國立政治大學經濟學系

碩士學位論文

中國的電子支付與貨幣需求

Electronic Payments and Money Demand in China

指導教授：黃仁德 博士

研究生：文　旻 撰

中 華 民 國 一 〇 九 年 七 月

DOI:10.6814/NCCU202001581

摘 要

本文將電子支付作為一個新變數加入到貨幣需求函數之中，並使用自我迴歸分配遞延（Autoregressive Distributed Lag, ARDL）邊界檢定方法探討中國的電子支付與貨幣需求之間的關係。實證結果顯示，貨幣需求函數之中的各變數之間存在共整合關係，電子支付變數與貨幣需求之間為負相關，長期而言，電子支付變數每增加 1%，對 M1 的需求就將減少約 0.02%；遞歸殘差累計加總（CUSUM）檢定以及遞歸殘差平方累計加總（CUSUMSQ）檢定也顯示加入電子支付變數後的貨幣需求函數是穩定的。此外，根據預測結果評估，加入電子支付變數之貨幣需求函數的預測準確度要優於不包含電子支付變數的貨幣需求函數。

關鍵詞：貨幣需求、電子支付、ARDL

DOI:10.6814/NCCU202001581

Abstract

This paper adds an electronic payments variable to the money demand function, and uses the Autoregressive Distributed Lag (ARDL) bounds testing approach to study the relationship between the electronic payments and money demand in China. The empirical results show that there is a cointegration relationship among the variables in the money demand function, and the e-payment variable is negatively correlated with the demand for money. According to the findings of this paper, in the long run, for per 1% increase in the e-payment variable, the demand for M1 will decrease by approximately 0.02%. In this paper, by performing the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ) tests, we find that the money demand function including the e-payment variable is stable. In addition, the money demand function that includes the e-payment variable performs better than the one that does not include the e-payment variable when carrying out the forecast evaluation.

Keywords: money demand, electronic payments, ARDL

DOI:10.6814/NCCU202001581

謝 詞

我很榮幸能夠得到在政治大學經濟學系學習的機會，兩年的碩士時間雖然短暫卻十分珍貴而有意義。在這裡，我得到了許多老師和同學們的幫助與關照，也對經濟學領域有了更深入的研究與體悟。

感謝我的指導教授黃仁德老師。黃老師幫助我很快地確定了論文的選題方向並建立了全文的框架，讓我的寫作思路在一開始就非常清晰明確。在撰寫論文的過程中，由於今年的疫情，我和老師經常通過網路進行交流討論，老師每次都認真地給我提出許多建議，使我受益匪淺。這是我第一次寫英文論文，在許多方面都很生疏，黃老師每次都會十分細緻地批改我的文章，並通過拍照的方式將修改稿件寄給我。在老師的指導下，我順利地完成了這篇論文，我很高興沒有辜負老師對我的期待。

感謝抽出暑假時間來參加我的論文口試的林馨怡老師和洪福聲老師！兩位老師對我的論文提出了寶貴的建議，使我的思考和表述更加嚴謹，我很榮幸能夠得到兩位老師的悉心指教！

感謝經濟學系辦公室的郭賀翔、莊典儒和莊馥維助教！由於疫情的發生，我這學期不在學校,郭賀翔助教一直幫助我處理各種事務,讓我能夠通過網路如期完成各項任務。莊典儒助教一直幫助黃仁德老師將論文的修改稿件轉寄給我。莊馥維助教為我的視訊口試提供了技術上的支援。這一學期我給各位助教添了太多麻煩，大家都不辭辛勞地給予我幫助，不勝感激！

最後，感謝我的家人一直以來對我的支持和照顧，在我心中，他們永遠是我最強大的後盾。

文旻 謹誌於政治大學

二〇二〇年八月十六日

DOI:10.6814/NCCU202001581

目　次

DOI:10.6814/NCCU202001581

Contents

DOI:10.6814/NCCU202001581

表　次

DOI:10.6814/NCCU202001581

圖　次

DOI:10.6814/NCCU202001581

1. Introduction

By 2020, China has been officially connected to the global Internet for 26 years. The application of Internet technology accelerates the flow of information, broadens the channels of information dissemination, reduces the cost of business operations, and effectively improves the productivity of various industries. As the Internet gradually became popular in China, many new consumption patterns were created, and the electronic commerce began to flourish. In China, consumer behavior began to expand from offline to online, and emerging electronic payments gradually began to replace traditional payment instruments. E-payment technology takes advantage of its rapidity and convenience, reduces the cost of cash withdrawals, and enables people to conduct transactions anytime and anywhere. In today's China, electronic payments, represented by the Internet payment and mobile payment, has become one of the most common means of payment. Most people prefer electronic payments rather than cash and checks for transactions. The change in the way of payment is bound to have a considerable impact on the demand for money.

The study of money demand is of great significance to the analysis of macro-economy. The central bank can make a reasonable monetary policy to regulate money supply based on the prediction of money demand, so as to stabilize the price level and promote economic growth. In order to make the prediction of monetary aggregates and their changing trend more accurate in a certain period, it is necessary to build a stable and effective money demand function. The money demand function is usually considered to be composed of scale variable, opportunity cost variable and some other variables that can measure economic activities. Generally, in addition to the conventional variables, the study of money demand must also consider some economic activities that may occur with the development of the times and technological changes and may have an impact on the demand for money. Today's electronic payments in China have a huge scale, which may affect the money demand, so we pay special attention to this effect in our research.

China is the second largest economy in the world, and the scale and popularity of

DOI:10.6814/NCCU202001581

electronic payments in China are leading the world. Taking China as the research object, it should be representative to analyze the impact of electronic payments on money demand, which is helpful to provide experience reference for other researchers. This paper will use the Autoregressive Distributed Lag (ARDL) bounds testing approach to study the money demand in China. In addition to the two conventional variables of gross domestic product and interest rate, an e-payment variable is also included in the model for analysis. This paper attempts to answer the question of whether the emergence and development of electronic payments will affect the demand for money in China, which is a hot issue.

The arrangement of this paper is as follows. Section 2 reviews the related research results of the predecessors. Section 3 briefly describes the development history of electronic payments in China. Section 4 introduces the empirical model used in this research. Section 5 shows the empirical process and results. Section 6 is conclusion.

2. Literature review

This section quotes some theoretical and empirical literature related to the research done in this paper. It mainly covers four categories: (1) Theoretical literature that explores whether financial innovation (represented by electronic payments in this paper) will affect money demand; (2) research on the analysis of money demand in China; (3) empirical literature that explores the relationship between financial innovation and money demand; and (4) the literature that uses the ARDL approach to do empirical research on money demand.

Will the electronic payment have an impact on money demand? Electronic payment can be described as a representative financial innovation. Some papers have discussed theoretically whether the innovation of financial technology will have an impact on the demand for money. For example, Lieberman (1977) believed that many technological advancements in the field of money management are due to the application of emerging technologies generated in other fields. Such as an increase in money substitutes or more efficient payment mechanisms, will help to reduce the demand for money. Therefore, it

DOI:10.6814/NCCU202001581

is necessary to set up a separate variable to measure the impact of exogenous innovation of technology. If the influence of technological innovation is ignored when establishing the money demand function, the estimation results will be biased. Lieberman introduced exponential decay term (the coefficient of this term is an estimate of the mean rate of technological change) into the function of money demand, and used time as a measure of technological change, and derived a new equation similar to the traditional one but not affected by the possible bias. Lieberman conducted research based on data from 1947 to 1973. The results show that the revised money demand function is highly stable. And with the passage of time, while other conditions remain unchanged, technological changes will cause the demand for money to decline at a rate of 1.5% to 2.5% per year.

Attanasio et al. (2002) used automated teller machines (ATM) as a proxy for transaction technology innovation. An exogenous technical progress term (probably a function of time) is set, considering the existence of trading technology innovation. Technological advances will affect people's optimal number of cash withdrawals. For example, people who use ATM cards will withdraw more times than people who do not use ATM cards. It is because that the time required for each of their transactions is reduced due to the application of new technologies, so they can withdraw more times and save their cash holdings. Alvarez and Lippi (2009) introduced an improved version of Baumol-Tobin model, simulated the effect of financial innovation (reducing the fixed cost of each cash withdrawal and increasing the number of withdrawals without fees), and deduced that financial innovation can reduce the level of money demand.

China began to carry out the economic reform and opening-up policies in 1978, introducing market mechanism reform into the planned economic system. For the first time, market mechanism has a place in the economic system of China. In the context of the dramatic changes in the economic system of China, the money demand in China has also received the attention of many studies. El-Shagi and Zheng (2019) reviewed the Chinese and English literature about the demand for money in China. Over the past 30 years, there have been numerous papers evaluating money demand functions of

DOI:10.6814/NCCU202001581

China, and most of the focus has been on income elasticity and stability. Chow (1987) used the annual data of China from 1952 to 1983 to estimate a long-run money demand function and attempt to explain the price level of China with the quantity theory of money. Yi (1993) used the annual data from 1952 to 1989 and the quarterly data from 1983 to 1989 to estimate the money demand in China before and after the economic reform by the generalized least squares (GLS) method. It was found that adding the monetization process and inflation expectation variables into the money demand function could significantly improve its explanatory power.

Hafer and Kutan (1994) used the Johansen technique to analyze the money demand in China during 1952-1988. The results show that there is a long-run equilibrium relationship among the money demand, the real national income and the national income deflator. Besides, the variables in the money demand function have expected signs and elasticities. Huang (1994) constructed an error correction model to analyze the dynamic adjustment process of the money demand in China during the period of economic reform (1979-1990), the results show that there is a long-run relationship among the demand for money, real income, price, and real interest rate. Qin (1994) used annual data from 1952 to 1991 and quarterly data from Q1 1978 to Q4 1991 to study the money demand during China's economic reform. The results show that, despite the great changes in China's economy during the reform process, the relation of money demand still remains relatively stable, which is maintained by common market variables such as GDP and interest rates.

In addition, the study by Girardin (1996) also showed that there did exist a long-run demand for money in China during 1988 to 1993. Chen (1997) used annual data from 1951 to 1991 to study the stability of the long-run money demand function in China. It is found that the long-run money demand function (using M0 and M2) existed and was stable throughout the sample period (including before and after the reform). Based on the quarterly data from 1996 to 2009, Zuo and Park (2011) used the time-varying cointegration method to study the money demand in China. Except to analyze income elasticity and interest rate elasticity, the research also identified and emphasized

DOI:10.6814/NCCU202001581

the role of stock prices as another determinant of demand for money. Bahmani-Oskooee et al. (2016) used a non-linear ARDL approach based on Shin et al. (2014) to study the money demand in China. The results show that in China, exchange rate changes have an asymmetric effect on the demand for money. When CNY appreciates, Chinese people expect CNY to appreciate further, so their demand for CNY increases. However, when CNY depreciates, people's demand for CNY also increases.

