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Essay on Monetary Policy and Bank Regulation

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Mirewuti Muhetaer

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مەن بۇ ئىلمى ماقالىلەر توپلىمىنى قەدىرلىك ئاپام ۋە دادامنىڭ ئۇزۇن يىللاردىن بۇيان ماڭا توختاۋسىز ئىلھام ۋە مەدەت بەرگەنلىكىنىڭ مېۋىسى دەپ ئويلايمان. ئەگەر سىلەرنىڭ ئاشۇ ئۇلۇغ شەخسىيەتسىز، جاپادىن باش ئەگمەيدىغان روھىڭلار بولمىغان بولسا، بەلكىن مېنىڭ ئاكادېمىك ھاياتىم خېلى بۇرۇنلار مەلۇم باسقۇچلاردا توختاپ قالغان بولغىيتى.

مەن مېنىڭ بەش يىللىك ئىقتىساد پەنلىرى دوكتورلۇق ئوقۇش ھاياتىمنىڭ نەتىجىسى بولغان بۇ ئىلمى نەتىجىلەرنى بۈيۈك ئاتام ۋە ئاپامغان سوغا سۈپىتىدە سۇنىمەن. ھارمىغايسىلەر !! سىلەرگە كۆپ تەشەككۈر.

مەنە شۇنداقلا يەنە ئاكام ۋە ئاچامنىڭ ھەر زامان ھەر جايدا، مېنىڭ ئۆگىنىش ئىشلىرىمغا بولغان قوللاپ قوللىشىغا، مەن ئۆيدىن يىراق بۇ 7 يىل مابەينىدە ئاتا-ئانامنىڭ ھالىدىن خەۋەر ئالغانلىقىغىمۇ ئالاھىدە رەھمەت ئېيتىمەن.

سىلەرنىڭ قوللىشىڭىسىز، بەلكىم مېنىڭ بۇ چەت يۇرتتىكى ئىلىم تەھلىل ئىشلىرىم ئۇنداق ئويلىغاندەك ئۇتۇقلۇق ۋە مۇۋەپپەقىيەتلىك بولمىغان بولغىيتى.

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ABSTRACT OF THE DISSERTATION

Essay on Monetary Policy and Bank Regulation

by

Mirewuti Muhetaer

Doctor of Philosophy, Graduate Program in Economics
University of California, Riverside, September 2021
Dr. Marcelle Chauvet, Chairperson

In this essay, there are three different papers regarding monetary policy and bank regulation. Welfare effect of currency substitution when private cryptocurrency is available is examined in the first paper. Modernized linear Taylor rule by relaxing the original assumption of the fixed natural rate of interest and implicit inflation target rate is studied in the third paper. The potential window dressing behavior of U.S. Global Systemic Important Banks is empirically examined in the second paper by using simple linear regression models.

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Chapter 1

Introduction

Technological improvement can improve the living standard of humans. When it comes to monetary policy and payment system, we have made great progress in the past several decades. The introduction of cryptocurrency that uses Distributed Ledger Technology caught the attention of central banks and different financial institutions. In this essay, considering the revolutionary implications of this new technology, Chapter (2) examines the welfare effect of currency substitution when Bitcoin and U.S. dollar co-exist in the economy. Linear Taylor rule has been proposed several decades ago and there has been some fundamental change in the U.S. economy and technological improvement. Thus, Chapter (4) develops a modernized Taylor rule with new features. What is more, Bank Holding Companies are subject to different types of capital regulation and one of them is the Global Systemically Important Banks (G-SIB) framework. Chapter (3) examines the potential window-dressing behavior of U.S. G-SIB banks.

Chapter (2) examines welfare implications of the currency substitution between a legal fiat currency and a private cryptocurrency when both can be used as the medium of exchange. I developed a Dynamic General Equilibrium model with many novel features, like time-varying transaction cost of the cryptocurrency. This paper concludes that a private cryptocurrency with a high rate of return and a low stable exchange rate can compete with domestic legal fiat currency and even has the potential of crowding it out. In addition, I also find that price has a small positive effect on welfare of the consumer while exchange rate has a significant mixed effect.

In Chapter (3), I examine the potential window dressing behavior of major U.S. international banks under G-SIB framework. This paper confirms the existence of window dressing practice among the U.S. G-SIBs. I also find that if a bank's systemic importance score is close to bucket thresholds in the previous year-end exercise, then it has a significant incentive to repress its systemic importance score the following year. I propose two different approaches to address the window dressing practice among the U.S. G-SIBs and the quarterly maximum approach is successful in punishing target banks with higher additional capital surcharges.

Chapter (4) examines the effectiveness of the modernized linear Taylor rule with both time-varying natural rate of interest and implicit inflation target rate, which have always been assumed to be fixed. I find that the modernized inertial Taylor rule implied policy rate is highly consistent with the actual Federal Funds Rate with tiny differences for the whole sample period of 1965Q1-2019Q1.

Chapter 2

Currency Substitution, Price, Exchange Rate, and Welfare

The Distributed Ledger Technology (DLT), which can eliminate the third party in a transaction, has been developing rapidly in recent years, with strong implications for monetary policy and payment system. This paper examines the potential welfare effect of currency substitution between fiat currency and private cryptocurrency when both can be used as a medium of exchange. A dynamic general equilibrium model is developed, which captures novel features of a currently operating private cryptocurrency payment processor and uses the relevant data of Bitcoin. The findings indicate that a private cryptocurrency with a high rate of return and a low stable exchange rate not only can compete with legal fiat currency but also has the potential of crowding it out. This significantly impacts the effectiveness of monetary policy. Changes in price have a small positive effect on consumer's welfare while the effect of the exchange rate is significant and mixed. The results also suggest that more R&D is necessary to improve the currently operating blockchain network and online cryptocurrency exchange market to increase users' welfare.

2.1 Introduction

Bitcoin (BTC) is a decentralized privately issued cryptocurrency in which the transaction takes place without intermediaries, using DLT.[1] This technology has been developing rapidly in recent years, especially in the private cryptocurrency sector, with strong implications for monetary policy and the payment system.

The goal of this paper is to examine the potential welfare effect of currency substitution when both privately issued cryptocurrency and domestic legal fiat currency co-exist in the economy. In particular, it investigates the welfare and policy implications associated with the transaction cost of using private cryptocurrency as a medium of exchange, and with the cost of replenishing monetary assets from nonmonetary assets.

A dynamic general equilibrium model is proposed to study the impact of cryptocurrency in the economy and in the monetary system. The model contains three agents: a representative household, a representative firm, and a government that plays the role of a central bank. Privately issued cryptocurrency (Bitcoin) and domestic legal fiat currency (U.S. dollar) can both be used to purchase goods and services, while only fiat currency has a unit of account function. When the cryptocurrency is used to make purchases, a private payment operator processes the transaction and charges an exogenous, time-varying transaction or network fee, which is independent of the transaction amount. The transaction fee for using fiat currency is assumed to be zero. A Cash-in-Advance (CIA) model along

[1] Bitcoin is the first-ever issued cryptocurrency and has been issued since 2009. Currently Bitcoin has the highest market capitalization value among all private cryptocurrencies. The detailed working principle of Bitcoin is described in [57] while [13] present a thorough review of the Bitcoin and related issues. Now there are many private cryptocurrencies with different designs. The coinmarketcap.com reports 5161 listed cryptocurrencies (as of March 04, 2020) and this number can be different on alternative tracking or exchange markets.

the lines of [30] and [60] is constructed by introducing an asset market, which is used to replenish cryptocurrency and fiat currency balances from nonmonetary assets. The introduction of an asset market for cryptocurrency is a novel deviation from the classic CIA model, in which consumption expenditure is assumed to be financed by gross returns on saved monetary assets from the previous period. Firms operate in a competitive market and produce according to a regular Cobb-Douglas production function. The government conducts monetary policy by injecting lump-sum fiat currency into the economy. The paper conducts a welfare analysis of the cost of changes in price and nominal exchange rate, and other core variables of the model, based on several assumptions related to private cryptocurrency. First, private cryptocurrency is universally available to both consumers and merchants and its supply is exogenous. Second, the rate of return on cryptocurrency is measured by using the median value of the gross appreciation rate of the cryptocurrency. Third, the steady-state or long-run nominal exchange rate of cryptocurrency is assumed to be one since actual Bitcoin values are very high and volatile, which discourages consumers from using it to purchase goods. Fourth, the rate of return on cryptocurrency is assumed to be independent of the nominal exchange rate of cryptocurrency. Bitcoin data are used for the quantitative analysis. Also, it is assumed that there is a private cryptocurrency payment processor such as BitPay in the economy to process cryptocurrency transactions.

This paper has several remarkable contributions. First, to the best of my knowledge, this is the first paper that incorporates the currently existing and operating private cryptocurrency payment processor features into a dynamic general equilibrium macroeconomic model. Second, this is the first paper to examine the welfare implication of currency substitution between fiat and private cryptocurrency by using an extended version of CIA model. Third, similar to [30] and [60], the choice of payment instrument when purchasing goods and services is endogenously determined by the consumer by comparing the expected opportunity cost of using fiat currency and cryptocurrency. Fourth, inspired by the mining fees of the Bitcoin blockchain network, an exogenous and time-varying transaction cost for each payment made by using cryptocurrency is included in the model. Fifth, different from the classic CIA model, an asset market is introduced to replenish money balances.[2] Therefore, money balances saved for the next period do not have to be the same as the money amount spent on purchasing goods and services in the current period. Sixth, this paper also examines the potential welfare impact of the transaction cost of using cryptocurrency as a payment instrument, and the replenishing cost of both currencies from nonmonetary assets. This is particularly important, given their striking policy and innovations implications for the cryptocurrency exchange platforms, cryptocurrency payment processors, and for the blockchain-powered Central Bank issued Digital Currency (CBDC). The proposed model is carefully calibrated to the U.S. economy. The model uses the exchange rate to denote the value of a CBDC or cryptocurrency in legal fiat currencies. Any changes in the price or exchange rate can impact the consumption and leisure choice of the consumer through wealth or substitution effect. With the availability of another currency that has the same or similar functions, the effect on the consumer's welfare is likely to be amplified. Until now, researchers mostly focused on the substitution or competition between the bank deposit

[2]The proposed model follows the currency substitution model of [60] and the endogenous fluctuations in monetary aggregates framework as in [30]. Bank deposit and fiat currency are used as means of payment in [30] while domestic currency, domestic bank deposits, and foreign currency are used as payment instruments in [60]. Similarly, in this paper both domestic fiat currency and privately issued cryptocurrency are used as payment instruments.

and cryptocurrency or cash and cryptocurrency, which includes both the CBDC and privately issued cryptocurrency. However, the question of the effect of currency substitution on welfare when a cryptocurrency is used to purchase goods like legal fiat currency has not been thoroughly examined yet.[3]

The findings of this paper are as follows. First, changes in price have a positive impact on consumer welfare and cryptocurrency balance, but a significant negative impact on the fiat currency balance and traveling times to the asset market to replenish money balances from nonmonetary assets. The welfare cost decreases slightly as price increases. However, the nominal exchange rate between Bitcoin and the U.S. dollar has a mixed effect on consumer welfare, cryptocurrency balance, and fiat currency balance. For example, for a 20% increase in the nominal exchange rate between cryptocurrency and fiat currency, the welfare cost rises by 6%, and fiat currency balance increases more than threefold, while private cryptocurrency balance decreases by around 100% at first. As the economy adjusts to the shock, fiat currency balance decreases some but continues to be higher than before the shock. Further, the welfare gains or losses are not as large as the corresponding increase in the price and nominal exchange rate given the relatively high appealing gross return on the cryptocurrency and very low transaction cost, which is the mean value of the time-varying transaction cost of the cryptocurrency. Second, the findings indicate that a private cryptocurrency with relatively high rate of return and low stable exchange rate can compete with legal fiat currency and has the potential to crowd it out. Third, the availability of the substitutable currency is likely to mitigate welfare losses. Both the substitution and

[3]As discussed in more detailed in Section (2.3), several papers study the case of Bitcoin or assumed central bank cryptocurrency having the function of a medium of exchange, but with different approaches, models, or in different environments.

wealth effect play an important role during the process. Fourth, in general, the replenishing cost of both currencies has a relatively big impact on the welfare of the consumers than the transaction cost of using cryptocurrency as a payment instrument. Thus, making it cheaper and convenient to buy or sell cryptocurrencies can enhance the usage of cryptocurrency as a payment instrument by decreasing the welfare losses of users. Additionally, having a stable and low transaction cost is also important to increase users' welfare.

The results have several important implications. First, countries experiencing higher inflation or high prices should be cautious about privately issued cryptocurrencies that can compete with the legal fiat currency both as a medium of exchange and a store of value. Second, the effect of the cryptocurrency exchange rate on the consumer welfare is negative and significant while the effect of changes in price is small and positive. Therefore, potential CBDC and private cryptocurrency issuers are recommended to closely monitor the fluctuations in the cryptocurrency value vis-à-vis changes in prices. Third, private cryptocurrency issuers can reduce consumer welfare losses by investing more in R&D to increase network capabilities and decrease the cost of exchanges between different types of currencies.

The paper is organized as follows. Section (2.2) gives a background on the developments of cryptocurrency and the associated technology. Section (2.3) discusses related literature. Section (2.4) describes the proposed general equilibrium macroeconomic model and the calibration of the model to U.S. data. Section (2.5) discusses the quantitative analysis of the welfare cost of price changes and nominal exchange rate related to currency substitution. It also reports sensitivity analysis and technology implications. Section (2.6) concludes and makes final remarks.

2.2 Background

The Distributed Ledger Technology is a database shared by independent computers (i.e., nodes) in different sites and geographical locations, by individual or institutions that are used to record and synchronize transactions in their electronic ledgers (see, e.g., [68]). That is, instead of keeping data centralized as in a traditional ledger, the data are decentralized in multiple locations by multiple parties. The use of DLT is becoming increasingly widespread and is starting to bring pervasive changes in an array of sectors.[4] The blockchain technology is the most well known type of DLT and it has gained wide application in many sectors. Decentralization is the key feature of blockchain technology, and cryptocurrency, especially Bitcoin, is the most important and well-known application of blockchain technology.[5]

Bitcoin is a decentralized privately issued cryptocurrency in which transaction is carried out without intermediaries. Since the 2008 financial crisis, the confidence in the traditional banking system has declined (see, e.g., [55], [14]). The popularity of decentralized DLT and the increasing demand for seamless, real-time, independent domestic or international payment system are the main driving forces behind the new central bank trend of

[4]For example, land registration and blockchain government in the public service sector, risk management, insurance, and cryptocurrency application in the financial sector, sharing economies, global authentication, and ownership in the data management sector (see, e.g., [48], [21], [70]).

[5]Major financial institutions and technological corporations have already realized the financial importance of blockchain technology. Some of them are conducting research while some others have even adopted it already. For example, JPM coin of J.P. Morgan Chase and Libra of Facebook. For more details of these two specific cryptocurrencies, check [39] and [50].

considering or implementing projects related to the blockchain-powered CBDC (see, e.g., [10]). As [69] and [5] point out, Bitcoin and other private cryptocurrencies are mostly treated as a speculative asset by holders rather than as currency. The main reasons are the extremely high volatility of Bitcoin, lack of trust in the Bitcoin system, and lack of wide merchant acceptance.[6] Figure (2.1) and Table (2.1) depict the volatility of Bitcoin price compared to the USD/EUR exchange rate. The advantages of a blockchain-powered CBDC include preventing tax evasion and fighting crimes, decreasing the unbanked section of the population, and reducing the cost of maintaining the payment system.[7] The users' welfare and the stability of the financial system are always of great importance to central bank regulators. It is highly unlikely that fiat currency will be replaced with CBDC in the very short run. In addition, fiat currency may still be used and valued by some sections of the population for quite some time. Therefore, the coexistence between domestic fiat currency and CBDC is expected.[8]

Significant progress has been made by private payment processors to increase the wider adoption of private cryptocurrency as a payment instrument. One of the leading private cryptocurrency payment processors in the U.S. is the BitPay, which works as an intermediary and the exchange rate shock absorber between the two sides of a transaction.[9] All the goods and services are priced with domestic legal currency and merchants are guaranteed to receive the exact amount in domestic currency for sold goods and services. Even though BitPay is not an ideal CBDC payment processor, it helps private cryptocurrency to

[6] See, e.g., [25], [64], [35], [38], etc.

[7] For the cost of maintaining the U.S. fiat payment system, see [12] and [20].

[8] Recently, El Salvador becomes the first country to make Bitcoin a legal tender. Therefore, both Bitcoin and U.S. dollars can be used together. Check [16] and [58] for more details.

[9] See [7] for more details.

capture one more function of money - a medium of exchange. Therefore, private cryptocurrency like Bitcoin can have the role of a medium of exchange and a store of value, which is one of the major motivations of this paper.

The second motivation is the necessity of modernizing the currently operating and widely used Real-Time Gross Settlement (RTGS) systems across the world.[10] Even though the transaction process is regarded as being in real-time, it does not complete in a second, and merchants have to bear most or all of the interchange fees according to the different local regulations.[11] When it comes to international transactions, the time needed for a complete transaction is much longer and the fees are higher.

The third motivation is the changing landscape of the payment instrument preference among consumers. Consumer-friendly mobile payments, card payments, and online payments have been gaining popularity and market shares thanks to the rapid technological advancement and the convenience they bring to users. Cash usages have already been low and still declining for many countries, particularly Sweden and Norway, while mobile payments like Wechat or Alipay have been crowding out cash in China.[12] However, there is a small decrease in cash usage in the U.S. from 2015 to 2018, while the cash payment value is relatively stable during this period.[13] Given the innovations in the blockchain technology accompanied with the increasing demand for modernizing payment systems, it is not prudent to ignore the possibility of employing a privately issued cryptocurrency with some basic money functions or a CBDC to meet the needs of the public.

[10]For example, the FedNew service in the U.S., Request to Pay in the U.K. See [11] and [26] for details.

[11]To have a better understanding of different types of inter-bank real-time retail payment system, see [49]. To understand the payment system and issues regarding the U.S. domestic payment system, refer to [23].

[12]See, e.g., [61], [44], [1], [65].

[13]See, e.g., [47], [46].

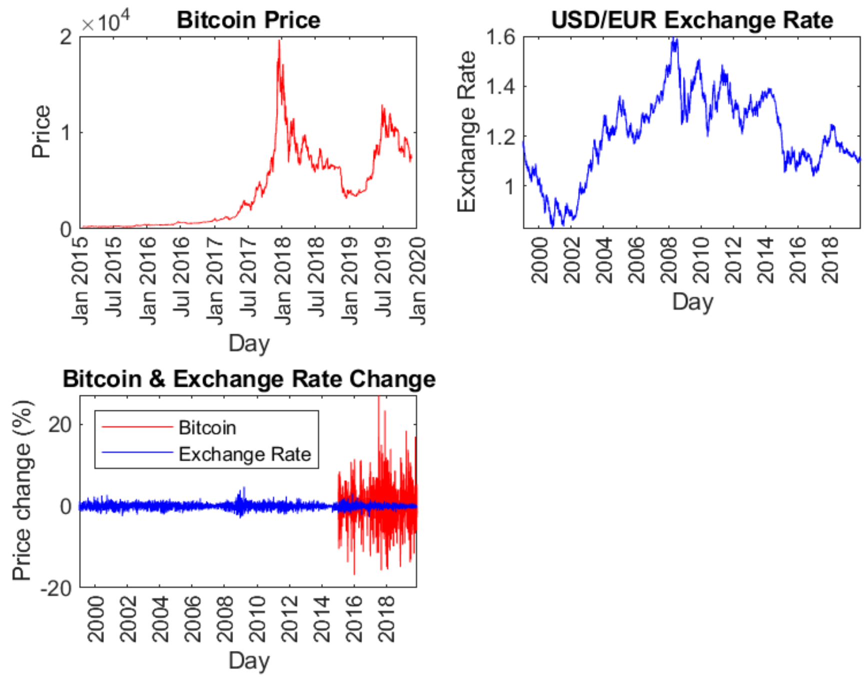

Figure 2.1: Volatility comparison of Bitcoin price and USD/EUR exchange rate. Note: The daily Coinbase Bitcoin price data is from [27] and the period is 01/19/2015-12/03/2019. The daily USD/EUR exchange rate is also obtained from [27] and the period is 01/04/1999-11/29/2019. Some not available (NA) values are dropped. Price changes are net increase in the percentage of both Bitcoin and exchange rate values from the previous day. Coinbase is a major online cryptocurrency exchange market.

	BTC price	BTC price change (%)	Exchange rate	Exchange rate change (%)
Mean	3930.2	0.2693	1.2031	0.00051678
SD	3978.3	3.8502	0.1662	0.6070
AC	0.9970	-0.0167	0.9990	0.0077

Table 2.1: Statistics of Bitcoin and USD/EUR exchange rate values. Note: This table shows descriptive statistics of Figure (2.1). SD stands for standard deviation, AC stands for the lag 1 autocorrelation. Here USD/EUR exchange rate is chosen to compare volatility with Bitcoin since the U.S. and the European Union are the world's two largest economic entities and their currencies are relatively more stable than most other currencies. Further, according to [37], the U.S. dollar and Euro are the two major reserve currencies for foreign exchange.

2.3 Literature Review

Since the DLT and CBDC are still at the early age of development, there is a limited amount of research on currency substitution and welfare regarding cryptocurrency. [4] examine the effect of issuing an interest-bearing and universally accessible CBDC, which competes with bank deposits, on the macroeconomy by using a rich Dynamic Stochastic General Equilibrium (DSGE) model. [42] also focus on the competition between CBDC and bank deposit, both of which are used as a medium of exchange, while studying the optimal design of cryptocurrency and conclude that CBDC can improve welfare, which is measured by the utility. [2] examines the impact of CBDC on monopolistic private banks when bank deposit competes with cryptocurrency by using an overlapping generations model. [24] examines the optimal monetary policy under different combination of cash and interest-bearing CBDC with a discrete two-subperiod model and finds that both cash and CBDC availability could reduce the overall welfare compared with when cash or CBDC is available exclusively. Both [42] and [24]'s models stress the micro-foundation of money. [36] study currency substitution between fiat currency and privately issued cryptocurrency with a search and match approach and investigate the crowding out effect. [33] study the interaction between the central bank and the private e-money issuer when the legal fiat currency competes with privately issued e-money. [45] examine the CBDC's implication on the stability of the financial system with a simple overlapping generations model and the interesting point in this paper is the direct competition between bank deposit and CBDC, which is directly accessible by consumers at their central bank account. What is more, there are also other papers like [29] and [31] that examine the competition between privately issued cryptocurrencies.

[41] examine the welfare implication of inflation when Bitcoin and fiat currency are both used as a medium of exchange by using a search model, in which miners and the Bitcoin transaction cost is modeled. [3] examine the unintended response of currency substitution between government fiat currency and private cryptocurrency to the technology, monetary, and preference shocks with a DSGE model, in which both currency balances are in the consumer's utility function and cryptocurrency producing firms, intermediate and final good producers are included. [63] analyze some basics of Bitcoin pricing with the availability of U.S. dollars, both of them can be used for transactions, in a simple model that central banks target a stochastic U.S. dollar inflation through money injection while the Bitcoin supply is deterministic in time. [6] study the currency competition in a two-country model when two national currencies and a global cryptocurrency are available. [62] is a theoretical paper that examines the relationship between currency substitution, asymmetric transaction costs, and the exchange fees. [62] is the most relevant paper in terms of using cryptocurrency as a mean of payment and considering the endogenous determination of payment instrument choice between fiat currency (Dollar) and cryptocurrency (Bitcoin). However, it is also different. First, my paper does not consider the possibility of exchanging currencies in either direction between the fiat currency and cryptocurrency in a period and the choice of payment instrument is based on comparing the expected opportunity cost of using respective currencies. Besides, the usage of the fiat currency does not incur transaction costs. Second, the private cryptocurrency transaction cost in my paper is time-varying and irrelevant to

the amount of purchase. Third, there is no specific exchange fee in my paper and the fluctuation in the cryptocurrency value is absorbed by the private cryptocurrency payment processor.

Without considering the availability of the cryptocurrency, currency substitution such as dollarization is old literature and there are plenty of papers that investigate different effects of the dual currency or asset competition. For money and credit as payment, please check [32], [52], and [51]. For domestic and foreign currency, please check [28], [56], [53], and [60]. For fiat currency and bank deposit competition, please check [34], [30], and [60].

2.4 Model

2.4.1 Households

The representative of a large number of infinitely lived identical households is endowed with one unit of time in each period and a stock of capital in the initial period, which is the period 0. The representative household values both consumption goods and leisure. In each period $t \geq 0$, a continuum of goods, of which types are indexed by $j \in [0,1]$, are consumed. The representative household is forward-looking and maximizes expected discounted lifetime utility. In each period t, the representative household consumes $c_t(j)$ from each type of goods j and enjoys leisure l_t. Therefore, the household maximizes:

$$\max E_0 \sum_{t=0}^{\infty} \beta^t u\Big[min\{\frac{c_t(j)}{(1-\omega)j^{-\omega}}\}, l_t\Big], \quad \omega \in R_- \tag{2.1}$$

The representative household's period utility function $u(c_t, l_t)$ is in Leontief form and the Leontief parameter ω captures the curvature of the consumption amount $c_t(j)$ of each type of good. The utility function $u(c_t, l_t)$ is assumed to be increasing in both c_t and l_t, quasi-concave, twice continuously differentiable and satisfy Inada conditions ([30]).

The representative household consumes $c_t(j)$ amount of each type of consumption good $j \in [0, 1]$ according to the optimization condition of Leontief ordering of the consumption goods[14]:

$$\frac{c_t(j)}{(1-\omega)j^{-\omega}} = c_t \tag{2.2}$$

Replacing the first item of the utility function in eq (2.1) with (2.2), then the representative household's optimization problem becomes:

$$\max E_0 \sum_{t=0}^{\infty} \beta^t u(c_t, l_t) \tag{2.3}$$

What is more, private cryptocurrency CC_t, fiat currency M_t, and capital K_t are the available assets for the household. Both private cryptocurrency and fiat currency can be used as means of payment for daily transactions. Fiat currency satisfies all three functions, a unit of account, a store of value, and a medium of exchange, of money while it is assumed that private cryptocurrency satisfies only two functions except for the unit of account. Therefore, the value of the goods is measured with domestic fiat currency (U.S. dollar). Whenever a household wants to pay with private cryptocurrency, the specific amount of cryptocurrency is needed to be converted into domestic fiat currency instantaneously, which is the point where the private cryptocurrency payment processor is needed. In this paper, I will not dis-

[14]Note that j is an index that represents the size of a good.

cuss the incentives for the household to use cryptocurrency as a payment instrument rather than just holding it as a speculative asset. Currently, most of the cryptocurrency users hold it because they expect to benefit from the value fluctuations. As far as I know, there is no any reliable survey or data that shows exactly what percentage of the cryptocurrency holders use it frequently to buy goods and services and the reasoning behind it.

Even though using fiat currency to purchase goods and services incur private and social transaction costs, it is simply assumed that the fiat currency transaction cost is equal to zero in this paper. But when it comes to the private cryptocurrency, from purchasing it on the online cryptocurrency exchange market and using it for purchasing consumption goods and services, it incurs several fees. If a consumer does not own any cryptocurrency, he can mine it or buy it using fiat currency (Online payment method such as PayPal and card payments), and it incurs transaction costs. Once the consumer possesses cryptocurrency and BitPay Prepaid Debit Card (After application, which costs $9.99), then he can use a different variety of BitPay supported cryptocurrencies to make a purchase. It should be highlighted that BitPay is a payment processor, not a blockchain network and it still operates on the specific cryptocurrency's network. As [7] describes, when a consumer decides to buy an item, the BitPay instantaneously locks the cryptocurrency exchange rate at the spot price and keeps at that rate for fifteen minutes. Therefore, the merchant will receive the exact amount in terms of fiat currency (The merchant can also choose the composition of cryptocurrency and fiat currency acceptance) while the consumer receives the goods and enjoys using this new technology. What is more, similar to the regular Bitcoin transaction, the consumer needs to add "tips", which is mining fees for the miner's transaction verification effort on the blockchain network, during the purchasing process and twice. One is for the consumer to BitPay period and the second, which is called "Network fee" by BitPay, for the period from BitPay to the merchant. It is also worth noting that those tips and network fees, which are in terms of cryptocurrency, are not calculated as the percentage of the transaction amount. Instead, they are determined by the network environment and file size ([9]). Thus, it is a one-time transaction cost regardless of the transaction amount. For more details of BitPay, please check [7].

Therefore, whenever cryptocurrency is used to purchase goods and services, it incurs the transaction cost τ_{cc} that fiat currency transaction is free from. For simplicity reasons, it is assumed that τ_{cc} is incurred only once during the whole transaction process.

At the beginning of each period $t \geq 0$, the representative household decides how much cryptocurrency and fiat currency to hold and the distribution ratio of monetary assets among the fiat currency and cryptocurrency will be kept constant until the beginning of the next period.[15] As it is mentioned earlier, fiat currency and cryptocurrency are both used as a payment instrument and a store of value. It is possible that the amount of money spent on purchasing goods and services may be more or less than the amount saved for the next period. Therefore, an asset market, which can be understood as a certain type of exchange market similar to private cryptocurrency online exchanges, is introduced to incorporate this issue. The representative household can replenish both fiat currency and cryptocurrency balance using nonmonetary assets in the asset market.[16] The n_t denotes the number of

[15] For example, if the agent decides to hold 30 dollars fiat currency and 70 dollars value of the cryptocurrency at the beginning of the period t, then the ratio of the 30:70 will be kept the same during this period t.

[16] Please note that exchange between the domestic fiat currency and the cryptocurrency within a period is not considered here since the household can change their mind of holding any type of currency during any

visits to the asset market and ϕ denotes the time cost of traveling to the asset market. The streams of income from the previous period are used to purchase consumption goods. After coming back from visiting the asset market each time in period t, it is assumed that the household makes symmetric purchases: buying the same combination of goods with different currencies each time. As [30] states "ϕ represents not the cost of going to the ATM, but the cost of replenishing all deposit and cash balances from nonmonetary assets" when studying the usage of bank deposit and cash as means of payment. Similarly, ϕ measures the cost of replenishing both cryptocurrency and fiat currency balances from nonmonetary assets. If a dollar is replenished n_t times, then consumption goods worth n_t dollars can be purchased in a single period. Each trip costs ϕ units of time, and thus ϕn_t units of the time is spent on replenishing the money balances. What is more, for a cryptocurrency exchange market in the real world, ϕ can be understood as a "convenience" parameter that measures the degree of convenience when conducting cryptocurrency exchanges by using other monetary assets. Therefore, it is the cost that private cryptocurrency issuers should decrease to attract more users.

Furthermore, the total consumption level c_t can be gained by integrating $c_t(j)$ in eq (2.2) from 0 to 1. Before conducting any purchase, the household needs to decide which currency to use for a given consumption level of c_t. Therefore, the household needs to compare the expected opportunity cost of using a private cryptocurrency to the opportunity cost of using fiat currency. Let $\theta_{t+1} = \frac{\Theta_{t+1}}{P_{t+1}}$ to denote the real gross appreciation rate of the cryptocurrency between period t and t+1 and $\bar{r}^k_{t+1}$ to represent the gross real rate of

time point in a period t because of the value fluctuation of cryptocurrency. Also, the frequency of the data used for the calibration is quarterly.

return on nonintermediated assets, which is capital acquired at time t in this model, net of depreciation rate.[17] After considering the time-varying transaction cost τ_{cct} for buying each item $c_t(j)$ and n_t times in each period, the expected opportunity cost of making the purchase with the cryptocurrency is:

$$E_t\Big[\frac{\Theta_{t+1}}{\pi_{t+1}} - \frac{S_t \tau_{cct}}{P_t}\frac{\bar{r}^k_{t+1} n_t}{c_t(j)}\Big] \tag{2.4}$$

where S_t is the nominal exchange rate of cryptocurrency and P_t is the price of consumption goods. It is assumed that the purchasing power parity holds in each period, which is consistent with the assumption made in [60]. The nominal exchange rate S_t is defined as:

$$S_t = \frac{Price\,of\;Domestic\,Fiat\;Currency_t}{Price\,of\;Private\,Cryptocurrency_t} \tag{2.5}$$

For example, for Bitcoin, if $S_t = 10$, then it means one unit of Bitcoin is worth 10 U.S. dollars in America. What is more, purchasing consumption goods with fiat currency is free from direct transaction cost and the only value change comes from inflation. Thus, the expected opportunity cost of using fiat currency is:

$$E_t\frac{P_t}{P_{t+1}} = E_t\frac{1}{\pi_{t+1}} \tag{2.6}$$

[17] θ_t and $\Theta_t = \frac{S_t}{S_{t-1}}$ are the real and nominal gross appreciation rate of a cryptocurrency respectively. I treat Θ as a variable independent from the nominal exchange rate S at the steady-state as [60] did. Otherwise, the gross appreciation rate of private cryptocurrency has to be one at the steady-state, which makes threshold level j^* as expressed in eq (2.8) infinite and cryptocurrency is not used during the transaction at all. What needs to be stressed is that I focus on the case when both the fiat currency and cryptocurrency are used as a transaction instrument, which means $j^*_t \in [0, 1]$.

where the inflation rate is expressed as $\pi_t = \frac{P_t}{P_{t-1}}$. From the expression (2.2), it is easy to observe that $c_t(j)$ is an increasing function of the payment instrument choice threshold j_t. Therefore, as the size of purchased consumption goods j_t increases, the per capita transaction cost of using cryptocurrency to purchase goods goes down and the opportunity cost of using cryptocurrency increases. Thus, the expression (2.4) is an increasing function of j_t while expression (2.6) is irrelevant to the purchase size. Consequently, it is obvious that there is a threshold level j_t^* such that the household will use cryptocurrency for purchases when $j_t^* < j_t \leq 1$ and use fiat currency if $0 \leq j_t < j_t^*$. The representative household is indifferent between using cryptocurrency and fiat currency to conduct transactions only if the expected opportunity cost of using cryptocurrency in a transaction is the same as the expected opportunity cost of using fiat currency. This condition can be expressed as:

$$E_t\left[\frac{\Theta_{t+1}}{\pi_{t+1}} - \frac{S_t\tau_{cct}}{P_t}\frac{\bar{r}_{t+1}^k n_t}{c_t(j)}\right] = E_t\frac{1}{\pi_{t+1}} \tag{2.7}$$

which then implies the optimal threshold level j_t^* is:

$$j_t^* = E_t\left(\frac{c_t}{n_t}\right)^{\frac{1}{\omega}}\left[\frac{\frac{1}{\pi_{t+1}}(1-\omega)(\Theta_{t+1}-1)}{\frac{S_t}{P_t}\tau_{cct}\bar{r}_{t+1}^k}\right]^{\frac{1}{\omega}} \tag{2.8}$$

Threshold choice level j_t^* is positively related to n_t, τ_{cct}, $\bar{r}_{t+1}^k$, and nominal exchange rate S_t while negatively related to c_t, P_t, and Θ_{t+1}. Any increase in τ_{cct} or S_t while keeping other variables constant makes the domestic currency value of the cryptocurrency transaction cost expenditure expensive. It implies an increase in the value of j_t^* to maintain equality in eq (2.7). Therefore, consumers will move to buy more goods with fiat currency. However, any increase in the price level P_t makes the real transaction cost of using cryptocurrency less expensive and can change the expected inflation rate of π_{t+1} at the same time because of the possible update in expected price level P_{t+1}. The increases or decrease in the expected opportunity cost of using a cryptocurrency or fiat currency for a payment, which then leads to the corresponding change in j_t^*, demand for cryptocurrency and fiat currency, depends on the magnitude of changes in both P_t and expected π_{t+1}. What is more, any increase in the gross nominal appreciation rate Θ_{t+1} of a cryptocurrency will increase the expected gross real return net of transaction cost on the cryptocurrency and induce the consumer to use or demand more cryptocurrency, which implies j_t^* is lowered to maintain the equality in eq (2.7).

The time-varying transaction cost τ_{cct} is an exogenous variable and here it is simply assumed that the deviation of τ_{cct} from its steady-state level τ_{cc} follows a simple autoregressive process of order one (AR(1)), which is:

$$\begin{aligned} \tilde{\tau_{cct}} = \rho_{cc}\tilde{\tau_{cct-1}} + \varepsilon_t^{cc}, \quad \varepsilon_t^{cc} \sim \mathcal{N}(0, \sigma_{cc}^2) \\ , \quad \tilde{\tau_{cct}} = (\tau_{cct} - \tau_{cc}) \end{aligned} \tag{2.9}$$

where $\rho_{cc} \in [0, 1]$ and measures the persistence of the transaction cost while ε_t^{cc} is an innovation shock drawn from a normal distribution with mean zero and variance σ_{cc}^2.

Both fiat currency and cryptocurrency are used to purchase consumption goods and services. As the assumption made earlier, the household conducts symmetric purchases and the money balances are replenished n_t times in each period. Therefore, the Cash-in-

Advance constraints can be written as below for both the fiat currency and cryptocurrency:

$$\int_0^{j_t^*} c_t(j)dj \leq n_t \frac{M_t}{P_t} \tag{2.10}$$

$$\int_{j_t^*}^1 c_t(j)dj \leq n_t \frac{CC_t S_t}{P_t} \tag{2.11}$$

The above constraints are binding. Plugging in $c_t(j)$ from eq (2.2), eq (2.10) and (2.11) can be simplified to:

$$c_t j_t^{*(1-\omega)} = n_t \frac{M_t}{P_t} \tag{2.12}$$

$$c_t(1 - j_t^{*(1-\omega)}) = n_t \frac{CC_t S_t}{P_t} \tag{2.13}$$

The budget constraint at period t is:

$$\begin{aligned} c_t + k_t - (1-\delta)k_{t-1} + \frac{M_t}{P_t} + CC_t \frac{S_t}{P_t} + \frac{S_t \tau_{cct}(1 - j_t^*)}{P_t} &= \\ r_t^k k_{t-1} + w_t h_t + CC_{t-1} \frac{S_t}{P_t} + tr_t + \frac{M_{t-1}}{P_t} & \end{aligned} \tag{2.14}$$

where k_t is the real capital lent to the producer and h_t is the working time supplied to the production sector at time t. The r_t^k and w_t are the real rate of return on capital and the real wage paid to a unit of labor employed at time t respectively. The tr_t is the real lump-sum fiat money transferred by the government to the household in each period t. Since the cryptocurrency is privately issued and the supply is exogenous in this model, the government can only supply and control fiat currency. The quantity of the private cryptocurrency is freely determined by the market or issuers or a cryptocurrency protocol. It is assumed that the demand for the cryptocurrency is always satisfied. The left side of eq (2.14) is the total expenditure, which includes consumption, investment, and savings of different currencies, of the representative households at time t with including the extra transaction expenditure involved by using the privately issued cryptocurrency. However, the right side of eq (2.14) is the total income received at time t. The income includes wage income, rental income, and return on money savings from the previous period.

The representative household is endowed with one unit of total time in each period and is distributed among leisure, working hours, and time spent on going to the asset market to replenish money balances. Therefore, the time constraint is:

$$l_t + h_t + \phi n_t = 1 \tag{2.15}$$

2.4.2 Firms

There are a large number of firms operating in the production sector at time t. Therefore, any firm in this sector is operating in a competitive market. A representative good producer employs capital k_t and hires labor h_t at rates of r_t^k and w_t at time t. It is assumed that production technology is given by a constant-returns-to-scale Cobb-Douglas production function, which is:

$$y_t = z_t k_t^{\alpha} h_t^{1-\alpha}, \quad \alpha \in (0,1) \tag{2.16}$$

where z_t is the exogenous productivity shocks and α measures the share of capital stock in the production. It is assumed that z_t follows an AR(1) process as in [60] and [67].

$$\ln z_t = \rho_z \ln z_{t-1} + \varepsilon_t^z, \quad \varepsilon_t^z \sim \mathcal{N}(0, \sigma_z^2) \tag{2.17}$$

where $\rho_z \in [0, 1]$ measures the persistence of the shocks while ϵ_t^z is the innovation with mean zero and variance σ_z^2. In each period t, the firm owner optimizes his profit Π_t, which is:

$$\Pi_t = y_t - r_t^k k_t - w_t h_t \tag{2.18}$$

Since the firm is operating in a competitive market, the profit Π_t is zero.

