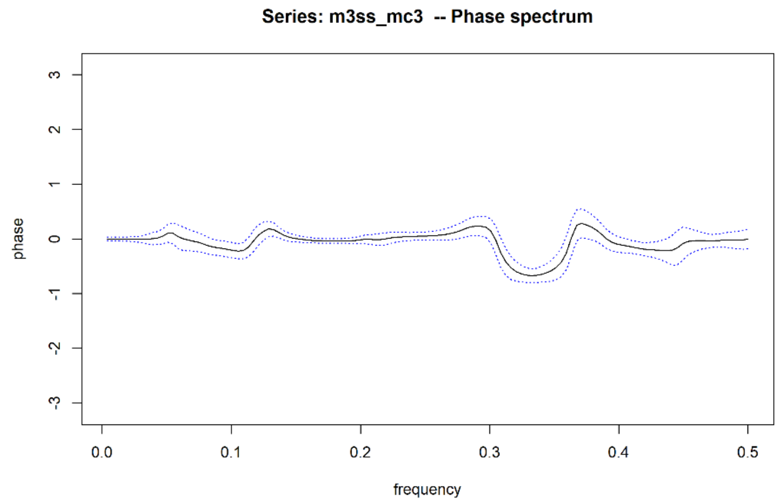
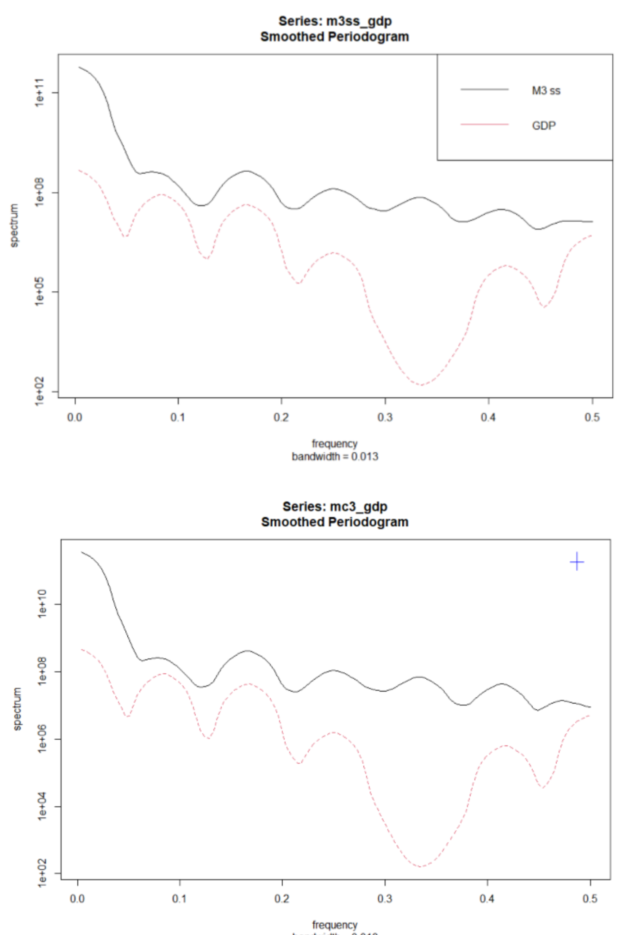


Power Spectrums of simple sum M3 and Divisia M3 – China



Phase spectrum for simple sum M3 and Divisia M3 – China



Power Spectrums of the two monetary aggregates and nominal GDP – China
(top: simple sum M3; bottom: Divisia M3)