After the 1960s, there have been innovative developments in financial instruments, financing technologies, and financial transaction processes. New financial products enable market participants to replace currency with other types of assets, and therefore may affect the money demand. In recent years, many empirical studies have explored the connection between technological innovation in the financial field and the demand for money. Arrau et al. (1995) re-discussed the issue of properly defining the money demand function, and analyzed the demand for money of 10 developing countries. It showed that financial innovation has an important impact on money demand and its fluctuations, and the importance of this effect is positively related to the inflation rate. Boeschoten (1998) conducted a study based on the Baumol-Tobin model, and the results showed that the use of automated teller machines would reduce the amount of residents' withdrawals each time and reduce the public's demand for money. Therefore, the advances of payment systems will significantly affect the demand for money, at least in quantity.

Lippi and Secchi (2009) took the number of financial institutions in Italian cities as a proxy variable for the technological innovation of withdrawal, and found that the more the number of financial institutions, the lower the demand for money of residents. Nagayasu (2012) used panel estimation methods (the Fully-Modified OLS and Dynamic OLS) to analyze the demand function of narrow money based on regional data of Japan. The results showed that financial innovation will reduce demand deposits, which may be the first study to use high-liquidity deposit data for reporting. Dunne and Kasekende (2018) measured financial innovation in terms of M2 / M1. Panel data estimation techniques were used to study the relationship between financial innovation

DOI:10.6814/NCCU202001581

and money demand in 34 sub-Saharan African countries from 1980 to 2013. The results showed that financial innovation is an important variable that determines the demand for money, whether it is in the long-run or short-run, it has a negative impact on money demand. The development of financial innovation has led to a reduction in the demand for money.

In recent years, there are many literatures that use the ARDL approach to conduct empirical research on money demand. Baharumshah et al. (2009) used the ARDL cointegration technique based on the quarterly data of China from Q4 1990-Q2 2007, and the bounds testing results indicate that there is a stable long-run relationship among the M2, real income, inflation, foreign interest rates and stock prices. If the stock price is not considered in the money demand function, it may lead to serious misspecifications. Geng et al. (2009) used the ARDL approach to analyze whether there is a stable money demand function during the economic transition period (along with monetization, banking reform, and financial liberalization, etc.) of China based on the annual data from 1978 to 2007, the results showed that there is a cointegration relationship among M1, real GDP, monetization factor, expected rate of inflation, and interest rate. M1 still can be maintained as monetary targeting policy. However, perhaps due to the impact of the expansion of the stock market in China since the mid-1990s, there is no cointegration relationship between M2 and the other variables mentioned above.

Akinlo (2006) used the ARDL method combined with the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMSQ) tests to study the cointegration and the stability of the money demand function in Nigeria. The results showed that the estimated money demand function is stable, and there is a cointegration relationship among the M2, income, interest rate, and foreign exchange rate. Hossain (2012) used the ARDL cointegration technique to determine whether there is an economically stable demand for narrow money in Australia based on the annual data from 1970 to 2009, the results showed that there is a long-run equilibrium relationship among real narrow money balances, real income, a representative domestic interest rate

DOI:10.6814/NCCU202001581

and the nominal effective foreign exchange rate of the Australian dollar. Furthermore, the estimated coefficients of each variable have the expected signs and are statistically significant. Despite Australia's financial deregulation and financial innovation since the early 1980s, the demand for a narrower definition of money has remained stable. However, it may be due to the impact of financial deregulation that Australia did not have a meaningful and stable broad money demand relationship during the sample period studied.

3. The development of electronic payments in China

Introducing the history of electronic payments in China, we should first talk about China's beginning to access the Internet. It is the popularity of the Internet that has laid the technical foundation for the development of e-commerce in China. From 1986 to 1994, a few Chinese scientific research institutions and researchers successively accessed and used the Internet. In 1995, the Internet in China began to provide access services to the public. China has successively built CHINANET,[1] CERNET,[2] CSTNET,[3] and CHINAGBN.[4] These four major computer networks were interconnected in June 1997, laying a preliminary foundation for Internet in China. Since then, the Internet in China has maintained a momentum of rapid development.

At the end of October 1997, China only had a total of 299,000 Internet computers, 620,000 Internet users, 4,066 domain names registered under CN, 1,500 websites, and international export bandwidth of 18.64Mbps. By the end of 2002, the number of Internet computers in China had increased to 20.83 million, the number of Internet users reached 59.1 million (ranking second in the world), the number of domain names registered under CN had increased to 179,000, the number of websites reached 371,000,

---

[1] CHINANET is China's first large-scale public computer Internet designed, constructed, operated and managed by the Chinese.

[2] China Education and Research Network (CERNET) is a nationwide academic computer internet network invested and constructed by the State, managed by the Ministry of Education, and undertaken by universities and colleges.

[3] CSTNET is an academic, non-profit scientific research computer network under the leadership of the Chinese Academy of Sciences.

[4] China Golden Bridge Network (CHINAGBN) is the infrastructure of national economy informatization in China.

DOI:10.6814/NCCU202001581

and the international export bandwidth increased to 9380Mbps.[5] The level and popularity of China's network technology already have the ability to support the development of e-commerce.

The vigorous development of the Internet in China has driven the rise of e-commerce, and the gradual prosperity of e-commerce has subsequently promoted the development of e-payment technology. In the mid and late 1990s, with the continuous expansion of the scale of Internet users, venture capital began to enter the Internet industry, and a large number of Internet companies were established (NetEase-1997, Sohu-1998, Tencent-1998, Sina-1998, Alibaba -1999, Baidu-2000, etc.). B2C websites selling books, computer software and other products online, as well as ticketing and travel services have appeared in large numbers. At the same time, a number of B2B websites began to provide a trading platform for e-commerce between enterprises. In 1998, the payment of the first online order in China was completed.

As of the end of June 2003, China had 91 financial institutions issuing cards, with a total of more than 569 million cards issued. The total amount of transactions through bank cards reached 7.57 trillion CNY, and there are about 200,000 merchants that accept bank cards and provide services to bank cards, a total of 53,000 ATMs equipped by financial institutions.[6] China has initially established a nationwide network for the exchange of bank card information across banks and regions. The operation quality of the inter-bank payment system has been effectively improved, and the online payment environment has been further improved. Before 2003, the major players in China's e-payment industry were major banking institutions, and the main payment methods were online banking. During this period, the pace of development of e-payment in China was relatively slow. In 2003, the SARS virus broke out. During the epidemic, the performance of a large number of offline stores declined, but e-commerce ushered in an important development opportunity. E-commerce conducts online transactions

[5] See Department of Electronic Commerce and Informatization, Ministry of Commerce of the People's Republic of China (2005), "White Paper of Electronic Commerce in China (2003)" in *Development Report of E-commerce in China*. Retrieved from http://dzsws.mofcom.gov.cn/article/ztxx/ndbg/200505/20050500088399.shtml.

[6] Ibid.

DOI:10.6814/NCCU202001581

through the Internet, and does not require close contact between people. This advantage makes the development prospects of e-commerce recognized and expected by more people. Many commercial retail companies have begun to shift the focus of their business strategy from offline to online, increasing the variety of online products and providing more types of online services. During the epidemic, the click-through rate of e-commerce websites increased rapidly, and sales rose sharply.

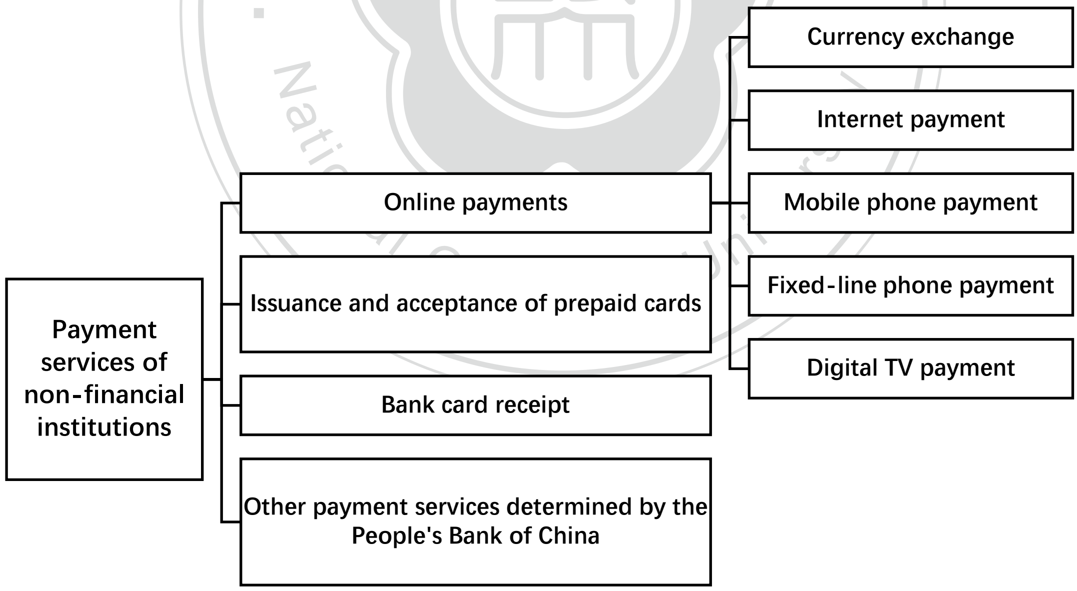
In May 2003, Taobao, founded by Alibaba Group, was established. In October of the same year, the third-party payment tool "Alipay" was born. Alipay proposes a secured transaction model, which effectively solves the credit problem in e-commerce transactions, enables consumers to trust online transactions on Taobao, and greatly promotes the success rate of online transactions. In 2004, Alipay became independent from Taobao and gradually provided payment services to more partners. As the third-party payment institutions represented by Alipay began to get involved in the payment business, the e-payment industry began to develop rapidly. At first, the e-payment methods in China were dominated by computer-based Internet payments, and this situation began to change after the advent of smartphones. China's e-payment, which is in a stage of rapid development, meets the megatrend of smartphone popularity. As a new product under this background, mobile payment quickly occupies a pivotal position in the market, becoming the preferred payment method when people use e-payment services. In 2008, Alipay released a mobile e-commerce strategy and launched a mobile payment service. In 2010, with the popularization of mobile smart terminals, mobile payment gradually began to become the protagonist in the field of e-payment. The major banks in China began to launch mobile banking apps, and Alipay also partnered with Bank of China to launch the quick payment service for credit cards.[7]

In order to promote the good development of the e-payment market, regulate

[7] The quick payment is a brand-new payment method launched by Alipay and major banks. No need to log in to online banking, you can directly enter the information of the bank card and the identity information of the cardholder, and then you can complete the contract or payment by verifying the mobile phone reserved by the bank to receive the verification code. Except for the annual fees that banks may charge for bank cards, Alipay will not charge for the opening of the quick payment service. When conducting transactions through the quick payment service, Alipay will not charge any fees regardless of the number of transactions.