2.4.3 Government

The government in this model plays the role of the central bank and is responsible for the monetary policy as in [60], [34], and [30]. However, there is a representative financial institution in all of those three models and this paper does not incorporate a bank in the model. Thus, stock of nominal fiat money rather than monetary base, which includes required reserves stored at a central bank, follows a certain growth path as in [67]. Nominal fiat money balance M_t growth at the gross rate of g_{mt} and the path can be expressed as:

$$M_t = g_{mt} M_{t-1} \tag{2.19}$$

The lump-sum transfer or injection TR_t of fiat currency is the net change in the fiat money balance between the period t and $t-1$. Therefore, it can be expressed as:

$$TR_t = (g_{mt} - 1)M_{t-1} \tag{2.20}$$

Adjusted by the price P_t, the real transfer amount is:

$$tr_t = (1 - g_{mt})\frac{M_{t-1}}{P_t} \tag{2.21}$$

It is assumed that the deviation of nominal fiat money balance growth rate from its steady-state level g_m, which is $\tilde{g_{mt}} = (g_{mt} - g_m)$, follows a simple AR(1) process as in [60]:

$$\tilde{g_{mt}} = \rho_m \tilde{g_{mt-1}} + \varepsilon_t^m, \quad \varepsilon_t^m \sim \mathcal{N}(0, \sigma_m^2) \tag{2.22}$$

where ρ_m and ε_t^m represents the persistence of the monetary policy and shocks (innovation) to the monetary policy. What is more, ε_t^m follows a normal distribution with mean zero and variance σ_m^2.

2.4.4 Equilibrium

In this model, there are three agents: a representative household, a representative firm, and the government. At any period t, the competitive equilibrium is a sequences of quantities $Q = \left\{c_t, k_t, M_t, CC_t, h_t, n_t, j_t^*\right\}_{t=0}^{\infty}$, a sequences of prices $V = \left\{P_t, r_t^k, w_t, \Theta_t, S_t\right\}_{t=0}^{\infty}$, and the initial given values of k_0, CC_0, and M_0 such that for any given price V and exogenous shock process z_t, $\tilde{\tau_{cct}}$, and $\tilde{g_{mt}}$:

- $\left\{c_t^d, k_t^s, M_t^d, CC_t^d, h_t^s, n_t, j_t^*\right\}_{t=0}^{\infty}$ solves the representative household's maximization problem.[18]

- $\left\{h_t^d, k_t^d, y_t^s\right\}_{t=0}^{\infty}$ solves firm's profit maximization problem.

- Transversality conditions hold.

- Markets are clear. This market includes the goods market, capital market, and money market.

  - Goods market: $y_t^s = c_t^d + k_t^d - (1-\delta)k_{t-1}^d$;
  - Capital market: $k_t^s = k_t^d$;
  - Labor market: $h_t^s = h_t^d$;
  - Fiat currency market: $M_t^s = M_t^d$;
  - Private cryptocurrency market: $CC_t^s = CC_t^d + \tau_{cct}(1 - j_t^*)$;[19]

2.4.5 Steady State and Calibration

For the calibration of the relevant parameters, quarterly U.S. data of period 2010Q4-2019Q3 is used and all the macroeconomic data about the U.S. economy and some of the cryptocurrency data are from [27] while some other private cryptocurrency data is gained from [8].[20] To the specific details of data set, please check the Appendix (2.8.2).[21]

[18]Please note that lowercase s stands for supply while lowercase d denotes for the demand. These notations s and d are only used here to differentiate demand and supply sides. The lowercase s has nothing to do with the uppercase S that denotes the nominal exchange rate of a cryptocurrency.

[19]The supply of the private cryptocurrency is assumed to be exogenous. Theoretically, private firms can supply as much cryptocurrency as demanded by consumers. In reality, there is a limit and demand affects exchange rate S.

[20]I sincerely appreciate Blockchain.com for making their data available for research.

[21]Regarding the calibration and simulation techniques, I refer to both [66] and [67].

The utility function is assumed to be in the following form:

$$u(c_t, l_t) = \frac{1}{1-\nu}\left[c_t^{\gamma} l_t^{1-\gamma}\right]^{1-\nu}, \quad \gamma \in (0,1), \quad \nu > 0 \tag{2.23}$$

where γ and ν are the share parameter and risk aversion parameter of the utility function respectively. The Leontief parameter ω captures the curvature of the consumption amount of each type of good, which is a function of the size of the good. Consumption amount $c_t(j)$ curves for multiple ω are shown in Figure (2.2).

When $\omega = -1$, consumption amount is linear in purchase size $j_t \in [0, 1]$. Thus, the household is indifferent with spending on different sizes of purchase. When $|\omega| > 1$, the consumption amount curve is convex and convexity increases as $|\omega|$ goes up. It implies that consumers are likely to buy more of the bigger size goods when $|\omega| > 1$. When $|\omega| < 1$, the consumption amount curve $c_t(j)$ is concave and concavity increase as $|\omega|$ goes down. Hence, consumers are likely to buy more of the smaller size goods. [30] simply study the case of $\omega = -1$ and [34] choose to set $\omega = -1.5$ after analyzing the cross-correlation between the price and output under three different policy regimes, different ω, and find that the price gets more counter-cyclical as $|\omega|$ increases. [60] follows [34]. In this paper, considering the mathematical feasibility of solving the model, I follow [30] and simply set $\omega = -1$.

As [30], I set the capital depreciation rate $\delta = 0.025$, which is consistent with the long-run investment to output ratio of 0.25 and capital to output ratio of 10, risk aversion parameter $\nu = 2$, and average time that the representative household allocates to work $h = 0.3$. The steady-state net real rate of return r_t^k on capital is set to be 0.04 as in [34] and it is consistent with the value of β.

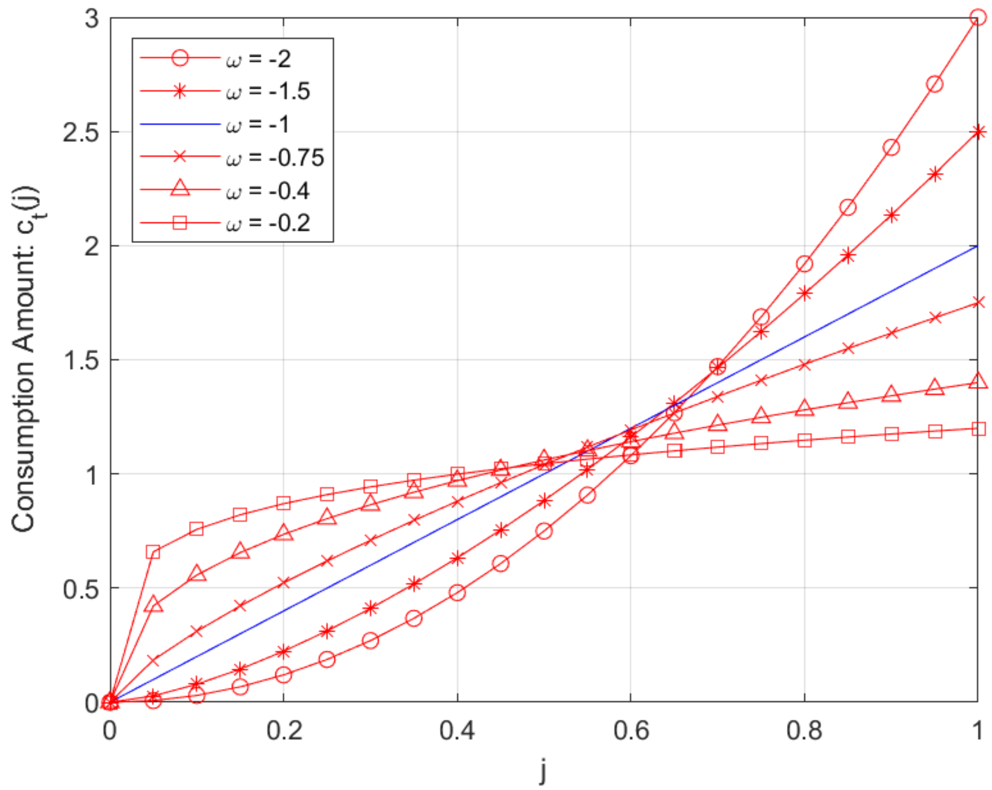

Figure 2.2: Consumption amount, size j, and ω.

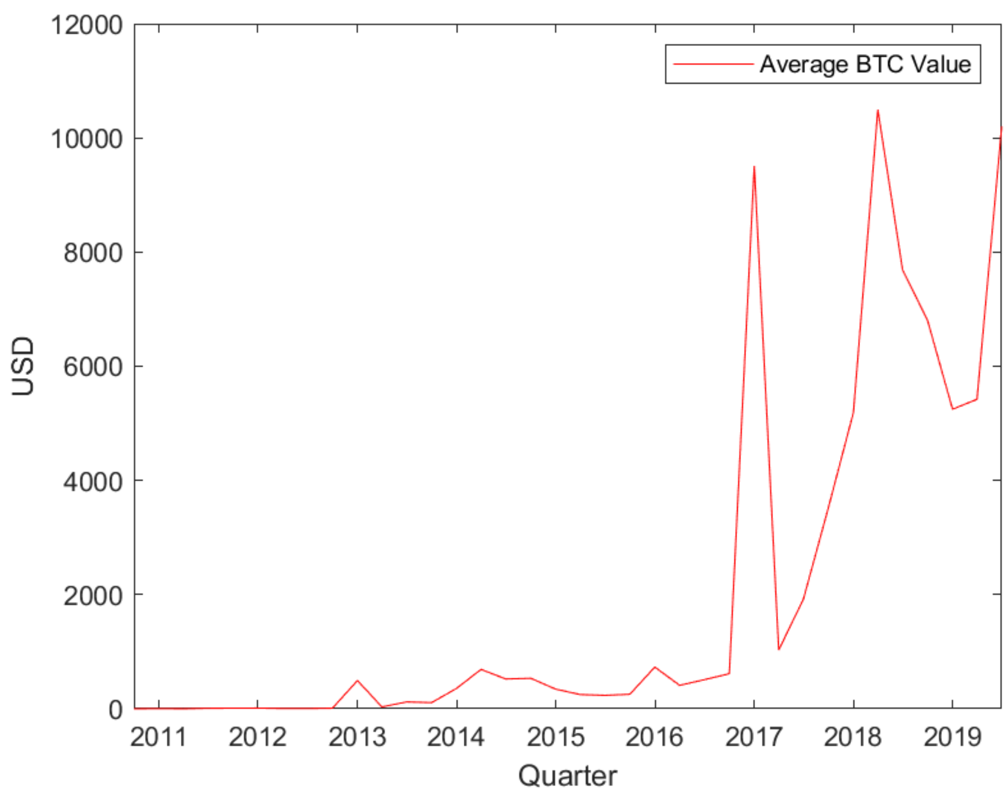

Figure 2.3: Quarterly average Bitcoin market value in U.S. Dollars (USD). Note: The data is daily data from [8] and the frequency is adjusted from daily into quarterly.

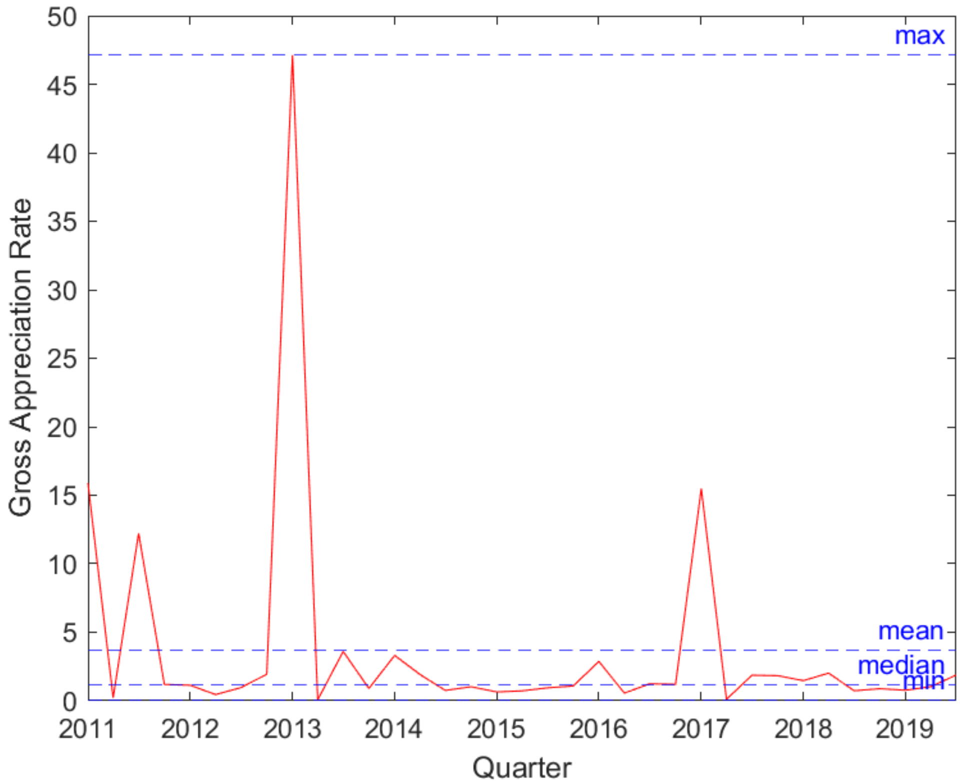

Figure 2.4: Quarterly Bitcoin gross appreciation rate (Not in percentage). Note: The maximum, mean, median, and minimum values of the gross appreciation rate are 47.1247, 3.7166, 1.1350, and 0.0674 respectively.

	Minimum	Medium	Mean	Maximum
ϕ	-0.00015	0.0014	0.00005	0.000003
n	177.1590	3.7129	1503.2	433340
j^*	-2.5918	0.3752	7.5499	128.1863
M	0.0413	0.0413	0.0413	0.0413
CC	-0.0352	0.2521	-0.0406	-0.0413

Table 2.2: Comparative outcomes for the different Bitcoin gross appreciation rate at the steady-state. The minimum, medium, mean, and maximum values are from Figure (2.4).

The capital stock share parameter α is calibrated such that the labor share of national income is 0.5938. Thus, α is approximated to be 0.40. Since $h = 0.3$, the share parameter γ of the utility function is restricted to 0.3537. The value of the representative household's discount factor β is calibrated to be 0.9852. The rate of return on capital $\bar{r}^k$ can be expressed as $r^k + 1 - \delta$ and it is 1.0150. The steady-state value of price level P is set to equal to the mean value of the core personal consumption expenditure price index and is 1.0431. Since the inflation is $\pi_t = \frac{P_t}{P_{t-1}}$, steady-state value of the inflation π is one.[22]

Whether it is a stablecoin (a type of private cryptocurrency that has relatively stable value and lower volatility or has designated specific target) or a volatile cryptocurrency such as Bitcoin, the net gain or loss is determined by the cryptocurrency value difference between the two different time points. Therefore, there is no any specific interest rate like bank deposit rate in [30], [34], and [60] designated for the private cryptocurrency.[23] However, the appreciation rate can be considered as the interest rate of a cryptocurrency. The challenge to calibrate the value of the Θ also comes from the fact that the domestic currency value of a cryptocurrency transaction cost τ_{cc} is also related to the exchange rate S_t of a cryptocurrency. Therefore, as I mentioned earlier, I will treat Θ as an independent variable and the nominal exchange rate S of a private cryptocurrency as another independent variable. This assumption enables this model to capture the net gains or losses from the cryptocurrency value fluctuations at the steady-state while also considering the domestic currency value of the transaction cost. Since Bitcoin is the most widely known cryptocur-

[22]Please note that since the values at the steady-state are very small, to get the possible highest accuracy, I will not approximate values during the coding process.

[23]In [60], he treats the domestic currency depreciation rate as return on foreign currency and the transaction cost of using aggregated foreign currency and bank deposit is a parameter pinned down by some ratio. Therefore, the transaction cost is irrelevant to the foreign currency exchange rate.

rency and ranked first in market value, I will employ most of the features of Bitcoin and Bitcoin blockchain network except the Bitcoin exchange rate as the features of an appealing private cryptocurrency that I study here.[24] I simply assume the steady-state nominal exchange rate S between the private cryptocurrency and the domestic legal fiat currency is one.

Figure (2.5) shows the quarterly average Bitcoin value of the cost of the per-transaction conducted on Bitcoin blockchain network and Figure (2.3) displays the quarterly average value of Bitcoin. The steady-state value of the cost per-transaction τ_{cc} is set to equal to the mean Bitcoin cost per-transaction and it is 0.0293. By comparing Bitcoin values in Figure (2.1) and (2.3), it is easy to observe that the peak of the quarterly average Bitcoin market value is nearly the half of the daily value peak shown in Figure (2.1).

Figure (2.4) shows the quarterly gross appreciation rate of the Bitcoin, and the highest value reaches as much as 47.1247. What is more, the appreciation rate of cryptocurrency can change the incentive of using Bitcoin for purchasing goods and this paper only focus on the case that both the fiat currency and private cryptocurrency are used as a medium of exchange, which suggests $j^* \in [0,1]$. Therefore, the selection of a proper appreciation rate of Bitcoin is necessary. Table (2.2) shows the steady-state values of the important variables corresponding to the minimum, median, mean, and maximum values of the Bitcoin gross appreciation rate. As the appreciation rate goes up, the threshold level j^* goes up. Only the median value of the Bitcoin gross appreciation rate offers a reasonable

[24] As shown in Figure (2.1), the daily value of Bitcoin is ranging from near zero to as high as $20000. If the mean value of that exchange rate is used as a steady-state value of the private cryptocurrency, it will make the domestic fiat currency value of the transaction cost of using Bitcoin as a payment instrument so high even the Bitcoin value of transaction cost is nearly negligible. This will greatly discourage consumers from using Bitcoin for payment purposes.

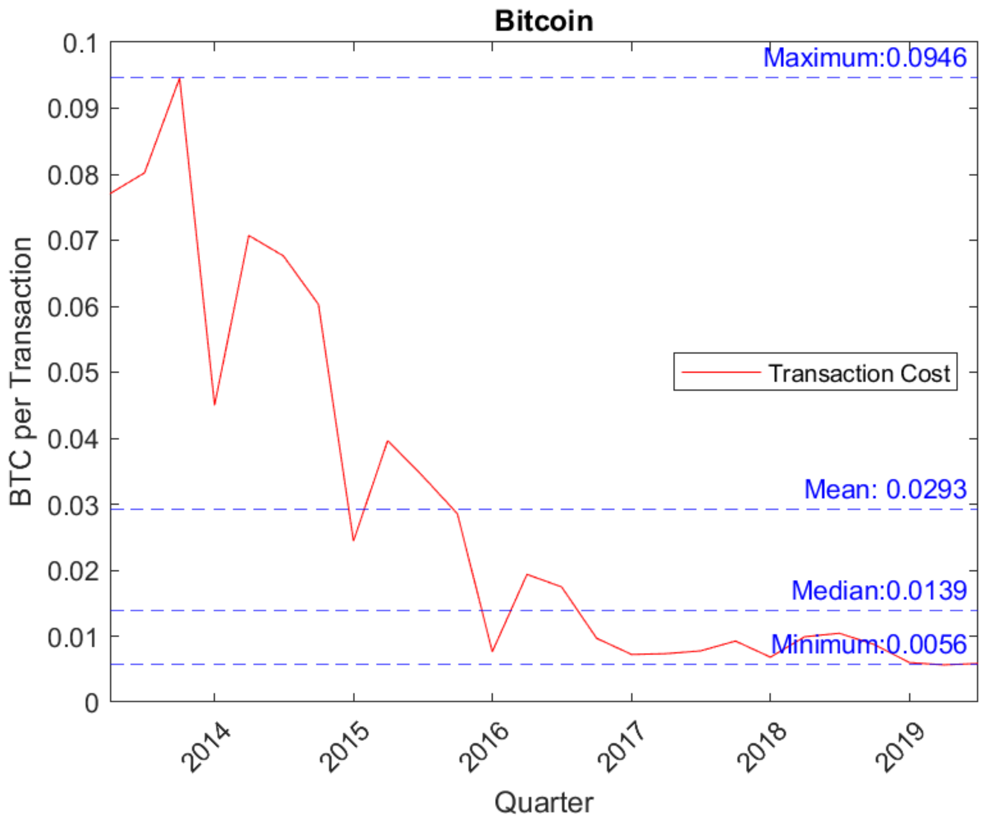

Figure 2.5: Per-transaction cost. Note: The transaction cost data is available at [8]. It is calculated by dividing the daily dollar value of the cost per-transaction by the market value of Bitcoin. Several outliers are dropped and the figure starts from 2013Q2. The exchange rate used here is the average across major exchange markets since the prices across different exchange markets differ slightly. The Bitcoin market value data from [27] is just from one single exchange market and only used once in Figure (2.1).

j^* that both the fiat currency and private cryptocurrency are used for trading goods and services. Therefore, the steady-state gross nominal rate of return Θ on the private cryptocurrency is set to equal to the median value of the quarterly gross appreciation rate of the Bitcoin exchange rate.[25] As a result, Θ is 1.1350.

The time cost ϕ of visiting the asset market to replenish money balances is not a common term used in the classic CIA models. I will pin down the value of ϕ as [30] and [60] did by setting the steady-state domestic currency to consumption ratio equal to the sample average. At the steady-state, ϕ can be expressed as:

$$\phi = \frac{\frac{\tau_{cc}^4(1-\beta)}{c^2} + (\frac{M}{Pc})^2 \frac{S}{P} \tau_{cc}^2 \left[\frac{2\frac{1}{\pi}(\Theta-1)}{\frac{S}{P}\bar{r}^k} \right]^3}{(\frac{M}{Pc})^2 wc \left[\frac{2\frac{1}{\pi}(\Theta-1)}{\frac{S}{P}\bar{r}^k} \right]^4} \tag{2.24}$$

As [40] estimates, around 60% of the U.S. dollar is circulating outside of the United States and this can be even higher for high-denomination bills such as \$100 and this ratio has been steadily increasing since the 1960s. I will simply set the domestic currency ratio equal to one-third as in [30]. Therefore, the steady-state real domestic currency to consumption ratio $\frac{M}{Pc}$ is 0.0379. Then the value of ϕ is pinned down to 0.0492, which implies that the representative household spends 5.1902 minutes each day for portfolio management. The time cost of visiting an asset market, which will be used to replenish bank deposit and fiat currency balances, in both [30] and [34] is 0.00076, which can be explained as the representative household spends around one hour quarterly for managing their assets. The much higher value of ϕ in this model can be explained by a relatively high transaction cost

[25] Several important and well-known statistical values of gross appreciation rate are tested in Table (2.2). It is clear that there is a range of gross appreciation rates that give a reasonable threshold level j^*. Therefore, the selection of the median gross appreciation rate is random.

of using private cryptocurrency and a higher rate of return on the cryptocurrency than the bank deposit. It suggests that if private cryptocurrency issuers want more customers to hold or use their currency while spending less time on managing their asset portfolio, then they are advised to keep the transaction cost τ_{cc} low and the price of their cryptocurrency less volatile and more stable.

The persistence parameters $\rho_m, \rho_z, \rho_{cc}$ and innovation variances $\sigma_m^2, \sigma_z^2, \sigma_{cc}^2$ of the shock processes are estimated by using the U.S. data and linear detrending method. Calibrated values of persistence parameters are $\rho_m = -0.2543$, $\rho_z = 0.80196$, and $\rho_{cc} = 0.4436$. Values of standard deviations are $\sigma_m = 0.0042$, $\sigma_z = 0.0035$, and $\sigma_{cc} = 0.0124$. Calibrated parameters are summarized in Table (2.3).

2.5 Quantitative Analysis

Table (2.4) shows the steady-state values of some important variables. The fraction of the time spent on managing monetary assets, which is $n\phi$, is 1.3931. This value corresponds to the average daily and quarterly portfolio management time of 5.1902 and 472.3125 minutes respectively.

2.5.1 Welfare Analysis

This goal of this paper is to examine the welfare effect of currency substitution in an environment where both the fiat currency and private cryptocurrency are used to conduct transactions. I focus on the change in price and nominal exchange rate and their ultimate effect on consumer welfare through different channels. In this paper, the cryp-

Parameter	Description	Value
δ	Capital depreciation rate	0.025
γ	Utility function consumption share parameter	0.3537
ω	Leontief utility parameter	-1
ν	Coefficient of relative risk aversion	2
α	Share of capital stock	0.4
β	Subjective discount factor	0.9852
τ_{cc}	Cost per-transaction cryptocurrency	0.0293
ϕ	Asset market trip cost	0.0014
P	Core PCE price level	1.0431
Θ	Gross rate of return on cryptocurrency (Bitcoin)	1.1350
ρ_z	Persistence of productivity shocks	0.8012
σ_z	Standard deviation of the productivity shock	0.0035
ρ_{cc}	Persistence of cryptocurrency transaction cost shock	0.4436
σ_{cc}	Standard deviation of the cryptocurrency transaction cost shock	0.0124
ρ_m	Persistence of the growth rate of money balance shock	-0.2543
σ_m	Standard deviation of the growth rate of money balance shock	0.0042

Table 2.3: Baseline calibration

Variable	c	j^*	n	M	CC
Value	1.0444	0.3752	3.7129	0.0413	0.2521

Table 2.4: Steady-state values of some critical variables.

tocurrency has some appealing features such as unit nominal exchange rate and a stable high rate of return. By following [60], the welfare cost function $\Gamma(\tilde{P})$ is defined as below:

$$u[(1+\Gamma(\tilde{P}))c(\tilde{P}), l(\tilde{P})] = u[c(P), l(P)] \tag{2.25}$$

where $c(P)$, $l(P)$, and P are the baseline steady-state values while $\tilde{P}$ is the new varying price level, which can be also understood as the inflation, that deviates from the steady-state price level P. The optimal level of labor and consumption are functions of the price level

P. Therefore, any change in the price level will affect the consumer's leisure-consumption decision and thus it will affect the welfare of the representative household. The welfare cost definition implies that the representative household needs consumption compensation under different price levels $\tilde{P}$ so that he still enjoys the same level of utility gained at the steady-state price level P. Using the definition expression (2.25) and the utility function form (2.23), the welfare cost function can be expressed as:

$$\Gamma(\tilde{P}) = \frac{c(P)l(P)^{\frac{1-\gamma}{\gamma}}}{c(\tilde{P})l(\tilde{P})^{\frac{1-\gamma}{\gamma}}} - 1 \tag{2.26}$$

If the $\Gamma(\tilde{P})$ is negative, it means the change in price level is welfare-enhancing and there is a welfare gain. However, if the $\Gamma(\tilde{P})$ is positive, then it suggests that the net change in the price level reduces the utility of the representative household and the household needs some additional consumption to maintain the original utility level. Therefore, it is a welfare loss.

Figure (2.6) shows how the welfare cost as a percentage, which implies $100 * \Gamma(\tilde{P})$, and in the form of the consumption good will be impacted by the increase in the price level. The welfare cost of the price is not as strong as I expected. The highest welfare cost corresponding to a 40% net increase in price level is just -0.9549%. Therefore, an increase in the price enhances the welfare of the consumer.[26] The relatively high welfare cost, which is compared to the approximately 0.25% welfare loss of inflation in [34] if the net inflation goes up from 0% to 20% when bank deposit is a substitute to the fiat currency, is likely

[26]The setting of this model is related to this low welfare cost. [22] point out that Bitcoin is nearly 500 times more costly than using fiat currency in a low inflation economy when both of the currencies are used as a medium of exchange. [22] find that 0.08% welfare cost under improved optimal Bitcoin design is equivalent to a fiat currency system with moderate inflation. [41] also point out that only when the inflation is sufficiently high, then Bitcoin can compete with fiat currency as a medium of exchange.

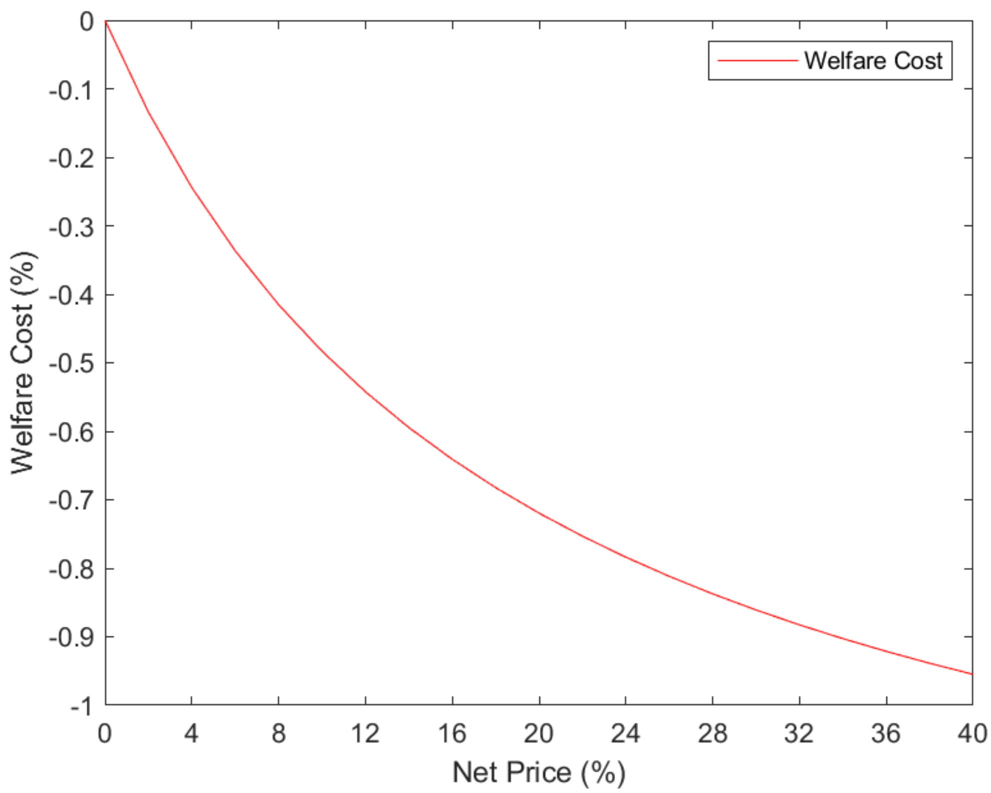

Figure 2.6: Welfare cost of the price.

caused by very stable and low exchange rate S, relatively high rate of return Θ, and higher transaction cost of using the private cryptocurrency. If we compare the Figure (2.6) here and Figure (2.18) in Appendix (2.8.3), it is easy to observe that the convexity (to the origin) of the welfare cost curve increases as the price level goes up further. Therefore, the marginal welfare cost decreases as the price level goes up. The relative flatness of the welfare cost curve at the high price level can be explained by the relatively low real transaction cost τ_{cc}, the fixed opportunity cost of using fiat currency, and a possible "already adjusted" mind to the price shocks because of the decaying effect of price on real return net of transaction cost of using private cryptocurrency. Besides, the availability of the currency substitution against the inflation tax on the fiat currency and the relatively big marginal increase in the real return net of transaction cost of using private cryptocurrency can account for the steepness of the welfare cost curve at the low price level.

The substitution effect drives consumers away from using or holding fiat currency while the wealth effect caused by increasing cryptocurrency balance with a high rate of return also induces consumers to demand more cryptocurrency. When the net price level goes up by 40 percent, the consumer chooses to consume more consumption goods as shown in Figure (2.15).[27] Once the amount of consumption goods is decided, then the representative

[27] This is caused by the availability of another safe asset since the consumer can move to buy more of them while keeping less of the fiat currency. As in Figure (2.7), the private cryptocurrency balance increases by 137.12% while the fiat currency balance decreases by 52.48% as the price increases by 40%. Since the opportunity cost of making purchases with the private cryptocurrency goes up because of the lower real transaction cost as the price level goes up, the consumer can buy more consumption goods by using the same private cryptocurrency while still getting the same gross real return net of transaction cost from it. Both wealth and substitution effects play an important role in the welfare cost of the price. For the optimal consumption, please check the Figure (2.15) and (2.17) in Appendix (2.8.3)

household decides the times of travel to the asset market, which is given by:

$$n = \left[\frac{c}{\frac{\phi w}{1-\beta} - \frac{1}{1-\beta} \frac{S^2}{P^2} \frac{\tau_{cc}^2}{c} \frac{\pi \bar{r}^k}{2(\Theta-1)}} \right]^{\frac{1}{2}} \tag{2.27}$$

The travel times n decreases as P goes up because the increase in the price dominates the increase in the consumption amount and forces the agent to travel less to the asset market. After the determination of the consumption amount c and the travel times n to the asset market, the threshold level j^* of the purchase instrument choice will also respond to all changes in P, c, and n. At the steady-state, j^* is given by:

$$j^* = \frac{n}{c} \frac{\pi S \tau_{cc} \bar{r}^k}{2P(\Theta - 1)} \tag{2.28}$$

Since both P and c increase, n decreases while keeping other variables in eq (2.28) constant, the threshold level j^* goes down further. The decrease in j^* implies that the fraction of the goods purchased by using private cryptocurrency CC increases while fewer goods are bought by using fiat currency M. The visual explanation of this analysis is shown in Figure (2.7) here and (2.23) in Appendix (2.8.3). What is more, the fiat currency balance decreases by 52.48%, private cryptocurrency balance increases by 137.12%, threshold level j^* decreases by 52.48%, the number of visits to the asset market decreases by 33.13%, and the consumption amount increases by 0.50% for a net 40% increase in the price level.

These findings are also consistent with economic intuition. Since an increase in the steady-state price level decreases the real transaction cost of using private cryptocurrency as a payment instrument and with the availability of another currency with a relatively

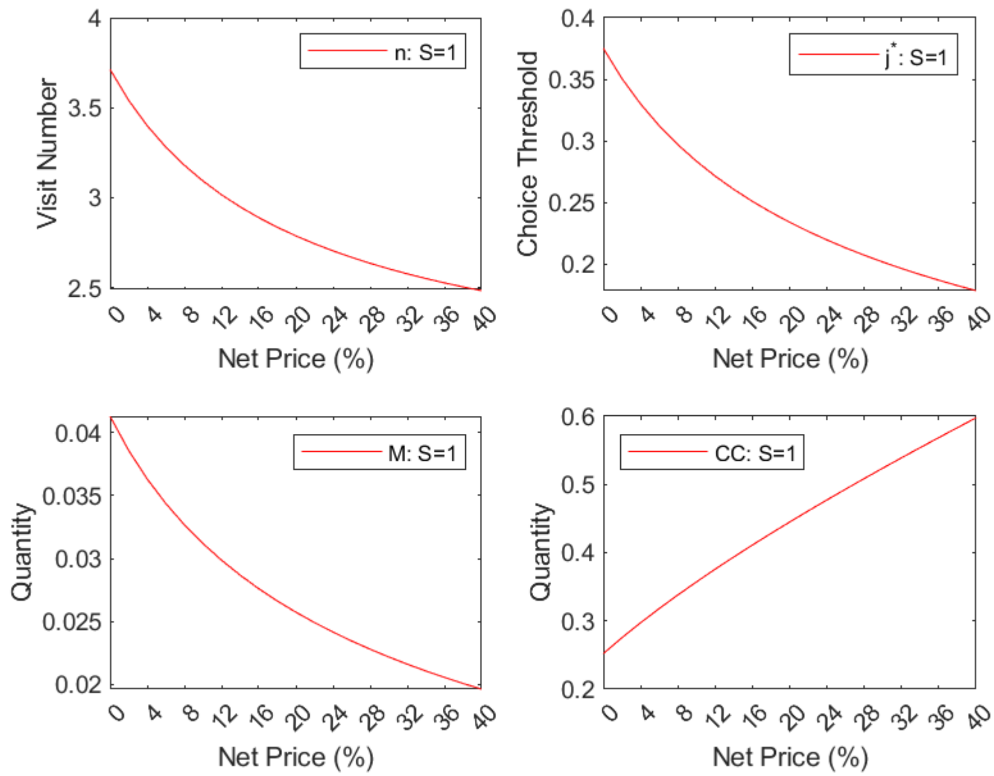

Figure 2.7: Changes in critical variables when price level changes.

high rate of return and low extra transaction cost, the rational agent will move to hold more of his wealth in the form of the appealing private cryptocurrency rather than the fiat currency. This finding has one important implication for countries considering issuing CBDC. Countries that suffer relatively high or volatile inflation or price should be very cautious when issuing CBDC while a private cryptocurrency (ones with similar features as in our model) is also available for the public. Even though the high price level enhances the welfare of the consumer when a private cryptocurrency like Bitcoin is used as money, it weakens a central bank's role in implementing monetary policy.[28] Countries can ban private cryptocurrencies that have similar or the same functions as money whenever they begin to issue CBDC or else central banks will face the tough problem of implementing their monetary policy through legal currencies, especially in the case of high inflation. Central banks can also try to pay higher interest on CBDC than private cryptocurrency in the case of an increase in the price level, but this will likely not last long since central banks face the tough problem of securing the interest payment from themselves or other sources such as government tax revenues.

Countries like the U.S. that have stable inflation do not have to worry about the welfare cost of price as much as other countries that experience frequent inflation or price shocks since the welfare cost of the price is not significantly big for a 40% increase in price

[28]Weakening a central bank's role will likely be further strengthened in this cycle. Since once more consumers choose to use private cryptocurrency in the wake of inflation or high price, they will bid the value of a cryptocurrency to a new higher level, which means the gross nominal return (gross appreciation rate) on cryptocurrency will go up. Besides, the fiat currency value of the transaction cost of cryptocurrency also goes up. This will likely further induce consumers to hold or demand more private cryptocurrency given their attractiveness.

in this specific setting.[29] As shown in Table (2.4), the steady-state private cryptocurrency balance is 0.2521, fiat currency balance is 0.0413, and the threshold level j^* is 0.3752. The representative household prefers storing the majority of his monetary assets in the form of private cryptocurrency rather than legal domestic currency. At the steady-state, the fraction of CC in the monetary asset, which is $M + SCC$, is 0.8592. If Bitcoin has all the assumed features like the private cryptocurrency in this model, then Bitcoin would dominate the U.S. dollar as both the main payment instrument and value storage of the monetary assets and the Federal Reserve would likely become obsolete. The details of the ratio of nominal cryptocurrency balance to the monetary assets corresponding to changes in the price or nominal exchange rate are shown in Figure (2.8).

As stated earlier, I simply assume the steady-state nominal exchange rate is one. But how do welfare and other critical variables respond to the increase in the nominal exchange rate?. Since it will affect the domestic currency value of the transaction cost when making purchases with private cryptocurrency. The domestic currency value of the saved cryptocurrency balance is also affected. On the one hand, an increase in the exchange rate induces the consumer to use fiat currency more often to conduct purchases, but on the other hand, the consumer is induced to demand more cryptocurrency. The welfare cost function $\Gamma(\tilde{S})$ can be similarly defined as in eq (2.25) for varying nominal exchange rates while the price stays at the steady-state level.

$$u[(1+\Gamma(\tilde{S}))c(\tilde{S}), l(\tilde{S})] = u[c(S), l(S)] \tag{2.29}$$

[29] The recent Venezuela hyperinflation and adoption of Bitcoin and other cryptocurrency assets for saving, spending, and sending is a good example of how inflation affects currency competition or substitution in real life. For more information, please refer to the following news articles: [43], [17], [15], [54], [59], and [19].