DOI:10.6814/NCCU202001581

payment-related services, prevent payment risks and protect the legitimate rights and interests of the parties, the People's Bank of China (the Central Bank of China) promulgated the management methods for payment services of non-financial institutions in June 2010. In 2011, the People's Bank of China issued the first batch of "payment business licenses". Enterprises with this license can engage in many payment services such as Internet payment, mobile phone payment, currency exchange, etc. A more detailed classification of payment businesses that non-financial institutions licensed by the government can engage in is listed in Figure 1. The development of electronic payments in China is supported by policies. In 2012, China Mobile (a large central enterprise in China engaged in the communications industry) and China UnionPay signed a business cooperation agreement on mobile payment,[8] unifying the NFC standard for mobile payment in China, and solving the technical differences that hinder the development of mobile payment, thus accelerating the popularity of mobile payment.



Source: Payment and Settlement Department, The People's Bank of China (2010), "Administrative Measures for Payment Services of Non-financial Institutions". Retrieved from http://www.pbc.gov.cn/zhifujiesuansi/128525/128535/128629/2811672/index.html.

Figure 1: Payment services of non-financial institutions licensed by the People's Bank of China

[8] China UnionPay is mainly responsible for the construction and operation of the unified national network for the exchange of bank card information across banks, as well as the formulation of relevant regulations and technical standards, etc.

DOI:10.6814/NCCU202001581

Compared with computer-based Internet payment, the main advantage of smart phone-based mobile payment is its portability. This portability can greatly expand the service field of electronic payments, and people can use electronic payments in more consumption scenarios to meet their various needs. Besides, the threshold for using smartphones is much lower than that for using computers. Using a smartphone through a touchable screen is much faster and easier than turning on a computer to browse the web. Portable, simple, and easy-to-use mobile payments can help people deal with more detailed needs in daily life anytime, anywhere. In 2012, taxi-hailing software on mobile phones appeared. Taking a taxi, a small and high-frequency transaction, perfectly matches with mobile payment and becomes the first popular field of mobile payment. Since then, mobile payment has gradually penetrated into people's daily life. In 2013, Alipay launched the "Yuebao" project, which was the first to expand electronic payment into the field of financial management, attracting more users, and increasing the frequency of users using Alipay. In the same year, Tencent's WeChat Pay was officially launched, and was quickly promoted based on its advantages on social networks. Sending red envelopes with money inside to friends via WeChat messages quickly became popular. In 2015, China UnionPay launched the "Yunshanfu" (a mobile payment app) product. In 2016, Apple Pay, Huawei Pay, Mi Pay, and Samsung Pay were launched in China one after another. In 2019, according to a survey from PwC Certified Public Accountants, the penetration rate of mobile payment in China has reached 86%.[9] The growth trend of e-payment transactions from Q4 2006 to Q3 2019 in China is shown in Figure 2.

In December 2016, the State Council of China proposed to strengthen the research and development of blockchain technology, and included blockchain technology for the first time in the national-level informatization plan. In January 2017, the People's Bank of China formally established the Digital Currency Research Institute to actively develop digital currency projects based on blockchain technology. In May 2018, China's first official white paper on the blockchain industry was released. In January

[9] See PricewaterhouseCoopers (2019), "Global Consumer Insights Survey". Retrieved from https://www.pwc.com/gx/en/consumer-markets/consumer-insights-survey/2019/report.pdf.

DOI:10.6814/NCCU202001581

2019, China issued regulations on the management of blockchain information services, which means that the government began to formally supervise blockchain information services. In March 2019, China announced the names and filing numbers of the first batch of 197 blockchain information services. In addition, the Digital Currency Research Institute of the People's Bank of China and the People's Bank of China branch in Shenzhen have built a trade finance platform based on blockchain technology. As of August 2019, nearly 30 banks have landed on this platform, with a business volume of more than 50 billion CNY. The State Administration of Foreign Exchange applied blockchain technology to build a blockchain service platform for cross-border finance. As of the end of October 2019, 6,370 accounts receivable financing had been completed, and the loan amount exceeded 40 billion CNY. There are 1,262 enterprises served by this blockchain platform, of which, small and medium-sized enterprises account for about 70%.[10]

In April 2020, the Digital Currency Research Institute of the People's Bank of China confirmed that the Digital Currency Electronic Payment (DCEP) is undergoing internal testing. The digital RMB is issued by the People's Bank of China and is a fiat currency with national credit endorsement and legal solvency. The People's Bank of China does not directly issue and exchange digital currency to the public, but first converts the digital currency to designated operating institutions (such as commercial banks or other commercial institutions), and then these institutions exchange the digital currency to the public. These designated operating agencies are required to pay 100% of the reserve to the central bank, which can ensure that the issuance of digital currency remains stable.[11]

In conclusion, more and more diversified electronic payment services provide people with a safe, rich and efficient way of consumption. In today's China, no matter in Beijing, Shanghai, Guangzhou, Shenzhen and other metropolises or remote towns

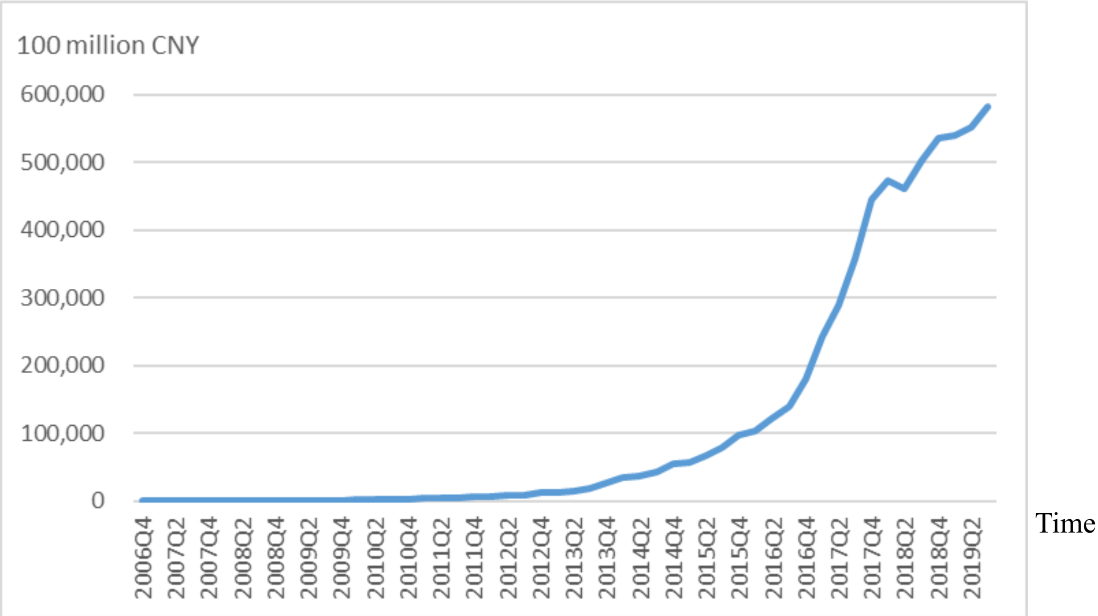
---

[10] See Blockchain Research Working Group, National Internet Finance Association of China (2020), "China Blockchain Financial Application and Development Research Report (2020)." Retrieved from http://www.nifa.org.cn/nifa/2955675/2955761/2987387/2020041417154589658.pdf.

[11] See the website of the Central Commission for Discipline Inspection of the Communist Party of China and the National Supervision Commission of the People's Republic of China. Retrieved from http://www.ccdi.gov.cn/yaowen/202006/t20200607_219642.html.

DOI:10.6814/NCCU202001581

and villages, taking out mobile phones to "scan" has become one of the most commonly used means of payment in daily consumption, going out without a wallet has gradually become a common phenomenon. The development of electronic payments in China for more than 20 years has profoundly influenced and changed people's lifestyles and has become an important force for economic and social development.



Note: The data is compiled based on the monitoring report of the third-party e-payment market in China released by the "Analysys".[12]

Figure 2: The transaction scale of electronic payments in China — Q4 2006-Q3 2019

4. Empirical model

Generally speaking, the variables that determine the scale of money demand (mainly income or wealth) and the opportunity cost variables of holding money (interest rate and inflation rate, etc.) are the key elements of the money demand function. In addition to considering the conventional determinants of the demand for money, this study also adds an e-payment variable. In order to explore whether the development of electronic payments has an impact on money demand, two money demand equations are set here,

[12] It was established in 2000 and is one of the leading big data companies in China. It is an analysis partner of Gartner Group in China, and its service customers include Alibaba, Tencent, Baidu, Industrial and Commercial Bank of China, etc. By Q1 2020, Analysys has covered 2.42 billion smart terminals and 610 million users.

DOI:10.6814/NCCU202001581

one includes only scale variable and opportunity cost variable, and the other adds an e-payment variable. The form of these two equations is expressed as follows:

$$m_t = \alpha + \beta y_t + \gamma IR_t + \lambda m_{t-1}\,, \tag{1}$$

$$m_t = \alpha + \beta y_t + \gamma IR_t + \delta EPAY_t + \lambda m_{t-1}\,, \tag{2}$$

where m_t is the real money demand, y_t is the real income as a variable of scale, IR_t is the short-term nominal interest rate, as an opportunity cost variable, m_{t-1} is the adjustment term of money demand, λ is the speed of adjustment (Goldfeld, 1973), and $EPAY_t$ is the ratio of "the transaction scale of electronic payments / total retail sales of consumer goods",[13] as a variable representing electronic payments. In theory, the value of β should be positive, the value of γ should be negative, δ is the key research object, and its value is also expected to be negative.

Initially, the main approaches used to study the money demand function were the OLS regression, the two-stage OLS regression, etc. With the development of econometrics, the two-step residual-based approach (Engle and Granger, 1987; Phillips and Ouliaris, 1990) and Johansen Test (Johansen, 1991, 1995) have become the most commonly used two approaches to test whether there is a cointegration relationship among variables, which were also applied by many papers that study the demand for money. However, using these two approaches also faces some limitations. Only when all variables are integrated of order 1 (i.e. I(1)), can these two cointegration techniques be used for analysis (Pesaran et al., 2001).[14] Therefore, using these two approaches

[13] "The transaction scale of electronic payments" is the transaction amount completed through electronic payments. "Total retail sales of consumer goods" refers to the amount of physical goods sold by businesses to individuals, social groups, non-production and non-business use, and the amount of income obtained by providing catering services. "Total retail sales of consumer goods" includes online retail sales of physical goods, but does not include online retail sales of non-physical goods. Online retail sales refer to the sum of retail sales of goods and services realized through public online trading platforms (including self-built websites and third-party platforms). Goods and services include physical goods and non-physical goods (such as virtual goods, service goods, etc.). Retrieved from http://www.gov.cn/xinwen/2018-01/18/content_5257970.htm.

[14] When the case of underlying variables is a mixture of I(0) and I(1) variables, although Johansen's approach can still be used for analysis, the likelihood testing for the cointegrating rank may be sensitive to the presence of I(0) variables (Rahbek and Mosconi, 1999).

DOI:10.6814/NCCU202001581

must first carry out a series of pre-tests, so that the analysis of long-run relations has some uncertainties (Cavanagh et al., 1995). Toda (1994) believes that it is unreliable to test the cointegration of variables using Johansen's approach when the sample size is small. Odhiambo (2009) used the ARDL bounds testing approach to study, and mentioned that when the analyzed sample size is too small, the two aforementioned cointegration techniques may not be very suitable.

The Autoregressive Distributed Lag (ARDL) bounds testing approach was developed by Pesaran and Shin (1999) and Pesaran et al. (2001). Compared with other cointegration techniques, the advantage of the ARDL bounds testing approach is that it can be applied to analyze whether the variables in the model are all I(0), all I(1), or the mixture of I(0) and I(1) (Pesaran et al., 2001). In addition, by using the ARDL approach, we can obtain unbiased estimates of the long-run model (Harris and Sollis, 2003). According to Pesaran et al. (2001), the statistic based on the ARDL bounds testing approach is the F-statistic or Wald statistic. In an unrestricted error correction regression, the statistic can test the significance of the lagged levels of the variables. Under the null hypothesis (that is, there is no relationship between the levels of the variables), the asymptotic distribution of the two statistics is non-standard.

Pesaran et al. (2001) provide two sets of asymptotic critical values: one set assumes that all the regression variables are I(1), and the other set assumes that all the regression variables are I(0). Unlike the two-step residual-based approach and Johansen Test, if the computed F-statistic or Wald statistic exceeds the range of the critical value, it can be concluded that there is a cointegration relationship among the variables without knowing whether the regression variables are I(0) or I(1). If the statistic falls within the range of the critical value, the inference will be uncertain, and the integration order of the variables needs to be considered. According to Narayan (2005), the critical value proposed by Pesaran et al. (2001) is based on the case of large samples and cannot be applied to the case of small samples. Therefore, Narayan (2005) further provides a set of critical values for the case of small sample size, with the range from 30 to 80.

Next, the general steps of ARDL bounds testing approach will be introduced. In

DOI:10.6814/NCCU202001581

this paper, the focus of our analysis is the relationship between electronic payments and money demand in China. Following the equation (1), the error correction regression for the equation (1) using the ARDL approach is as follows:

$$\triangle LM_t = c + \sum_{i=1}^{n} \beta_{1i} \triangle LM_{t-i} + \sum_{i=0}^{n} \beta_{2i} \triangle LGDP_{t-i} + \sum_{i=0}^{n} \beta_{3i} \triangle IR_{t-i} + \alpha_1 LM_{t-1} + \alpha_2 LGDP_{t-1} + \alpha_3 IR_{t-1} + u_t. \quad (3)$$

Following the equation (2), the error correction regression for the equation (2) using the ARDL approach is as follows:

$$\triangle LM_t = c + \sum_{i=1}^{n} \beta_{1i} \triangle LM_{t-i} + \sum_{i=0}^{n} \beta_{2i} \triangle LGDP_{t-i} + \sum_{i=0}^{n} \beta_{3i} \triangle IR_{t-i} + \sum_{i=0}^{n} \beta_{4i} \triangle EPAY_{t-i} + \alpha_1 LM_{t-1} + \alpha_2 LGDP_{t-1} + \alpha_3 IR_{t-1} + \alpha_4 EPAY_{t-1} + u_t, \quad (4)$$

where $\triangle$ is the first-order difference, LM is the natural logarithmic form of the real monetary aggregate (in this paper, our research object is M1),[15] $LGDP$ is the natural logarithmic form of real gross domestic product, IR is the weighted average of 1 month inter-bank lending rate. The definition of $EPAY$, as mentioned above, is a variable used to measure electronic payments. n is the maximum lag order that can be set manually, and u_t is a random error term. The coefficients β_{1i}, β_{2i}, β_{3i}, and β_{4i} denote the short-run dynamics of the variables in the ARDL model. The coefficients α_1, α_2, α_3, and α_4 denote the long-run relationship of variables. The key to the ARDL bounds testing approach is the F-statistic which is derived according to the joint null hypothesis, that is, the coefficients of one period lagged variables (LM_{t-1},

[15] The electronic payments mainly convert the cash held by people into demand deposits that can be drawn at any time, which all belong to the category of M1. Therefore, we choose M1 as the research object.

DOI:10.6814/NCCU202001581

$LGDP_{t-1}$, IR_{t-1}, and $EPAY_{t-1}$) are zero. Following the equation (3), the null hypothesis that the variables are not cointegrated is defined as:

$$H_0: \alpha_1 = \alpha_2 = \alpha_3 = 0.$$

The coefficients α_1, α_2, and α_3 correspond to the long-run relationship in the equation (3). The null hypothesis above indicates that there is no cointegration relationship among the variables. The alternative hypothesis of the equation (3) is defined as:

$$H_1: \alpha_1 \neq 0,\ \alpha_2 \neq 0,\ \alpha_3 \neq 0.$$

That is, there is a cointegration relationship among the variables. Following the equation (4), the null hypothesis that the variables are not cointegrated is defined as:

$$H_0: \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0.$$

The coefficients α_1, α_2, α_3, and α_4 correspond to the long-run relationship in the equation (4). The null hypothesis above indicates that there is no cointegration relationship among the variables. The alternative hypothesis of the equation (4) is defined as:

$$H_1: \alpha_1 \neq 0,\ \alpha_2 \neq 0,\ \alpha_3 \neq 0,\ \alpha_4 \neq 0.$$

That is, there is a cointegration relationship among the variables. Then, compare the F-statistic based on the above joint hypotheses with the critical values (I(0) or I(1)) proposed by Pesaran et al. (2001). If the F-statistic exceeds the upper critical bounds value, the null hypothesis that there is no cointegration relationship among the variables in the model is rejected. If the F-statistic falls within the range of critical bounds value,

DOI:10.6814/NCCU202001581

the existence of the cointegration relationship is not certain. If the F-statistic is lower than the lower critical bounds value, then accept the null hypothesis that there is no cointegration relationship among the variables. In addition, based on the ARDL bounds testing procedures, the long-run estimated coefficients of each explanatory variable in the model can also be obtained. By studying the error correction form of the ARDL model, a short-run model can be derived, and the existence of cointegration relationship among the variables in the model can be further tested according to the coefficient of the error correction term.

Next, we will use the cumulative sum of recursive residuals (CUSUM) test and the cumulative sum of squares of recursive residuals (CUSUMSQ) test to test the stability of the money demand function established in this paper. Brown et al. (1975) considered methods for studying the stability over time of regression relationships, proposed the CUSUM test and the CUSUMSQ test, and analyzed three real examples in the field of economics with these two new methods. One example is based on the research of Khan (1974), using the CUSUM test and the CUSUMSQ test to analyze the stability of the money demand function over time in the United States, and draws a positive conclusion. According to Brown et al. (1975), the main idea of the CUSUM test is that the equation repeats the estimation of the coefficient (β) by using the expanding sample data until all samples (n) are used up. Each estimated value of β is used to predict the next value of the dependent variable, thereby obtaining a prediction error. Based on the variance of the prediction error, a recursive residual is further derived. The null hypothesis of the CUSUM test is that the parameters of the model estimated by using different samples should be equal. If this hypothesis is rejected, it means that the model is unstable. Under the null hypothesis (that is, the model is stable), the recursive residuals will be normally distributed with mean 0 and variance σ^2. Cumulatively add up all the recursive residuals to get the CUSUM, which should fluctuate around zero. If it deviates far from zero, it means that the model is not stable. If the fluctuation of the CUSUM is kept within the critical line of 5% significance level, it means that the model is stable. The CUSUMSQ test is mainly to test the stability of the variance of the prediction error.

DOI:10.6814/NCCU202001581

Pesaran et al. (2001) also used the CUSUM and the CUSUMSQ tests to test the stability of regression coefficients during the sample period when using the ARDL bounds testing approach for empirical applications. Baharumshah et al. (2009), Geng et al. (2009), Hossain (2012), and Akinlo (2006) also applied the CUSUM test and the CUSUMSQ test to analyze the stability of the money demand function when using the ARDL approach to study the demand for money.

Finally, we evaluate the forecast accuracy of the two money demand functions set in this paper. We first use the Diebold-Mariano test proposed by Diebold and Mariano (1995) to verify whether the two models (with and without the e-payment variable) have the same forecast accuracy. Diebold-Mariano test is mainly used to analyze whether there is a significant difference between the predictive accuracy of the two models. A brief introduction of the main process of this test is as follows:

Let $\{\hat{y}_{it}\}_{t=1}^{T}$ and $\{\hat{y}_{jt}\}_{t=1}^{T}$ denote the two forecasts of the actual data series $\{y_t\}_{t=1}^{T}$. Let the associated forecast errors be $\{e_{it}\}_{t=1}^{T}$ and $\{e_{jt}\}_{t=1}^{T}$, where $e_{it} = y_t - \hat{y}_{it}$ and $e_{jt} = y_t - \hat{y}_{jt}$. Let $g(\cdot)$ denote the loss function of the forecast error. That is, $g(y_t, \hat{y}_{it}) = g(e_{it})$ and $g(y_t, \hat{y}_{jt}) = g(e_{jt})$. The commonly used loss functions are absolute-error loss function (i.e. $g(y_t, \hat{y}_{it}) = g(e_{it}) = \sum_{t=1}^{T}|e_{it}|$ and $g(y_t, \hat{y}_{jt}) = g(e_{jt}) = \sum_{t=1}^{T}|e_{jt}|$) and squared-error loss function (i.e. $g(y_t, \hat{y}_{it}) = g(e_{it}) = \sum_{t=1}^{T}(e_{it})^2$ and $g(y_t, \hat{y}_{jt}) = g(e_{jt}) = \sum_{t=1}^{T}(e_{jt})^2$).