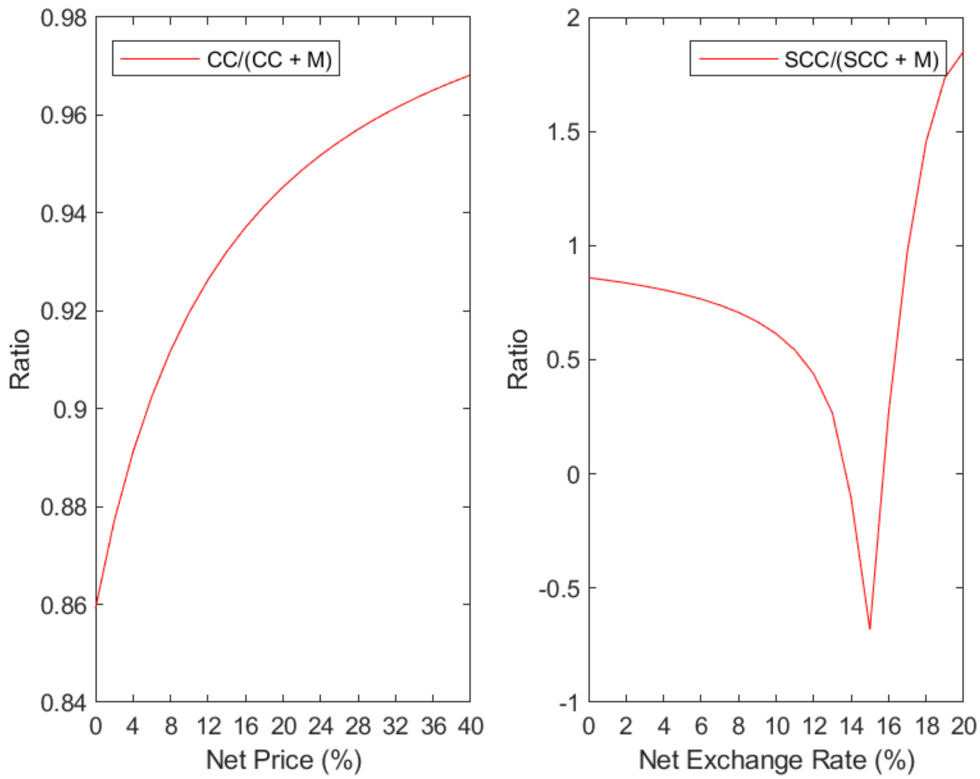

Figure 2.8: Ratio of CC. Note: Ratio of CC=$\frac{SCC}{SCC+M}$. Cryptocurrency values corresponding to the changes in exchange rate are real parts of complex numbers. The steady-state exchange rate is one, thus, S is ignored for the ratio of CC for net price change.

and the welfare cost function can be expressed as:

$$\Gamma(\tilde{S}) = \frac{c(S)l(S)^{\frac{1-\gamma}{\gamma}}}{c(\tilde{S})l(\tilde{S})^{\frac{1-\gamma}{\gamma}}} - 1 \tag{2.30}$$

the welfare cost, which is $100 * \Gamma(\tilde{S})$, of the nominal exchange rate between private cryptocurrency and the domestic fiat currency is shown as in Figure (2.9). The meaning of the welfare cost is the same as before.[30] As the net exchange rate increases from 0% to 15%, the welfare cost increases from 0 to 6.3218%. However, the welfare cost decreases from 6.3218% to -0.2169% as the net exchange rate further increases to 20%. Here the welfare cost is positive until the net exchange rate increases by 19%, which implies that as the nominal exchange rate increases, the representative household needs some extra consumption goods to maintain the same level of utility when the nominal exchange rate is one. Thus, an increase in the nominal exchange rate S leads to an increase in the welfare cost of the representative household at first but then the trend reverses later. It is obvious that the substitution effect dominates in the pre-15% net increase period and the wealth effect dominates the post-15% period. Figure (2.22) in Appendix (2.8.3) describes the welfare cost curve for a 0-100% range of net nominal exchange rate increase. The welfare cost increases at first but then it begins to decrease sharply. However, the decrease in the welfare cost will not last long and it stays nearly flat after the net exchange rate reaches around 40%. The minimum welfare cost, which corresponds to the 100% net exchange rate increase, is -2.8439%. Even with the relatively high rate of return Θ on the private cryptocurrency, the opportunity cost of using

[30] Please note that optimal consumption of varying nominal exchange rates turns up to be a complex number. As a result, the real part of the c, n, j^*, M, CC, and welfare cost is used for both graphing and analysis.

private cryptocurrency decreases significantly at the beginning until S goes up by 15%. Therefore, the change in S is big enough to "frighten" the representative household and discourage even stopping them from demanding private cryptocurrency at first as shown in Figure (2.10). What is more, the demand for the private cryptocurrency returns positive at some net exchange rate level between 20% and 24% and this low level of CC balance stays flat for the further increases as shown in Figure (2.24). However, both CC and M balances are very low and near to zero. It is probably because of the very high exchange rate of private cryptocurrency and zero net interest rate on the fiat currency. Therefore, holding a tiny unit of cryptocurrency is enough to store most of the household's monetary assets with preferable rate of returns.

The representative household determines the optimal consumption level once he observes the increase in the exchange rate. The optimal consumption level goes down for the first 15% net increase in the exchange rate as shown in Figure (2.19) in Appendix (2.8.3).[31] But the magnitude of the decrease in consumption level is nearly negligible. For the net 15% increase in the nominal exchange rate, the optimal consumption level goes down by 3.1915%. However, the optimal consumption level reverses the previous trend and goes up for the rest of the net 20% increase in the exchange rate. The magnitude of this increase is 3.2858%. The effect of a wider range of net exchange rate increase on the consumption is shown in Figure (2.21) in Appendix (2.8.3) and it is clear that after some increase, the optimal consumption level nearly stays constant. What is more, as shown

[31] Since the gross real appreciation rate of the cryptocurrency is fixed, the immediate effect of the increasing nominal exchange rate is on the real rate of return net of transaction cost on the private cryptocurrency and it will decrease because of the increasing transaction cost. Therefore, the consumer offsets the effect of high transaction costs on the opportunity cost of using private cryptocurrency by purchasing less using private cryptocurrency. Besides, an increase in the exchange rate also increases the value of saving in cryptocurrency. Thus, it induces the household to save more and consume less, which will create a wealth effect.

in Figure (2.10), the increasing exchange rate and decreasing level of consumption in the denominator dominates the numerator in eq (2.27) and induces the consumer to travel more to the asset market, which implies n goes up at first. Once c, n choice is determined, then it is evident from eq (2.28) that all three variables put upward pressure on the threshold level j^*. As a result, the representative household decides to use more fiat currency M and less private cryptocurrency CC when purchasing consumption goods until the net increase in the nominal exchange rate is 15%. However, the trend for all five variables above is reversed for further increases in the nominal exchange rate. The most possible explanation for this sudden reversal of the trend is the wealth effect of the initial increase in the exchange rate and the household is inclined to purchase goods and services by spending big amounts of cryptocurrency with less frequency to avoid the extra total transaction expenditure and welfare loss for further increase in the exchange rate.

The availability of currency substitution plays an important role in mitigating the welfare cost of the exchange rate. Once the nominal exchange rate begins to go up, the representative household begins to feel the heat of rising transaction costs of purchasing goods with private cryptocurrency while the opportunity cost of using fiat currency is still the same.[32] Intuitively, as a rational agent, the representative household will move to hold a higher fraction of his monetary assets in the form of fiat currency rather than private cryptocurrency. As shown in Figure (2.10), the fiat currency balance increases by 322.37% at first but then decreases by 47.55% while the private cryptocurrency balance decreases by 104.40% initially but then increases by 24.28% as the nominal net exchange rate increases

[32] [24] finds that the cost of using CBDC in the transaction is relevant to achieve the best welfare outcome when CBDC and cash are perfect substitute in conducting purchases.

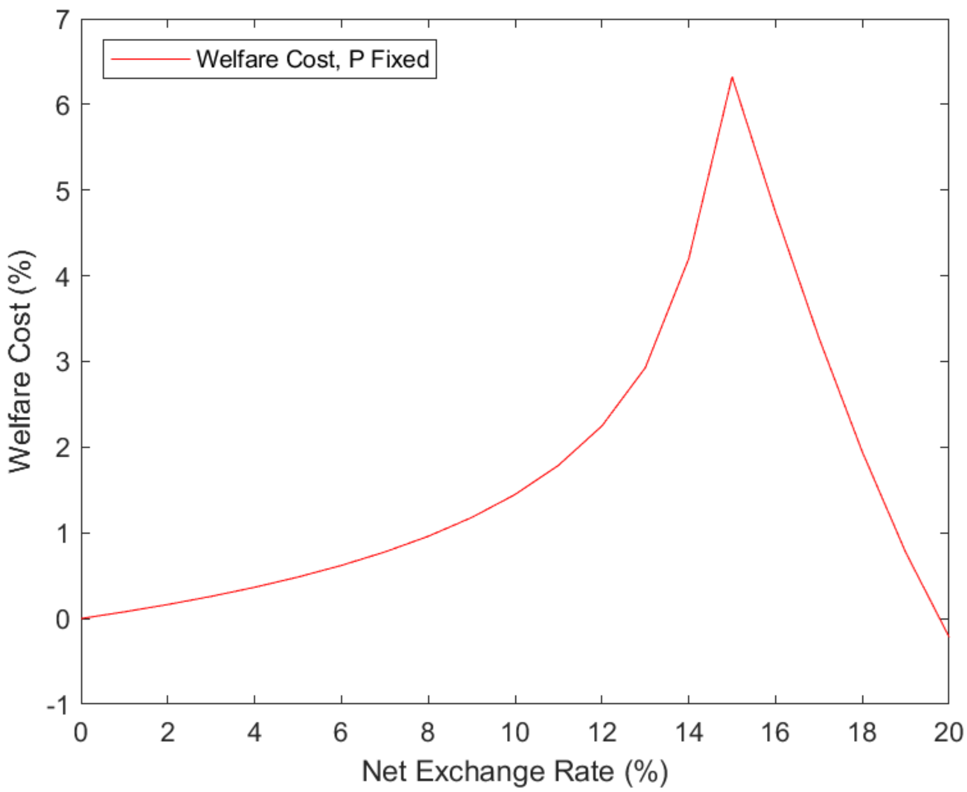

Figure 2.9: Welfare cost of the nominal exchange rate. Note: Real parts of complex numbers are plotted here.

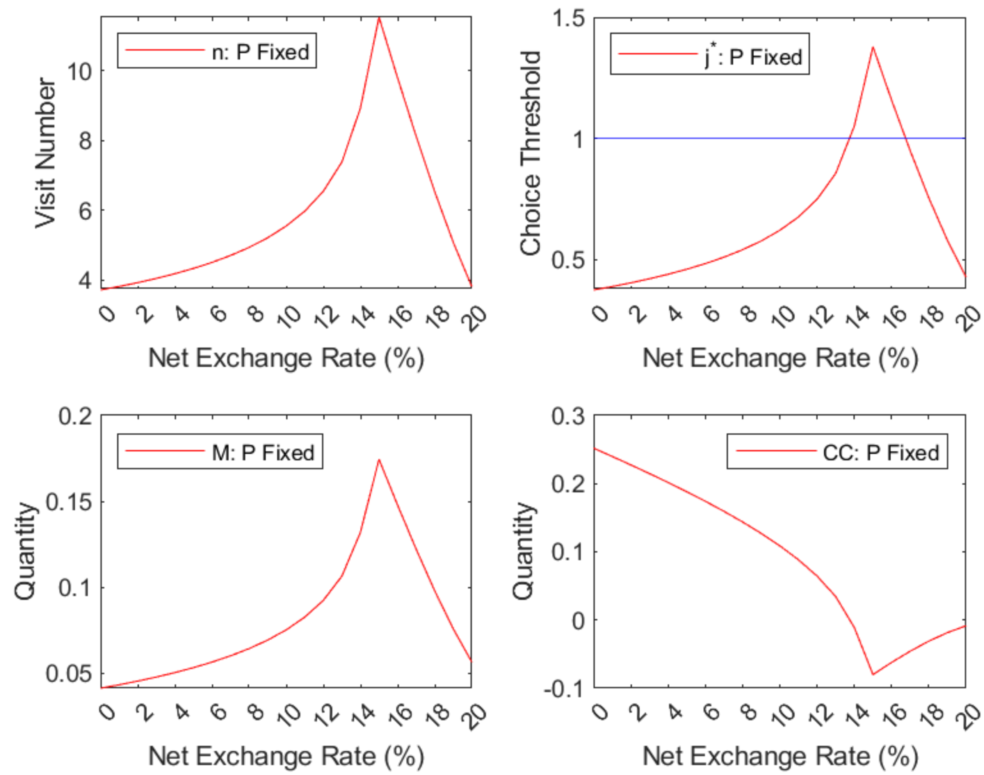

Figure 2.10: Changes in critical variables when nominal exchange rate changes. Note: Since the values of n, j^*, CC, and M are complex numbers, only the real parts are plotted.

by 20%. What is more, the threshold level j^* also increases by 267.28% for the first 15% net increase in the exchange rate but then decreases by 49.74%. The times of travel to the asset market goes up by 210.81% first but then goes down by 49.24% further for a 20 percent net increase in the exchange rate.

The welfare cost of the nominal exchange rate also has important implications for countries that consider issuing CBDC. First, if a central bank offers CBDC in the future, will the banks or financial institutions that operate the payment system charge the transaction fees according to the amount of the transactions or the size of the CBDC file that the consumer sends?. If the banks charge on the amount it sends, any change in the nominal exchange rate is likely to influence the saving or holding amount of cryptocurrency more than the behavior of purchasing goods by using cryptocurrency. It is worth noting that more research is needed to understand the interaction between the nominal exchange rate, cryptocurrency balance, and fiat currency balance when both currencies are used as a payment instrument and transaction cost is charged based on the purchase amount. However, if banks decide to charge fees according to the CBDC file size and network environment, then any slight fluctuations in the value of CBDC (assume that the value of CBDC in domestic currency is freely determined by the market with a small fluctuation around a trend or central bank target rate and the transaction cost is in the cryptocurrency unit. To be consistent, it is simply assumed the CBDC has an independent interest rate, which can be net value deviation from the sample mean or the central bank target value, from its value.[33]) can change the demand for CBDC that be used for carrying out transactions. If the exchange rate increases by a large percentage, then it would make CBDC less preferable to the fiat currency or private cryptocurrency that offer the same or similar service. Second, with the availability of the private cryptocurrency with a relatively high rate of return that can be used for both storing values and making purchases like the cash, any slight increase in the nominal exchange rate of CBDC in an economy with stable inflation will likely to force CBDC holders or users to increase the ratio of the private cryptocurrency or fiat cur-

[33]Not being able to express the return on the cryptocurrency as a function of the exchange rate is one shortcoming of this paper. Central banks can issue CBDC that value is freely determined by the market and net change in the value is the gain or loss to the holders or users. Because of the static nature of our analysis, if the gross return on CBDC is measured in terms of the exchange rate, then, at the steady-state, its gross return is one as I mentioned earlier. As a result, with the existing transaction cost of using CBDC on some types of blockchain network like Bitcoin blockchain, the j^* goes to infinity, which means CBDC will never be used in purchasing consumption goods.

rency in their asset portfolio and the corresponding increase in fiat currency and private cryptocurrency combined is likely higher than the respective decrease in CBDC balance similar to the case in Figure (2.10). Third, in the case of the transaction fees charged based on the CBDC file size, the central bank can adjust the rate of return on the CBDC to offset the declining demand for CBDC by keeping the opportunity cost of using the CBDC relatively constant. Fourth, what is more, the welfare loss from the 15% increase in the exchange rate is significantly larger than welfare gains from the same increase in the price level. Therefore, Central Banks that manage CBDC should be more sensitive about the fluctuation of CBDC value than the inflation or price level.

Figure (2.11) displays the quantitative analysis of the potential source, which includes the opportunity cost and transaction cost of holding different currencies, of welfare cost of both price and nominal exchange rate. The definition of those costs here is consistent with [60] and [34]. The total transaction expenditure (or cost) of purchasing goods with private cryptocurrency is $\frac{S\tau_{cc}(1-j^*)}{P}$. The opportunity cost of replenishing money balances is $wn\phi$. The opportunity cost of holding domestic fiat currency is $(r^k + 1 - \delta - \frac{1}{\pi})\frac{M}{P}$. The opportunity cost of holding private cryptocurrency is $(r^k + 1 - \delta - \frac{\Theta}{\pi})\frac{SCC}{P}$.

In Figure (2.11), for the net increase in the price level from 0% to 40%, the opportunity cost of holding fiat currency, private cryptocurrency, the replenishment cost, and the summation of all costs all decrease by 66.06%, 69.37%, 33.13%, and 691.54% respectively while the transaction expenditure of using private cryptocurrency as a payment instrument increases by 4.27% until the net price increases by 10% and then it decreases by 9.91% for the further increase in the price. What is more, it is worth noting that the change in price

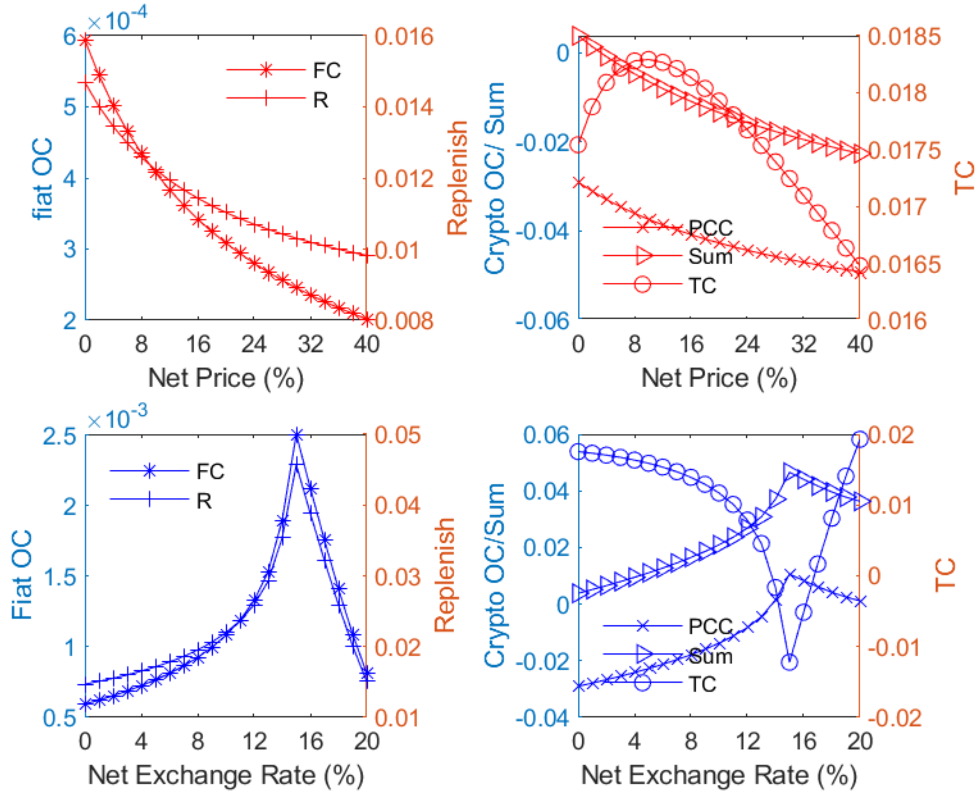

Figure 2.11: Source of the welfare cost of the price and nominal exchange rate. Note: FC stands for the fiat currency, R stands for the replenishment of money balances, PCC stands for the private cryptocurrency, TC stands for the total transaction expenditure, OC stands for the opportunity cost and Sum is the summation of all the costs. The net change in both price and exchange rate shows the net percentage increase from steady-state values. The opportunity costs are the values. The figure depicts the opportunity cost of replenishing money balances, transaction expenditure of using private cryptocurrency, opportunity cost of holding private cryptocurrency, and opportunity cost of holding fiat currency. Corresponding cost values to the varying price are real numbers while corresponding cost values to the varying exchange rate are real parts of complex numbers.

level does not change the opportunity cost of holding unit private cryptocurrency or fiat currency. Thus, the significant change in the opportunity cost of holding fiat or cryptocurrency is mainly driven by the changes in the price level and the corresponding changes in the fiat or cryptocurrency balance. The change in the transaction expenditure is not as significant as other costs and it is probably the result of a combined effect of a decrease in j^* and increase in P. As we know from previous analysis, the threshold level decreases by 52.48% for a 40% increase in the price and the j^* is convex to the origin. Therefore, we can observe a concave transaction expenditure curve here. What is more, the change in the opportunity cost of holding cryptocurrency is the biggest among all the costs studied here (except the summation). It is probably because of the bigger change in the cryptocurrency balance. The decreasing opportunity cost of holding fiat currency is mainly driven by the combined effect of an increase in the price and a decrease in the fiat money balance. It should be emphasized that the risk aversion character of the household can influence the money choice process when there is a shock to the price or nominal exchange rate and can impact the results here. It is apparent from the Figure (2.11) that currency substitution improves welfare for any increase in the price level through the wealth and substitution effect.[34]

What is more, for an increase in the exchange rate from 0% to 20%, the opportunity cost of holding the fiat currency, private cryptocurrency, replenishment cost, and the summation of all costs all increase by 322.37%, 136.52%, 210.81%, and 1117.6% respectively at first but then they reverse the rend and decrease by 67.62%, 89.1%, 67%, and 21.98%

[34]Please note that the opportunity cost of holding PCC is always negative, which implies the consumer is losing wealth by not holding PCC.

respectively. However, the transaction expenditure for using private cryptocurrency to purchase goods and services decreases by 169.59% at first but then increases by 257.95% for the further increase in the nominal exchange rate. Since Θ is assumed to be independent of the nominal exchange rate S, any change in the nominal exchange rate does not impact the opportunity cost of holding unit private cryptocurrency. Besides, the opportunity cost of holding fiat currency is solely driven by the increase in fiat currency balance. The fiat money balance responds to the increase in the nominal exchange rate dramatically as described earlier. Therefore, the change in the opportunity cost of holding fiat currency is initially significantly larger than other costs. However, the increasing exchange rate and decreasing cryptocurrency balance offset each other for some degree at first, but then they move in the same direction. Therefore, the change in the opportunity cost of holding cryptocurrency is relatively small at first and bigger later compared to others. What is more, the transaction expenditure is affected by both the nominal exchange rate and threshold level j^*, which goes up first but goes down later and itself depends on n, c, and S. Therefore, the change in j^* offsets some motion of the increase in the nominal exchange rate at first but then enhances the effect of the increasing nominal exchange rate on the transaction expenditure later. In both cases of price and exchange rate, the change in the opportunity cost of replenishing money balance is simply and solely driven by the change in the times of the visit to the asset market. Both the wealth and substitution channels have mixed effects on welfare when there are relatively big changes in the nominal exchange rate.

2.5.2 Sensitivity

In this section, I will examine how the present results in the Section (2.5.1) (referred to as benchmark case thereafter) would fare if critical parameters are re-calibrated to alternative values. In the benchmark case, the value of steady-state private cryptocurrency transaction cost τ_{cc} is assumed to equal to the sample average of the τ_{cct} over the period of 2013Q2-2019Q3. But it is easy to observe from the Figure (2.5) that there is a relatively large gap between the maximum and the average values of the τ_{cct}, not to mention already dropped extra large values. What is more, the value of the asset market trip cost ϕ is pinned down by using the sample average ratio of the real domestic currency to real consumption. As shown in [40], the share of U.S. currency of all denominations abroad over the period of 2000-2016 ranges from 40% to 60%, and the ratio ranges from 60% to approximately 80% for the $100 bills. [30] also state that the ratio of the U.S. dollars held abroad ranges from two-thirds to three-quarters. Thus, alternative values for the domestic currency over the consumption ratio and τ_{cc} are used in this section to test the effectiveness of the benchmark case. For the τ_{cc}, the minimum, median, mean, and maximum values are chosen from the sample and the values are 0.0056, 0.0139, 0.0293, and 0.0946 respectively. The values of one-quarter, one-third, and one-half are used for the domestic currency to consumption ratio.

Table (2.5) displays the response of the key parameter and core variables to the alternative values of domestic currency to consumption ratio and the transaction cost of using the private cryptocurrency as a payment instrument. Please note that the values in the second row and third column in all panels of the Table (2.5) corresponds to the results of the benchmark case. Hence, any difference of the values from the coordinate $(2, 3)$ implies deviation from the benchmark case. In panel A, any changes in $\frac{M}{Pc}$ does not have a significant impact on ϕ for the smaller values of τ_{cc}. However, the effect begins to magnify significantly as the transaction cost goes up further. The transaction cost has a significant positive effect on ϕ while domestic currency to consumption ratio has a varying degree, which depends on the value of the transaction cost, of negative impact on ϕ. The maximum value of ϕ is 0.088, which implies the household needs to spend more time on asset management than the benchmark case. What is more, panel B shows the response of travel times to the asset market. The domestic currency to consumption ratio has a significant positive impact on the number of asset market visits n while the visit times goes down dramatically as the transaction cost τ_{cc} increases. The representative household visits the market with the highest frequency when half of the money is spent on the consumption goods and the transaction cost is the least, which is in line with the smallest value of ϕ. The minimum and maximum value of visit numbers are 0.26 and 134.79 respectively.

Panel C describes the response of the threshold level j^*. As the ratio of the domestic currency spent on the consumption goods increases, the threshold level begins to go up significantly. What is more, the transaction cost τ_{cc} has a negative impact on the j^*, which is also consistent with the theoretical and quantitative analysis in the benchmark case. The upward pressure placed by the tiny decrease in consumption and significant increase, of which absolute value is small, in the transaction cost is offset by the downward pressure put by the significant decrease in the travel times to the asset market. Therefore, from the eq (2.28), it is obvious that τ_{cc} has a negative impact on the threshold level j^*. The panel

Panel A: Asset market travel time cost: ϕ

$\frac{M}{Pc}$	Per-transaction cost: τ_{cc}			
	0.0056	0.0139	0.0293	0.0946
0.25	0.0000388	0.0002678	0.0017336	0.0883450
0.33	0.0000384	0.0002518	0.0014209	0.0543425
0.5	0.0000381	0.0002403	0.0011975	0.0300549

Panel B: Number of asset market visit: n

$\frac{M}{Pc}$	Per-transaction cost: τ_{cc}			
	0.0056	0.0139	0.0293	0.0946
0.25	66.1134269	12.0952707	2.7838824	0.2610872
0.33	84.9784282	16.0878488	3.7128563	0.3506887
0.5	134.790726	25.2654622	5.6255502	0.5304238

Panel C: Payment choice threshold: j^*

$\frac{M}{Pc}$	Per-transaction cost: τ_{cc}			
	0.0056	0.0139	0.0293	0.0946
0.25	1.2776944	0.5787289	0.2809733	0.0897886
0.33	1.6455360	0.7715483	0.3752167	0.1191584
0.5	2.6221437	1.2187332	0.5709052	0.1785673

Panel D: Private cryptocurrency balance: CC

$\frac{M}{Pc}$	Per-transaction cost: τ_{cc}			
	0.0056	0.0139	0.0293	0.0946
0.25	-0.0105027	0.0602488	0.3608768	3.9274091
0.33	-0.0220187	0.0275004	0.2520910	2.9410847
0.5	-0.0479399	-0.0208769	0.1299805	1.9273794

Panel E: Fiat currency balance: M

$\frac{M}{Pc}$	Per-transaction cost: τ_{cc}			
	0.0056	0.0139	0.0293	0.0946
0.25	0.0271076	0.0303410	0.0309317	0.0319201
0.33	0.0349118	0.0404499	0.0413068	0.0423611
0.5	0.0556316	0.0638945	0.0628497	0.0634812

Panel F: Welfare Cost (%)

$\frac{M}{Pc}$	Per-transaction cost: τ_{cc}			
	0.0056	0.0139	0.0293	0.0946
0.25	-1.4741437	-1.1109744	-0.2467725	10.4943005
0.33	-1.0983435	-0.6707314	0	7.9997439
0.5	-0.0806343	0.4384440	0.8081533	6.1150705

Table 2.5: Sensitivity analysis: core variables. Note: The transaction cost τ_{cc} is in the cryptocurrency unit. Since the difference between some values are very small, the values are rounded to 7 digits to observe the differences. The values of all the variables including the optimal consumption level except ϕ are complex numbers. Thus, real parts of complex numbers are used in this table.

D and E display the response of the private cryptocurrency and fiat currency balances for alternative values of τ_{cc} and $\frac{M}{Pc}$. In both panels, an increase in the money to consumption ratio has opposite effects on the currencies: negative on private cryptocurrency balance and positive on fiat currency balance, which is consistent with the movement of j^*. What is more, the transaction cost has a significant positive effect on the cryptocurrency balance. The significant increase in the cryptocurrency balance is mainly driven by the upward pressure put by the dramatic decrease in the n and a significant increase in $1 - {j^*}^2$. It is probably that the wealth effect induces the consumer to hold more cryptocurrency. When it comes to the fiat currency balance, the effect of the transaction cost depends on the value of the domestic currency to consumption ratio. When domestic currency to consumption ratio is small like 0.25 and 0.33, transaction cost also has a positive effect on the fiat currency balance. However, when the ratio is big enough like 0.5, the transaction cost has a complicated effect on the fiat currency balance. The fiat currency balance first goes up, then goes down, and goes up slightly again later as the transaction cost goes up. Another interesting finding in panel E is that consumers are very sensitive to the initial "sudden" increase in the transaction cost for all values of the domestic currency to consumption ratio. Therefore, the fiat currency balance increases bigger when the transaction cost goes up from 0.0056 to 0.0139 than the further increases.[35]

Panel F shows the corresponding welfare costs. The 3D visualization, which is Figure (2.28), is shown in Appendix (2.8.3). As panel F describes, the domestic currency to consumption ratio has a positive impact on the welfare cost for small values of the

[35]Transaction cost of 0.0139 is approximately 2.5 times of the 0.0056 and 0.0946 is approximately 3.3 times of the 0.0293. But the corresponding change in fiat currency balance is much larger for the increase from 0.0056 to 0.0139.

transaction cost and the magnitude of the impact is relatively big. However, the ratio of domestic currency to consumption has a negative impact on the welfare costs when transaction cost is large enough like 0.0946. The increase in the domestic currency to consumption ratio reduces the welfare of the consumer for small transaction costs while enhances consumer's welfare for the large transaction costs. Therefore, central banks can reduce the welfare cost of consumers when the transaction cost of using a CBDC is relatively high by encouraging them to spend a higher fraction of their money in the domestic market. What is more, the transaction cost τ_{cc} has a positive impact on the welfare cost. The maximum welfare loss occurs when the transaction cost is at maximum and the domestic currency to consumption ratio is at minimum. Domestic currency to consumption ratio plays a critical role when $\tau_{cc} = 0.0293$. The slightest decrease in that ratio from the benchmark rate of 0.33 leads to welfare gains while an increase creates welfare losses.

The effect of the domestic currency to consumption ratio on other core variables is generated solely through the travel time cost to the asset market. However, the transaction cost of the private cryptocurrency can impact the variables and welfare costs through both the travel time cost and the transaction cost involved while conducting transactions. As shown in Figure (2.11), the total transaction expenditure is one of the major sources of the welfare cost of both price and nominal exchange rate. The travel time cost to the asset market is not individually significantly sensitive to the change in $\frac{M}{Pc}$ ratio when the transaction cost is low. However, the sensitivity increases as the transaction cost goes up. What is more, the combined effect of the transaction cost on both the ϕ and the total transaction expenditure amplifies the impact and generates more significant changes in critical variables. That is the major reason why we observe the welfare cost values in Table (2.5).

In general, the change in the domestic currency to consumption ratio does generate an impact on parameter ϕ, variables n, j^*, CC, M, and the welfare cost. The significance of the impact on some variables depends on the transaction cost of using cryptocurrency. However, the change in transaction cost of using private cryptocurrency as a payment instrument can generate a more significant impact on the core variables and parameters of interest. The domestic currency to consumption ratio magnifies its impact on the welfare cost as the transaction cost increases. Therefore, our benchmark welfare costs and steady-state variables are very sensitive to the changes in the transaction cost of using the private cryptocurrency. However, it is less sensitive to the changes in the domestic currency to consumption ratio.

2.5.3 Technology Implications

As mentioned in Section (2.5.2), the welfare results are sensitive to the transaction cost incurred while using private cryptocurrency as a payment instrument. The variables τ_{cct} and ϕ also have important implications for the cryptocurrency issuers and cryptocurrency payment system evolution. The value of ϕ measures the cost of converting nonmonetary assets like capital into monetary assets like private cryptocurrency and fiat currency in this model. The higher the cost of visiting the asset market, then the representative household will likely to visit less frequently or just quit visiting. For a cryptocurrency, ϕ can be understood as the fees that users have to pay when they buy or sell private cryptocurrency or converting between different supported cryptocurrencies on the online private cryptocurrency asset exchange market. For the fiat currency, it can be explained as the opportunity cost of the time spent on converting nonmonetary assets into fiat currency or other extra costs involved during the conversion process.[36] What is more, the transaction cost is the fee paid to miners or payment system operators that make and facilitate each transaction on the Bitcoin or other cryptocurrency networks. If the blockchain network has robust hardware and high-quality miners or operators, it can cope with volatile transaction demands relatively smoothly and the fluctuations of the transaction cost become relatively flat. Therefore, I will examine the welfare implications of both the time cost of visiting the asset market and the transaction cost of using private cryptocurrency while keeping other parameters and variables the same as in the benchmark case.[37] For this analysis, the value of the transaction cost ranges from the sample average of 0.0293 to twice, which is 0.1892, the maximum value as shown in Figure (2.5) with an increment of 0.0080. The traveling time cost ϕ starts with the benchmark value of 0.0014 and the highest value is twice, which is 0.1767, of the maximum value of ϕ in panel A of Table (2.5). The increment of the ϕ is 0.0088.

Figure (2.12) shows how the welfare is affected by the travel time cost ϕ and the transaction cost τ_{cc} with a 3D graph. Except for the curve corresponding to the benchmark ϕ value of 0.0014, which will be discussed later, the welfare cost of the transaction cost shows an increasing trend in general for the other values of the ϕ. However, for the values

[36]Please note that it is possible that the representative household visits the asset market and converts nonmonetary assets into fiat currency first and then uses that fiat currency to buy private cryptocurrency. Or converting nonmonetary assets directly into both currencies can happen at the same time. Both cases do not have an impact on our analysis.

[37]Please note that value selection of ϕ and τ_{cc} is random. To keep the results comparable to the benchmark case, the values of ϕ and τ_{cc} are selected from Table (2.5).

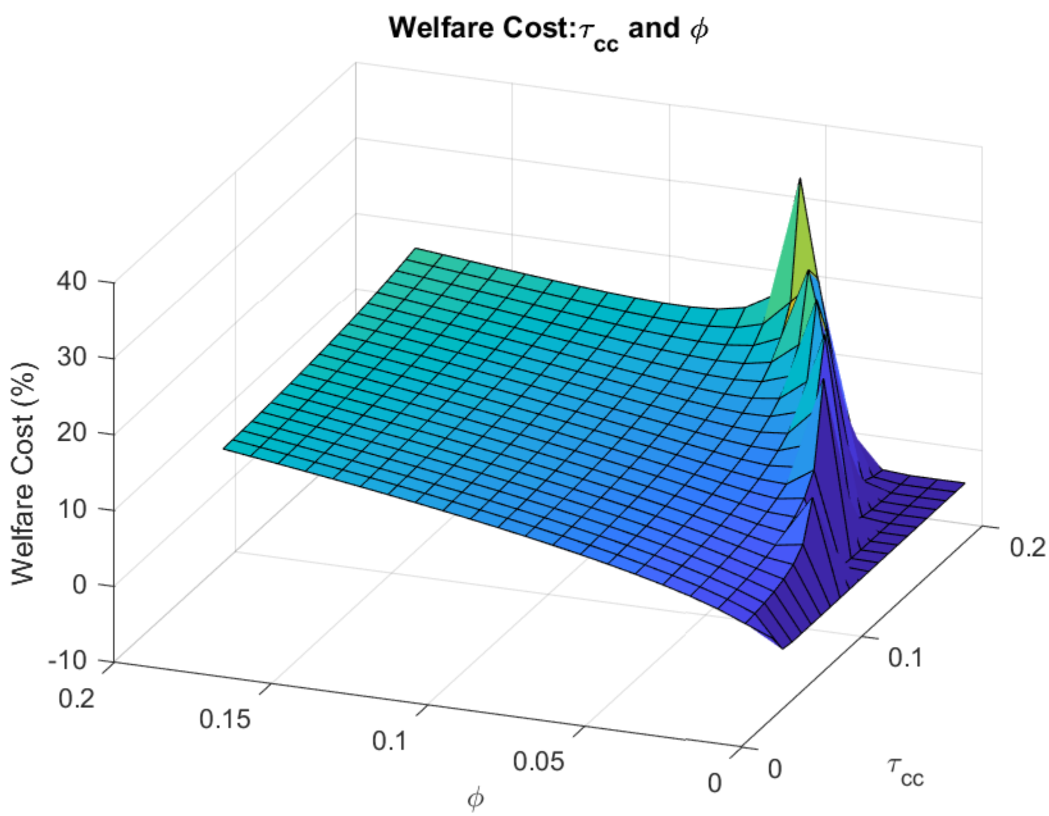

Figure 2.12: Welfare cost: ϕ and τ_{cc}. Note: Welfare cost values are real parts of complex numbers.