The null hypothesis of the Diebold-Mariano test is as follows:

$$H_0：E[g(e_{it})] = E[g(e_{jt})], \text{ or } H_0：E[d_t] = 0,$$

where $d_t = [g(e_{it}) - g(e_{jt})]$ is the loss differential. That is, both forecasts have the same accuracy. The alternative hypothesis is as follows:

$$H_1：E[g(e_{it})] \neq E[g(e_{jt})], \text{ or } H_1：E[d_t] \neq 0.$$

DOI:10.6814/NCCU202001581

That is, the two forecasts do not have the same accuracy. If the null hypothesis of Diebold-Mariano test is rejected, it is considered that the forecast accuracy of the two models (with and without the e-payment variable) are significantly different. If the results of the Diebold-Mariano test show that there is indeed a difference between the forecast accuracy of the two models, then we will compare the forecast evaluation statistics (RMSE, MAE, etc.) of the two models to determine which model has the better forecast accuracy.

The variables used in this study include M1, GDP, IR and EPAY. The data range is from Q1 1997 to Q3 2019, with a total of 91 samples. The original data of M1, IR and total retail sales of consumer goods are monthly data, which are converted into quarterly data by taking the average value every three months. Both M1 and GDP data are adjusted based on CPI in 2010. Internet payment and mobile payment are the two main payment methods in China. Therefore, in this study, the data of "the transaction scale of electronic payments" is mainly composed of the addition of Internet payment and mobile payment.[16] Since the data of the transaction scale of electronic payments collected in this research started from Q4 2006, the data of e-payment before Q4 2006 was set to zero. The data of M1 and interest rate are derived from the People's Bank of China, GDP and total retail sales of consumer goods are derived from the National Bureau of Statistics of China, the transaction scale of electronic payments is derived from Analysys,[17] and CPI is derived from the International Monetary Fund.

5. Empirical process and results

5.1 Unit root test

Although the ARDL bounds testing approach can be applied to the variables that are

[16] This paper takes two emerging payment methods (Internet payment and mobile payment) as the representative of electronic payments. The data of "the transaction scale of electronic payments" is the sum of the transaction amount of Internet payment and mobile payment. "Mobile payment" means payment based on mobile phones. "Internet payment" means other online payments besides mobile payment.

[17] The data of electronic payments in this research is compiled based on the monitoring report of the third-party e-payment market in China released by Analysys (https://www.analysys.cn) and related news.

DOI:10.6814/NCCU202001581

I(0) or I(1), it should be noted that according to Ouattara (2004), when the variables are integrated of order 2 (i.e. I(2)), the ARDL approach is not applicable, and the F-statistic computed by the bounds testing procedures are considered invalid. Therefore, it is still necessary to carry out the unit root test. Here consider three conditions: (1) the test equation includes intercept; (2) the test equation includes time trend and intercept; and (3) the test equation does not include time trend and intercept. The results of the unit root test show that the underlying variables ($LM1, LGDP, IR,$ and $EPAY$) are all stationary in the case of the first-order difference (as shown in Table 1). None of the variables are integrated of order 2, so we can proceed to the next step of the ARDL bounds test.

Table 1: Results of Phillips-Perron unit root test — Q1 1997- Q3 2019

Variable	Intercept	Time trend and intercept	Without time trend and intercept
LM1	-2.41	-0.66	7.18
LGDP	-1.27	-6.58***	5.54
IR	-4.36***	-4.04**	-2.93***
EPAY	3.22	1.22	3.90
△LM1	-7.86***	-8.39***	-4.15***
△LGDP	-27.65***	-29.55***	-13.37***
△IR	-10.75***	-11.08***	-10.66***
△EPAY	-6.42***	-7.76***	-5.78***

Note: The numbers in Table 1 are τ-Statistics computed by unit root test. △ denotes the first difference. *** and ** denote the null hypothesis of a unit root is rejected at 1% and 5% significance levels, respectively.

5.2 Bounds test

This paper will set up two models for the ARDL bounds test. The variables in Model 1 include $LM1$ (as the dependent variable), $LGDP$, and IR, as described in the equation (3). The bounds testing results of Model 1 are shown in Table 2. Based on the Akaike information criterion (AIC), the optimal number of lag periods for $LM1$, $LGDP$, and IR is 3, 3, and 0, respectively. Table 2 lists the critical bounds values of I(0) variables and I(1) variables at 95% significance level and 99% significance level, respectively. The variables of Model 1 are all integrated of order 1, so the computed F-statistic should

DOI:10.6814/NCCU202001581

be compared with the critical bounds value of I(1) listed in Table 2. The results show that the computed F-statistic (8.29) far exceeds the critical bounds value of I(1) at 99% significance level, so the null hypothesis that there is no cointegration relationship among the variables in Model 1 is rejected. Therefore, there is a cointegration relationship among M1, GDP, and interest rate.

Table 2: Bounds test results for cointegration analysis — Model 1

Variables in Model 1	F-statistic	Critical bound			
		95% Significance level		99% Significance level	
		I(0)	I(1)	I(0)	I(1)
$LM1(3),\ LGDP(3), IR(0)$	8.29	3.79	4.85	5.15	6.36

Note: Figures in parentheses behind the variables in Model 1 indicate the optimal number of lag periods for each variable, which is selected by EViews based on the Akaike information criterion (AIC), and the maximum number of lag periods is set to 4 periods.

Subsequently, a series of diagnostic tests are carried out on Model 1, including: (1) Normality Test, which can measure a goodness of fit of a normal model to the data. The p-value calculated by this test is 0.55, which is greater than 0.05 (95% significance level), so the null hypothesis that the data is normally distributed cannot be rejected, indicating that the data set is well-modeled by a normal distribution in Model 1; (2) Breusch-Godfrey Serial Correlation LM Test, which can test for the presence of serial correlation that has not been included in a model structure. The p-value calculated by this test is 0.63, which is greater than 0.05 (95% significance level), so the null hypothesis cannot be rejected, indicating that there is no serial correlation in the residuals in Model 1; (3) Breusch-Pagan-Godfrey Test, which can determine whether there is heteroscedasticity in the model. The p-value calculated by this test is 0.22, which is greater than 0.05 (95% significance level), so the null hypothesis cannot be rejected, indicating that there is no autoregressive heteroscedasticity for the residuals in Model 1; and (4) Ramsey RESET Test, which can detect whether the model has setting errors. Here we use the square of the fitted values to carry out the test, and the calculated p-value is 0.63, which is greater than 0.05 (95% significance level), so the

DOI:10.6814/NCCU202001581

null hypothesis cannot be rejected, indicating that there is no setting bias in Model 1.

Following the equation (3), the long-run estimated coefficients in Model 1 ($\alpha_2 = 1.07, \alpha_3 = -4.75$) can be written as follows:

$$LM1 = 0.18 + 1.07LGDP - 4.75IR, \tag{5}$$
$$(0.63) \quad (45.81)^{***} \quad (4.78)^{***}$$

where figures in parentheses indicate the t-statistic. ***, **, and * denote 99%, 95%, and 90% significance levels, respectively. As shown in the equation (5), the estimated long-run coefficient of $LGDP$ is 1.07, and it is significant at 99% level, this is consistent with economic theory. The estimated long-run coefficient of IR is -4.75, and it is significant at 99% level, this is consistent with economic theory too. After finding the cointegration relationship among M1, GDP, and interest rate and obtaining the estimated coefficients of the long-run money demand function, we continue to estimate the short-run model. Following the aforementioned equation (3), the equation (6) shows the ARDL error correction regression of Model 1 as follows:

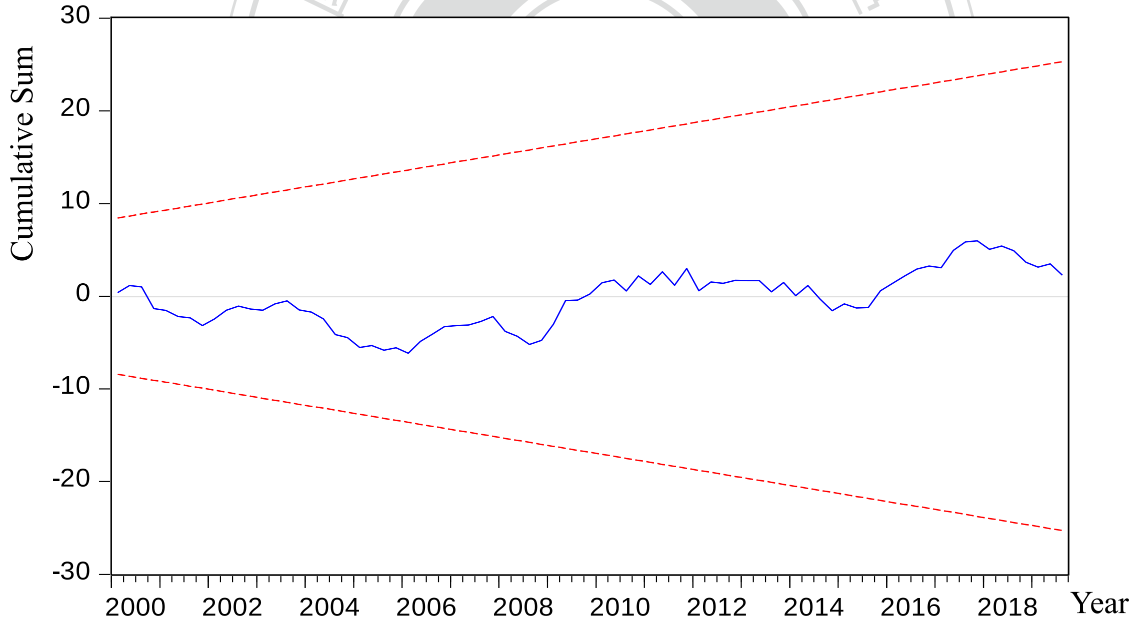
$$\begin{aligned}
\triangle LM1_t = {} & 0.18 \triangle LM1_{t-1} + 0.40 \triangle LM1_{t-2} + 0.18 \triangle LGDP_t + \\
& (1.70)^{*} \qquad\qquad (4.41)^{***} \qquad\qquad (8.58)^{***} \\
& 0.04 \triangle LGDP_{t-1} - 0.04 \triangle LGDP_{t-2} - \\
& (1.28) \qquad\qquad (2.17)^{**} \\
& 0.62 \triangle IR_t - 0.13ECT_{t-1}. \qquad (6) \\
& (3.58)^{***} \quad (4.29)^{***}
\end{aligned}$$

The ECT_{t-1} in the equation (6) is the error correction term. According to the equation (6), it can be found that the coefficient of ECT_{t-1} (also known as the adjustment coefficient) is -0.13, which means that every quarter, about 13% of the discrepancy between the actual value and equilibrium value of M1 in the previous quarter is corrected. When the coefficient of ECT_{t-1} is statistically significant and its

DOI:10.6814/NCCU202001581

value is between -1 and 0, it is another way to determine the cointegration relationship.[18] The coefficient of ECT_{t-1} in the equation (6) has the expected negative sign and value, and is significant at 99% level, proving that the cointegration relationship among the variables in Model 1 does exist.

Next, we applied the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMSQ) tests to test the stability of Model 1. If the plots of the CUSUM and the CUSUMSQ statistics are kept within the 5% significance level, the estimated money demand function in Model 1 can be considered stable. As shown in Figure 3 and Figure 4, the CUSUM and the CUSUMSQ statistics (represented by a curve in the middle) are within the critical bounds (represented by two symmetrical straight lines on both sides), indicating that Model 1 is stable, which proves the stability of the money demand function composed of M1, GDP and interest rate in China.



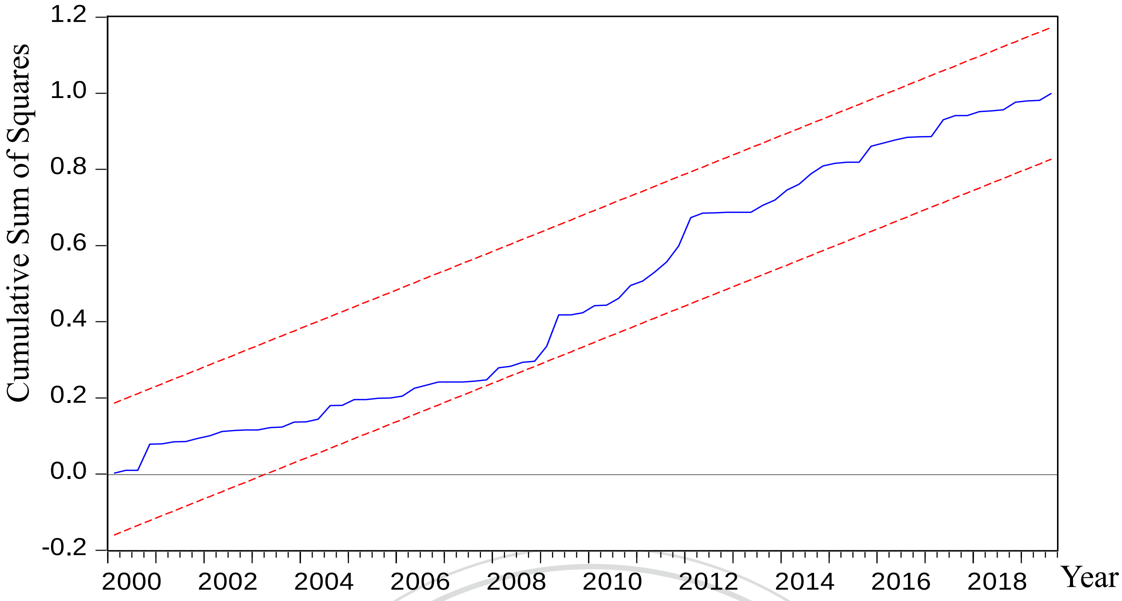
Note: 1. The two straight dotted lines (------) represent 5% significance level.

2. Due to the existence of the lag period, the starting time of CUSUM test and CUSUMSQ test is later than the starting time of the collected data.

Figure 3: CUSUM test for Model 1

[18] According to Kremers et al. (1992), if the coefficient of the error correction term is statistically significant, the cointegration relationship can be established more effectively.

DOI:10.6814/NCCU202001581



Note: The two straight dotted lines (------) represent 5% significance level.

Figure 4: CUSUM of squares test for Model 1

The variables in Model 2 include $LM1$ (as the dependent variable), $LGDP$, IR, and $EPAY$, as described in the equation (4). The bounds testing results of Model 2 are shown in Table 3. Based on the Akaike information criterion (AIC), the optimal number of lag periods for $LM1$, $LGDP$, IR, and $EPAY$ is 3, 3, 0, and 2, respectively. Table 3 lists the critical bounds values of I(0) variables and I(1) variables at 95% significance level and 99% significance level, respectively. The variables of Model 2 are all integrated of order 1, so the computed F-statistic should be compared with the critical bounds value of I(1) listed in Table 3. The results show that the computed F-statistic (6.85) far exceeds the critical bounds value of I(1) at 99% significance level, so the null hypothesis that there is no cointegration relationship among the variables in Model 2 is rejected. Therefore, there is a cointegration relationship among M1, GDP, interest rate, and the e-payment variable.

Subsequently, a series of diagnostic tests are carried out on Model 2, including: (1) Normality Test, and the computed p-value is 0.46, which is greater than 0.05 (95% significance level), so the null hypothesis that the data is normally distributed cannot be rejected, indicating that the data set is well-modeled by a normal distribution in Model 2; (2) Breusch-Godfrey Serial Correlation LM Test, and the computed p-value

DOI:10.6814/NCCU202001581

Table 3: Bounds test results for cointegration analysis — Model 2

Variables of Model 2	F-statistic	Critical bound			
		95% Significance level		99% Significance level	
		I(0)	I(1)	I(0)	I(1)
$LM1(3),\ LGDP(3),\ IR(0),\ EPAY(2)$	6.85	3.23	4.35	4.29	5.61

Note: Figures in parentheses behind the variables in Model 2 indicate the optimal number of lag periods for each variable, which is selected by EViews based on the Akaike information criterion (AIC), and the maximum number of lag periods is set to 4 periods.

is 0.86, which is greater than 0.05 (95% significance level), so the null hypothesis cannot be rejected, indicating that there is no serial correlation in the residuals in Model 2; (3) Breusch-Pagan-Godfrey Test, and the computed p-value is 0.34, which is greater than 0.05 (95% significance level), so the null hypothesis cannot be rejected, indicating that there is no autoregressive heteroscedasticity for the residuals in Model 2; and (4) Ramsey RESET Test, and the computed p-value is 0.15, which is greater than 0.05 (95% significance level), so the null hypothesis cannot be rejected, indicating that there is no setting bias in Model 2.

Following the equation (4), the long-run estimated coefficients in Model 2 ($\alpha_2 = 1.06, \alpha_3 = -5.13, \alpha_4 = -0.02$) can be written as follows:

$$LM1 = 0.27 + 1.06LGDP - 5.13IR - 0.02EPAY. \quad (7)$$

(0.89) (42.35)*** (4.70)*** (2.52)**

As shown in the equation (7), the estimated long-run coefficient of $LGDP$ is 1.06, and it is significant at 99% level, this is consistent with economic theory. The estimated long-run coefficient of IR is -5.13, and it is significant at 99% level, this is consistent with economic theory too. The estimated long-run coefficient of $EPAY$ is -0.02, and it is significant at 95% level. It is an important finding that meets the expectations of this study and confirms the theoretical hypothesis. The e-payment variable proved to be negatively related to M1. In addition, the estimated coefficient in the equation (7) shows that in the long run, for per 1% increase in the $EPAY$ variable, $LM1$ will

DOI:10.6814/NCCU202001581

decrease by approximately 0.02%. After finding the cointegration relationship among M1, GDP, interest rate, and the e-payment variable and obtaining the estimated coefficients of the long-run money demand function, we continue to estimate the short-run model. Following the aforementioned equation (4), the equation (8) shows the ARDL error correction regression of Model 2 as follows:

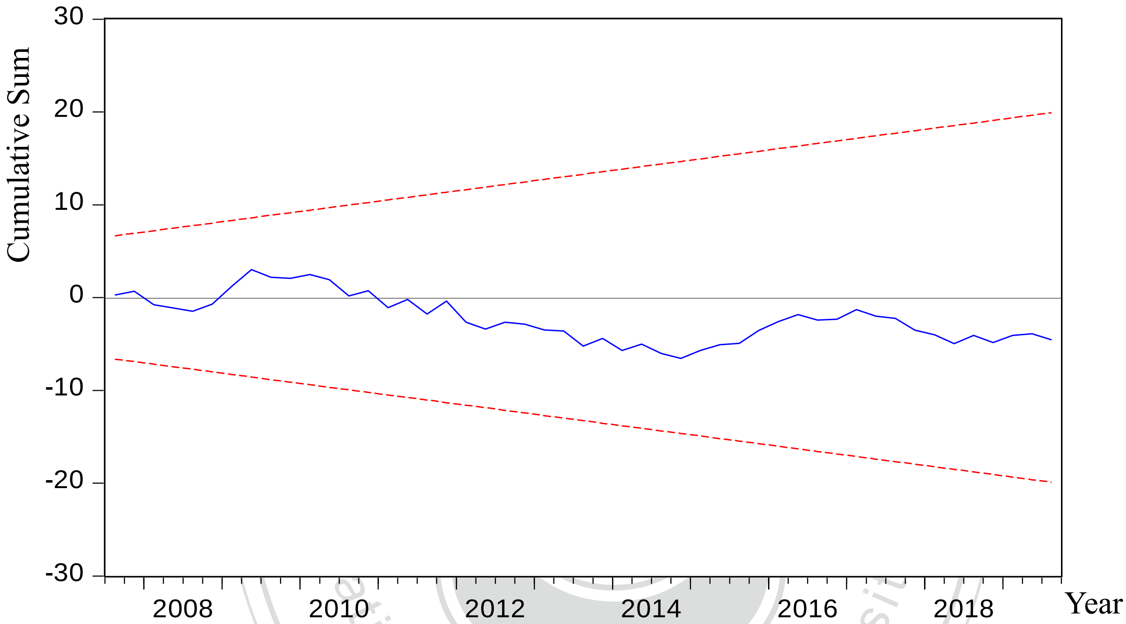
$$
\begin{aligned}
\triangle LM1_t = {} & 0.17 \triangle LM1_{t-1} + 0.34 \triangle LM1_{t-2} + 0.18 \triangle LGDP_t + \\
& (1.48) \qquad\qquad (3.49)^{***} \qquad\qquad (7.95)^{***} \\
& 0.03 \triangle LGDP_{t-1} - 0.04 \triangle LGDP_{t-2} - 0.73 \triangle IR_t + \\
& (1.25) \qquad\qquad (1.92)^{*} \qquad\qquad (4.15)^{***} \\
& 0.004 \triangle EPAY_t + 0.03 \triangle EPAY_{t-1} - 0.14 ECT_{t-1}. \qquad (8) \\
& (0.59) \qquad\qquad (3.28)^{***} \qquad\qquad (4.88)^{***}
\end{aligned}
$$

According to the equation (8), it can be found that the coefficient of ECT_{t-1} is -0.14, which means that every quarter, about 14% of the discrepancy between the actual value and equilibrium value of M1 in the previous quarter is corrected. The coefficient of ECT_{t-1} in the equation (8) has the expected negative sign and it is significant at 99% level, proving that the cointegration relationship among the variables in Model 2 does exist. In addition, it can be seen that the coefficient of $\triangle EPAY_{t-1}$ ($+0.03$) is positive and significant at 99% level, indicating that in the short run, the rate of change of the e-payment variable is positively correlated with the rate of change of M1. Usually, people who use e-payment services bind their credit cards to their e-payment accounts. Furthermore, the e-payment service itself also includes many popular short-term lending services. Therefore, when the amount of e-payment transactions increased in the previous quarter, the loan to be repaid in the next quarter will also increase, and the demand for money will increase accordingly. So, it is reasonable that the coefficient of $\triangle EPAY_{t-1}$ is positive.