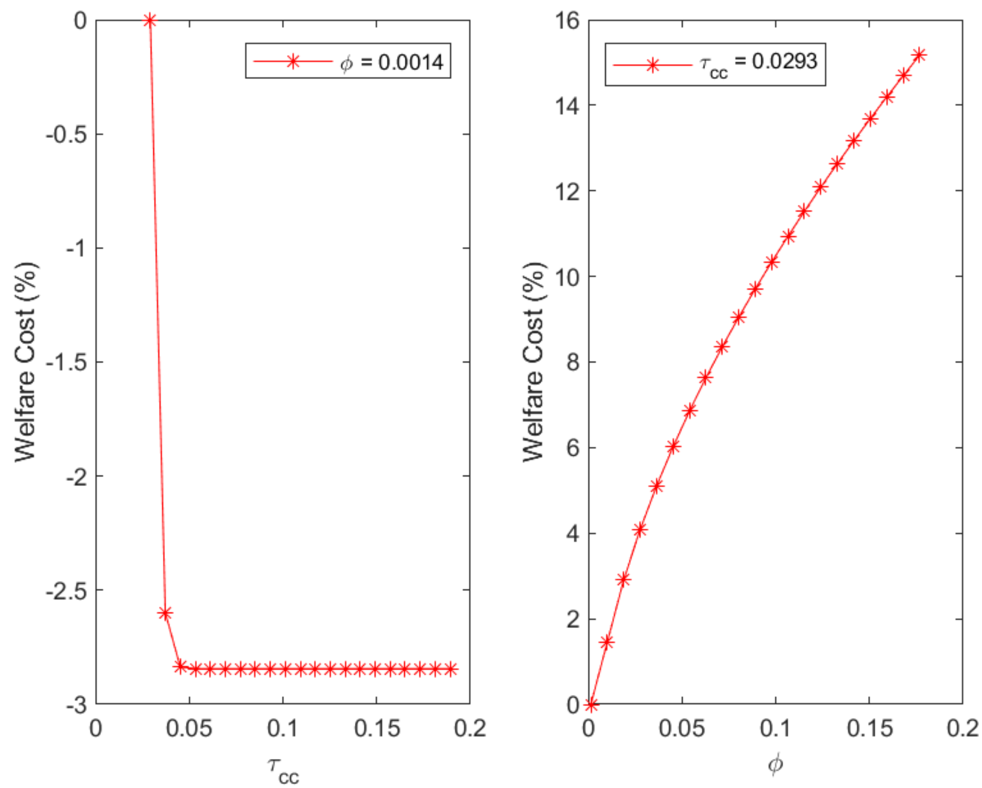

Figure 2.13: Welfare cost: ϕ and τ_{cc}. Note: The definition of the welfare cost is the same as in eq (2.25) and the only difference is that now ϕ or τ_{cc} are the changing variables rather than P. The welfare cost values of τ_{cc} are the real parts of complex numbers.

of the ϕ between 0.0102 and 0.0452, the welfare cost of the transaction cost shows similar trends as the welfare cost of the nominal exchange rate described in Figure (2.9). For example, when ϕ is 0.0452, the welfare cost of the transaction cost increases from 6.0169% to 25.1878% at first till $\tau_{cc} = 0.1732$ but then decreases dramatically to 14.1332% for the further increase in the transaction cost. For the initial small values of ϕ, there is even having welfare gains, which implies negative welfare cost, for the bigger values of the τ_{cc} at the end of the decreasing section of the welfare cost curve. What is more, the welfare cost of the transaction cost corresponding to ϕ larger than 0.0452 shows a steady increasing trend. Thus, the effect of the transaction cost on the welfare of the consumer depends on the cost of visiting the asset market, and mostly it reduces the welfare. Since an increase in the transaction cost reduces the real rate of return net of transaction cost on the private cryptocurrency, it induces the household to buy consumption goods using cryptocurrency less than before. In addition, it reduces the amount of the consumption goods that they can afford under the same income or wealth. What is more, the sudden decreasing trend of the welfare cost of the transaction cost for the small ϕ values and the bigger transaction costs is because of the relatively large increase in the fiat currency balance, threshold level j^*, and decrease in the cryptocurrency balance before the dramatic turn. Therefore, the consumer can afford to reduce the positive welfare cost with a small amount of accumulated wealth. However, after the welfare cost reaches the peak, the cryptocurrency balance stays relatively flat while j^* and M decrease dramatically, which implies the household is increasing the ratio of the private cryptocurrency that pays relatively high interest in his monetary assets. As a result, the household owns more resources to increase his consumption, which further decreases the welfare cost. Figures describing the corresponding changes in other core variables are given in Appendix (2.8.3).

However, the welfare cost curve of the travel time cost is concave for the small transaction costs and the impact is significant, which is shown in Figure (2.12) and (2.13). As the transaction cost goes up further, the shape of the welfare cost of the travel time cost ϕ changes dramatically and becomes more obvious. The welfare cost of the travel time cost increases slightly at first and then it increases sharply to the possible maximum values. However, once it reaches the highest welfare cost, it decreases dramatically for a short range of ϕ. But, again it goes up steadily as the travel time cost goes up further. For example, when τ_{cc} is at its maximum of 0.1892, the welfare cost of the travel time cost increases slightly from -2.8435% to -2.5653% for the travel time cost range of 0.0014-0.0277. Then welfare cost goes up sharply to 34.4837% for another range of 0.0277-0.0452. This increasing trend does not last long and begins to decrease dramatically. The welfare cost drops down to 15.4784% for the travel time cost range of 0.0452-0.0891. However, the welfare cost goes up again slowly for the further increase in the travel time cost and the net increase is relatively small. What is more, the kink in the welfare cost curve of the travel time cost for the bigger τ_{cc} is mainly caused by the dramatic increase in the threshold level j^*, cryptocurrency and fiat currency balance, which have wealth effect, before the turning point. Since the household increases both the cryptocurrency and fiat currency balances even for the increasing threshold level j^* for the initial increase in the travel time cost, this slightly increases the wealth of the consumer and thus increases the consumption for a very short range of ϕ. Therefore, the welfare cost is reduced. However, this will not last long.

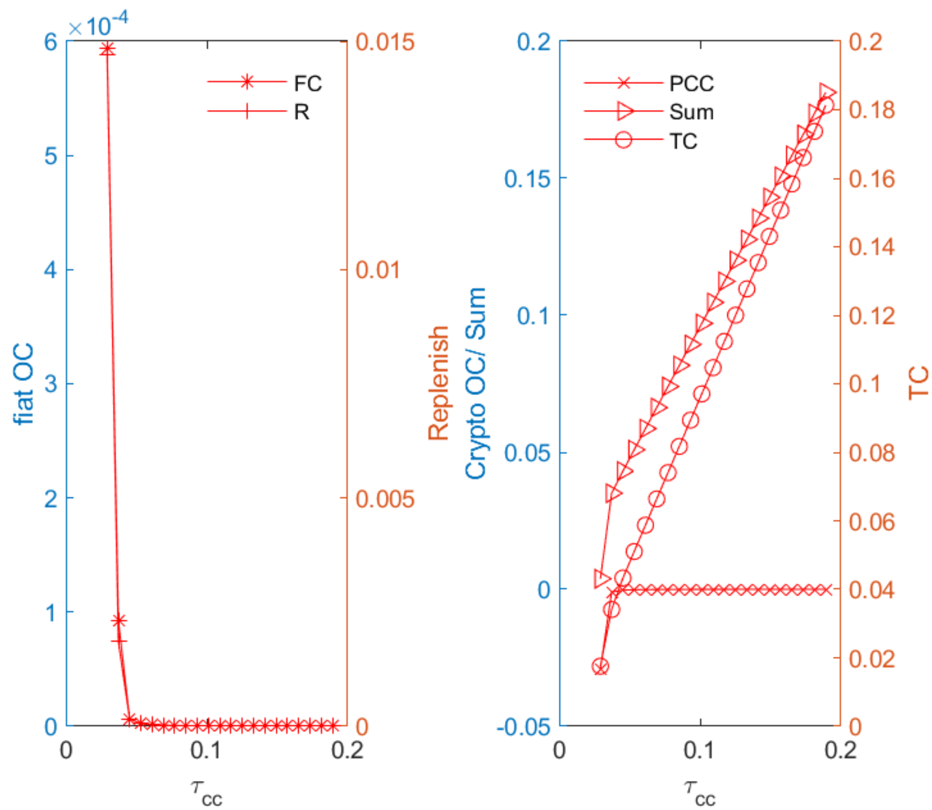

Figure 2.14: Source of the welfare cost when ϕ is at the benchmark level, Note: FC stands for the fiat currency, R stands for the replenishment of money balances, PCC stands for the private cryptocurrency, TC sands for the total transaction expenditure and OC stands for the opportunity cost and Sum stands for the summation of the TC, OC of PCC and FC, and R. The values are the real parts of complex numbers.

Figure (2.13) shows the welfare cost of the transaction cost and travel time cost while keeping other variables at the benchmark level. It is easy to understand the concavity of the welfare cost curve of the travel time cost. However, a dramatic decrease in the welfare cost of the transaction cost τ_{cc} when $\phi = 0.0014$ is just the opposite of what I expected since higher transaction costs are supposed to create welfare losses rather than welfare gains. To understand this puzzle, it is important to check the opportunity cost of holding different currencies. Figure (2.14) shows how the opportunity costs, total transaction expenditure of conducting transactions with cryptocurrency, and replenishment cost change when the transaction cost goes up. The opportunity cost of holding fiat currency and the replenishment cost both decreases by 99.9891% and 99.9847% respectively while the transaction expenditure, opportunity cost of holding cryptocurrency, and summation of all costs all increase by 933.7173%, 99.9708%, and 4642.1% respectively. The dramatic changes happen only for the initial transaction cost range of 0.0293-0.0453 for the replenishment cost and the opportunity cost of holding fiat currency and cryptocurrency. What is more, from the Figure (2.35) and (2.36) in Appendix (2.8.3), it is observed that cryptocurrency balance, fiat currency balance, threshold level j^*, and travel times to the asset market all decrease dramatically for the initial increase in the transaction cost while the consumption goes up dramatically. The dramatic response of the consumer to the initial small increase in the transaction cost by increasing consumption sharply is very likely caused by the consumer's fear of potential further increase in the transaction cost and shrinking of his expected wealth and consumption in the future. As a result, the household sharply increases consumption as a response to the initial small increase in the transaction cost and to take advantage of relatively lower transaction cost before it is too late. However, for the further increase in the transaction cost, the consumer's reaction is far more stable by slightly increasing the consumption level. This suggests that consumers are very sensitive to small deviations of transaction cost from the steady-state rate they get used to paying when the travel time cost ϕ is at the steady-state level. What is more, an initial increase in the transaction cost dominates the corresponding increase in the consumption level and thus the travel times initially goes down dramatically according to the eq (2.27).[38] The magnitude of changes in the c, n, and τ_{cc} determines the trend of other variables in a similar way.

The findings here have important implications for the future development direction of the private or a central bank issued cryptocurrency. First, the cost of traveling to the asset market has a significant effect on the representative household's consumption behavior in general and thus on the welfare cost. This effect becomes more obvious as the transaction cost goes up. Therefore, if private cryptocurrency firms want their products to be more consumer-friendly and to minimize the welfare loss of users, it is a wise decision to invest more in R&D to improve the network hardware and reduce the fees of buying, selling, or converting between different private cryptocurrencies.[39] The same logic goes to central banks. Second, the transaction cost of using private cryptocurrency as a payment instrument has a varying impact on the welfare of the consumer and it depends on the travel time cost. For small values of the travel time cost, the consumer's response varies dramatically for the increase in the transaction cost while it is relatively stable for the bigger

[38]Please note that τ_{cc}^2 in eq (2.27) plays an important role in determining the initial dramatic decreasing trend of n. Change in τ_{cc}^2 is totally dominated by the corresponding change in consumption for the initial increase in τ_{cc}.

[39]For example, increasing number of transactions that Bitcoin blockchain network can process in a second by developing new protocols or technological improvement like Lightning Network. Bitcoin's scalability problem is a major challenge to the widespread adoption of Bitcoin.

values of the travel time cost. Thus, if the private cryptocurrency network is robust enough to absorb most of the demand related shocks and travel time cost is relatively high, it will not seriously discourage consumers from using the network to make transactions. However, the transaction cost still has a dramatic effect on the welfare of consumers if the travel time cost is relatively small.[40] Third, If central banks issue CBDC, generally, they should be more sensitive about the potential change in the fees regarding the conversion between fiat currency and CBDC than the transaction cost of using the CBDC. Fourth, the results suggest that consumers react very dramatically to the slight deviation of the transaction cost from the level they got used to in the past. Therefore, CBDC issuers are advised not to react to the dramatic response of consumers to the initial tiny deviation of the transaction cost from the long-run stable level.

2.6 Conclusion

This paper is motivated by the fast development of the DLT applications like BitPay and its potential implications for monetary policy, financial system, and especially the currently outdated so-called "real-time" gross settlement system. Some novel and important features of the private cryptocurrency payment processor of BitPay are incorporated in the dynamic general equilibrium model. The main aim of this paper is to examine the welfare effect of the currency substitution between fiat currency and private cryptocurrency when both can be used as a medium of exchange. Compared to existing literature regarding cryptocurrency, this model has several novel features. For example, the choice of the pay-

[40] [18] point out that the cost of verification, which is the transaction cost I use here, and the cost of networking is affected by the blockchain technology

ment instrument is endogenously determined by the consumer by comparing the expected opportunity cost of using fiat currency and cryptocurrency. The transaction cost of using cryptocurrency to make purchases is time-varying and irrelevant to the transaction amount. Also, consumers can travel multiple times to the asset market to replenish money balances to satisfy their demand for consumption goods and services.

The dynamic general equilibrium model in this paper is very simple and has three agents: a representative household, firm, and government. The government plays the role of a central bank and is responsible for monetary policy. The welfare cost of both the price and nominal exchange rate is examined at the steady-state. A net increase in the steady-state price level by 40% decreases the welfare cost by 0.9549%, which is little. The representative household decreases the fiat currency balance by 52.48% and increases the private cryptocurrency balance by 137.12%. The relatively large increase in the private cryptocurrency balance can be explained by the decreasing real transaction cost of using it as a medium of exchange and high net real return on private cryptocurrency while the same rate is zero for the fiat currency. The choice threshold of payment instruments goes down by 52.48%, which implies less fiat currency is used as a medium of exchange. However, for a net 20% increase in the nominal exchange rate, the welfare cost increases by 6.3218% for the first 15% net increase but then decreases by 6.5387% for the rest. An increase in the nominal exchange rate directly affects the domestic currency value of the cryptocurrency balance saved and the transaction cost of using a private cryptocurrency as a payment instrument, which implies that the gross real return net of transaction cost on the private cryptocurrency decreases. As the nominal exchange rate increases by 20%, the fiat currency balance increases by 322.37% first but then decreases by 47.55% while the private cryptocurrency balance decreases by 104.40% first but then increases by 24.28%. Bitcoin price is very volatile and if any CBDC is issued in the future, it is very unlikely that central banks pay such high net interest on it. Therefore, the welfare cost of price and nominal exchange rate can be amplified if the net appreciation rate of a cryptocurrency is small or similar to the bank deposit rates. For the future CBDC, it is appealing to have features like a specific exchange rate target with relatively stable fluctuations such that any value changes between buying and selling prices can be considered as the interest on the CBDC, which is also a useful additional monetary policy tool for central banks.

In this paper, the robustness of the results to some changes in specific parameters and variables is also examined. The steady-state welfare cost results are very sensitive to changes in the transaction cost of using private cryptocurrency as a payment instrument. What is more, the ratio of domestic currency to consumption, which is used to pin down the time cost of traveling to the asset market, can also generate a significant impact on the welfare cost. Except for the sensitivity, the impact of the time cost of traveling to the asset market and cryptocurrency transaction cost on welfare is also examined separately since both have significant implications for the payment system technological innovations. Both the traveling time cost and transaction cost have complicated effects on the welfare cost. In general, an increase in the travel time cost decreases the welfare of consumers and this effect is also influenced by the transaction cost. Therefore, for private cryptocurrency payment systems or online cryptocurrency exchange market operators, it is important to invest more in R&D to cut the cost of buying, selling, or converting between cryptocurrencies if they want to attract more customers and reduce the welfare loss of private cryptocurrency users. This also implies that to minimize the consumer's welfare losses, for any central bank that will issue CBDC, it is recommended to make it as convenient and cheap as possible to convert between domestic fiat currency and CBDC or other assets. What is more, keeping the transaction cost (in cryptocurrency units) relatively stable with small fluctuations is also a wise strategy for central banks if they seek to avoid a significant increase in the welfare loss of consumers.

Private cryptocurrency, cryptocurrency payment system, and blockchain technology are the newly developing areas and there are still uncertainties and legal barriers that exist for a CBDC. It is necessary for us to scientifically understand its shortcomings and advantages by employing the important features and data of currently available private cryptocurrencies. There are several promising directions for future research. First, since an interest-bearing cryptocurrency is a potential competitor for the bank deposit, researchers can examine the welfare implications of the currency substitution when domestic fiat currency, private cryptocurrency, and bank deposits are all available for consumers. This case is very similar to [60], in which domestic currency, bank deposit, and foreign currency are all available as a payment instrument for domestic users. Second, the importance of the data increases as artificial intelligence, blockchain technology, and other information technologies develop. Today, data is as important as oil in the 20th century. It is of great importance to understand whether the transaction fees will be charged as a percentage of the consumption amount or the same or similar setting as in this paper. Besides, examining the welfare implications from the perspective of both a private cryptocurrency payment system operating firm and a consumer is also a promising avenue for future research. Third, it is also worth examining the welfare-maximizing optimal rate of return on cryptocurrency and the policy rule of achieving such an optimal rate.

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2.8 Appendix

2.8.1 Proof and Solution

Proof for the Payment Instrument Choice Condition

The equation (2.7) that determines threshold level j_t can be explained intuitively as in Section (2.4.1), but it is also determined by the first-order optimality conditions of the system of equations implied by this paper. For a given optimal consumption level c_t^*, the consumer needs to solve the following Lagrangian optimization with rational expectation

($\omega = -1$ is already plugged in).

$$L = E_t\Bigg\{\sum_{t=0}^{\infty}\Bigg[\beta^t u\big[r_t^k k_{t-1} + w_t h_t + CC_{t-1}\frac{S_t}{P_t} + \frac{M_{t-1}}{P_t} + tr_t - k_t + (1-\delta)k_{t-1}$$
$$-\frac{M_t}{P_t} - CC_t\frac{S_t}{P_t} - \frac{S_t\tau_{cct}(1-j_t)}{P_t}, 1 - h_t - \phi n_t\big] + \eta_{1t}\big[n_t\frac{M_t}{P_t} - c_t j_t^2\big] + \tag{2.31}$$
$$\eta_{2t}\big[n_t CC_t\frac{S_t}{P_t} - c_t(1-j_t^2)\big]\Bigg]\Bigg\}$$

The derivatives for the k_t, CC_t, M_t, j_t, n_t, and h_t (The first four derivatives is enough to get eq (2.7)) are as follows:

$$k_t: \quad E_t r_{t+1}^{\bar{k}} = E_t\frac{u_{ct}}{u_{ct+1}\beta} \tag{2.32}$$

$$CC_t: \quad E_t\frac{1}{\beta}\frac{S_t}{P_t}\frac{u_{ct}}{u_{ct+1}} = E_t\left[\eta_{2t}\frac{n_t S_t}{\beta^{t+1}P_t u_{ct+1}} + \frac{S_{t+1}}{P_{t+1}}\right] \tag{2.33}$$
$$M_t: \quad E_t\frac{1}{\beta}\frac{1}{P_t}\frac{u_{ct}}{u_{ct+1}} = E_t\left[\eta_{1t}\frac{n_t}{\beta^{t+1}P_t u_{ct+1}} + \frac{1}{P_{t+1}}\right] \tag{2.34}$$

$$j_t: \quad \eta_{1t} = \eta_{2t} + \beta^t u_{ct}\frac{S_t\tau_{cct}}{2c_t j_t P_t} \tag{2.35}$$

After simplification, eq (2.33) will become:

$$E_t\left[\eta_{2t}\frac{n_t}{\beta^{t+1}u_{ct+1}} + \frac{S_{t+1}}{S_t}\frac{P_t}{P_{t+1}}\right] = E_t\frac{1}{\beta}\frac{u_{ct}}{u_{ct+1}} \tag{2.36}$$

Eq (2.34) becomes:

$$E_t\left[\eta_{1t}\frac{n_t}{\beta^{t+1}u_{ct+1}} + \frac{P_t}{P_{t+1}}\right] = E_t\frac{1}{\beta}\frac{u_{ct}}{u_{ct+1}} \tag{2.37}$$

Now subtracting eq (2.37) from eq (2.36), and then using eq (2.32), (2.35), definition of Θ_t, and the inflation π_t, we can get:

$$E_t\left[\frac{\Theta_{t+1}}{\pi_{t+1}} - \frac{1}{\pi_{t+1}}\right] - E_t r_{t+1}^{\bar{k}}\frac{n_t S_t\tau_{cct}}{2c_t j_t P_t} = 0 \tag{2.38}$$

which is the same as eq (2.7):

$$E_t\Big[\frac{\Theta_{t+1}}{\pi_{t+1}}-\frac{S_t\tau_{cct}}{P_t}\frac{\bar{r}^k_{t+1}n_t}{c_t(j)}\Big]=E_t\frac{1}{\pi_{t+1}} \tag{2.39}$$

Please note that $\bar{r_t^k}=r_t^k+1-\delta$.

Model Solution

After plugging j_t^* expression into the budget constraint and CIA constraints, then the representative household solves the following Bellman equation (Please note that the same equation (2.39) can be extracted by using the Bellman approach):

$$\begin{aligned}V_t(k_{t-1},M_{t-1},CC_{t-1})=\max_{c_t,k_t,M_t,CC_t,h_t,n_t}u(c_t,1-h_t-\phi n_t)+\\
\beta E_tV_{t+1}(k_t,M_t,CC_t)+\lambda_t\Bigg\{r_t^kk_{t-1}+w_th_t+CC_{t-1}\frac{S_t}{P_t}+tr_t+\frac{M_{t-1}}{P_t}-c_t-k_t\\
+(1-\delta)k_{t-1}-\frac{M_t}{P_t}-CC_t\frac{S_t}{P_t}-\frac{S_t\tau_{cct}}{P_t}+\\
E_t\frac{S_t}{P_t}c_t^{\frac{1}{\omega}}n_t^{\frac{-1}{\omega}}\tau_{cct}^{\frac{\omega-1}{\omega}}\left[\frac{\frac{1}{\pi_{t+1}}(1-\omega)(\Theta_{t+1}-1)}{\frac{S_t}{P_t}\bar{r^k_{t+1}}}\right]^{\frac{1}{\omega}}\Bigg\}+\\
\mu_{1t}\Bigg\{n_t\frac{M_t}{P_t}-E_tc_t^{\frac{1}{\omega}}n_t^{\frac{\omega-1}{\omega}}\left[\frac{\frac{1}{\pi_{t+1}}(1-\omega)(\Theta_{t+1}-1)}{\frac{S_t}{P_t}\tau_{cct}\bar{r^k_{t+1}}}\right]^{\frac{1-\omega}{\omega}}\Bigg\}\\
+\mu_{2t}\Bigg\{n_t\frac{CC_tS_t}{P_t}-c_t+E_tc_t^{\frac{1}{\omega}}n_t^{\frac{\omega-1}{\omega}}\left[\frac{\frac{1}{\pi_{t+1}}(1-\omega)(\Theta_{t+1}-1)}{\frac{S_t}{P_t}\tau_{cct}\bar{r^k_{t+1}}}\right]^{\frac{1-\omega}{\omega}}\Bigg\}\end{aligned} \tag{2.40}$$

FOC:

$$\begin{aligned}c_t:u_{ct}+\lambda_t\Bigg\{-1+E_t\frac{1}{\omega}c_t^{\frac{1}{\omega}-1}n_t^{\frac{-1}{\omega}}\tau_{cct}^{\frac{\omega-1}{\omega}}\frac{S_t}{P_t}\left[\frac{\frac{1}{\pi_{t+1}}(1-\omega)(\Theta_{t+1}-1)}{\frac{S_t}{P_t}\bar{r^k_{t+1}}}\right]^{\frac{1}{\omega}}\Bigg\}+\\
\mu_{1t}\Bigg\{-E_t\frac{1}{\omega}c_t^{\frac{1}{\omega}-1}n_t^{1-\frac{1}{\omega}}\tau_{cct}^{\frac{\omega-1}{\omega}}\left[\frac{\frac{1}{\pi_{t+1}}(1-\omega)(\Theta_{t+1}-1)}{\frac{S_t}{P_t}\bar{r^k_{t+1}}}\right]^{\frac{1-\omega}{\omega}}\Bigg\}+\\
\mu_{2t}\Bigg\{-1+E_t\frac{1}{\omega}c_t^{\frac{1}{\omega}-1}n_t^{1-\frac{1}{\omega}}\tau_{cct}^{\frac{\omega-1}{\omega}}\left[\frac{\frac{1}{\pi_{t+1}}(1-\omega)(\Theta_{t+1}-1)}{\frac{S_t}{P_t}\bar{r^k_{t+1}}}\right]^{\frac{1-\omega}{\omega}}\Bigg\}=0\end{aligned} \tag{2.41}$$

$$k_t : \beta E_t V_{t+1,k_t} = \lambda_t \tag{2.42}$$

$$M_t : \beta E_t V_{t+1,Mt} = \frac{1}{P_t}(\lambda_t - \mu_{1t} n_t) \tag{2.43}$$

$$CC_t : \beta E_t V_{t+1,cct} = \frac{S_t}{P_t}(\lambda_t - \mu_{2t} n_t) \tag{2.44}$$

$$h_t : u_{lt} = \lambda_t w_t \tag{2.45}$$

$$\begin{aligned} n_t : -\phi u_{lt} + \lambda_t \Big\{ - E_t \frac{1}{\omega} c_t^{\frac{1}{\omega}} n_t^{-\frac{1}{\omega}-1} \tau_{cct}^{\frac{\omega-1}{\omega}} \frac{S_t}{P_t} \left[\frac{\frac{1}{\pi_{t+1}}(1-\omega)(\Theta_{t+1}-1)}{\frac{S_t}{P_t} r_{t+1}^{\bar{k}}} \right]^{\frac{1}{\omega}} \Big\} + \\ \mu_{1t} \Big\{ \frac{M_t}{P_t} - E_t \frac{\omega - 1}{\omega} c_t^{\frac{1}{\omega}} n_t^{\frac{-1}{\omega}} \tau_{cct}^{\frac{\omega-1}{\omega}} \left[\frac{\frac{1}{\pi_{t+1}}(1-\omega)(\Theta_{t+1}-1)}{\frac{S_t}{P_t} r_{t+1}^{\bar{k}}} \right]^{\frac{1-\omega}{\omega}} \Big\} + \\ \mu_{2t} \Big\{ \frac{CC_t S_t}{P_t} + E_t \frac{\omega - 1}{\omega} c_t^{\frac{1}{\omega}} n_t^{\frac{-1}{\omega}} \tau_{cct}^{\frac{\omega-1}{\omega}} \left[\frac{\frac{1}{\pi_{t+1}}(1-\omega)(\Theta_{t+1}-1)}{\frac{S_t}{P_t} r_{t+1}^{\bar{k}}} \right]^{\frac{1-\omega}{\omega}} \Big\} = 0 \end{aligned} \tag{2.46}$$

Envelope conditions:

$$M_{t-1} : V_{t,M_{t-1}} = \lambda_t \frac{1}{P_t} \tag{2.47}$$

$$k_{t-1} : V_{t,k_{t-1}} = \lambda_t (r_t^k + 1 - \delta) \tag{2.48}$$

$$CC_{t-1} : V_{t,cc_{t-1}} = \lambda_t \frac{S_t}{P_t} \tag{2.49}$$

Combining updated envelope conditions and first-order conditions:

Eq (2.42) + eq (2.48)

$$\lambda_t = \beta E_t \lambda_{t+1} (r_{t+1}^k + 1 - \delta) \tag{2.50}$$

Eq (2.43) + eq (2.47)

$$\beta E_t \lambda_{t+1} \frac{1}{P_{t+1}} = \frac{1}{P_t}(\lambda_t - \mu_{1t} n_t) \tag{2.51}$$

Eq (2.44) + eq (2.49)

$$\beta E_t \lambda_{t+1} \frac{S_{t+1}}{P_{t+1}} = \frac{S_t}{P_t}(\lambda_t - \mu_{2t} n_t) \tag{2.52}$$

At the steady-state, eq (2.51) and (2.52) become:

$$\mu_1 = \frac{1}{n}\lambda(1-\beta) \tag{2.53}$$

$$\mu_2 = \frac{1}{n}\lambda(1-\beta) \tag{2.54}$$

Thus, the following equations determine the corresponding values of the consumer's optimization problem: (2.41), (2.45), (2.46), (2.50), (2.51), (2.52).

The fiat money balance M_t growth rule can be simplified as:

$$\frac{M_t}{P_t} = \frac{g_{mt}}{\pi_t}\frac{M_{t-1}}{P_{t-1}} \tag{2.55}$$

Thus, at steady-state: $g_m = \pi = 1$.

At the steady-state, travel times can be expressed as:

$$n = \left[\frac{c}{\frac{\phi w}{1-\beta} - \frac{1}{1-\beta}\frac{S^2}{P^2}\frac{\tau_{cc}^2}{c}\frac{\pi \bar{r}^k}{2(\Theta-1)}}\right]^{\frac{1}{2}} = \left[\frac{c(1-\beta)}{\phi w - \frac{S}{P}\frac{\tau_{cc}^2}{c}\frac{1}{A}}\right]^{\frac{1}{2}} \tag{2.56}$$

Simplifying eq (2.41) at the steady-state, we get:

$$\frac{u_c}{u_l}w - \frac{S}{P}\frac{\tau_{cc}^2}{c^2}\frac{n}{A} = 1 + \frac{1-\beta}{n} \tag{2.57}$$

After combing eq (2.56) and (2.57) and simplifying further, eq (2.57) becomes a cubic equation, which is

$$a_{11}c^3 + a_{12}c^2 + a_{13}c + a_{14} = 0 \tag{2.58}$$

where

$$a_{11} = (1-\beta)\phi w\left[\frac{w\gamma}{1-\gamma}\frac{1}{B} + 1\right]^2 \tag{2.59}$$

$$a_{12} = -2(1-\beta)\phi w\frac{w\gamma}{1-\gamma}\left[\frac{w\gamma}{1-\gamma}\frac{1}{B}+1\right] - (1-\beta)\frac{S}{P}\frac{\tau_{cc}^2}{A}\left[\frac{w\gamma}{1-\gamma}\frac{1}{B}+1\right]^2 - \left[\frac{(1-\beta)w\phi}{1-\gamma}\right]^2 \tag{2.60}$$

$$a_{13} = (1-\beta)\phi w\left[\frac{w\gamma}{1-\gamma}\right]^2 + 2(1-\beta)\frac{S}{P}\frac{\tau_{cc}^2}{A}\frac{w\gamma}{1-\gamma}\left[\frac{w\gamma}{1-\gamma}\frac{1}{B} + 1\right] \tag{2.61}$$

$$a_{14} = -(1-\beta)\frac{S}{P}\frac{\tau_{cc}^2}{A}\left[\frac{w\gamma}{1-\gamma}\right]^2 \tag{2.62}$$

where[41]

$$A = \frac{2P(\Theta - 1)}{\pi S\bar{r}^k} \tag{2.63}$$

$$B = \left[\frac{\frac{1}{\beta} + \delta - 1}{\alpha}\right]^{\frac{\alpha}{\alpha-1}} - \delta\left[\frac{\frac{1}{\beta} + \delta - 1}{\alpha}\right]^{\frac{1}{\alpha-1}} \tag{2.64}$$

What is more,

$$M = \frac{c}{n}(j^*)^2 P \tag{2.65}$$

$$CC = \frac{c}{n}(1-(j^*)^2)\frac{P}{S} \tag{2.66}$$

Besides,

$$\frac{u_c}{u_l} = \frac{\gamma}{1-\gamma}\frac{l}{c} \tag{2.67}$$

$$\frac{c}{h} = B \tag{2.68}$$

[41]Removing $1-\beta$ from above four coefficients, a_{11}, a_{12}, a_{13}, a_{14}, will not affect the final result. I used above coefficient expressions for Matlab coding.

2.8.2 Data Sources

The following table describes the source of the data used for the quantitative analysis in the paper.

Variable	Source
Real Personal Consumption Expenditure	[27]
Gross Domestic Product	[27]
Monetary Base: Currency in Circulation	[27]
Core PCE Price Index	[27]
Gross Fixed Capital Formation	[27]
Total Non-farm Employment	[27]
Consumption of Fixed Capital	[27]
Average Weekly Hours of All Employees (Total Private)	[27]
USD/EUR Exchange Rate	[27]
Coinbase Bitcoin Price	[27]
Share of Labor Compensation in GDP	[27]
Bitcoin Network Cost Per-Transaction	[8]
Average Bitcoin Market Value	[8]

Table 2.6: Data source.

2.8.3 Additional Figures

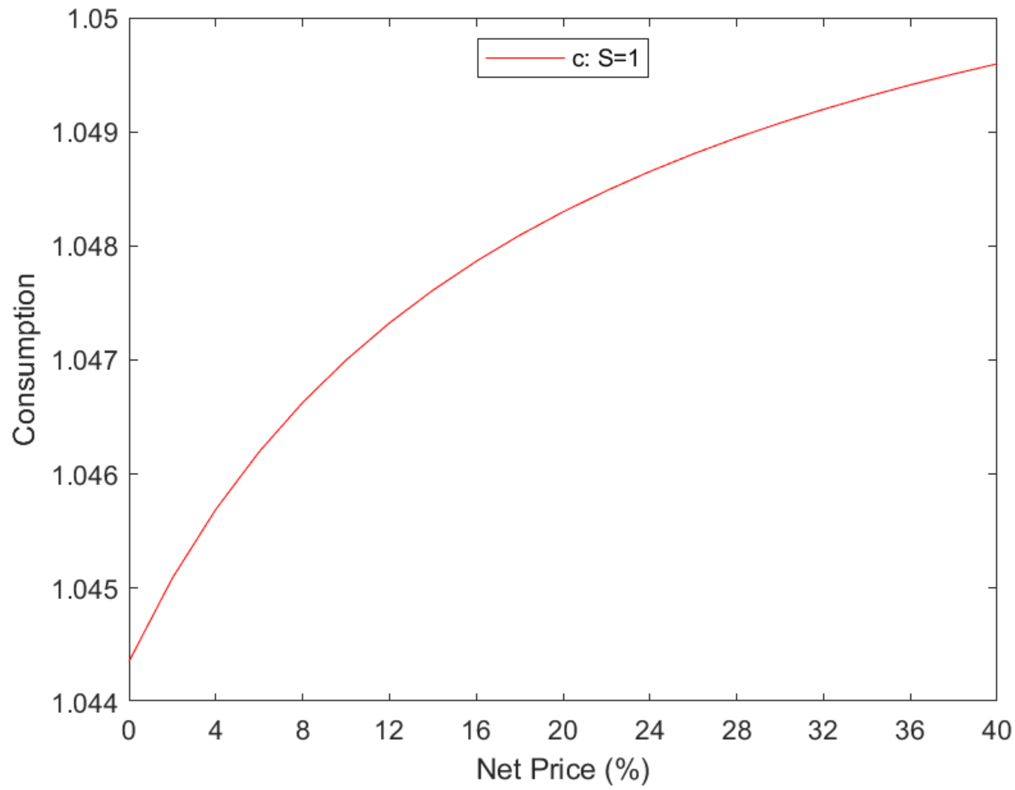

Figure 2.15: Optimal consumption response to changes in the price (%).

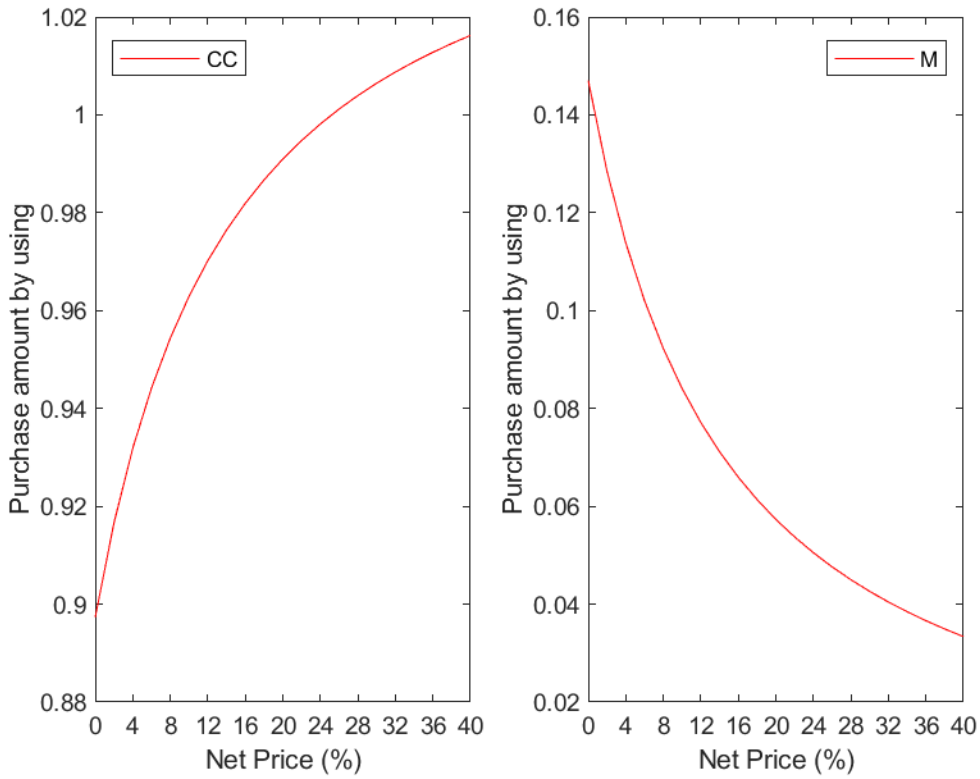

Figure 2.16: Consumption amount purchased by using different currencies: response to changes in the price. Note: The consumption amount by different currencies are defined as: $\frac{Mn}{P} = cj^*$, $\frac{CCSn}{P} = c(1 - j^*)$.

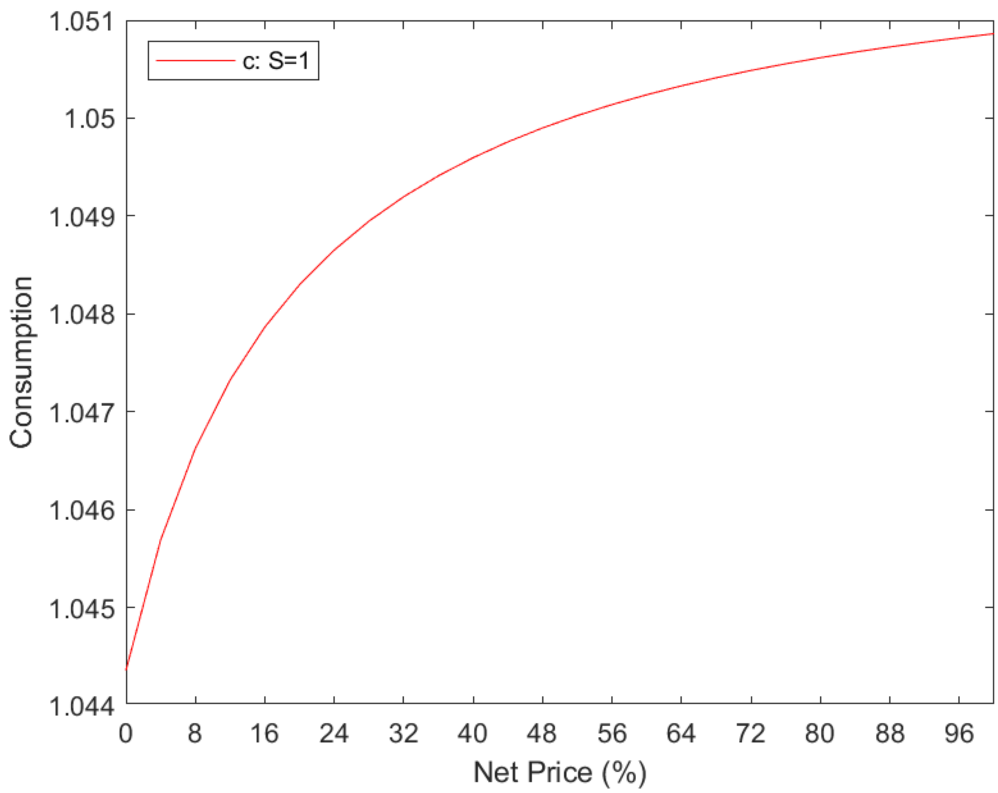

Figure 2.17: Optimal consumption response to changes in the price (0-100% range).

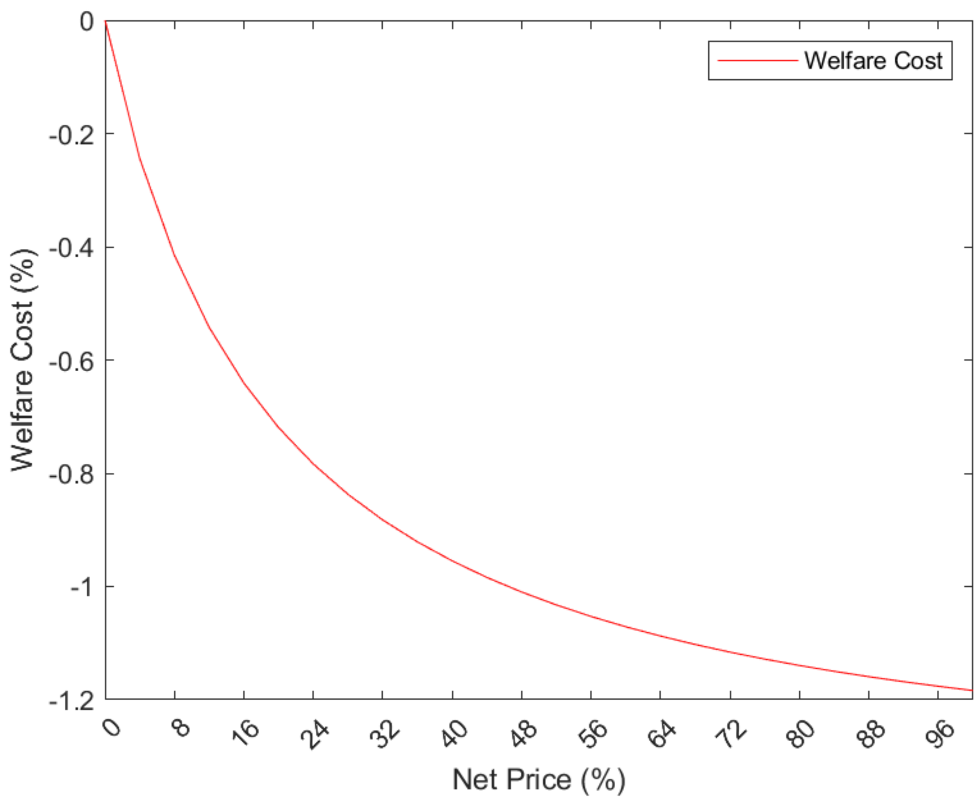

Figure 2.18: Welfare cost of the price.

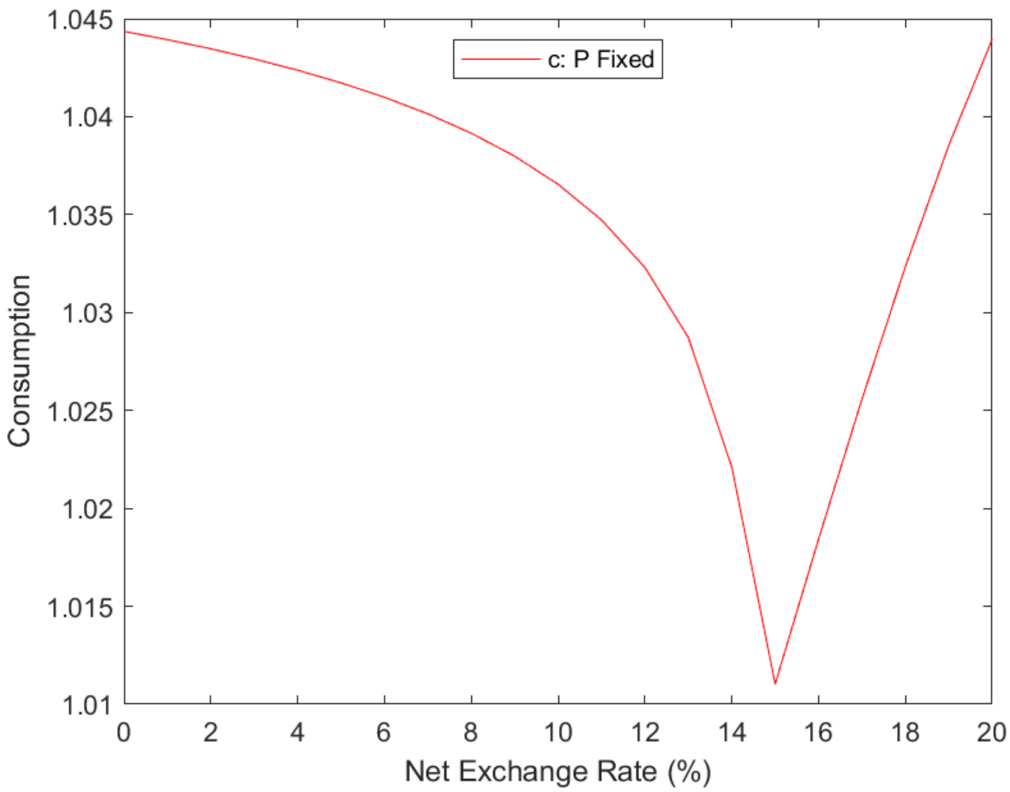

Figure 2.19: Optimal consumption response to change in the nominal exchange rate (%). Note: Consumption values are real parts of complex numbers.

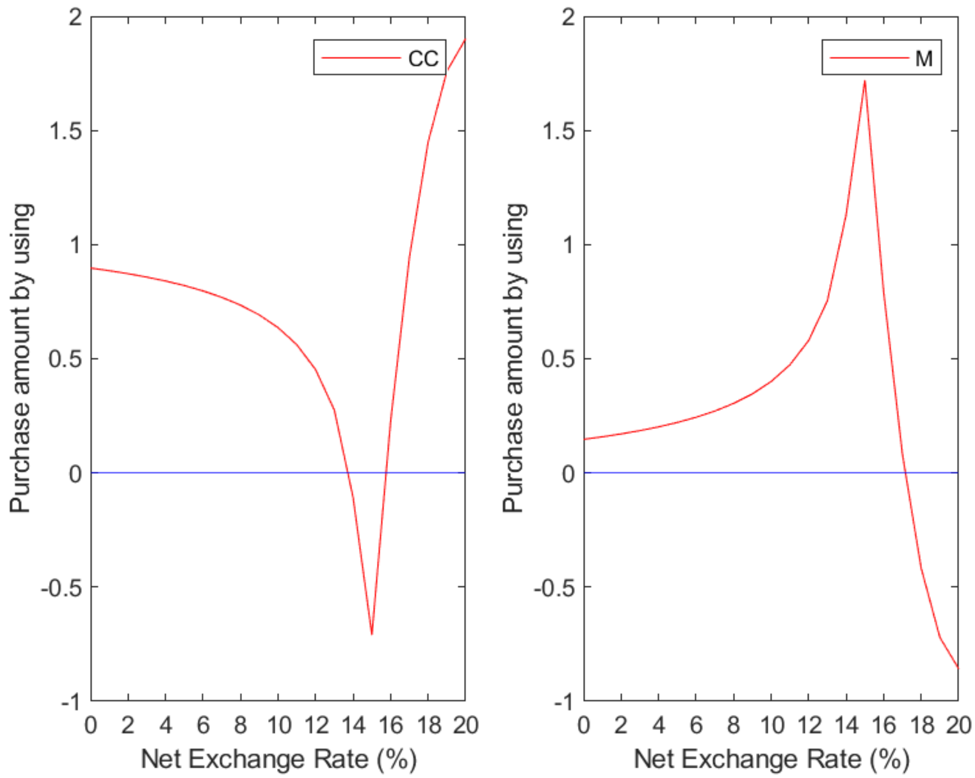

Figure 2.20: Consumption amount purchased by using different currencies: response to changes in the nominal exchange rate. Note: The consumption amount by different currencies are defined as: $\frac{Mn}{P} = cj^*$, $\frac{CCSn}{P} = c(1 - j^*)$. Values of the purchase amount are real parts of complex numbers.

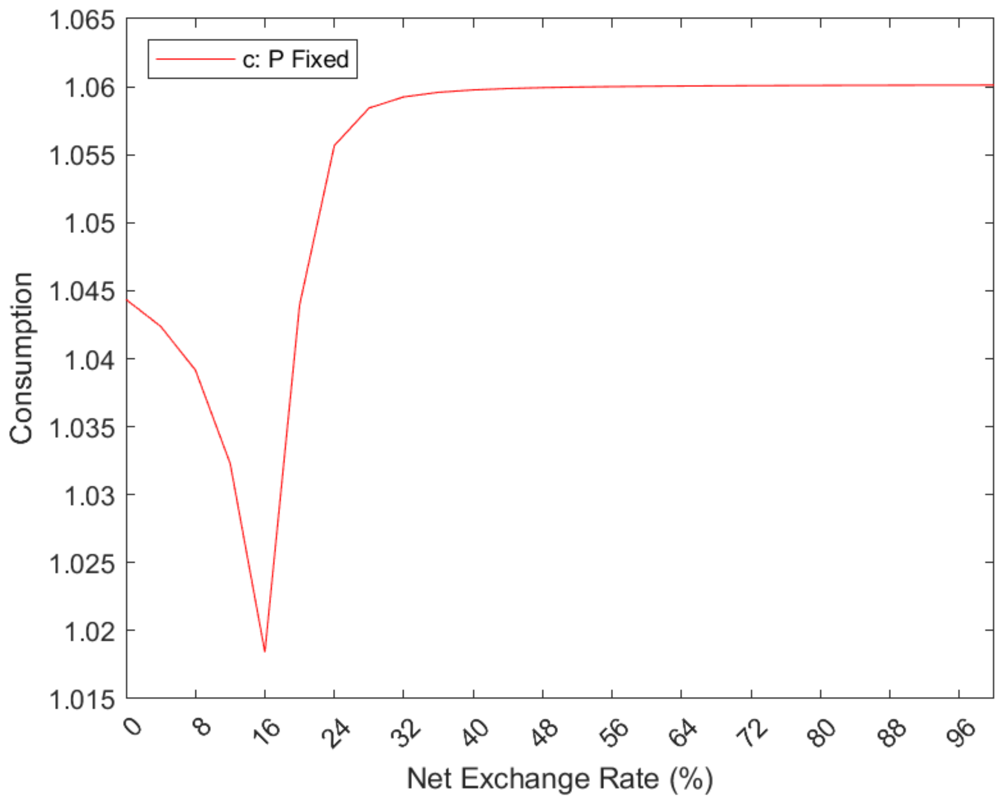

Figure 2.21: Optimal consumption response to changes in the nominal exchange rate (0-100% range). Note: Consumption values are real parts of complex numbers.

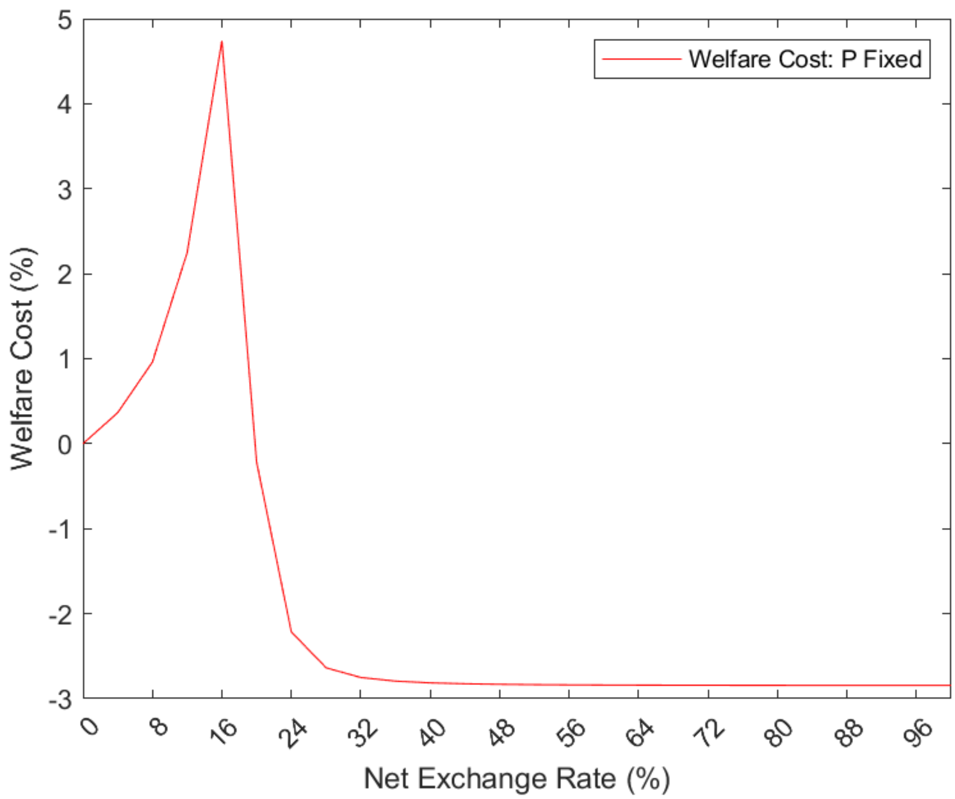

Figure 2.22: Welfare cost of the nominal exchange rate. Note: Welfare cost values are real parts of complex numbers.

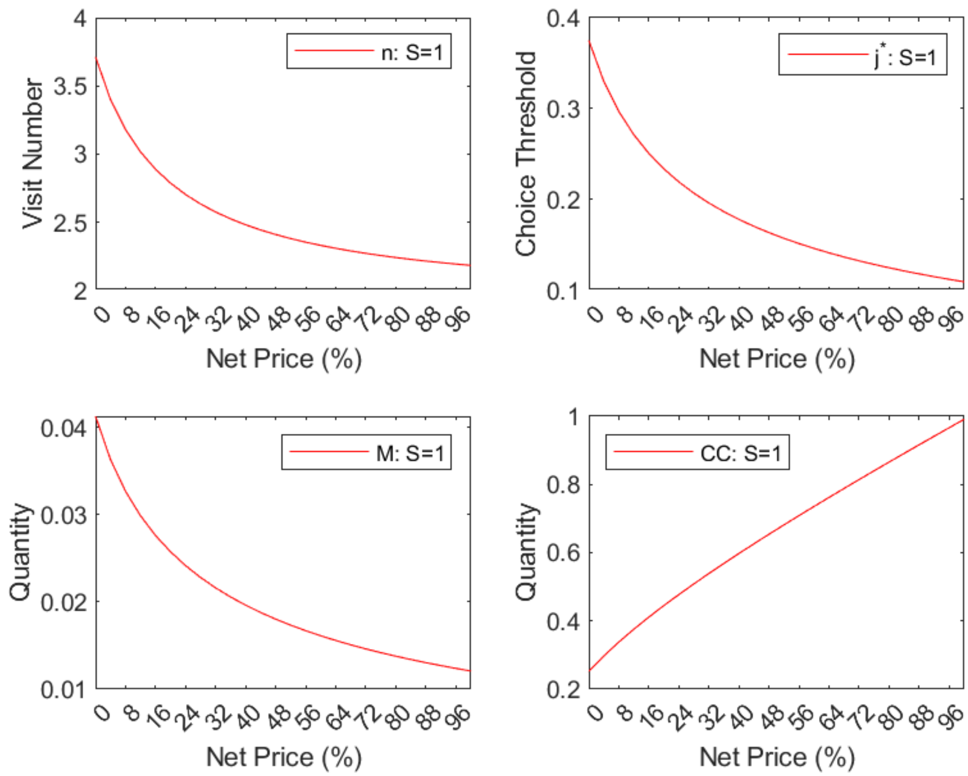

Figure 2.23: Changes in critical variables when the price changes.

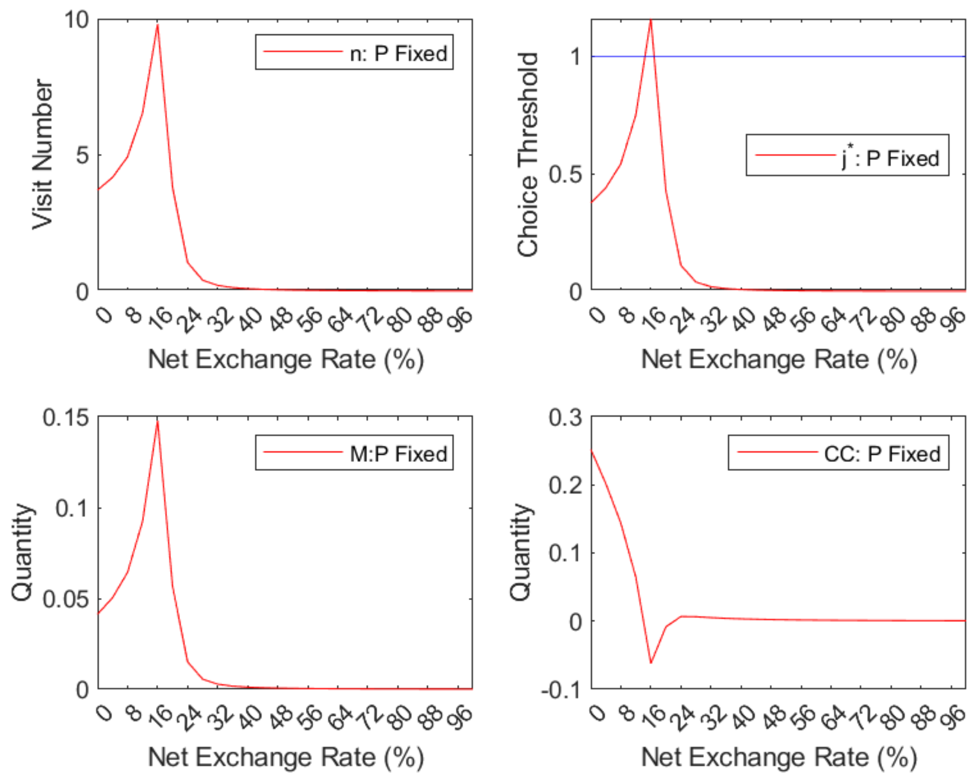

Figure 2.24: Changes in critical variables when nominal exchange rate changes. Note: Since the values of n, j^*, CC, and M are complex numbers, only the real parts are plotted.

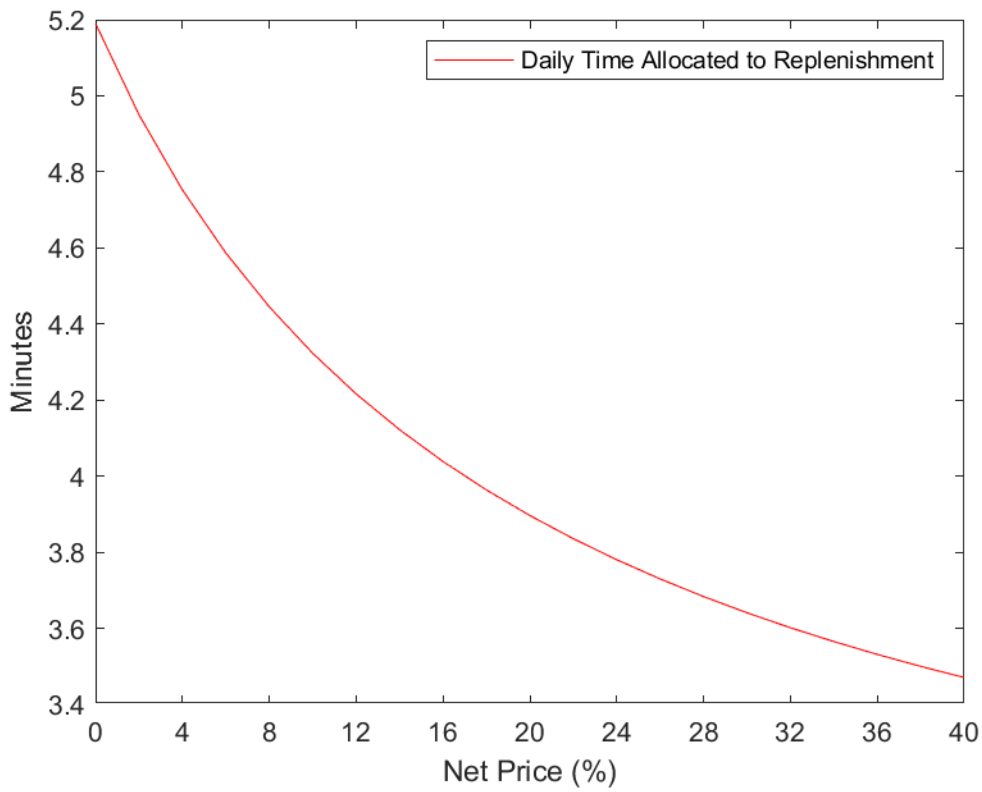

Figure 2.25: Average daily time spent on visiting the asset market (or managing asset portfolio) when the price changes. Note: Values of average daily time are real parts of complex numbers.

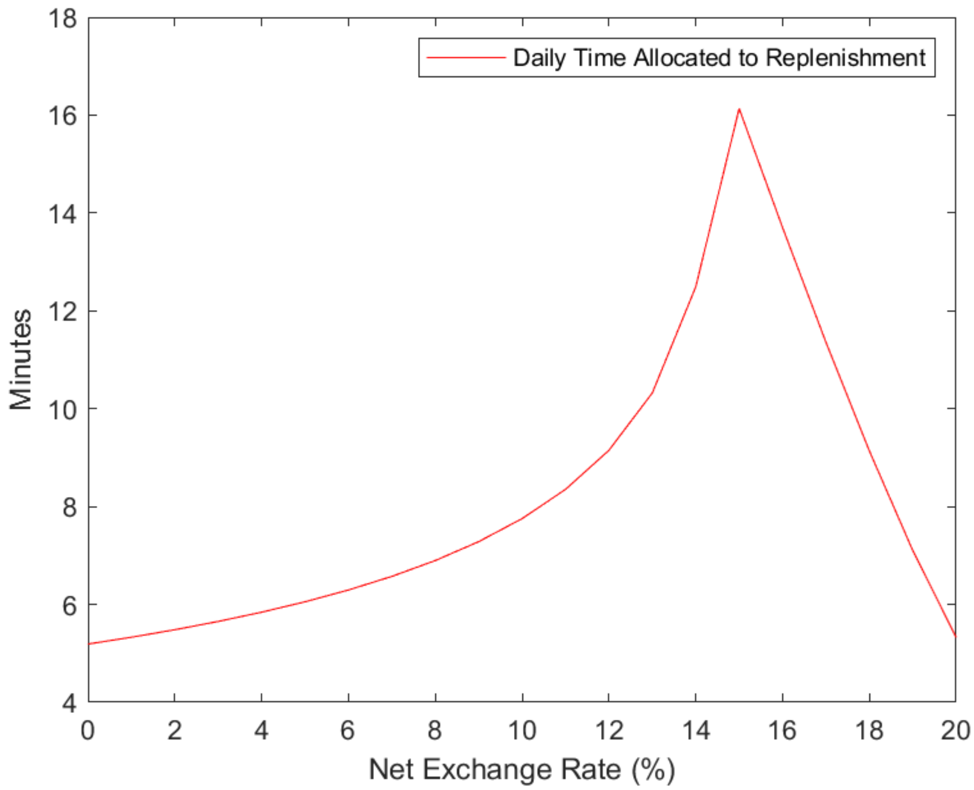

Figure 2.26: Average daily time spend on visiting the asset market (or managing asset portfolio) when the nominal exchange rate changes. Note: Values of average daily time are real parts of complex numbers.

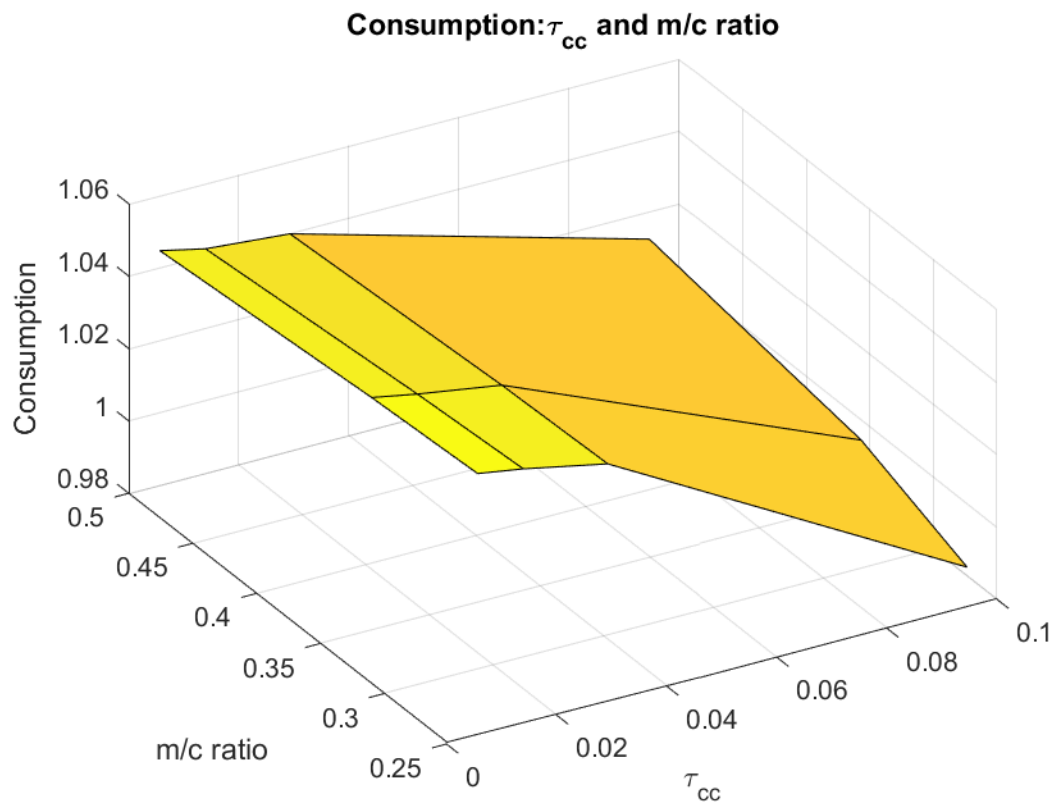

Figure 2.27: Sensitivity analysis - consumption: transaction cost of using cryptocurrency as payment instrument and domestic currency to consumption ratio. Note: Optimal consumption goes down slightly as the domestic currency to consumption ratio goes up. This trend is not obvious in this graph. Consumption values are real parts of complex numbers.

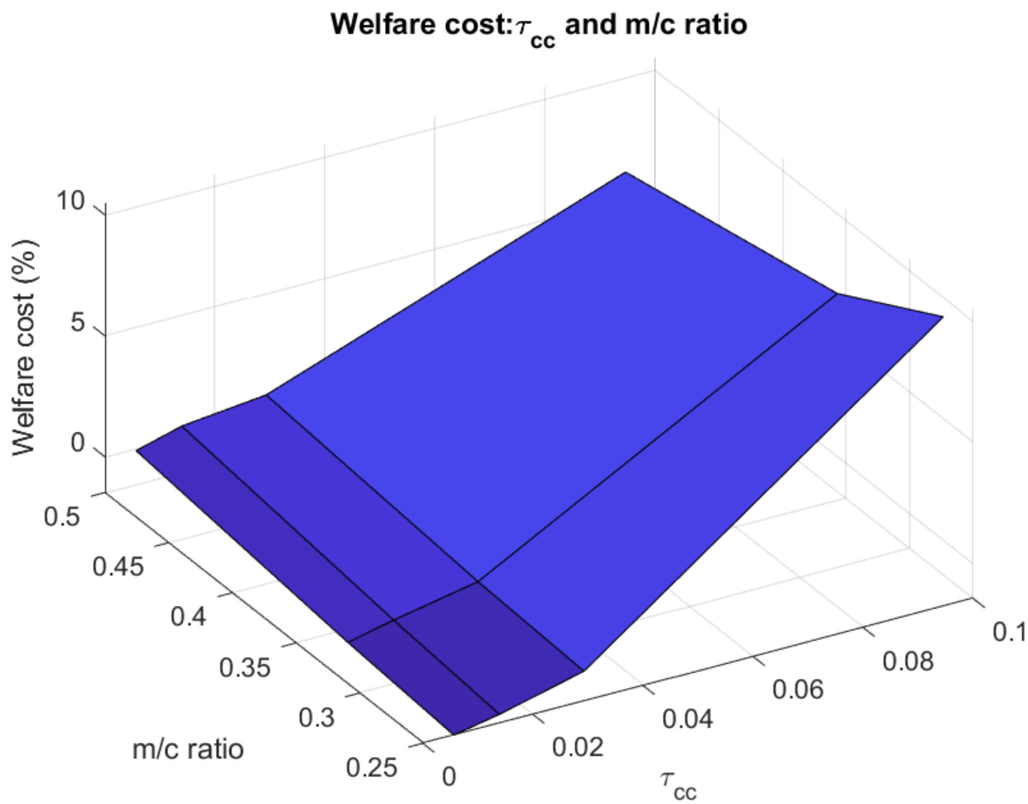

Figure 2.28: Sensitivity analysis - welfare cost: transaction cost of using cryptocurrency as payment instrument and domestic currency to consumption ratio. Note: Welfare cost values are real parts of complex numbers.

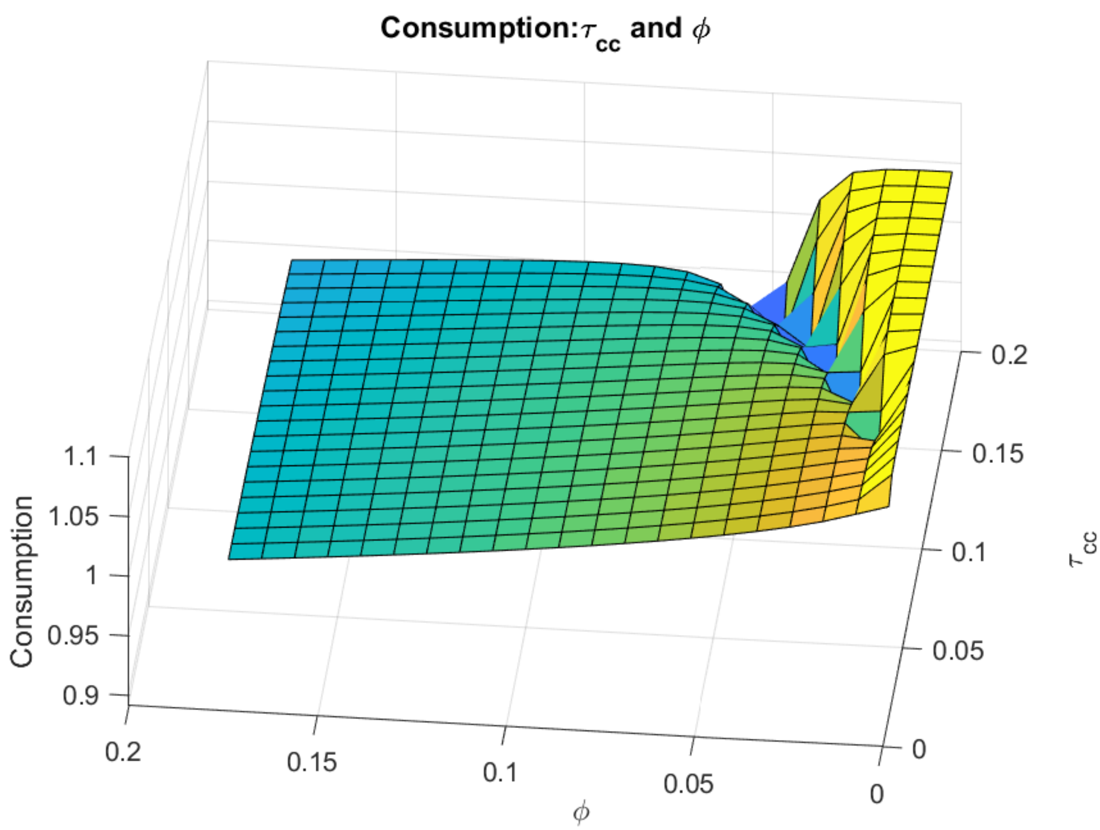

Figure 2.29: Technological implications - real consumption: transaction cost τ_{cc} and asset market travel time cost ϕ. Note: Consumption values are real parts of complex numbers.

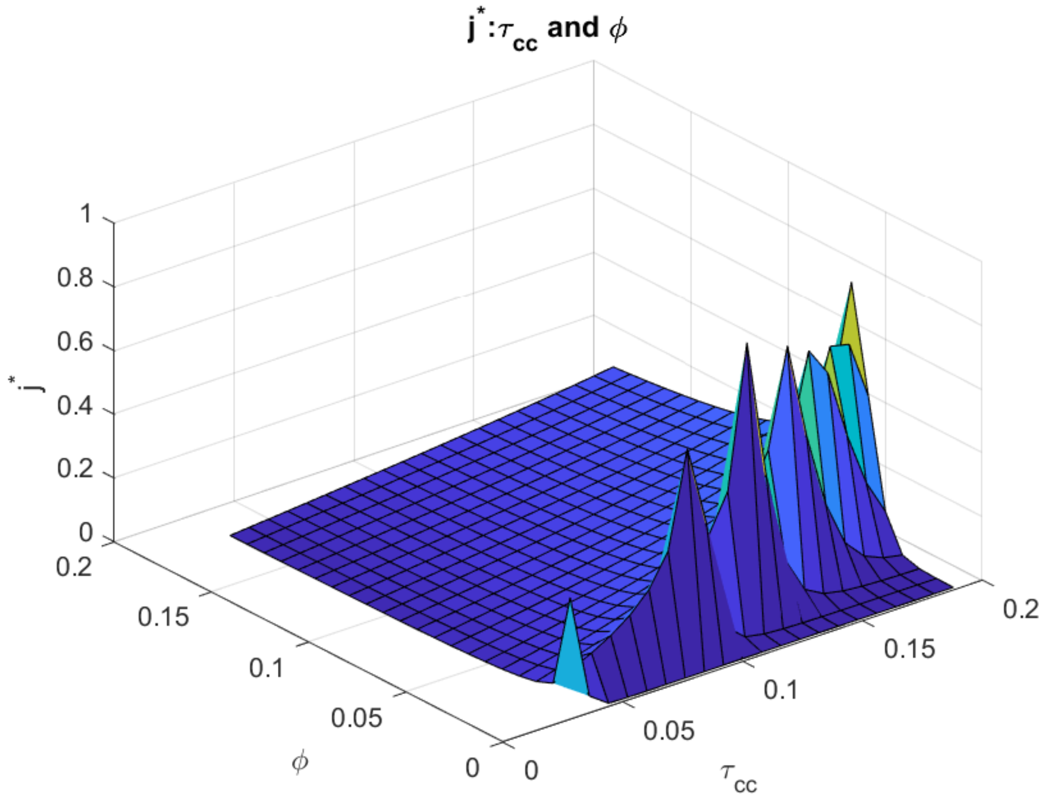

Figure 2.30: Technological implications - threshold j^*: transaction cost τ_{cc} and asset market travel time cost ϕ. Note: Threshold level values are real parts of complex numbers.

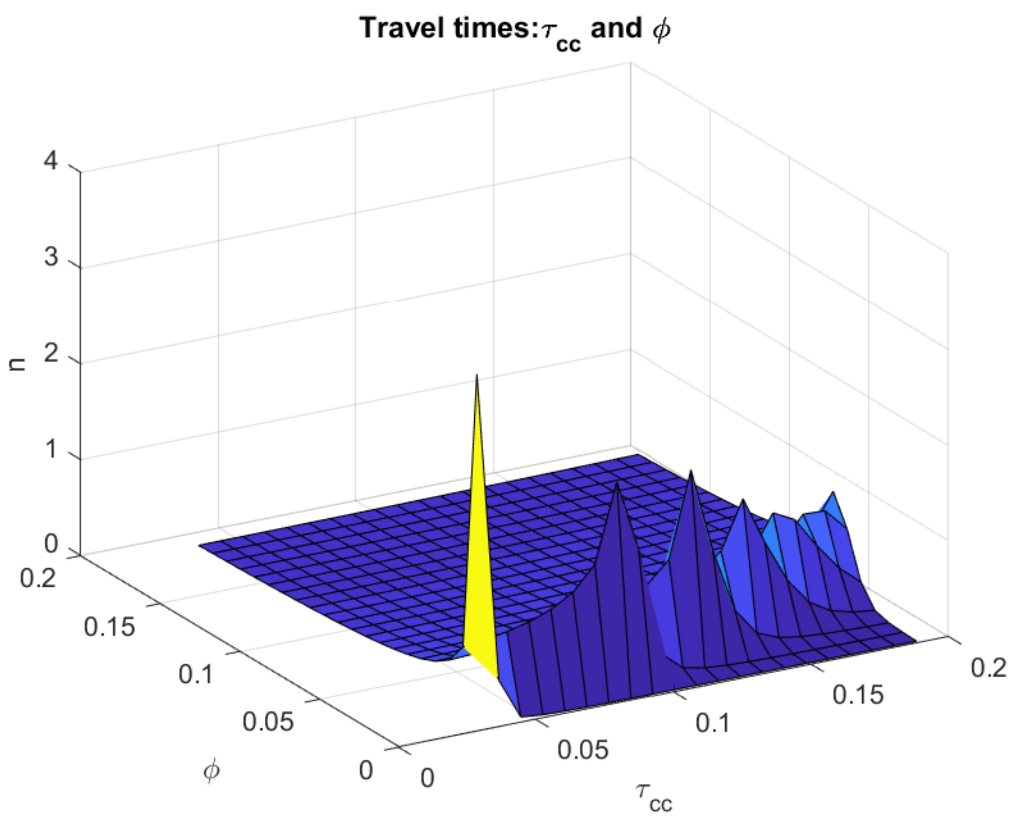

Figure 2.31: Technological implications - asset market travel times: transaction cost τ_{cc} and asset market travel time cost ϕ. Note: Values of n are real parts of complex numbers.

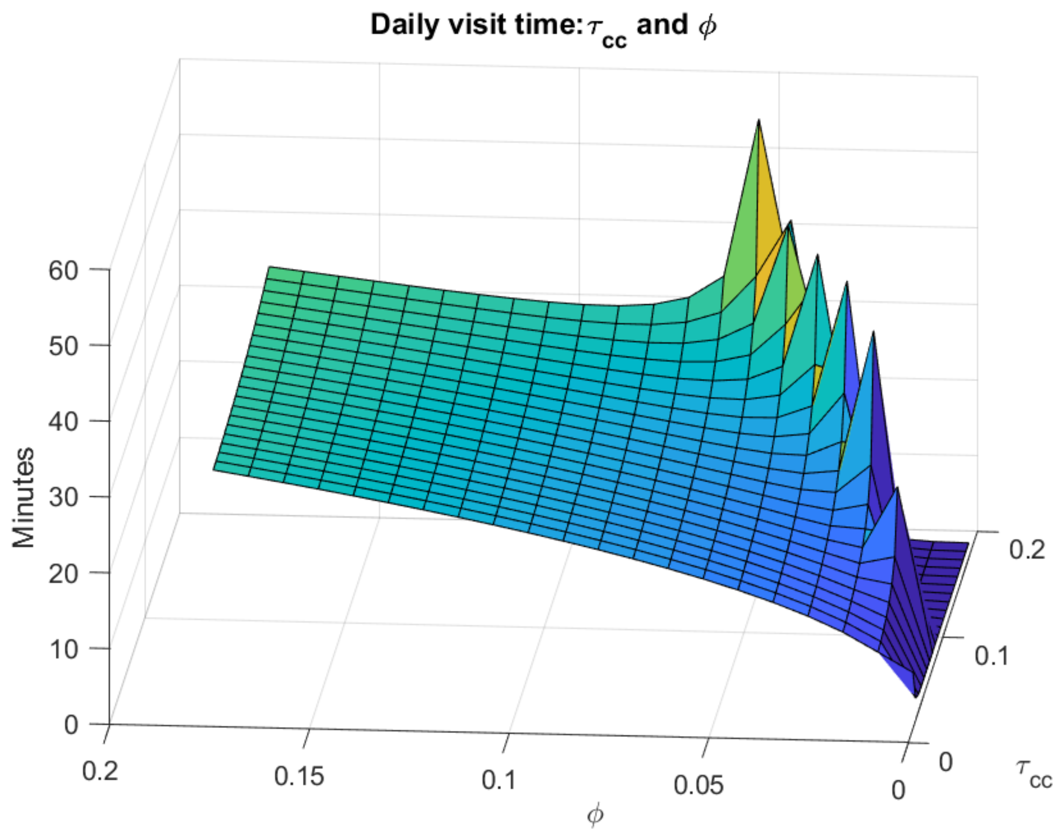

Figure 2.32: Technological implications - average daily time spent on asset managing: transaction cost τ_{cc} and asset market travel time cost ϕ. Note: Average daily time values are real parts of complex numbers.