Next, we applied the CUSUM and the CUSUMSQ tests to test the stability of Model 2. As shown in Figure 5 and Figure 6, the CUSUM and the CUSUMSQ statistics

DOI:10.6814/NCCU202001581

(represented by a curve in the middle) are within the critical bounds (represented by two symmetrical straight lines on both sides), proving the stability of the money demand function composed of M1, GDP, interest rate, and the e-payment variable in China, indicating that it is reasonable to add the e-payment variable to the money demand function. Taking the electronic payments into consideration does not destabilize the demand for money in China.



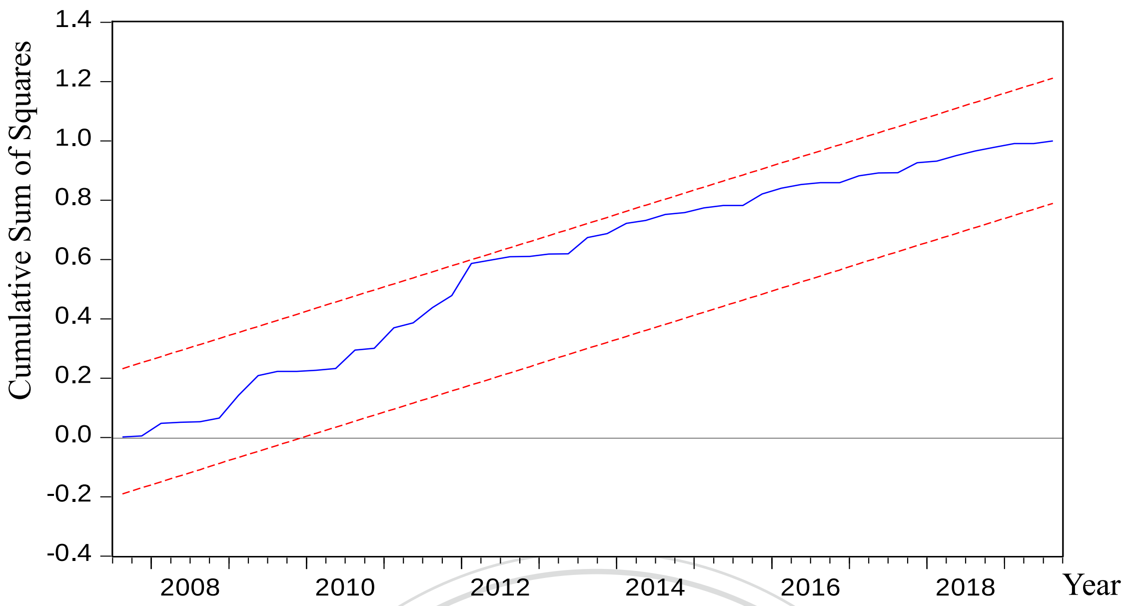
Note: 1. The two straight dotted lines (------) represent 5% significance level.
2. Due to the existence of the lag period and the e-payment data before Q4 2006 is set to zero, the starting time of CUSUM test and CUSUMSQ test is later than the starting time of the collected data.

Figure 5: CUSUM test for Model 2

5.3 Forecast evaluation

The above ARDL bounds testing procedures prove that the increase in the e-payment variable will reduce the demand for M1. The next step will test whether the money demand function after adding the e-payment variable can achieve a more accurate forecast. In this section, we evaluate the forecast accuracy of Model 1 and Model 2. First, use the Diebold-Mariano test to confirm whether there is a significant difference between the forecast accuracy of Model 1 and Model 2. The results are shown in Table

DOI:10.6814/NCCU202001581



Note: The two straight dotted lines (-------) represent 5% significance level.

Figure 6: CUSUM of squares test for Model 2

4. It can be seen that the p-value based on absolute error (approximately 0.001) and the p-value based on squared error (approximately 0.004) are both less than 0.05. Therefore, the null hypothesis that Model 1 and Model 2 have the same forecast accuracy is rejected. There is indeed a significant difference between the forecast accuracy of Model 1 and Model 2. Next, we observe a series of forecast evaluation statistics to analyze which of Model 1 and Model 2 has better forecast accuracy. We forecast the data of Q2 2017-Q3 2019 and evaluate the forecast accuracy of Model 1 and Model 2, and the results are also shown in Table 4.

Table 4: Forecast evaluation of Model 1 and Model 2

Diebold-Mariano test (Null hypothesis: Both forecasts have the same accuracy)					
Accuracy		Statistic		Probability	
Absolute error		5.02		0.0007	
Squared error		3.88		0.0037	
Forecast evaluation statistics					
Forecast	RMSE	MAE	MAPE	Theil U1	Theil U2
Model 1	0.037970	0.034115	0.262589	0.001462	2.001585
Model 2	0.009910	0.007642	0.058824	0.000381	0.512203

The root mean square error (RMSE) is the square root of the average of squared

DOI:10.6814/NCCU202001581

differences between prediction and actual observation. RMSE is a non-negative value and the closer its value is to zero, the better the model fits the data. In the comparison of RMSE values, the RMSE value of Model 2 (approximately 0.01) is lower and closer to zero than that of Model 1 (approximately 0.04). The mean absolute error (MAE) is the average of the absolute differences between prediction and actual observation. It is also a non-negative value, and is equal to zero when the predicted value is exactly the same as the actual value. The greater the error, the greater the value of MAE. In the comparison of MAE values, Model 2 (approximately 0.01) is lower and closer to zero than Model 1 (approximately 0.03). The mean absolute percentage error (MAPE) is the average of the sum of all percentage errors for a given data set, regardless of sign. The closer the MAPE value is to 0%, the better the forecast accuracy of the model. In the comparison of MAPE values, Model 2 (approximately 0.06) is lower and closer to 0% than Model 1 (approximately 0.26).

Table 4 also shows Theil U1 statistic proposed by Theil (1961) and Theil U2 statistic proposed by Theil (1966), both are used to measure the quality of forecast too. The value of Theil U1 is between 0 and 1. The closer Theil U1 value is to zero, the better the forecast accuracy of the model. If Theil U2 < 1, the forecast of the model is better than a naïve forecast;[19] if Theil U2 = 1, there is no difference between the forecast of the model and a naïve forecast; and if Theil U2 > 1, the forecast of the model is not better than a naïve forecast. In the comparison of the Theil U1 statistic, Model 2 (approximately 0.0003) is lower and closer to zero than Model 1 (approximately 0.0015). Besides, it can be seen that the Theil U2 statistic of Model 1 (approximately 2.00) exceeds 1, indicating that the forecast of Model 1 is worse than a naïve forecast. The Theil U2 value of Model 2 (approximately 0.51) is less than 1, which indicates that the forecast of Model 2 is better than a naïve forecast, and of course it is better than the forecast of Model 1. In summary, it can be found that Model 2 is dominant in all comparisons with Model 1. Model 2 that includes the e-payment variable undoubtedly has better forecast accuracy than Model 1.

[19] According to Makridakis et al. (1998), naïve forecasts are forecasts obtained with a minimal amount of effort and data manipulation and are based solely on the most recent available information.

DOI:10.6814/NCCU202001581

Finally, we carry out the dynamic forecasting on the value of M1 based on Model 1 and Model 2, respectively, with a forecast interval of Q1 1997-Q3 2019, and compare it with the actual value of M1. The dynamic forecasting result is shown in Figure 7.

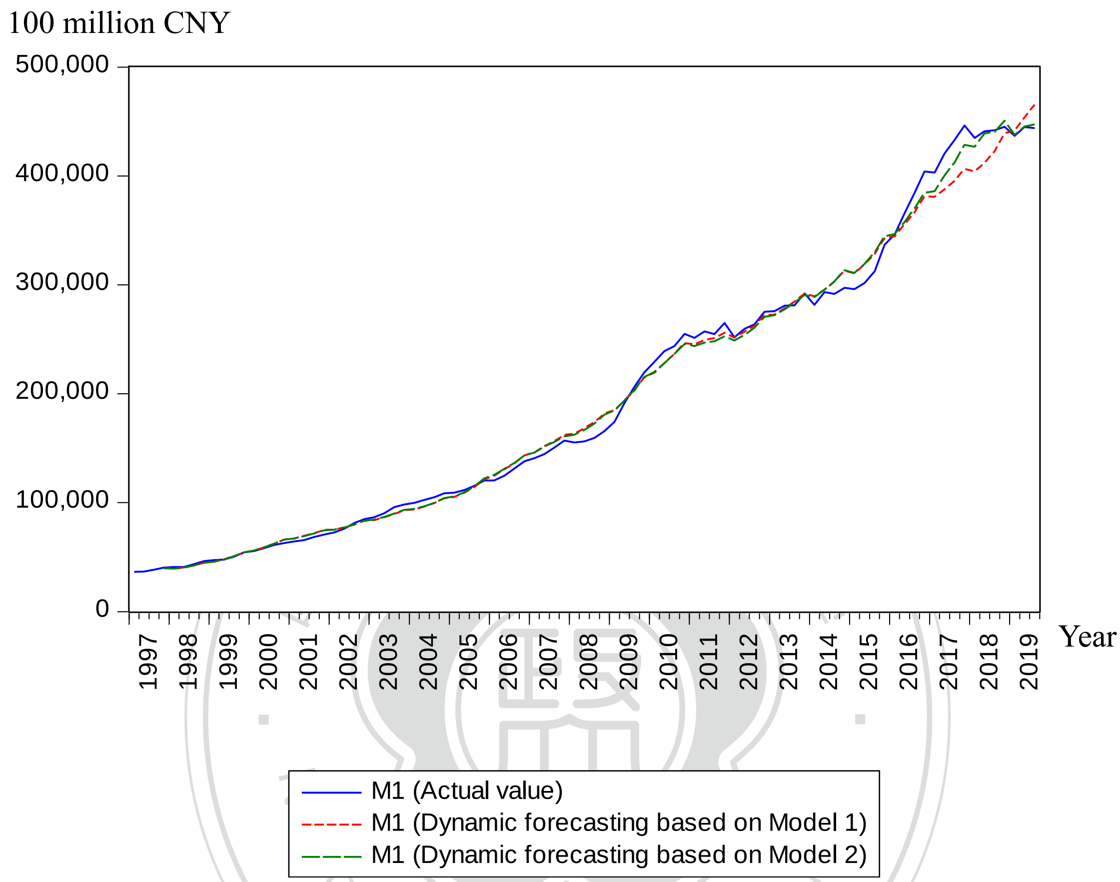


Figure 7: The dynamic forecast based on Model 1 and Model 2

As can be seen from Figure 7, before 2017, the dynamic forecasting of Model 1 and Model 2 is similar. Since then, as electronic payments have grown very rapidly (see Figure 2), its impact on the demand for money has gradually become apparent. We can find that after 2017, the dynamic forecasting of the money demand function that added the e-payment variable (Model 2) is more accurate than the forecast of Model 1. By the dynamic forecasting results, it can be seen that the slower development of electronic payments in the early years has not yet caused a significant impact on money demand. Afterwards, as the volume and scale of electronic payments continued to expand in China, the advantages of Model 2 over Model 1 gradually emerged. The electronic payment should be one of the important considerations in the study of money demand