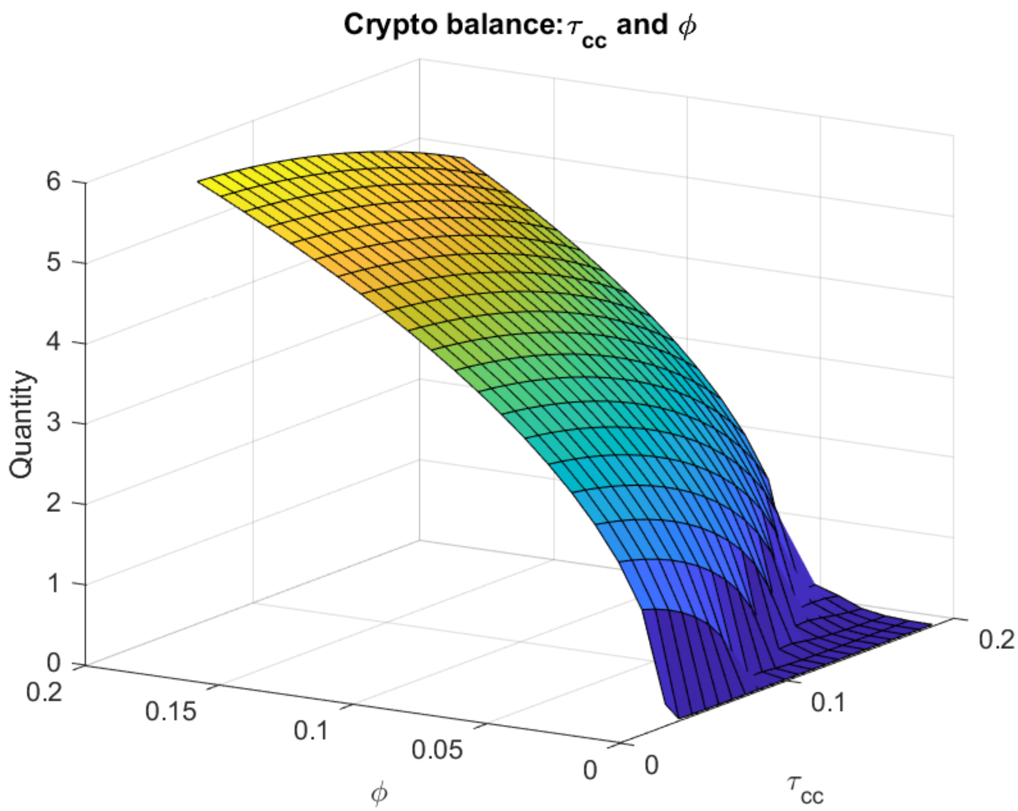

Figure 2.33: Technological implications - cryptocurrency balance: transaction cost τ_{cc} and asset market travel time cost ϕ. Note: Values of cryptocurrency balance are real parts of complex numbers.

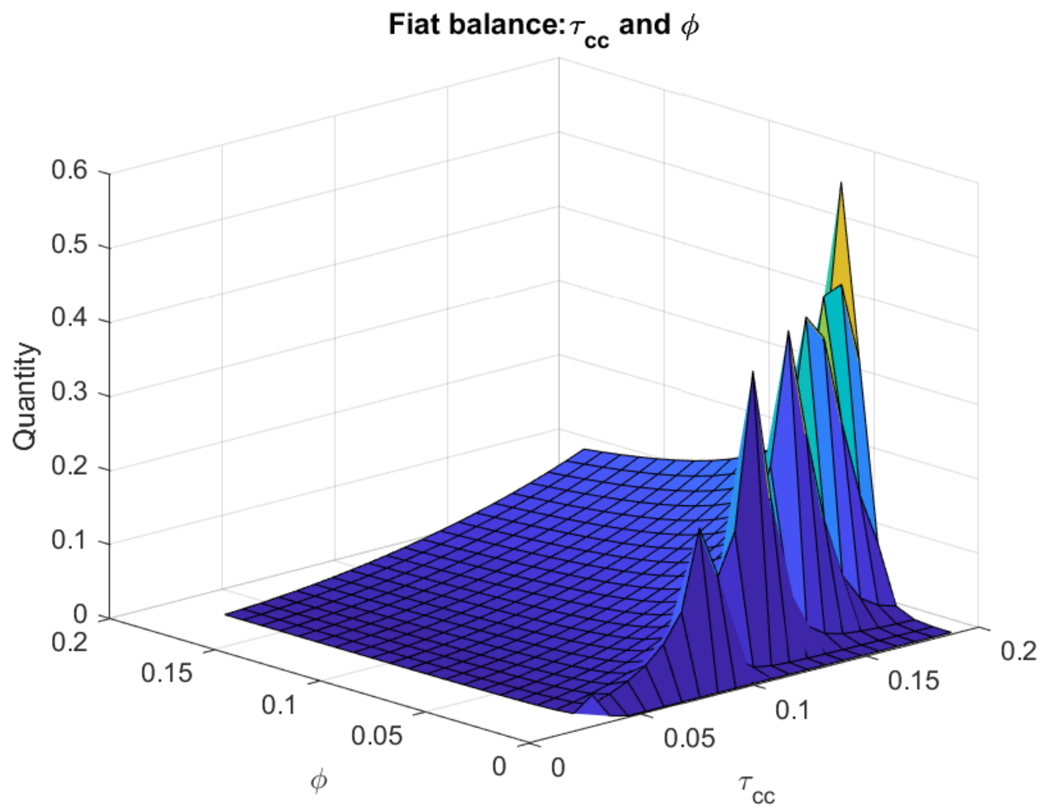

Figure 2.34: Technological implications - nominal fiat currency balance: transaction cost τ_{cc} and asset market travel time cost ϕ. Note: Values of nominal fiat currency balance are real parts of complex numbers.

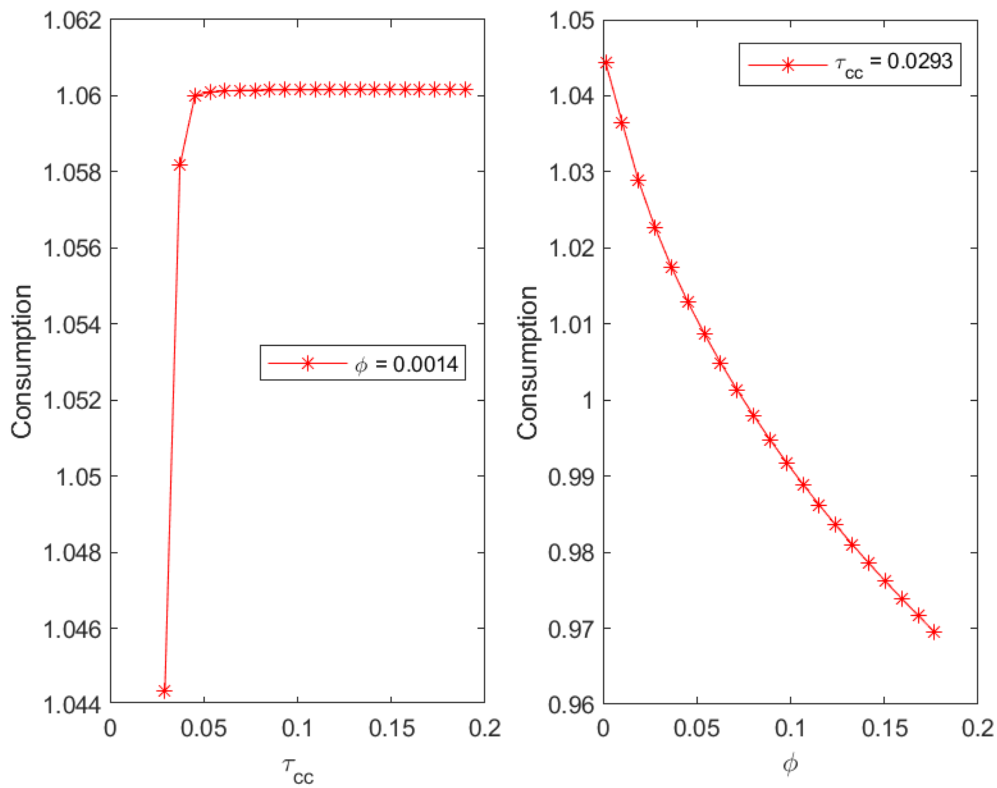

Figure 2.35: Technological implications - real consumption: τ_{cc} and ϕ at the steady-state (one of them is fixed in each case). Note: Values of consumption response to the τ_{cc} are real parts of complex numbers.

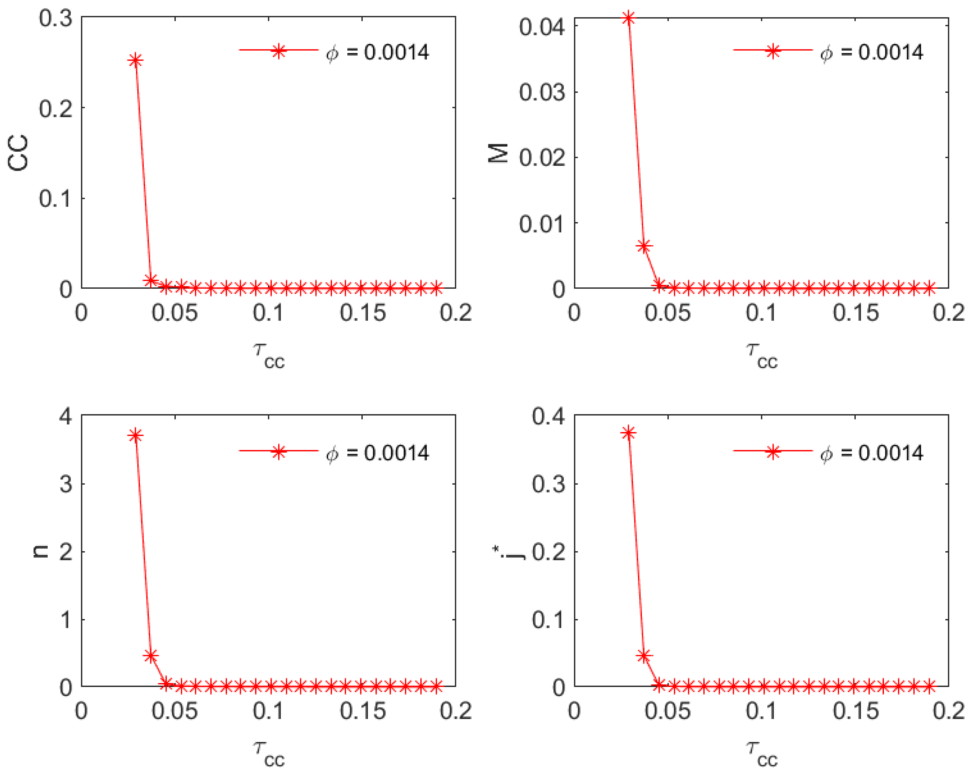

Figure 2.36: Response of critical variables to the transaction cost when $\phi = 0.0014$. Note: Values of critical variables are real parts of complex numbers.

Chapter 3

Window Dressing Behavior of the U.S. Global Systemically Important Banks

This paper examines window dressing behavior among the U.S. Global Systemically Important Banks (G-SIBs). Using supervisory data from large U.S. Bank Holding Companies (BHCs), I find that the U.S. G-SIBs repress their systemic importance scores in the year-end to lower their capital surcharges assigned by bank regulators. The priority and feasibility of reduction of scores in the five categories, which are size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity, differ and complexity scores are the most reduced in the fourth quarter. I also show how macroeconomic activity and financial condition affect the systemic importance score. I find that U.S. specific method 2 (more strict) dominates the internationally accepted method 1 both in scores and in additional capital surcharges for the eight U.S. G-SIBs. However, under the year-end approach, banks are still deviating from the original intentions of the regulation. Based on my findings, I propose two new approaches to assign additional capital surcharges based on systemic importance scores of G-SIBs: Quarterly Average and Quarterly Maximum. The quarterly maximum approach is the most efficient in targeting banks that practice window dressing. Overall, the findings provide new evidence regarding the window dressing behavior of the U.S. banks and the effectiveness of the G-SIB framework, with implications for policymakers and bank supervisors.

3.1 Introduction

Too Big to Fail (TBTF) is a very common term used in economics and implies that potential failure of big banks has a disastrous effect on the greater economic system. During and after the 2008 Financial Crisis, a large number of banks, some of which are Systemically Important Financial Institutions (SIFIs), went bankrupt or failed to act. As [14] states "the failure and near-failure of SIFIs were the key drivers of the 2007-08 Financial crisis and the resulting recession. They were also key drivers of the public sector response to the crisis,...". The importance of the stability of the banking system to the health of the whole economy is highlighted again with deep pain and losses. To address the systemic issues regarding the resilience and solvency of banks exposed by the 2008 Financial crisis and to reduce the probability and severity of the failure of SIFIs in the future, the global banking community developed a new macroprudential framework of Global Systemically Important Banks (G-SIBs).[1] The Basel Committee on Banking Supervision (BCBS) in coordination with the national authorities has identified G-SIBs since 2011 and the new list of G-SIBs is published in November every year. Those banks that are designated as G-SIBs are subject to additional capital surcharges, which is according to year-end systemic importance scores of banks.[2] The aim of this additional capital surcharge is to enable SIFIs to absorb greater losses without becoming insolvent ([14]).

An indicator-based quantitative approach is used to identify the G-SIBs. BHCs in the U.S. that have met certain asset criteria are required to submit their quarterly report to

[1] In the U.S., the Dodd–Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act (DFA) in short) of 2010 strengthens the regulations of major financial institutions whose failure could have a series negative impact on the U.S. economy.

[2] This additional capital surcharge is justified by the belief that failure of SIFIs could pose greater negative externalities than could the failure of a not systemically important financial institution ([14]).

the Federal Reserve since June 30, 2016, before which it is annual. The relevant performance of BHCs is classified into five major individual risk categories and twelve individual risk indicators. As shown in [23], those five individual risk categories are size, interconnectedness, complexity, substitutability, and cross-jurisdictional activity with an equal weight of 20% each. More details of the five individual risk categories and twelve individual risk indicators are shown in Table (3.1). The size category is measured by the total exposure amount, which is the total amount that financial institutions may lose in investments. For example, derivative exposures and securities financing transaction exposures. Today, we are living in a global village and the world's economy is interconnected and integrated. No bank can isolate itself from other financial institutions and cooperation between banks or financial institutions are necessary for the smooth and stable functioning of the global financial system. The interconnectedness of a bank with other financial institutions intensifies as the size of the bank grows. It is expected that a bank's systemic importance or the potential risk it puts on the financial system is positively related to its interconnectedness. The intra-financial system assets and liabilities, and securities outstanding are used to measure the interconnectedness of a financial institution with an equal weight of one-fifteenth.

If a major bank is dominant in offering a variety of banking or financial products and services, then the systemic effect of failing that specific bank is more significant than a financial or banking industry with multiple alternatives. [23] points out that "the systemic impact of a bank's distress or failure is expected to be negatively related to its degree of substitutability as both a market participant and client service provider". Therefore, bank regulators use the payment activity, assets under custody, and the underwritten transactions in debt and credit markets of a bank with an equal weight of approximately 6.67% to assess the substitutability feature of that financial institution.[3] What is more, bank operations these days are not simply constrained to accepting bank deposits and making loans as old times and it is complicated. The complexity of banks implies business, structural, and operational complexity as pointed out in [23]. As the complexity of a bank grows, the systemic importance also increases. The notional amount of over-the-counter (OTC) derivatives, level 3 assets, and trading and available-for-sale securities are used to measure the complexity of a bank. The last category is cross-jurisdictional activity, which is an important feature because of the globalization and integration of the financial system worldwide. This category, which includes both cross-jurisdictional claims and liabilities with an equal weight of 10%, measures a bank's activity related to outside of the home jurisdiction ([23]). As we observed from the 2008 crisis, a financial crisis can spillover and this effect can be more significant if the failed bank or financial institution has a more global footprint.

[9] also points out that systemic important banks rather than those banks that are dominant in the provision of payment, underwriting, and asset custody service are greatly affected by the substitutability category, which is consistent with the findings of this paper. Therefore, a cap of 500 has been placed on the substitutability category to the currently implemented version of G-SIBs framework. However, [9] and [8] state that they are considering the possible removal of the cap on substitutability by employing alternative methodology in the coming 3-year review cycle. What is more, as shown in [11], the

[3] In [23], the substitutability has three individual indicators as here with an equal weight of 6.67%. However, according to the newly released and updated [9], the substitutability has four individual indicators by including the trading volume. The weight for the trading volume and underwriting is 3.33% each while the weight for the other two stays the same. But this updated version will be implemented starting from 2021 based on year-end data of 2020.

Category	Individual Indicator	Indicator Weight
Size	Total Exposure	20%
Interconnectedness	Intra-financial system assets	6.67%
	Intra-financial system liabilities	6.67%
	Securities outstanding	6.67%
Substitutability	Payment activity	6.67%
	Asset under custody	6.67%
	Underwriting	6.67%
Complexity	OTC derivatives	6.67%
	Trading and available-for-sale securities	6.67%
	Level 3 assets	6.67%
Cross-jurisdictional activity	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%

Table 3.1: Individual risk categories and indicators for assessing BHCs' systemic importance: Method 1. Source: [11], [23]. Note: The summation of the individual weights is equal to one.

individual indicator score is calculated according to:

$$Indicator\,Score(bps) = \frac{Bank\,Indicator\,Value}{Sample\,Total\,Value} * 10000 \tag{3.1}$$

Once the individual indicator score is calculated, then the final individual bank score can be gained by putting the corresponding weight as in Table (3.1) and rounding the weighted score to the nearest whole basis point. Then, the banks that attended the G-SIBs assessment exercise grouped into G-SIBs and non G-SIBs according to their systemic importance scores. Those G-SIBs are further divided into five buckets and assigned the corresponding additional capital surcharges according to bucket thresholds as shown in Table (3.2). The final individual bank systemic importance score does not have to be consistent with the published bucket level of a bank by the Financial Stability Board (FSB) since national bank supervisors can adjust the final score by taking other factors into account.

Bucket	Score Range	Capital Surcharge Rate
5	530-629	3.5%
4	430-529	2.5%
3	330-429	2.0%
2	230-329	1.5%
1	130-229	1.0%

Table 3.2: Cut-off scores and capital surcharges: Method 1. Source: [9]. Note: the capital surcharge rate is the minimum higher loss absorbency (HLA) requirement and the capital here implies Common Equity Tier 1 (CET1) capital. Thus, the 1% capital surcharge for bucket 1 implies that the designated BHC has to hold 1% of its Risk-Weighted Assets (RWA) in the form of CET1 capital.

All the methodology details I discussed so far are about the internationally accepted G-SIB framework and it is simply called Method 1. However, Method 2 score should be also calculated for the banks in the U.S. that are designated as a G-SIB according to method 1 and the capital surcharge for a U.S. G-SIB is the highest of method 1 and method 2 capital surcharges. The major difference of method 2 from method 1 is that the substitutability category of method 1 is replaced by the short-term wholesale funding in method 2. Method 2 employs fixed-coefficients rather than individual weights as in method 1. However, applying the more strict method 2 for the U.S. banks is a controversial move among the U.S. banking community as they argue that this reduces the competitiveness of the U.S. banks while other non-U.S. major banks do not have to comply with the strict capital regulations as they do ([40]; [26]). For the details of the method 2 categories, indicators, and bucket thresholds, please check Table (3.5) and (3.6) in Appendix (3.7.1).

Banks that are part of the G-SIB assessment exercise report their systemic risk data at the end of each quarter. However, only the year-end or the fourth-quarter data is used to determine whether a bank is G-SIB or not and the corresponding additional capital surcharge. Therefore, there is always the possibility that a reporting bank may change or adjust its certain activities at the end of a year, which is the so-called "window dressing", to avoid being designated as a G-SIB or risk facing higher capital surcharges. Window dressing is defined as "the practice by which regulated entities adjust their activity around an anticipated reporting or disclosure date, with the objective of appearing safer or, in the case of the G-SIB framework, less systemically important to the regulator, supervisor, or market participants" in [12]. The possible window dressing behavior or patterns of banks can be observed by their systemic importance scores. However, the systemic importance score of banks can be also influenced by other factors such as the macroeconomic condition and volatility of the financial market. Besides, the individual category or indicator value's contribution to the periodic change in the final systemic importance score can vary. [13] point out that reducing the OTC derivatives in the fourth quarter of each year is the main strategy for the U.S. banks to compress their G-SIB scores.

Several evaluations suggest that G-SIBs are relatively better prepared for the 2019-2020 Covid-19 crisis than the 2008 Financial crisis. [22] report points out that G-SIBs have improved their loss-absorbing capacity in the past decade and are better capitalized this time. Claudia Buch, who is the vice president of the Deutsche Bundesbank, points out the potential effectiveness of those policy reforms regarding the TBTF banks and stresses the importance of further research to understand it according to a news report [30]. Therefore, it is important to know not only how effective bank regulation policies are, but also how banks respond to supervision policies by playing smart tricks. If banks are employing tactics like window dressing and suppressing their certain operations at certain periods in each year, this probably reduces the effectiveness of bank prudential policies and sends false signals to bank regulators, who firmly oppose it for obvious reasons. For example, [10] clearly points out that the window dressing practice of banks is not acceptable since the major objective of bank regulators is undermined by this type of unexpected practice.

The goal of this paper is to examine the possible window dressing behavior of the U.S. G-SIBs in greater detail and offering helpful insights and policy recommendations to bank supervisors regarding the effectiveness of the G-SIB framework in the U.S. Especially, at this critical moment of the Covid-19 pandemic, it is more important to assess and understand the effectiveness of G-SIB framework. Furthermore, this paper also examines the potential relationship between the bank's systemic importance score and other macro variables such as growth rate of Gross Domestic Product (GDP), repurchase agreement (repos) amount, and financial market conditions while controlling some other relevant factors and variables. Considering the possible reform of the currently implemented G-SIB framework, this paper also proposes two approaches to address the window dressing practice of the U.S. G-SIBs.

The findings of this paper are as follows. First, findings suggest the existence of window dressing practice among the U.S. G-SIBs. Second, the suppression of the category scores in the fourth quarter varies and complexity is the most reduced category among all. Third, Being close to bucket thresholds with certain degrees in the fourth quarter of previous year significantly affects systemic importance scores following year. Fourth, real macroeconomic activity, financial conditions, and repos growth rate have different significant effects on the systemic importance scores by bank or category. Fifth, U.S. bank regulators are more strict on U.S. G-SIBs by employing the additional method 2 framework, which dominates the internationally adopted method 1 framework both in scores and capital surcharges. Sixth, I propose two new approaches, which are Quarterly Average and Quarterly Maximum, to address the issue of window dressing behavior of U.S. G-SIBs. The quarterly maximum approach is more efficient and accurately targets those banks that perform window dressing by subjecting them to a higher capital surcharge.

This paper has several important contributions. First, to the best of my knowledge, this is the first paper to systematically examine window dressing behavior among U.S. banks. Therefore, it extends the literature on the window dressing practice of financial institutions or G-SIBs. Second, this paper also contributes to the literature on bank regulations and supervision in the U.S. My finding highlights that U.S. G-SIBs are being subject to more strict regulation compared to their major European counterparts in terms of the G-SIB framework because of the U.S. specific method 2. The cost of applying this tight method 2 on U.S. G-SIBs is not known yet. However, bank supervisors should balance the cost and benefit of the method 2 application in the U.S. Third, to address the highlighted window dressing behavior of U.S. G-SIBs, the new proposed approach, which is called Quarterly Maximum, manages to target those specific banks that perform window dressing with higher capital surcharges. This can force those banks to avoid window dressing and ensure the effectiveness of the G-SIBs framework.

The remainder of the paper is organized as follows. Section (3.2) discusses the related literature regarding G-SIBs and window dressing. Section (3.3) discusses the background information about the Basel and G-SIBs regulations and describes the data sources and descriptive statistics. Section (3.4) layouts the identification strategies and empirical results. Section (3.5) concludes.

3.2 Related Literature

This paper is specifically related to the literature on window dressing of the financial institutions and the regulation of the G-SIB. The window dressing of the financial institution can be a response to different types of regulatory requirements. For example, leverage ratio regulation ([10], [7]).

There is plenty of literature regarding the window dressing of banks or other financial institutions. [3] study banks' intention of engaging window dressing behavior empirically and it is first of its kind as they claim. [4] examine the effect of Basel 3 regulation on the repos market and conclude that the new regulation enhances the window dressing behavior of European repo borrowers. For more papers regarding repo market window dressing practice of the financial institutions around the world, please check [28] and [39]. However, window dressing behavior is not only limited to the repo market. [2] and [38] examine the alleged window dressing behaviors in the different types of mutual funds market. For the latest study of the window dressing behavior of banks in other markets, please check [32] and [17].

The regulation of the G-SIBs also has been an interest of recent research. [27] point out that the importance of the G-SIBs has declined in these years after empirically examining the probability of distress of those banks. [35] empirically examine the effect of G-SIB regulation on the market value of the large banks and find that new designation of a bank as G-SIB has a negative impact on the stock returns compared to other banks and may do not serve the aim of regulating TBTF banks by changing the perception of investors. [42] study the effect of G-SIB designation of a bank on its activities and find that the speed of the expansion of a bank's balance sheet is reduced for a bank that is designated as a G-SIB. The impact of Basel 3 and DFA regulation on the G-SIBs' risk-taking behavior from the pre-2008 crisis period to the post-European crisis period is examined by [36] and a significant increase in the several types of risk for the G-SIBs is observed. [41] find that the designation of a bank as G-SIB does not significantly change the value of credit rating uplifts. [29] examines whether Credit Default Swap (CDS) prices of banks that are designated as G-SIB are impacted by the change in the capital surcharge of those banks and finds that the effect is temporary. [5] study the source and funding cost differences for the G-SIBs and non G-SIBs in the U.S. by controlling firm-specific credit risk, macroeconomic factors, and conclude that moderate cost advantage in the domestic deposits and smaller cost advantages of credit spreads on senior, unsecured debt is observable for the G-SIBs.

However, there is limited literature about the window dressing behavior of the banks regarding the G-SIB regulation. [12] examine the potential window dressing behavior of the European banks participating in G-SIB reporting by employing quarterly data. Eight out of the twelve indicators are measured by using proxy variables in [12] and proxy variables for the rest indicators can not be built because of the lack of data. [12] find there is window dressing practice among those reporting banks and the effect is stronger for those reporting banks whose G-SIB scores are close to the certain bucket thresholds in the previous year. [13] study the potential channels used by the U.S. G-SIBs to adjust their systemic indicator score to lower their surcharges. [13] find that G-SIBs suppress their notional amount of over-the-counter (OTC) derivatives in the fourth quarter of each year to lower their surcharges.

3.3 Background, Data, and Descriptive Analysis

Banks are subject to many types of capital regulations. Basel is the most important and well-known international bank regulation accord. Basel 1, 2, and 3 regulations stress the importance of the international banks on financial stability and require a set of strict regulations such as minimum 8% capital to RWA ratio, supervisory review, enhanced disclosure, and enhanced minimum capital and liquidity requirement ([6]). As [6] points out, the Basel 3 regulation is introduced as a response to the Financial crisis. Under the Basel 3 regulation, international banks need to satisfy the following several types of requirements: higher minimum tier 1 capital, capital conservation buffer, countercyclical counter buffer, higher minimum CET1, Supplemental Leverage Ratio (SLR), and Liquidity Coverage Ratio (LCR) ([37]). For example, the minimum CET1 requirement is 4.5% and SLR is 3%.

Even though international banks are subject to strict regulations like Basel 3 from their respective central banks, the importance of the big international banks on the stability of the global financial system came to the spotlight during the 2008 Financial crisis. The failure of some globally important financial institutions created immense stress and panic in the financial system and the negative effect is not limited to the financial sector only. As a result, additional capital surcharges for those designated globally systemic important financial institutions have been introduced since 2011. Eight banks in the U.S. have been designated as G-SIB continuously since 2011 and they are JPMorgan Chase, Citigroup, Bank of America, Goldman Sachs, Wells Fargo, Bank of New York Mellon, Morgan Stanley and State Street. JPMorgan Chase has always been in the fourth bucket since 2012 and the only one that has kept this record ([24]). According to the [21], a total of 30 banks are identified as G-SIBs in 2019 and eight of them are the U.S. financial institutions, in which Citigroup is in the third bucket, Bank of America, Goldman Sachs, and Wells Fargo are in the second bucket, Bank of New York Mellon, Morgan Stanley, and State Street are in the first bucket. For the historical bucket identification details of those eight U.S. banks, please check the Table (3.7) in Appendix (3.7.1).

A bank's systemic importance score is affected by many factors such as macroeconomic condition and financial stability. To control the effect of noises from the potential non G-SIB regulations such as CET1 in Basel 3 and window dressing behavior in other markets like the repo market on the systemic importance score, control variables are used in the empirical analysis. Extra control variables used in [12] are the CET1 ratio, LCR, and total repurchase agreement activities. In my paper, considering the availability of data, I will control CET1 ratio and repos activity for all sample banks. To examine the impact of the real economic activity and financial market volatility on the bank's systemic importance score, the growth rate of the real GDP and the volatility index (VIX) is used to measure the macroeconomic activity and financial market conditions.

According to the Federal Reserve regulation based on the Dodd-Frank Wall Street Reform and Consumer Protection Act, BHCs that have total consolidated assets of $50 billion or more are required to submit the FR Y-15 form ([15]). The values of 13 indicators are manually gathered from the FR Y-15 form, which is publicly available on [20]. This quarterly data is from 2016Q2 to 2019Q4. What is more, the repos data is also manually gathered from the FR Y-9C form, which is also available on [20].[4] Banks that have total consolidated assets of $3 billion or more need to submit FR Y-9C form in each quarter. The real GDP data of the U.S. can be gained from the Federal Reserve Economic Data (FRED). Following [1], the Chicago Board Options Exchange (CBOE) market volatility index is used to define the VIX index. CBOE volatility index is used to measure the stock market's expectations of volatility based on the S&P 500 options. The maximum value of the daily frequency close-of-day VIX index is converted into quarterly frequency by averaging. Besides, as the indicator score expression (3.1) shows, the sample total value is needed to calculate the indicator risk scores. To keep the approach of calculating systemic indicator scores in this paper consistent with the Financial Stability Board (FSB) and Basel Committee on Banking Supervision (BCBS) methodology, the global aggregate indicator amounts for each systemic indicator, which is also called G-SIB denominators, is used to replace sample total value in the expression (3.1). The G-SIB denominator data in U.S. dollars is available at [16]. The standardized CET1 ratio and LCR are collected manually from the publicly available disclosed data of each bank.[5] The LCR data is very limited since it was implemented late. As a result, only the G-SIBs have the highest length of LCR disclosure since 2017Q2.

[4]Please note that the full name of the repos activity on FR Y-9C is "securities sold under agreements to repurchase" and the index name is B995.

[5]Please note that there are several types of CET1 ratios reported in different banks such as standardized or advanced ratio, Basel 3 transitional or fully phased-in ratio. How to measure credit risk RWA is one of the key factors that differentiate the standardized and advanced approach ([31]). In the case of both standardized and advanced ratios are reported, the standardized one is used to keep sample banks consistent with each other.

Banks	Total Assets ($000)	G-SIB	Short Names
JPMorgan	2,687,379,000	Yes	jpmorgan
Citigroup	1,951,158,000	Yes	citigroup
Bank of America	2,434,079,000	Yes	boamerica
Goldman Sachs	992,996,000	Yes	goldmansachs
Wells Fargo	1,927,555,000	Yes	wellsfargo
Bank of New York Mellon	381,508,000	Yes	bonymellon
Morgan Stanley	895,429,000	Yes	morganstanley
State Street	245,610,000	Yes	statestreet
Ally Bank	180,644,000	No	allybank
BBVA USA	93,603,606	No	bbvausa
BMO Financial	172,874,960	No	bmobank
Capital One	390,364,866	No	captitalone
Citizens Financial	166,089,890	No	citizensbank
Discover Financial	113,995,854	No	discoverbank
Fifth Third Bank	169,369,169	No	fiftythirdbank
HSBC North America	249,096,021	No	hsbcamerica
Huntington Bank	109,001,821	No	huntington
Key Bank	145,569,632	No	keybank
M&T Bank	119,872,757	No	mtbank
MUFG Americas	170,809,743	No	mufgamerica
Northern Trust	136,828,388	No	northerntrust
PNC Financial	410,373,281	No	pncfinance
Regions Financial	126,633,000	No	regions
Santander USA	149,499,477	No	santanderusa
TD Bank	408,604,662	No	tdbank
U.S. Bank	495,426,000	No	usbank

Table 3.3: Sample banks and their assets (2019). Note: the data is from [20] and for the 2019 year-end. There are a total of 26 banks in the sample. Short names are used in the graphs. As you notice from regression results in the Appendix (3.7.1), only 22 banks are used as an effective sample. Four banks that are not used because of CET1 availability are TD Bank, BMO Financial, HSBC North America, and MUFG Americas.

The threshold level of $50 billion in total assets is employed to sample the banks used in the analysis. However, considering the data availability of maximum possible length and practical reasons, data of total 26 banks are collected for the analysis. Table (3.3) displays the 26 sample banks, their assets, and their designation as G-SIB. Eight of them are G-SIBs and 18 of them are non G-SIBs, which are simply called non G-SIB reporting banks. The total asset of sample banks is $15.324 trillion. According to the total assets of all commercial banks data from the FRED, the total assets of the U.S. commercial banks is $17.755 trillion on Jan 1, 2020. Therefore, the assets of sample banks here accounts for

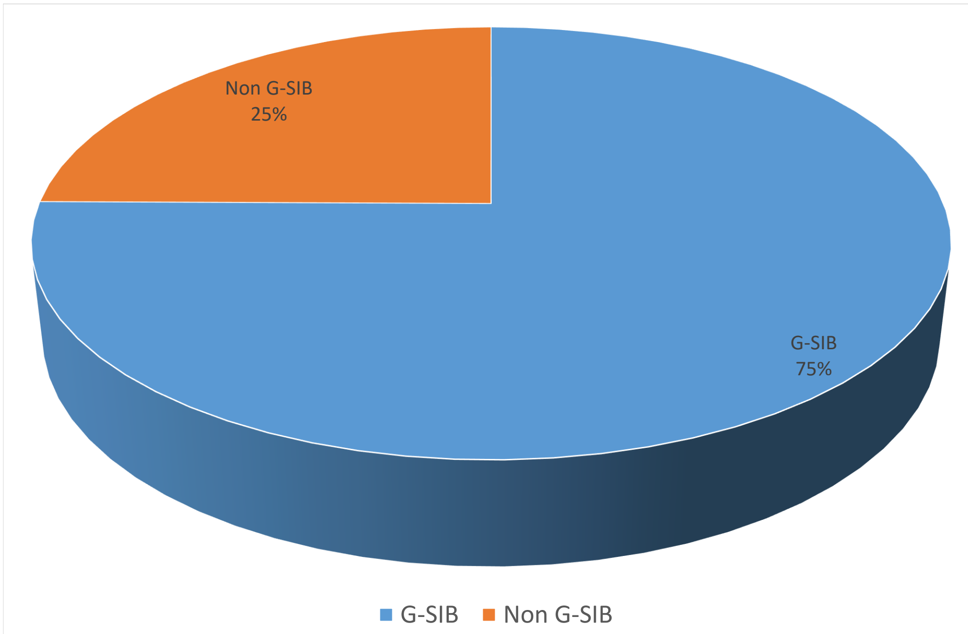

Figure 3.1: Sample banks total assets by type.

approximately 86.3% of the U.S. total bank assets. What is more, the pie chart (3.1) shows the asset distribution among sample banks by bank type. The eight G-SIBs have total assets of $11.515 trillion and it accounts for approximately 75% of the total assets of all sample banks.

Table (3.4) displays the summary statistics of the 12 indicators and 5 categories for the 26 sample banks in Table (3.3). The substitutability cap of 500 is already employed. According to the mean values of indicator scores, the assets under custody score is the largest while the cross-jurisdictional claims has the smallest scores. However, the standard deviation of the assets under custody indicator is the highest. As I observed during data

Risk Indicators	Mean	SD	Min	Max	Mean Category Score		
					All	G-SIB	Non G-SIB
Size					82.87	207.38	27.53
Total Exposures	82.87	2.62	79.06	86.52			
Interconnectedness					28.71	231.52	21.50
Intra-financial assets	81.46	2.05	78.19	84.61			
Intra-financial liabilities	69.78	3.40	64.92	76.54			
Substitutability					63.02	389.50	27.62
Payments	157.21	6.20	146.65	166.92			
Assets under custody	259.99	12.23	245.30	285.72			
Underwriting	150	7.30	132.44	160.56			
Complexity					41.29	358.54	18.69
OTC derivatives	143.05	9.85	125.87	156.15			
Trading and AFS securities	127.56	8.76	115.10	140.19			
Level 3 assets	100.62	8.36	86.72	113.78			
Cross-Jurisdictional Activity					31.60	195.12	4.58
Cross-jurisdictional claims	60.91	2.10	57.13	64.33			
Cross-jurisdictional liabilities	65.51	2.88	62.24	72.20			

Table 3.4: Indicator and category score summary. Note: This table displays basic summary statistics of the systemic indicator scores and category scores for 26 sample banks for a period of 2016Q2-2019Q4. The 500 cap of substitutability is already applied. The mean category score is the average value of importance scores by category for different bank type. Risk indicators are the row scores of each 12 systemic indicators before applying any weights. SD , Min, and Max stand for the standard deviation, minimum, and maximum.

analysis, several G-SIBs such as JPMorgan, Citigroup, State Street, and Bank of New York Mellon have benefited from the substitutability cap, which is in line with the observation of [25] and [23]. When it comes to the average score of systemic importance by category, it is apparent and expected that G -SIBs dominate non G-SIBs in every category.

Figure (3.3) shows the quarterly differences in the systemic importance score of effective sample banks. It is easy to observe that there is a potential window dressing behavior among the U.S. G-SIBs. However, it needs more quantitative analysis and conclusive evidence to build a solid link between the G-SIB framework and window dressing practice. When it comes to non G-SIB U.S. banks in the sample, no persistent pattern of window dressing is observed. The Northern Trust Bank displays certain window dressing patterns for the year of 2016 and 2017. However, this pattern disappears in the coming years. Figure (3.5) in Appendix (3.7.1) shows the method 1 scores of effective sample banks. What is more, Figure (3.4) in Appendix (3.7.1) shows the average systemic importance score of banks by five major categories and bank type. It seems there is potential window dressing in some specific categories for G-SIBs. But it is not clear. Figure (3.2) displays the quarterly difference in systemic importance scores by category and bank type. It is obvious that there are changes in scores in any category for the G-SIBs in the fourth quarter of each year. However, the variance and adjustment of score in the fourth quarter of each year is more pronounced for the complexity category. The decrease of the complexity scores at the year-end in the past three years strongly suggests window dressing practice of G-SIBs in complexity. Other categories of the G-SIB also show some degree of adjustment of scores

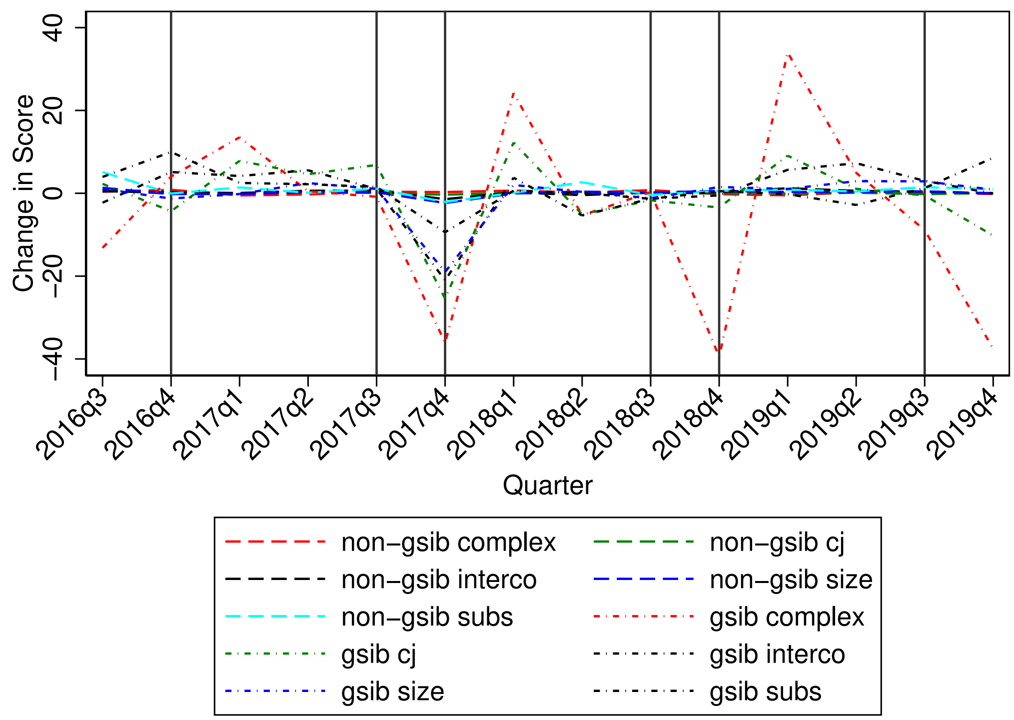

Figure 3.2: Quarterly differences in the average importance score of five categories by bank type. Note: Non-gsib = Non G-SIB, gsib=G-SIB, complex=complexity, interco=interconnectedness, subs=substitutability, cj=cross-jurisdictional activity. 26 sample banks are used.

in the fourth quarter in certain years. However, It is not as strong and persistent as the complexity.

Window dressing patterns by banks and categories are present in the figures above. However, conclusive evidence is necessary to draw a strong conclusion regarding the window dressing behavior of G-SIBs rather than just a simple descriptive analysis. As it is mentioned earlier, banks are required to follow more than just G-SIB regulations and it is possible that the year-end window dressing pattern I observed here is related to other different regulations or simply a random quarterly pattern. Including banks that are not required to report their

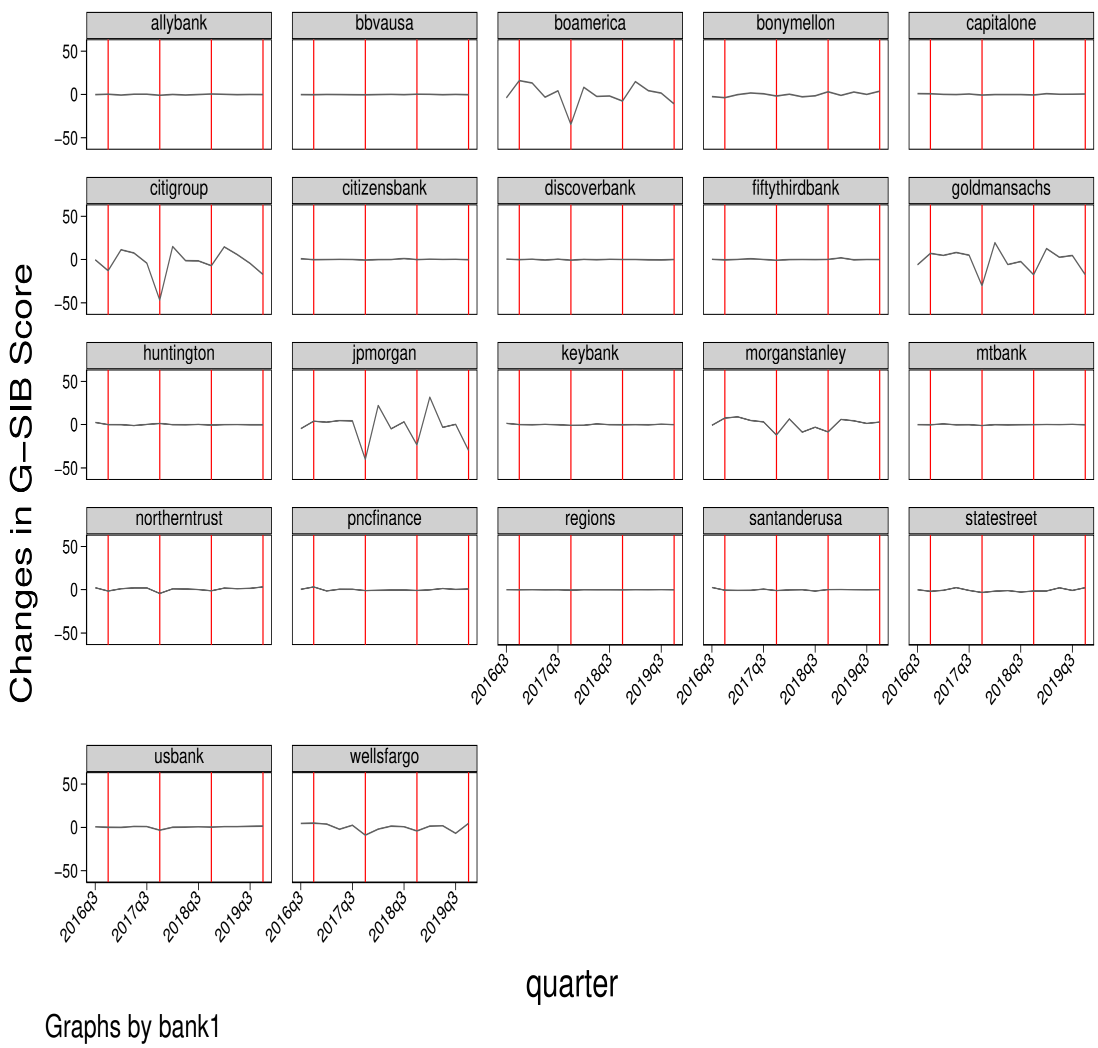

Figure 3.3: Quarterly differences in bank's systemic importance scores. Note: The period of the scores is 20163-2019Q4. The red vertical line describes the fourth quarter of the year 2016, 2017, 2018, and 2019.

FR Y-15 can improve the quality of the analysis. However, the data for those non-reporting banks is not publicly available.

3.4 Identification and Empirical Results

In this section, I will explore whether G-SIBs in the U.S. are induced to adjust their certain activities at the year-end to avoid higher capital surcharges under the currently implemented G-SIB framework by using compiled data from the reporting banks. Whether the incentive for window dressing varies according to the closeness of their previous year-end score to bucket thresholds is also examined. Besides, The potential relationship between the window dressing practice and other variables such as macroeconomic activity and financial conditions is also studied. Simple linear regression method is used for the analysis. I follow the identification strategy of [12] to examine the window dressing practice of the U.S. G-SIBs.

3.4.1 Identification Methodology

To identify the reduction of G-SIB scores at the fourth quarter of each year compared to the other three quarters, I use the following specification:

$$\Delta Score_{i,t} = \alpha_i + \alpha_{year} + \beta_1 . [Q_4 \times GSIB_i] + \Gamma^{'} V_{i,t} + \epsilon_{i,t} \tag{3.2}$$

where $\Delta Score_{i,t}$ is the quarterly differences in systemic importance scores of bank i between the current quarter t and the previous quarter $t-1$ ($\Delta Score_{i,t}$ is also the quarterly differences of the systemic importance scores of each category when the window dressing pattern of five categories are examined). The α_i and α_{year} are the bank fixed effects and year fixed effects, which are used to control bank and time specific impacts on the results. Q_4 is a dummy variable, which is equal to 1 if it is the fourth quarter of a year and zero otherwise.[6] $GSIB_i$ is a bank dummy variable, which is equal to one if the bank is one of the eight designated G-SIBs as shown in the Table (3.3). V is a set of control variables that include CET1 ratio and total repurchase agreements amount. $\epsilon_{i,t}$ is the standard error of the regression and checked for robustness.

What is more, there is always the possibility that those banks whose systemic importance score in the fourth quarter of previous year is near to any bucket threshold levels have relatively strong incentives to adjust their operations in the following year or at the end of the following year to avoid higher capital surcharges. Therefore, to identify such effect of closeness to the bucket threshold levels, the following linear model is estimated:

$$\Delta Score_{i,t} = \alpha_i + \alpha_{year} + \beta_1[GSIB_i \times Close_{i,t-4}] + \beta_2 Close_{i,t-4} + \Gamma' V_{i,t} + \epsilon_{i,t} \tag{3.3}$$

where $close_{i,t-4}$ is a dummy variable that is equal to one if the systemic importance score of a bank i in the fourth quarter of the previous year is within a certain range of bucket threshold levels. The closeness of 10, 20, and 30 around thresholds are examined. Since the sample size is relatively small, the closeness of being above or below threshold levels is not examined separately. To identify whether banks that are designated as G-SIB have a stronger incentive to adjust their activity if their fourth quarter score of previous year

[6] Note that Q_4 is the same as $Q_{4,t}$.

is close to certain threshold levels, the interaction between G-SIBs and Closeness is also examined in the specification (3.3).

To lower their surcharge capital requirement, banks have the choice of adjusting some of their operations to suppress scores of certain categories or indicators. Not all bank operations can be scaled down in the short run. For example, [13] point out that OTC derivatives, one of 12 indicators, is significantly reduced by 13.4% for the U.S. G-SIBs compared to non G-SIBs. Besides, it is also possible that the window dressing behavior of G-SIBs is driven by other operations that show similar patterns in the fourth quarter of a year. As I discussed earlier in section (3.2), there is a window dressing practice in repos and mutual fund markets. Repos, also called overnight repurchase agreements, is a short-term borrowing agreements between financial institutions. As [12] point out, size, interconnectedness, and cross-jurisdictional indicators of G-SIB framework can be affected by the repos because of its inter-bank character in the global capital market. I examine the possible contribution or the effect of repos on the window dressing behavior among the sample banks by estimating the following specification:

$$\Delta Score_{i,t} = \alpha_i + \alpha_{year} + \beta_1 ReposGR_{i,t} + \beta_2[Q_4 \times ReposGR_{i,t}] + \Gamma' V_{i,t} + \epsilon_{i,t} \qquad (3.4)$$

where $ReposGR_{i,t}$ is the net growth rate of repos activity of a bank i between time t and $t-1$. The interactive term of fourth quarter and repos growth rate captures the potential window dressing effect of repos on all sample banks.[7] However, It is possible that window

[7]The net growth rate of repos is used in this paper rather than the logarithm of a bank's total repo activity as used by [12] Since some of the sample banks in this paper have zero repos activity and it reduces the effective sample size if logarithm is adopted for the repos. Therefore, the growth rate of repos is used instead. Please note that $V_{i,t}$ in eq (3.4) and (3.5) is a vector of CET1 only.

dressing pattern of repos of G-SIBs is different from non G-SIBs and its impact on the systemic importance is probably stronger and significant than non G-SIBs. To distinguish the effect of repos growth rate of G-SBIs and non G-SIBs on the quarterly differences of systemic importance scores, the following specification is estimated:

$$\begin{aligned}\Delta Score_{i,t} = \alpha_i + \alpha_{year} + \beta_1 ReposGR_{i,t} + \beta_2[Q_4 \times ReposGR_{i,t}] + \beta_3[Q_4 \times GSIB_i] \\ +\beta_4[GSIB_i \times ReposGR_{i,t}] + \beta_5[Q_4 \times GSIB_i \times ReposGR_{i,t}] + \Gamma^{'} V_{i,t} + \epsilon_{i,t}\end{aligned} \tag{3.5}$$

What is more, the impact of the real macroeconomic activity on the systemic importance score of the sample banks by their types are also examined by using the following specification:

$$\begin{aligned}\Delta Score_{i,t} = \alpha_i + \alpha_{year} + \beta_1 RgdpGR_t + \beta_2[Q_4 \times GSIB_i] + \beta_3[GSIB_i \times RgdpGR_t] + \\ \beta_4[Q_4 \times RgdpGR_t] + \beta_5[Q_t \times GSIB_i \times RgdpGR_t] + \Gamma^{`} V_{i,t} + \epsilon_{i,t}\end{aligned} \tag{3.6}$$

where $RgdpGR_t$ represents the net growth rate of the real GDP at time t. In the specification (3.6), the impact of triple interaction between the real GDP growth rate, fourth quarter dummy variable, and bank type dummy variable on the possible window dressing pattern on the systemic importance scores of banks is also examined. Because I am interested in whether G-SIBs respond to the variation in the macroeconomic activity at the year-end differently from non G-SIBs or the previous three quarters. What is more, BHCs are financial institutions that offer a large variety of services or products to customers. Therefore, the possibility of G-SIB score is impacted or driven by the volatility in the financial market can not be simply ruled out. The impact of the financial market condition on the systemic importance score is examined by using the following specification:[8]

$$\Delta Score_{i,t} = \alpha_i + \alpha_{year} + \beta_1 VIX_t + \beta_2[Q_4 \times GSIB_i] + \beta_3[GSIB_i \times VIX_t] + \beta_4[Q_4 \times VIX_t] + \beta_5[Q_t \times GSIB_i \times VIX_t] + \Gamma^{`} V_{i,t} + \epsilon_{i,t} \tag{3.7}$$

where VIX_t is the volatility index at time t. The dummy variables of Q_4, $GSIB_i$, and their interactions with the VIX_t are also included in the specification (3.7) to control possible noises from those variables to get a higher quality estimate of β_1.

3.4.2 Empirical Results

In this section, the results of the analysis by banks and category are presented. Besides, the results of the method 2 score analysis of eight U.S. G-SIBs are also discussed.

Method 1 Score Analysis

Table (3.8) and (3.16) display the regression results of the specification (3.2) by bank and category by using scores gained by method 1. Table (3.8) suggests that G-SIB banks conduct window dressing to avoid higher capital surcharge at the end of a year. Because the coefficient estimates of interaction between the fourth quarter and G-SIB bank type are negative and statistically significant at the 1% level for all four columns, which implies that the effect is robust to the inclusion of time and bank fixed effects. One unexpected interesting finding is that the yearly effect is significant for 2017 and 2018. Besides, the coefficient estimate of 2017, 2018, and 2019 are decreasing in absolute values. This may

[8] Even if LCR is not part of the control variable $V_{i,t}$ in all specifications here because of a relatively short period of availability, I attached the LCR figure for observation in the Appendix.

indicate that banks have been gradually improving their ability to follow this new G-SIB regulation over the years. The flexibility of adjusting certain categories is more limited than others. To further examine possible window dressing in certain categories, the specification (3.2) is re-estimated with category scores. The results in Table (3.16) show that not all the categories behave in the same pattern. The coefficient estimate of $Q_4 * GSIBS$ for the substitutability is positive and not statistically significant while the rest have negative coefficient estimates and statistically significant.[9] The coefficient estimate of G-SIBs at the fourth quarter for the complexity is -31.50 and is statistically significant at the level of 1%. The window dressing behavior of G-SIBs in the complexity category is strongest among all five categories. The significant window dressing practice of G-SIBs in the complexity category is in line with the findings of [13], in which they find that OTC derivatives indicator of the category of complexity is significantly reduced at the end of a year for G-SIBs. It is highly possible that the significant reduction in the complexity score of G-SIBs in the fourth quarter of a year is solely driven by the OTC derivatives indicator score.

To further examine whether the window dressing behavior among the U.S. G-SIBs is driven by particular banks or all of them, I re-estimate the specification (3.2) for eight individual U.S. banks.[10] Table (3.25) shows the results of the analysis. Among those eight banks, JPMorgan Chase and Goldman Sachs show window dressing behaviors and coefficient estimates are statistically significant at the 1% level while Bank of America is statistically significant at the 10% level. In terms of the degree of window dressing practice,

[9]If the cap of 500 on the substitutability is not applied, it is possible that the coefficient estimate of substitutability is negative and statistically significant. As I mentioned earlier, several G-SIBs exclusively benefited from this cap.

[10]Since all the eight U.S. banks used here are the G-SIBs. Therefore, no need to use the dummy variable of GSIB and its interaction with the fourth quarter dummy variable as in the specification (3.2).

the coefficient estimate of JPMorgan is the most pronounced. However, State Street and Bank of New York Mellon have positive coefficient estimates, which imply they rather increase their systemic importance score in the fourth quarter of a year. Overall, the results illustrate that not all the U.S. G-SIBs perform window dressing and the window dressing of the U.S. G-SIBs is mainly driven by several specific banks.

Table (3.11) and (3.19) show the regression results of the specification (3.3) by employing bank and category systemic importance scores. In Table (3.11), the coefficient estimates of Close, which is equal to one if the systemic importance score in the fourth quarter of previous year is 10 points below or above bucket thresholds, are all statistically significant and robust to the inclusion of time and bank fixed effects. Being 10 points around bucket thresholds in the previous year-end induces banks to significantly reduce their systemic importance scores by 9.66. Table (3.19) shows the results of the category score analysis. Only the coefficient estimates of complexity and cross-jurisdictional activity are statistically significant. The coefficient estimate of complexity is -42.71 and is statistically significant at the 1% level. This suggests that banks have the strongest incentive to significantly suppress their complexity scores if they were being 10 points close to the bucket thresholds in the previous year-end. What is more, G-SIBs reduce their interconnectedness and size scores significantly. The results confirm that banks, whose systemic important scores were too near to bucket thresholds in the previous year-end, suppress their scores following year and the complexity category is the main target.

Table (3.12) and (3.20) show the analysis of specification (3.3) by using bank can category systemic importance scores. Close is a dummy variable that measures whether the systemic importance score in the previous fourth quarter is 20 points around the different bucket thresholds or not. Table (3.12) results confirm the possible link between the 20 points closeness to bucket thresholds in the previous fourth quarter and the systemic importance score repression in the following year. The coefficient estimate of the Close in column (4) is -9.56 and is statistically significant at the 1% level. The results in Table (3.20) show that size, cross-jurisdictional activity, and complexity are significantly sensitive to banks' systemic importance score in the fourth quarter of previous year being 20 points close to bucket thresholds. Compared with other columns, the complexity column displays that banks suppress their complexity scores more than others if their year-end score in previous year is 20 points around the bucket thresholds. However, the coefficient estimate of Close for complexity is smaller than the same coefficient in the Table (3.19) and the difference is around 10, which indicates that the being relatively closer to the threshold buckets in the fourth quarter of previous year drive banks to suppress their complexity category scores more.

To further analyze the effect of a bank's systemic importance score in the fourth quarter of previous year being 30 points around bucket thresholds on bank score following year, I will re-estimate the specification (3.3) with Close having the same meaning as before but with 30 points around the thresholds. The results in Table (3.13) show that being "Close" to the bucket thresholds significantly induces banks to suppress their scores in the following year. However, compared with results in column (4) in Table (3.11) and (3.12), of which coefficient estimates of the Close are -9.66 and -9.56, the coefficient estimate of Close here does not differ dramatically. But it is worth pointing out that the response of the banks in the following year does not show a clear increasing or decreasing trend as the distance to bucket thresholds in the fourth quarter of previous year goes up from 10 to 30, which contradicts the common perception that the response of banks grow weaker as the distance goes up.[11] Table (3.21) presents the results of employing category scores. The coefficient estimates are statistically significant only for complexity, cross-jurisdictional activity, and size categories. Comparing results in Table (3.19), (3.20), and (3.21), it is easy to observe that the response of complexity and cross-jurisdictional activity categories to being close to bucket thresholds in the previous fourth quarter is always statistically significant. Besides, the coefficient estimates of the Close for the complexity category are -42.71, -32.47, and -30.15, which shows a clear decreasing trend in terms of absolute value. In addition, the degree of suppression of complexity score in the following year in response to being close to the bucket thresholds in the previous fourth quarter dominates all other four categories.

To examine other possible sources of window dressing behavior of G-SIBs, I analyze the specification (3.4) and (3.5) by employing bank and category scores. Table (3.14) and (3.15) shows the results for banks score data. As I mentioned earlier, there is a window dressing in the repos market around the reporting date to adjust the balance sheet. The results in Table (3.14) indicate that the growth rate of repos does have a negative effect on the quarterly differences in G-SIB scores but the effect is not statistically significant for all sample banks used. However, column (4) of Table (3.15) shows that the coefficient estimate of interaction between G-SIB and repos growth rate is 11.98 and is statistically significant at the 10% level. The unexpected finding here is the positive sign of this coefficient estimate of 11.98. It suggests that banks are likely not to adjust repos transactions at the year-end to

[11] Coefficient estimates of Close in the column (4) of Table (3.11), (3.12), and (3.13) are compared.

suppress their systemic importance scores. The repos growth rate and quarterly differences in systemic importance scores of the sample banks may be unrelated as repos are used by banks to satisfy other bank regulations such as leverage ratio at the end of the reporting date. Table (3.22) and (3.23) display results of analysis by category score. Complexity, cross-jurisdictional activity, and substitutability are significantly affected by the repo growth rate at the fourth quarter for all sample banks. However, the significance disappears if the G-SIBs dummy variable is also included in the analysis. Only the interconnectedness of G-SIBs in the fourth quarter responds to the repos growth rate significantly and the coefficient estimate is -24.74. The repos are conducted between two financial institutions. Therefore, it suggests that G-SIBs suppress their interconnectedness score in the fourth quarter by adjusting their repos transactions significantly. But I can not confirm whether this relationship is the result of intended actions of G-SIBs under G-SIB regulation framework or is just an unexpected relationship caused by actions taken for other purposes.

Table (3.9) shows the regression results of the specification (3.6). The coefficient estimate, which is in column (4), of the interaction between real GDP growth rate, fourth quarter, and G-SIBs is -2410.19 and it is statistically significant at the 10% level. After controlling other variables, real GDP growth rate has a significant positive impact on the quarterly differences of G-SIB scores for all sample banks as shown in column (4). Therefore, it suggests banks generally increase their G-SIB scores when the economic conditions improve. But G-SIBs manage to reduce their systemic importance score significantly in the fourth quarter of a year when the real economy grows. This is probably driven by the strong incentive for G-SIBs to benefit from a growing economy to maximize their profit while avoiding higher capital surcharges. Table (3.17) shows the results of the analysis by using quarterly differences in category scores. The specification (3.2) with linear addition of real GDP growth rate is used. The macroeconomic condition has a significant negative effect on quarterly differences of all category scores except complexity for all sample banks. The coefficient estimate of real GDP for the complexity is 675.89, which suggests banks increase their complexity scores when the economy grows.

I further examine the impact of financial conditions on the quarterly differences in G-SIB scores by using specification (3.7). Results in Table (3.10) indicate that G-SIBs significantly increase their systemic importance scores if the financial market gets more volatile. This is possibly because of the decreasing room for the banks to adjust their certain types of activities as banks shift their priorities from suppressing G-SIB scores to deal with the worsening financial conditions. Table (3.18) shows the results of analysis by employing category scores with a similar specification for Table (3.17). The results indicate that financial market conditions have a significant positive impact on the quarterly differences of all category scores except substitutability.

Method 2 Score Analysis

Considering the data availability of short-term wholesale funding metrics for the maximum possible length of period, I will use the eight U.S. G-SIBs as a sample for the method 2 analysis. Figure (3.9) and (3.11) graph the systemic importance scores measured by using method 2 and their quarterly differences for eight U.S.banks. It can be observed from the figures that not all the U.S. G-SIBs show the pattern of window dressing. However, possible window dressing patterns are relatively stronger for the banks with higher total consolidated assets. To examine the possible window dressing behavior of the eight U.S. banks, I use the method 2 systemic importance scores and apply it to the specification (3.2). The results in Table (3.24) confirm that not all the U.S. G-SIBs adjust certain activities to suppress the method 2 scores. The coefficient estimates of the fourth quarter for the Bank of America, Citigroup, Goldman Sachs, and JPMorgan are -29.44, -32.10, -36.89, and -53.84 and they are all statistically significant at the 1% level. JPMorgan has the highest total consolidated assets among the eight U.S. G-SIBs. Comparing absolute values of estimated coefficients, JPMorgan also suppresses its method 2 scores in the fourth quarter by the biggest amount. However, in general, It seems that the degree of suppression of the systemic importance score in the fourth quarter of a year is not related to the total assets of a bank. Replacing substitutability in method 1 with short-term wholesale funding is the major difference between method 1 and method 2. It is also very likely that the short-term wholesale funding ratio is significantly suppressed at the year-end. [27] find that the wholesale funding ratio of the U.S. G-SIBs has declined more than Euro G-SIBs for the post-2012 period. Because of limited data availability, method 2 score analysis by category is left for future research.

Figure (3.13) shows that method 2 scores always dominate the method 1 scores for the eight U.S. G-SIBs. What is more, Figure (3.12) shows the assigned capital surcharges for the eight U.S. G-SIBs according to the bucket thresholds described in Table (3.2) and (3.6).[12] It is very obvious that method 2 capital surcharges always dominate method 1 capital

[12]Please note that the assigned capital surcharges in this paper are probably different from the final list released by BIS or Federal Reserve as shown in Table (3.7). It is probably because central banks have the authority to adjust the final capital surcharge if they see it necessary by taking other factors into account.

surcharges for all banks except for the State Street Bank.[13] This finding has important implications for policymakers and bankers. [34] find that the market treats the G-SIB designation of a bank as “good” news while the capital surcharge followed is not and this phenomenon is particularly driven by the Eurozone banks. Banking community in the U.S. has been complaining about the adoption of the extra method 2 for the U.S. banks and they argue that this will reduce the competitiveness of the U.S. international banks compared to their European counterparts.[14] My analysis here proves that U.S. banks suffer higher capital surcharges under Federal Reserve’s extra strict regulation than under international standard one, which is method 1. This reduces the amount of capital available that banks can use to invest or lend. Furthermore, this reduces their profit and competitiveness as fewer resources are available for banks to conduct their profitable operations. Since the U.S. is the financial center of the world and experienced the 2008 Financial crisis, during which the importance of big major international institutions on global financial stability is highlighted, It is reasonable to assume that strict regulations are necessary from the perspective of regulators. But, what is the cost of this? As [27] point out that the systemic importance of the G-SIBs has declined in the past several years, is it time to relax the strict G-SIB regulation for the U.S. international banks? It seems U.S. bank regulators prioritize financial stability more than the performance and competitiveness of U.S. international banks at this moment. However, the trade-off between the benefit of strict regulation of the U.S. G-SIBs and the cost U.S. G-SIBs endures should be measured accurately to make sure that the method 2 application does not discriminate against U.S. international banks.

[13] Please note that State Street has the lowest total consolidated asset among the eight U.S. G-SIBs as shown in Table (3.3).

[14] Please note that the highest capital surcharge among the method 1 and method 2 surcharges is assigned to the U.S. G-SIBs.

New Approach Proposal

Previous results suggest the existence of window dressing practice among the U.S. G-SIBs. Then, how can we discourage banks from conducting window dressing and achieve the goal of the bank regulators at the same time? I propose to assign capital surcharges according to the quarterly average systemic importance score in a year and simply call it the "Quarterly Average" approach. Figure (3.14) and (3.15) show the quarterly average scores and capital surcharges by method 1 and method 2. Even for the quarterly average approach, method 2 score dominates method 1 score for each U.S. G-SIB. However, when it comes to the capital surcharge, method 2 dominates method 1 for all banks except for the State Street Bank, which is consistent with the year-end approach findings from the Figure (3.12). Figure (3.16) and (3.17) describes the comparison of the G-SIB scores implied by the newly proposed quarterly average approach with the approach currently in effect, which is the year-end approach. It is hard to observe any significant difference between the two approaches. Figure (3.18) and (3.19) show the comparison of capital surcharge assignment under the two different approaches for the two different methods. For method 1, the quarterly average approach only affects the capital surcharge of Bank of American for the year 2017 and 2018. However, the effect is more obvious for method 2. Both Goldman Sachs and JPMorgan have to face higher capital surcharges in certain years under the new quarterly average approach. The highest surcharge among method 1 and 2 matters. Figure (3.20) shows the results of the maximum capital surcharge under the quarterly average and year-end approaches. Only Goldman Sachs and JPMorgan are affected by the newly proposed quarterly average approach by being subjected to higher capital surcharges than the year-end approach in certain years of the past three years. According to regression results shown in Table (3.24) and (3.25), both JPMorgan and Goldman Sachs significantly repress their G-SIB scores at the fourth quarter of a year and the absolute value of coefficient estimates are the highest compared to other banks both under method 1 and method 2. Therefore, it is not surprising to find out that both Goldman Sachs and JPMorgan are affected by the quarterly average approach.

If the U.S. regulators seek to address the issue of window dressing of the U.S. G-SIBs by exclusively subjecting window dressing banks to even higher additional capital surcharges, the quarterly average approach is not satisfying. Therefore, I propose another new approach to assign capital surcharge based on the quarterly maximum G-SIB score in a year.[15] This new approach is simply called the "Quarterly Maximum" approach. Figure (3.21) and (3.22) show the systemic importance scores under the quarterly maximum and year-end approaches. The slight score differences can be observed for both method 1 and method 2 for certain banks and years. However, it is not significant enough. Figure (3.23) and (3.24) describe assigned capital surcharges under two different approaches. For method 1, the quarterly maximum approach only affects Bank of America and Morgan Stanley. However, more banks are affected by this quarterly maximum approach when it comes to method 2. Figure (3.25) shows the highest capital surcharges based on method 1 and method 2 scores under two different approaches. Bank of America, Citigroup, Goldman Sachs, and JPMorgan would have been affected by the quarterly maximum approach and end up being subject to higher capital surcharges in certain years or all past three years

[15] Quarterly maximum score of a year for both method 1 and method 2 is taken and corresponding capital surcharges are assigned. Then according to the principle of highest surcharge matters, the highest of the two surcharges under the quarterly maximum approaches are applied to banks.

if this approach was adopted. As Table (3.24) and (3.25) describe, Bank of America, Citigroup, Goldman Sachs, and JPMorgan are the four banks that perform window dressing at different significant levels according to the method 2 scores while three of them except the Citigroup do the same for method 1. Besides, we already find out that method 2 scores and surcharges dominate method 1 for nearly all the U.S. G-SIBs. Therefore, if bank regulators want to discourage even stopping current U.S G-SIBs from performing window dressing, then it is a wise move for them to adopt the quarterly maximum approach to assign the annual capital surcharges for the potential future U.S. G-SIBs. Comparing the quarterly maximum approach with the year-end approach and quarterly average approach, the quarterly maximum approach triumphs the other two approaches in terms of achieving financial stability and making international big banks more resilient in case of a new financial crisis.

3.5 Conclusion

This paper investigates the possible window dressing behavior of the U.S. G-SIBs. FR Y-15 and FR Y-9C forms that report the systemic importance and total repos activity data of individual BHC are available on [20]. Other bank characteristic data are manually compiled from the publicly available data disclosure of BHCs on their official websites. The frequency of the data is quarterly and the period is 2016Q2-2019Q4. There are a total of 26 U.S. sample banks and 22 of them are used for the analysis. I present robust evidence to suggest that there is window dressing behavior among the U.S. G-SIBs and it varies among those banks.

Using OLS regression, I show that U.S. G-SIBs repress certain of their operations or activities in the fourth quarter of a year to avoid higher capital surcharge assigned by regulators according to the systemic importance score gained by using method 1. Besides, I also show that the complexity category is significantly reduced more than other categories in the fourth quarter of a year and this finding is consistent with the previous literature. Furthermore, I also find that being close to bucket thresholds with certain degrees in the previous year-end has a significant effect on the systemic importance scores following year. Besides, the effect of real macroeconomic activity and financial condition on the systemic importance score varies. Another important finding is that both method 2 surcharge and scores dominate the corresponding variables for method 1. I also present the evidence that not all the U.S. G-SIBs practice window dressing and the window dressing behavior of U.S. G-SIBs is driven by several of them.

Considering the ongoing discussion of reforming the G-SIB regulation in the U.S, I proposed two new approaches, which are Quarterly Average and Quarterly Maximum, to assign annual additional capital surcharges. The quarterly maximum approach punishes those banks currently conducting window dressing by subjecting them to higher capital surcharges. Therefore, this is a useful approach for policymakers to address the window dressing issues of the U.S. G-SIBs and ensure that the G-SIB framework achieves its initial goal of financial stability. This study makes significant contributions in studying the existence of window dressing behavior among the U.S. G-SIBs and analyzing the effectiveness of the G-SIB framework. The findings of this paper are relevant to U.S. financial institutions and have important implications for policymakers and bank supervisors. My analysis suggests that U.S. bank regulators need to balance the cost and benefit of applying more strict method 2 to U.S.banks and avoid discriminating against U.S. banks by overly prioritizing financial stability.

The size of the bank sample in this paper is relatively small given data availability and the results presented here could vary if bigger sample size is used. What is more, investigating the differences in window dressing behavior among different countries with rich data is a promising avenue for future research. Or Investigating the window dressing behavior of the U.S. BHCs with a higher frequency of data such as monthly is another direction for future research.

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3.7 Appendix

3.7.1 Appendix A: Background Information and Method 1 Score Regression Analysis

Category	Individual Indicator	Coefficient Value
Size	Total Exposure	4.423%
Interconnectedness	Intra-financial system assets	12.007%
	Intra-financial system liabilities	12.490%
	Securities outstanding	9.056%
Short-term wholesale funding	Short-term wholesale funding metric	3.5
Complexity	OTC derivatives	0.155%
	Trading and available-for-sale securities	30.169%
	Level 3 assets	161.177%
Cross-jurisdictional activity	Cross-jurisdictional claims	9.277%
	Cross-jurisdictional liabilities	9.926%

Table 3.5: Category, individual indicator and weights for assessing BHC systemic importance: Method 2. Source:[33], [19], and [18]. Note: The short-term wholesale funding metric is the ratio of total short-term wholesale funding to the average risk-weighted assets. The data of the metric reported in FR Y-15 is already in percentage.

Score Range	Capital Surcharge Rate
1030-1129	5.5%
930 - 1029	5.0%
830 - 929	4.5%
730 - 829	4.0 %
630 - 729	3.5%
530 - 629	3.0%
430 - 529	2.5%
330 - 429	2.0 %
230 - 329	1.5%
130 - 229	1.0%

Table 3.6: Cut-off scores and capital surcharges: Method 2. Source: [19], [18], and [33].

Banks	2012	2013	2014	2015	2016	2017	2018	2019
JP Morgan	4	4	4	4	4	4	4	4
Citigroup	4	3	3	3	4	3	3	3
Bank of America	2	2	2	2	3	3	2	2
Goldman Sachs	2	2	2	2	2	2	2	2
Wells Fargo	1	1	1	1	2	2	2	2
New York Mellon	2	1	1	1	1	1	1	1
Morgan Stanley	2	2	2	2	1	1	1	1
State Street	1	1	1	1	1	1	1	1

Table 3.7: U.S. G-SIBs historical bucket category. Note: The data is available on [24]. The first time list of 2011 is not categorized by buckets.

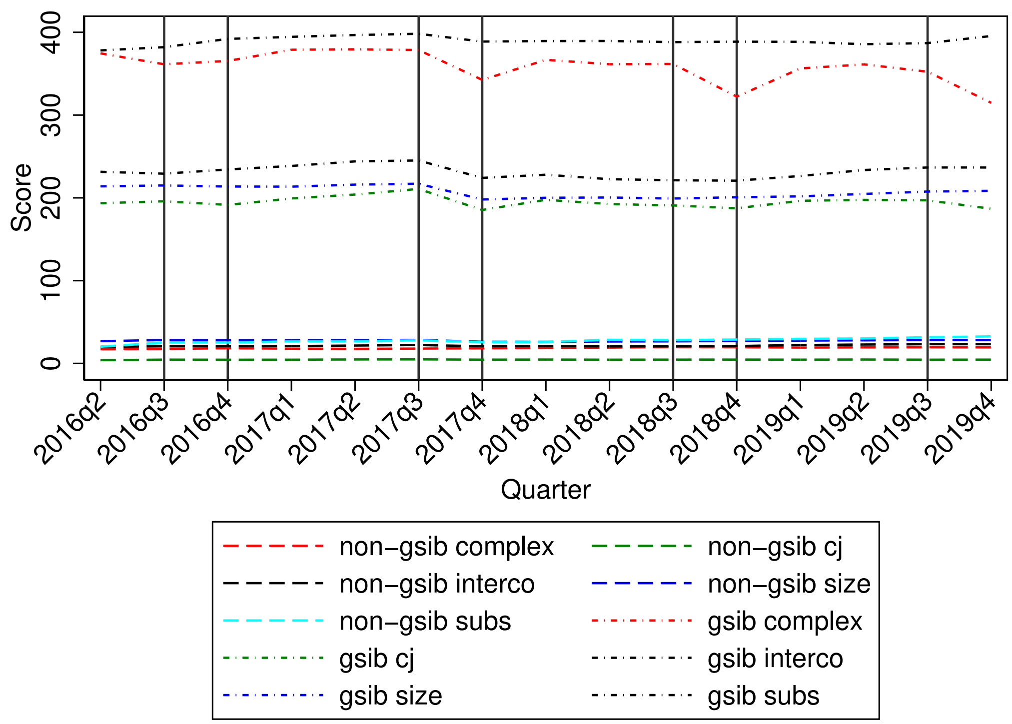

Figure 3.4: Average importance score of five categories by bank type. Note: Non-gsib = Non G-SIB, gsib=G-SIB, complex=complexity, interco=interconnectedness, subs=substitutability, cj=cross jurisdictional activity. 26 sample banks are used.

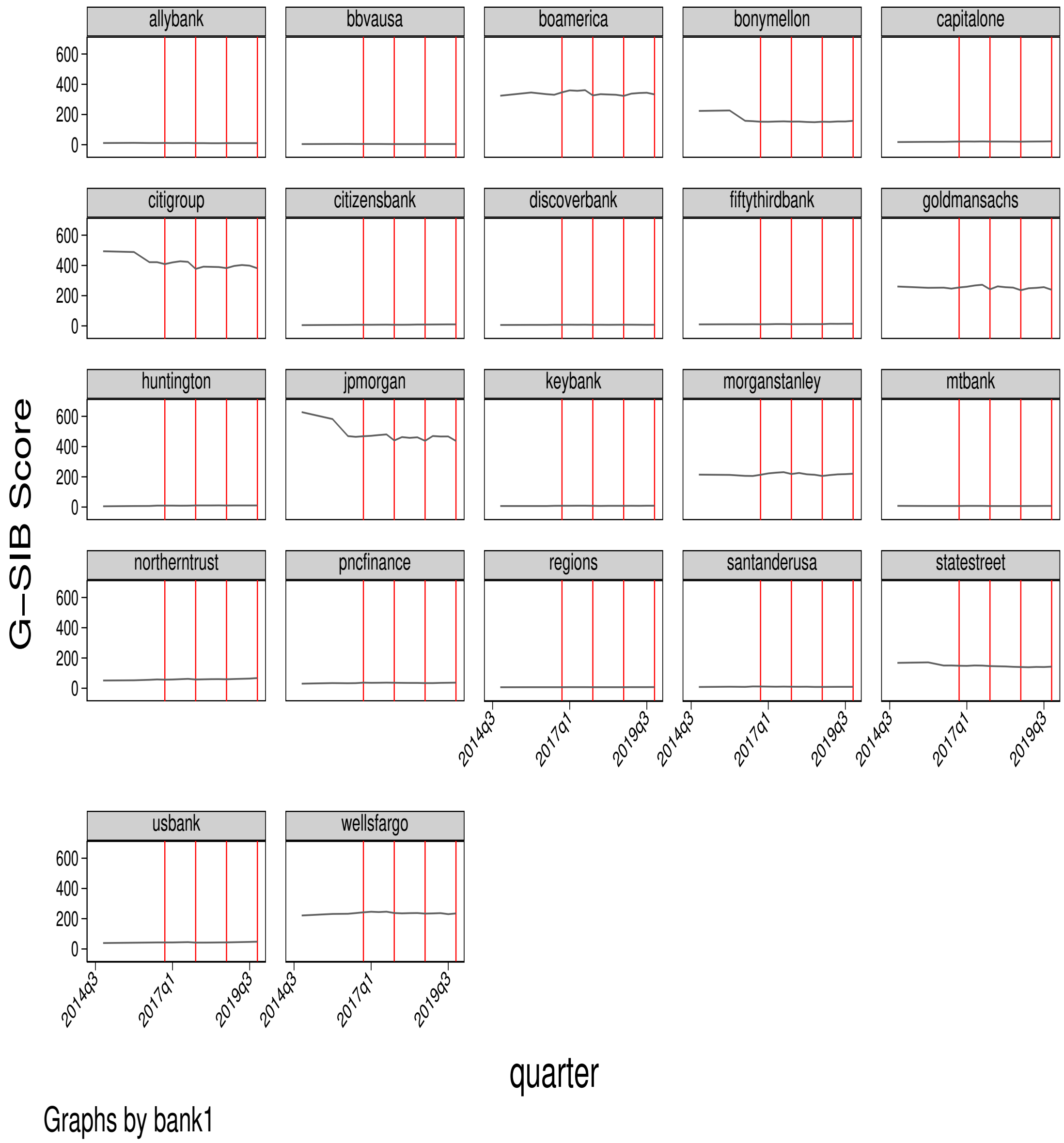

Figure 3.5: Bank systemic importance scores. Note: This figure shows G-SIB scores calculated according to method 1. The period of this score is 2014Q4-2019Q. There are only fourth quarter scores for 2014 and 2015. The red vertical line in each graph is corresponding to the fourth quarter of 2016, 2017, 2018, and 2019.