DOI:10.6814/NCCU202001581

in China.

6. Conclusion

This paper uses the ARDL bounds testing approach to explore the relationship between China's money demand and electronic payments. After a series of empirical analysis, the results show that there is a cointegration relationship among the variables in the money demand function that includes the M1, GDP, interest rate, and the e-payment variable. Besides, electronic payments do have a negative impact on money demand. This finding confirms the theoretical hypothesis stated in this paper and some previous studies, and is consistent with the judgment based on economic intuition. Furthermore, the estimated coefficients derived from the ARDL model in this paper indicate that in the long run, for per 1% increase in the electronic payment variable, the demand for M1 will decrease by approximately 0.02%. In addition, as the scale of electronic payments continues to expand in China (especially since 2017), the money demand function that includes the e-payment variable also performs better in the dynamic forecasting of M1 after 2017.

With the continuous development of the electronic payment, its substitution effect on currency will become more and more obvious, and it may cause more uncertainty in the money demand function. From a policy perspective, the growing electronic payments have made it difficult for central banks to predict the demand for money. While advancing the development of electronic payments and currency electronization, China should further improve relevant legal supervision and try to explore some innovative monetary policies.

DOI:10.6814/NCCU202001581

References

Akinlo, A. E. (2006), "The Stability of Money Demand in Nigeria: An Autoregressive Distributed Lag Approach," *Journal of Policy Modeling*, 28:4, pp. 445-452.

Alvarez, F. and Lippi, F. (2009), "Financial Innovation and the Transactions Demand for Cash," *Econometrica*, 77:2, pp. 363-402.

Arrau, P., Gregorio, J. D., Reinhart, C. M., and Wickham, P. (1995), "The Demand for Money in Developing Countries: Assessing the Role of Financial Innovation," *Journal of Development Economics*, 46:2, pp. 317-340.

Attanasio, O. P., Guiso, L., and Jappelli, T. (2002), "The Demand for Money, Financial Innovation, and the Welfare Cost of Inflation: An Analysis with Household Data," *Journal of Political Economy*, 110:2, pp. 317-351.

Baharumshah, A. Z., Mohd, S. H., and Masih, A. M. M. (2009), "The Stability of Money Demand in China: Evidence from the ARDL Model," *Economic Systems*, 33:3, pp. 231-244.

Bahmani-Oskooee, M., Xi, D., and Bahmani, S. (2016), "Asymmetric Effects of Exchange Rate Changes on the Demand for Money in China," *Applied Economics Letters*, 23:15, pp. 1104-1109.

Boeschoten, W. C. (1998), "Cash Management, Payment Patterns and the Demand for Money," *De Economist*, 146:1, pp. 117-142.

Brown, R. L., Durbin, J., and Evans, J. M. (1975), "Techniques for Testing the Constancy of Regression Relationships over Time," *Journal of the Royal Statistical Society: Series B (Methodological)*, 37:2, pp. 149-163.

Cavanagh, C. L., Elliott, G., and Stock, J. H. (1995), "Inference in Models with Nearly Integrated Regressors," *Econometric theory*, 11:5, pp. 1131-1147.

Chen, B. (1997), "Long-run Money Demand and Inflation in China," *Journal of Macroeconomics*, 19:3, pp. 609-617.

Chen, C. H. (1989), "Monetary Aggregates and Macroeconomic Performance in Mainland China," *Journal of Comparative Economics*, 13:2, pp. 314-324.

Chow, G. C. (1987), "Money and Price Level Determination in China," *Journal of

DOI:10.6814/NCCU202001581

Comparative Economics, 11:3, pp. 319-333.

Diebold, F. X. and Mariano, R. S. (1995), "Comparing Predictive Accuracy," *Journal of Business and Economic Statistics*, 13:3, pp. 253-263.

Dunne, J. P. and Kasekende, E. (2018), "Financial Innovation and Money Demand: Evidence from Sub-Saharan Africa," *South African Journal of Economics*, 86:4, pp. 428-448.

El-Shagi, M. and Zheng, Y. (2019), "Money Demand in China: A Meta Study," *Emerging Markets Finance and Trade*, https://www.tandfonline.com/doi/abs/10.1080/1540496X.2019.1643317.

Geng, S., Jusoh, M., and Tahir, M. Z. M. (2009), "The Stability of Money Demand in China: An Application of the ARDL Model," *Econometric Theory*, 11, pp. 1131-1147.

Girardin, E. (1996), "Is there a Long Run Demand for Currency in China?" *Economics of Planning*, 29:3, pp. 169-184.

Goldfeld, S. M. (1973), "The Demand for Money Revisited," *Brookings Papers on Economic Activity*, 3, pp. 577-638.

Hafer, R. W. and Kutan, A. M. (1994), "Economic Reforms and Long-Run Money Demand in China: Implications for Monetary Policy," *Southern Economic Journal*, 60:4, pp. 936-945.

Harris, R. and Sollis, R. (2003), "Applied Time Series Modelling and Forecasting," https://eprints.gla.ac.uk/33105/.

Harvey, D., Leybourne, S., and Newbold, P. (1997), "Testing the Equality of Prediction Mean Squared Errors," *International Journal of Forecasting*, 13:2, pp. 281-291.

Hossain, A. A. (2012), "Modelling of Narrow Money Demand in Australia: an ARDL Cointegration Approach, 1970–2009," *Empirical Economics*, 42:3, pp. 767–790.

Huang, G. (1994), "Money Demand in China in the Reform Period: An Error Correction Model," *Applied Economics*, 26:7, pp.713-719.

Johansen, S. (1991), "Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models," *Econometrica: Journal of the*

DOI:10.6814/NCCU202001581

Econometric Society, 59:6, pp. 1551-1580.

Johansen, S. (1995), *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford University Press: Oxford.

Johansen, S. and Juselius, K. (1990), "Maximum Likelihood Estimation and Inference on Cointegration — With Applications to the Demand for Money," *Oxford Bulletin of Economics and Statistics*, 52:2, pp. 169-210.

Kremers, J. J. M., Ericsson, N. R., and Dolado, J. J. (1992), "The Power of Cointegration Tests," *Oxford bulletin of economics and statistics*, 54:3, pp. 325-348.

Lieberman, C. (1977), "The Transactions Demand for Money and Technological Change," *Review of Economics and Statistics*, 59:3, pp. 307-317.

Lippi, F. and Secchi, A. (2009), "Technological Change and the Households' Demand for Currency," *Journal of Monetary Economics*, 56:2, pp. 222-230.

Makridakis, S., Wheelwright, S. C., and Hyndman, R. J. (1998), *Forecasting: Methods and Applications*, 3rd ed. New York: John Wiley & Sons.

Nagayasu, J. (2012), "Financial Innovation and Regional Money," *Applied Economics*, 44:35, pp. 4617- 4629.

Narayan, P. K. (2005), "The Saving and Investment Nexus for China: Evidence from Cointegration Tests," *Applied Economics*, 37:17, pp. 1979-1990.

Odhiambo, N. M. (2009), "Energy Consumption and Economic Growth Nexus in Tanzania: An ARDL Bounds Testing Approach," *Energy policy*, 37:2, pp. 617-622.

Ouattara, B. (2006), "Foreign Aid and Fiscal Policies in Senegal," *Journal of International Development*, 18, pp. 1105-1122.

Pesaran, M. H. and Shin, Y. (1998), "An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis," *Econometric Society Monographs*, 31, pp. 371-413.

Pesaran, M. H., Shin, Y., and Smith, R. J. (2001), "Bounds Testing Approaches to the Analysis of Level Relationships," *Journal of Applied Econometrics*, 16:3, pp. 289-326.

DOI:10.6814/NCCU202001581

Phillips, P. C. B. and Ouliaris, S. (1990), “Asymptotic Properties of Residual Based Tests for Cointegration,” *Econometrica*, 58, pp. 165-193.

Qin, D. (1994), “Money Demand in China: The Effect of Economic Reform,” *Journal of Asian Economics*, 5:2, pp. 253-271.

Rahbek, A. and Mosconi, R. (1999), “Cointegration Rank Inference with Stationary Regressors in VAR Models,” *Econometrics Journal*, 2:1, pp. 76-91.

Shin, Y., Yu, B., and Greenwood-Nimmo, M. (2014), “Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework,” in R. C. Sickles and W. C. Horrace eds., *Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications* (New York: Springer), pp. 281-314.

Theil, H. (1966), *Applied Economic Forecasting*. Amsterdam: North-Holland.

Theil, H. (1961), *Economic Forecasts and Policy*. Amsterdam: North-Holland.

Toda, H. Y. (1994), “Finite Sample Properties of Likelihood Ratio Tests for Cointegrating Ranks When Linear Trends are Present,” *Review of Economics and Statistics*, 76:1, pp. 66-79.

Yi, G. (1993), “Towards Estimating the Demand for Money in China,” *Economics of Planning*, 26:3, pp. 243-270.

Zuo, H. and Park, S. Y. (2011), “Money Demand in China and Time-varying Cointegration,” *China Economic Review*, 22:3, pp. 330-343.

DOI:10.6814/NCCU202001581