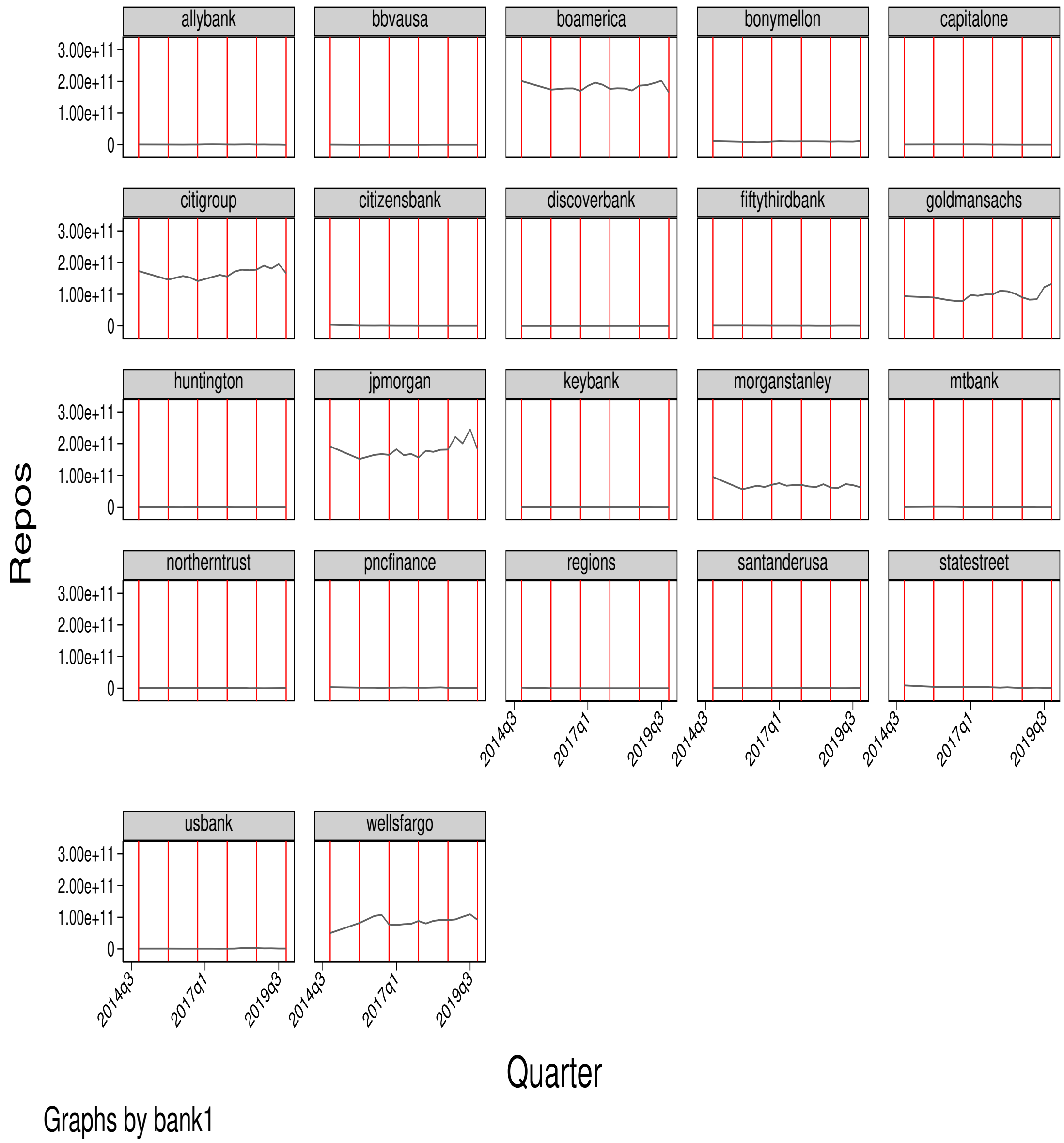

Figure 3.6: Total repos activities by banks. Note: The data is manually collected from the FR Y-9C reporting files. The data is continuous from 2016Q2 to 2019Q4. However, 2014Q4 and 2015Q4 are just extra two year-end values. The red vertical lines here represent the fourth quarter of each year for a period of 2014-2019.

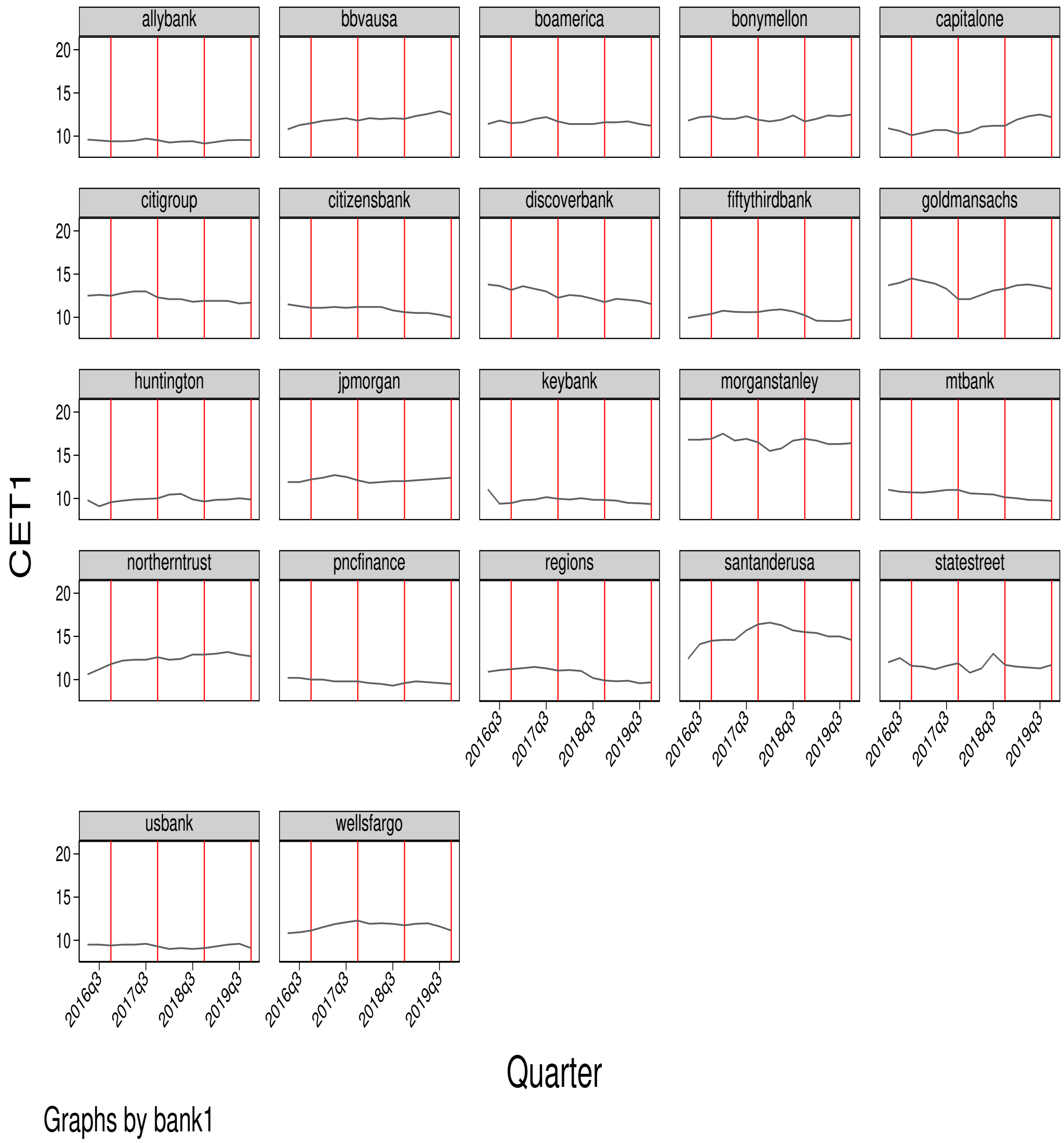

Figure 3.7: Common equity tier 1 ratio by banks. Note: The period of the data is 2016Q2 - 2019Q4. The red vertical lines represent the fourth quarters of 2016, 2017, 2018, and 2019. The CET 1 ratio is in percentage. The data is manually collected from the disclosures of individual banks.

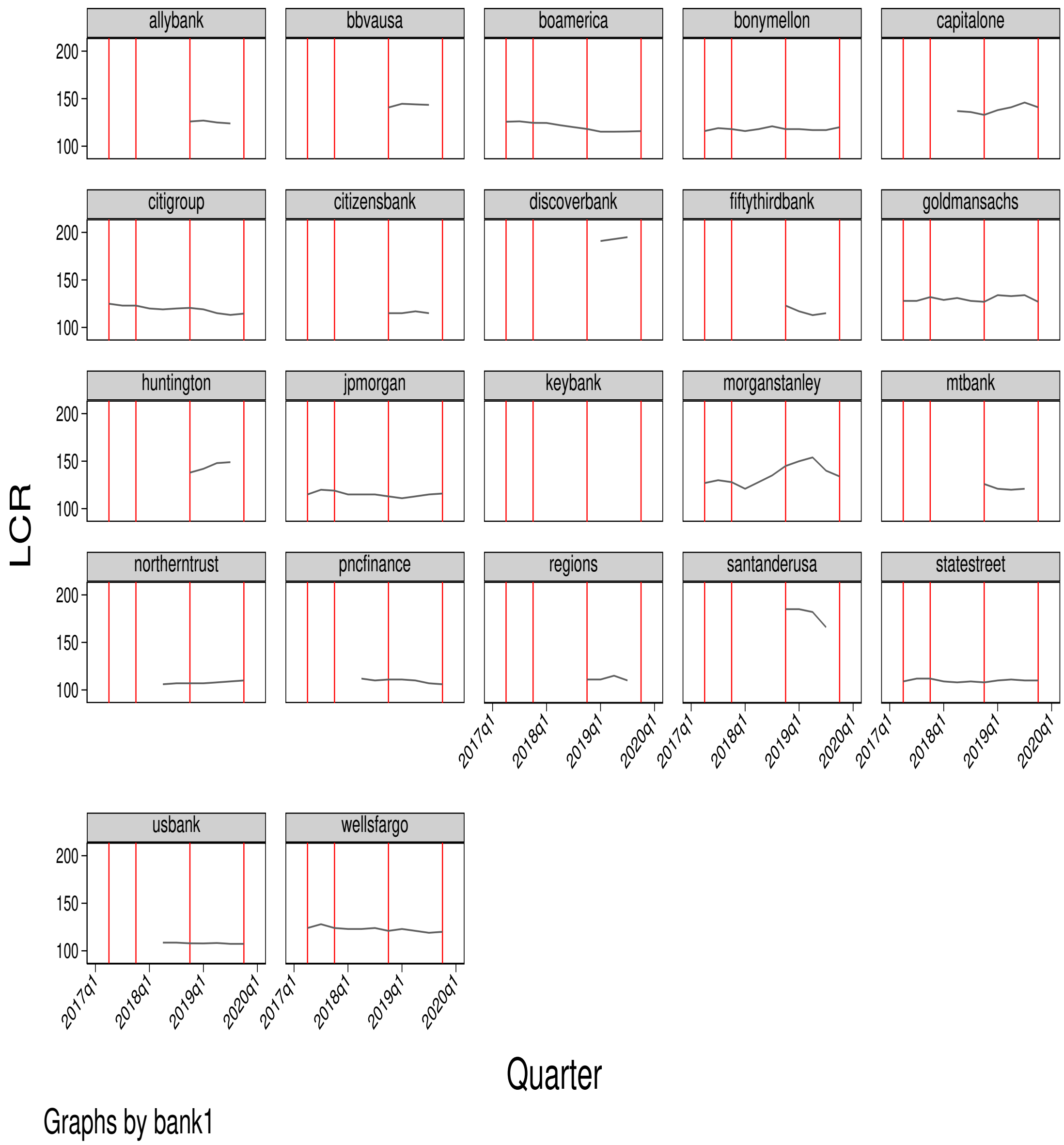

Figure 3.8: Liquidity coverage ratio by banks. Note: The first vertical red line is the starting quarter of 2017Q2 and the rest are corresponding to the 2017Q4, 2018Q4, and 2019Q4 in order. The LCR is in percentage and manually gathered from the LCR or other disclosure files. The G-SIBs have the maximum length of the data available starting from 2017Q2 while other non G-SIBs vary.

	(1) $\Delta GSIBS$ b/se	(2) $\Delta GSIBS$ b/se	(3) $\Delta GSIBS$ b/se	(4) $\Delta GSIBS$ b/se
Q4	-0.40**	-0.69***	-0.36*	-0.66**
	(0.17)	(0.24)	(0.21)	(0.26)
GSIBS	2.73**	2.70**	-5.89	-6.42
	(1.23)	(1.23)	(9.00)	(8.91)
Q4*GSIBS	-11.03***	-11.04***	-10.55***	-10.57***
	(2.73)	(2.65)	(2.61)	(2.54)
CET1	10.28	12.66	41.23	66.71
	(15.09)	(14.99)	(74.32)	(77.60)
Repos	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
2017		-2.84**		-3.03**
		(1.29)		(1.34)
2018		-2.03*		-2.24**
		(1.08)		(1.09)
2019		-1.01		-1.47
		(1.14)		(1.09)
Obs	308.00	308.00	308.00	308.00
R_Squared	0.22	0.25	0.25	0.27
TimeFE	No	Yes	No	Yes
BankFE	No	No	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00

Table 3.8: G-SIB scores: baseline regressions. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table shows the regression results of the specification (3.2). $\Delta GSIBS$ is the quarterly difference of G-SIB scores of the sample banks. The period of the analysis is 2016Q3-2019Q4. Even though the sample size is 26, some banks are not used because of the lack of CET1 data. Wells Fargo is omitted automatically during the regression because of collinearity. Therefore, the effective bank sample size is 21. Each bank has 14 observations for the $\Delta GSIBS$. All the G-SIB scores are measured by using Method 1 except extra notification. The coefficients of the Repos are nearly zero because the values of the total repos activities are usually in millions or billions if it is not zero. The four BHCs that are not used because of limited data availability in CET1 are TD Bank, BMO Financial, HSBC North America, and MUFG Americas.

	(1)	(2)	(3)	(4)
	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$
	b/se	b/se	b/se	b/se
Q4	0.35	3.78**	0.37	3.80**
	(0.46)	(1.75)	(0.51)	(1.81)
GSIBS	3.93	3.93	-3.88	-4.33
	(3.94)	(3.87)	(11.46)	(11.09)
Q4*GSIBS	1.70	1.70	2.41	2.45
	(7.09)	(6.90)	(7.33)	(7.12)
RgdpGR	-34.66	406.14**	-50.78	388.58**
	(44.20)	(190.98)	(50.63)	(179.77)
Q4*RgdpGR	-144.54*	-745.36**	-143.72	-752.90**
	(82.76)	(298.08)	(91.28)	(304.85)
GSIBS*RgdpGR	-177.95	-177.84	-70.27	-66.69
	(561.21)	(549.11)	(619.66)	(607.90)
Q4*GSIBS*RgdpGR	-2373.14*	-2373.17*	-2408.93*	-2410.19*
	(1331.42)	(1305.99)	(1330.74)	(1301.64)
CET1	10.09	10.19	38.43	36.58
	(15.21)	(14.63)	(67.33)	(67.53)
Repos	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
2017		-1.66		-1.81*
		(1.04)		(1.07)
2018		-3.05**		-3.28**
		(1.28)		(1.32)
2019		-0.85		-1.28
		(1.09)		(1.01)
Obs	308.00	308.00	308.00	308.00
R_Squared	0.31	0.33	0.32	0.34
TimeFE	No	Yes	No	Yes
BankFE	No	No	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00

Table 3.9: G-SIB scores: effect of real macroeconomic activity. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays the regression results of the specification (3.6). Wells Fargo is omitted automatically during the regression process because of collinearity. Therefore, the effective bank sample size is 21. The period of the sample is 2016Q3 - 2019Q4. $\Delta GSIBS$ is the quarterly difference of a bank's G-SIB score.

	(1) $\Delta GSIBS$ b/se	(2) $\Delta GSIBS$ b/se	(3) $\Delta GSIBS$ b/se	(4) $\Delta GSIBS$ b/se
Q4	-1.21	-2.53	-1.28	-2.53
	(2.78)	(2.78)	(2.85)	(2.85)
GSIBS	-2.77	-2.78	-10.10*	-10.49*
	(2.82)	(2.77)	(5.74)	(5.70)
Q4*GSIBS	-15.86***	-15.85***	-15.05***	-14.97***
	(4.62)	(4.55)	(4.77)	(4.70)
VIX	-0.01	0.07	-0.01	0.07
	(0.07)	(0.09)	(0.07)	(0.09)
Q4*VIX	0.04	0.07	0.04	0.07
	(0.12)	(0.12)	(0.12)	(0.12)
GSIBS*VIX	0.26**	0.26**	0.26**	0.26**
	(0.12)	(0.12)	(0.13)	(0.12)
Q4*GSIBS*VIX	0.19	0.19	0.17	0.16
	(0.20)	(0.19)	(0.20)	(0.20)
CET1	14.01	14.65	83.96	91.31
	(20.14)	(19.85)	(74.17)	(73.81)
Repos	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
2017		-1.67		-1.88
		(1.12)		(1.15)
2018		-3.93***		-4.08***
		(1.20)		(1.23)
2019		-1.46		-1.79
		(1.09)		(1.14)
obs				
R_Squared	0.28	0.31	0.30	0.33
TimeFE	No	Yes	No	Yes
BankFE	No	No	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00

Table 3.10: G-SIB scores: effect of financial market conditions. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table shows regression results of the specification (3.7). Wells Fargo is omitted during the regression because of the collinearity. Therefore, the effective bank sample size for the regression is 21. The period of the sample is 2016Q3-2019Q4. $\Delta GSIBS$ is the quarterly difference of the G-SIB score.

	(1)	(2)	(3)	(4)
	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$
	b/se	b/se	b/se	b/se
GSIBS	-0.25	-0.22	-14.56	-14.75
	(0.84)	(0.83)	(10.49)	(10.48)
Close	-7.75*	-8.42**	-9.00**	-9.66**
	(4.04)	(4.04)	(4.29)	(4.22)
CET1	7.02	9.44	62.20	91.40
	(14.35)	(14.62)	(85.20)	(91.00)
Repos	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
2017		-2.04*		-2.50**
		(1.14)		(1.26)
2018		-1.06		-1.54*
		(0.87)		(0.91)
2019		0.14		-0.75
		(0.90)		(0.88)
Obs	308.00	308.00	308.00	308.00
R_Squared	0.04	0.06	0.10	0.11
TimeFE	No	Yes	No	Yes
BankFE	No	No	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00

Table 3.11: G-SIB scores: 10 points around the threshold. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.3). For this table, Close is a dummy variable that is equal to one if a bank's year-end systemic importance score in previous year is 10 points below or above from the threshold levels of different buckets. Our sample size is relatively small and all the banks that have $Close = 1$ are the same as $GSIBS * Close$. Therefore, the interactive term of GSIBS and Close is omitted both in the regression process and this table. Wells Fargo is omitted during the regression and the effective bank sample size is 21. The period of the sample is 2016Q3-2019Q4.

	(1)	(2)	(3)	(4)
	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$
	b/se	b/se	b/se	b/se
GSIBS	0.79	0.80	-12.64	-13.11
	(1.01)	(1.01)	(10.49)	(10.50)
Close	-8.48***	-8.64***	-9.35***	-9.56***
	(3.06)	(2.99)	(3.03)	(2.95)
CET1	12.88	15.56	75.38	103.43
	(13.74)	(14.01)	(84.32)	(90.83)
Repos	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
2017		-2.06*		-2.49*
		(1.21)		(1.31)
2018		-1.05		-1.50
		(0.97)		(0.99)
2019		-0.14		-0.99
		(1.02)		(0.99)
Obs	308.00	308.00	308.00	308.00
R_Squared	0.09	0.10	0.15	0.16
TimeFE	No	Yes	No	Yes
BankFE	No	No	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00

Table 3.12: G-SIB scores: 20 points around threshold. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays the regression results of the specification (3.3). For this table, Close is a dummy variable that is equal to one if a bank's year-end systemic importance score in previous year is 20 points below or above from the threshold levels of different buckets. Our sample size is relatively small and all the banks that have $Close = 1$ are the same as $GSIBS * Close$. Therefore, the interactive term of GSIBS and Close is omitted both in the regression process and this table. Wells Fargo is omitted during the regression and the effective bank sample size is 21. The period of the sample is 2016Q3-2019Q4.

	(1)	(2)	(3)	(4)
	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$
	b/se	b/se	b/se	b/se
GSIBS	2.07*	2.08*	-10.34	-10.74
	(1.20)	(1.20)	(10.23)	(10.25)
Close	-9.71***	-9.79***	-9.92***	-10.03***
	(3.06)	(2.99)	(3.09)	(3.01)
CET1	14.81	17.34	63.80	89.49
	(14.81)	(14.90)	(76.08)	(80.50)
Repos	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
2017		-2.00		-2.34*
		(1.24)		(1.31)
2018		-1.17		-1.57
		(1.05)		(1.05)
2019		-0.15		-0.89
		(1.11)		(1.04)
Obs	308.00	308.00	308.00	308.00
R_Squared	0.14	0.16	0.19	0.21
TimeFE	No	Yes	No	Yes
BankFE	No	No	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00

Table 3.13: G-SIB scores: 30 points around the threshold. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.3). For this table, Close is a dummy variable that is equal to one if a bank's year-end systemic importance score in previous year is 30 points below or above from the threshold levels of different buckets. Our sample size is relatively small and all the banks that have $Close = 1$ are the same as $GSIBS * Close$. Therefore, the interactive term of GSIBS and Close is omitted both in the regression process and this table. Wells Fargo is omitted during the regression and the effective bank sample size is 21. The period of the sample is 2016Q3-2019Q4.

	(1)	(2)	(3)	(4)
	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$
	b/se	b/se	b/se	b/se
Q4	-4.86***	-5.19***	-4.84***	-5.15***
	(1.21)	(1.25)	(1.20)	(1.23)
ReposGR	-0.01	-0.01	-0.01	-0.01
	(0.03)	(0.03)	(0.04)	(0.04)
Q4*ReposGR	1.01	0.99	0.84	0.79
	(0.65)	(0.65)	(0.64)	(0.65)
CET1	-2.66	-0.91	12.15	44.40
	(15.42)	(15.12)	(98.47)	(100.58)
2017		-3.10**		-3.18**
		(1.43)		(1.49)
2018		-2.30**		-2.30**
		(1.08)		(1.11)
2019		-1.22		-1.22
		(1.18)		(1.19)
Obs	280.00	280.00	280.00	280.00
R_Squared	0.10	0.12	0.12	0.14
TimeFE	No	Yes	No	Yes
BankFE	No	No	Yes	Yes
BankNumber	20.00	20.00	20.00	20.00

Table 3.14: G-SIB scores: effects of total repos activity. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.4). Wells Fargo is not omitted during the regression. The two banks that are not part of this analysis are Discover Bank and Regions Bank (because of 0 repos for all the period). The effective sample size is 20. The period of the sample is 2016Q3-2019Q4.

	(1)	(2)	(3)	(4)
	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$	$\Delta GSIBS$
	b/se	b/se	b/se	b/se
Q4	-0.44**	-0.77***	-0.41*	-0.71**
	(0.19)	(0.28)	(0.22)	(0.28)
Q4*GSIBS	-10.40***	-10.45***	-10.42***	-10.49***
	(2.75)	(2.65)	(2.74)	(2.62)
ReposGR	0.01	0.00	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Q4*ReposGR	-0.01	-0.01	-0.14	-0.15
	(0.29)	(0.29)	(0.30)	(0.31)
GSIBS*ReposGR	11.14*	10.79*	12.25*	11.98*
	(5.91)	(5.90)	(6.64)	(6.63)
Q4*GSIBS*ReposGR	-6.06	-6.49	-7.48	-8.26
	(15.24)	(14.93)	(14.83)	(14.45)
CET1	12.74	15.11	34.04	67.13
	(16.62)	(16.63)	(89.11)	(90.58)
2017		-3.11**		-3.21**
		(1.43)		(1.49)
2018		-2.20*		-2.22*
		(1.19)		(1.24)
2019		-1.28		-1.32
		(1.25)		(1.27)
Obs	280.00	280.00	280.00	280.00
R_Squared	0.24	0.26	0.25	0.27
TimeFE	No	Yes	No	Yes
BankFE	No	No	Yes	Yes
BankNumber	20.00	20.00	20.00	20.00

Table 3.15: G-SIB scores: effects of total repos activity and G-SIBs. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.5). Wells Fargo is omitted during the regression. The two banks that are not part of this analysis are Discover Bank and Regions Bank (because of 0 repos for all the period). The effective sample size is 19. The period of the sample is 2016Q3-2019Q4.

	$\Delta CategoryScore$				
	Complex.	Cross-Juris.	Interconn.	Size	Substit.
	b/se	b/se	b/se	b/se	b/se
Q4	-0.11	-0.29	-0.72**	-0.76***	-1.40**
	(0.63)	(0.23)	(0.34)	(0.18)	(0.59)
GSIBS	-10.55	-9.08	-9.86	-8.28*	5.64
	(29.77)	(11.75)	(7.28)	(4.74)	(5.80)
Q4*GSIBS	-31.50***	-13.78***	-5.19*	-4.66***	2.29
	(6.95)	(2.93)	(2.73)	(1.67)	(2.86)
2017	-4.28	-1.93	-2.86*	-2.75***	-3.31*
	(3.31)	(1.41)	(1.52)	(0.87)	(1.69)
2018	-4.03	-1.28	-2.18*	-0.74	-2.96**
	(3.32)	(1.19)	(1.13)	(0.51)	(1.48)
2019	-3.20	-1.78	-0.24	-0.47	-1.64
	(3.42)	(1.15)	(1.09)	(0.55)	(1.54)
CET1	135.51	55.79	120.73	11.28	10.23
	(203.68)	(84.01)	(88.54)	(35.96)	(62.24)
Repos	0.00	0.00	0.00	0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	308.00	308.00	308.00	308.00	308.00
R_Squared	0.27	0.27	0.14	0.27	0.11
TimeFE	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00	22.00

Table 3.16: Category scores: baseline regressions. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table shows regression results of the specification (3.2). $\Delta CateogoryScore$ is the quarterly difference of G-SIB category scores of sample banks. The period of the analysis is 2016Q3-2019Q4. Even though the sample size is 26, some banks are not used because of the lack of CET1 data. Wells Fargo is omitted automatically during the regression because of collinearity. Therefore, the effective bank sample size is 21. Each bank has 14 observations for the $\Delta CateogoryScore$. The coefficients of the Repos are nearly zero because the values of the total repos activities are usually in millions or billions if it is not zero. The four BHCs that are not used because of limited data availability in CET1 are TD Bank, BMO Financial, HSBC North America, and MUFG Americas.

	$\Delta CategoryScore$				
	Complex.	Cross-Juris.	Interconn.	Size	Substit.
	b/se	b/se	b/se	b/se	b/se
Q4	0.47	-1.03**	-1.58***	-1.47***	-1.79***
	(0.86)	(0.45)	(0.51)	(0.34)	(0.66)
GSIBS	-10.80	-8.75	-9.48	-7.96*	5.81
	(29.68)	(11.87)	(7.14)	(4.46)	(5.76)
Q4*GSIBS	-31.47***	-13.81***	-5.23**	-4.69***	2.27
	(6.95)	(2.83)	(2.61)	(1.52)	(2.84)
RgdpGR	675.89	-858.36***	-995.67***	-820.98***	-455.35**
	(682.19)	(306.93)	(311.86)	(184.81)	(228.11)
2017	-5.27	-0.67	-1.40	-1.55**	-2.64*
	(3.38)	(1.23)	(1.34)	(0.64)	(1.59)
2018	-4.58	-0.59	-1.38	-0.08	-2.59*
	(3.45)	(1.18)	(1.11)	(0.46)	(1.50)
2019	-3.46	-1.45	0.14	-0.16	-1.47
	(3.40)	(1.14)	(1.08)	(0.53)	(1.54)
CET1	130.05	62.73	128.77	17.91	13.91
	(206.59)	(82.24)	(85.65)	(33.73)	(61.52)
Repos	0.00	0.00	0.00	0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	308.00	308.00	308.00	308.00	308.00
R_Squared	0.27	0.29	0.19	0.36	0.12
TimeFE	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00	22.00

Table 3.17: Category scores: impact of real macroeconomic activity. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.2) with the linear addition of the real GDP growth rate. The specification of (3.6) is not used here because of multiple individual and interactive terms as in table (3.9) are omitted during regression. Wells Fargo is omitted automatically during the regression process because of collinearity. Therefore, the effective bank sample size is 21. The period of the sample is 2016Q3-2019Q4. $\Delta CategoryScore$ is quarterly differences of G-SIB category scores of sample banks.

	$\Delta CategoryScore$				
	Complex.	Cross-Juris.	Interconn.	Size	Substit.
	b/se	b/se	b/se	b/se	b/se
Q4	-0.92	-1.00**	-1.17***	-1.04***	-1.56**
	(0.84)	(0.42)	(0.37)	(0.22)	(0.63)
GSIBS	-10.34	-8.90	-9.74	-8.21*	5.68
	(29.48)	(11.71)	(7.18)	(4.72)	(5.80)
Q4*GSIBS	-31.54***	-13.81***	-5.21*	-4.67***	2.28
	(6.94)	(2.86)	(2.69)	(1.64)	(2.86)
VIX	0.36*	0.32***	0.20***	0.12***	0.07
	(0.19)	(0.09)	(0.06)	(0.03)	(0.05)
2017	-2.41	-0.31	-1.84	-2.11***	-2.94*
	(3.30)	(1.35)	(1.42)	(0.78)	(1.59)
2018	-7.10**	-3.96***	-3.86***	-1.79***	-3.57**
	(3.38)	(1.25)	(1.31)	(0.59)	(1.67)
2019	-4.26	-2.71**	-0.82	-0.84	-1.85
	(3.51)	(1.24)	(1.14)	(0.61)	(1.60)
CET1	146.23	65.14	126.60	14.96	12.35
	(197.27)	(79.18)	(85.77)	(35.44)	(62.66)
Repos	0.00	0.00	0.00	0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	308.00	308.00	308.00	308.00	308.00
R_Squared	0.28	0.30	0.16	0.29	0.11
TimeFE	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00	22.00

Table 3.18: Category scores: effect of financial market conditions. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.2) with the linear addition of VIX (Max). Wells Fargo is omitted automatically during the regression process because of collinearity. Therefore, the effective bank sample size is 21. The period of the sample is 2016Q3-2019Q4. $\Delta CategoryScore$ is quarterly differences of G-SIB category scores of sample banks.

	$\Delta CategoryScore$				
	Complex.	Cross-Juris.	Interconn.	Size	Substit.
	b/se	b/se	b/se	b/se	b/se
GSIBS	-30.80	-19.81	-15.20*	-13.64**	5.71
	(30.44)	(13.57)	(8.89)	(6.28)	(6.78)
Close	-42.71***	-11.17**	-0.53	1.68	4.45
	(13.90)	(5.50)	(4.10)	(1.66)	(4.12)
2017	-3.72	-1.31	-2.33	-2.15**	-2.98*
	(2.91)	(1.52)	(1.43)	(0.85)	(1.79)
2018	-2.72	-0.47	-1.65*	-0.18	-2.69
	(2.99)	(1.15)	(0.98)	(0.39)	(1.63)
2019	-1.50	-0.97	0.21	-0.04	-1.45
	(2.91)	(1.03)	(0.97)	(0.46)	(1.59)
CET1	174.90	83.50	141.49	33.41	23.72
	(226.23)	(101.33)	(93.08)	(43.87)	(62.70)
Repos	0.00	0.00	0.00	0.00**	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	308.00	308.00	308.00	308.00	308.00
R_Squared	0.19	0.10	0.08	0.14	0.11
TimeFE	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00	22.00

Table 3.19: Category scores: 10 points around the threshold. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.3). For this table, Close is a dummy variable that is equal to one if a bank's year-end systemic importance score in previous year is 10 points below or above from the threshold levels of different buckets. Our sample size is relatively small and all the banks that have $Close = 1$ are the same as $GSIBS * Close$. Therefore, the interactive term of GSIBS and Close is omitted both in the regression process and this table. Wells Fargo is omitted during the regression and the effective bank sample size is 21. The period of the sample is 2016Q3-2019Q4.

	$\Delta CategoryScore$				
	Complex.	Cross-Juris.	Interconn.	Size	Substit.
	b/se	b/se	b/se	b/se	b/se
GSIBS	-27.45	-18.16	-14.16	-11.93*	6.15
	(31.22)	(13.72)	(8.97)	(6.22)	(6.03)
Close	-32.47***	-10.45***	-2.91	-3.37*	1.39
	(9.46)	(3.20)	(2.36)	(2.00)	(4.25)
2017	-3.28	-1.28	-2.43*	-2.38***	-3.11*
	(3.21)	(1.51)	(1.43)	(0.87)	(1.64)
2018	-2.34	-0.41	-1.69*	-0.29	-2.77*
	(3.09)	(1.16)	(1.00)	(0.41)	(1.50)
2019	-2.29	-1.23	0.13	-0.13	-1.42
	(3.28)	(1.10)	(0.99)	(0.49)	(1.51)
CET1	226.14	97.29	142.63	32.32	18.78
	(227.88)	(101.53)	(93.32)	(44.73)	(63.56)
Repos	0.00	0.00	0.00	0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	308.00	308.00	308.00	308.00	308.00
R_Squared	0.21	0.14	0.09	0.17	0.10
TimeFE	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00	22.00

Table 3.20: Category scores: 20 points around the threshold. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.3). For this table, Close is a dummy variable that is equal to one if a bank's year-end systemic importance score in previous year is 20 points below or above from the threshold levels of different buckets. Our sample size is relatively small and all the banks that have $Close = 1$ are the same as $GSIBS * Close$. Therefore, the interactive term of GSIBS and Close is omitted both in the regression process and this table. Wells Fargo is omitted during the regression and the effective bank sample size is 21. The period of the sample is 2016Q3-2019Q4.

	$\Delta CategoryScore$				
	Complex.	Cross-Juris.	Interconn.	Size	Substit.
	b/se	b/se	b/se	b/se	b/se
GSIBS	-21.79	-14.73	-12.49	-10.41*	5.74
	(31.40)	(13.38)	(8.37)	(6.12)	(5.80)
Close	-30.15***	-12.32***	-4.59	-4.65**	1.57
	(7.94)	(3.45)	(3.47)	(1.92)	(3.29)
2017	-2.66	-1.15	-2.43*	-2.35***	-3.13*
	(3.16)	(1.44)	(1.47)	(0.83)	(1.67)
2018	-2.47	-0.52	-1.75	-0.34	-2.76*
	(3.16)	(1.20)	(1.06)	(0.44)	(1.50)
2019	-1.91	-1.15	0.13	-0.12	-1.43
	(3.27)	(1.12)	(1.04)	(0.51)	(1.53)
CET1	183.50	80.42	136.54	26.07	20.94
	(205.85)	(88.06)	(90.42)	(39.12)	(63.16)
Repos	0.00	0.00	0.00	0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	308.00	308.00	308.00	308.00	308.00
R_Squared	0.23	0.20	0.11	0.22	0.11
TimeFE	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes
BankNumber	22.00	22.00	22.00	22.00	22.00

Table 3.21: Category scores: 30 points around the threshold. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.3). For this table, Close is a dummy variable that is equal to one if a bank's year-end systemic importance score in previous year is 30 points below or above from the threshold levels of different buckets. Our sample size is relatively small and all the banks that have $Close = 1$ are the same as $GSIBS * Close$. Therefore, the interactive term of GSIBS and Close is omitted both in the regression process and this table. Wells Fargo is omitted during the regression and the effective bank sample size is 21. The period of the sample is 2016Q3-2019Q4.

	$\Delta CategoryScore$				
	Complex.	Cross-Juris.	Interconn.	Size	Substit.
	b/se	b/se	b/se	b/se	b/se
Q4	-13.25***	-6.14***	-3.06**	-2.86***	-0.44
	(3.31)	(1.47)	(1.24)	(0.83)	(1.13)
ReposGR	-0.04	-0.05	0.03	-0.02	0.04
	(0.11)	(0.05)	(0.04)	(0.03)	(0.03)
Q4*ReposGR	4.17**	1.47*	-0.10	0.21	-1.78*
	(2.04)	(0.82)	(0.58)	(0.36)	(1.05)
2017	-4.44	-1.96	-2.93*	-2.82***	-3.74*
	(3.52)	(1.70)	(1.66)	(0.99)	(1.92)
2018	-4.21	-1.19	-2.18*	-0.58	-3.37*
	(3.56)	(1.26)	(1.19)	(0.49)	(1.72)
2019	-2.83	-1.42	0.24	-0.02	-2.10
	(3.95)	(1.35)	(1.14)	(0.46)	(1.82)
CET1	76.85	25.43	99.03	-23.03	43.73
	(267.13)	(111.20)	(108.49)	(44.83)	(69.18)
Obs	280.00	280.00	280.00	280.00	280.00
R_Squared	0.14	0.12	0.10	0.18	0.10
TimeFE	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes
BankNumber	20.00	20.00	20.00	20.00	20.00

Table 3.22: Category scores: effects of total repos activity. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.4). Wells Fargo is not omitted during the regression. The two banks that are not part of this analysis are Discover Financial and Regions bank. The effective sample size is 20. The period of the sample is 2016Q3-2019Q4.

	$\Delta CategoryScore$				
	Complex.	Cross-Juris.	Interconn.	Size	Substit.
	b/se	b/se	b/se	b/se	b/se
Q4	-0.05	-0.32	-0.81**	-0.85***	-1.54**
	(0.69)	(0.23)	(0.38)	(0.22)	(0.66)
Q4*GSIBS	-29.37***	-13.22***	-6.40**	-5.55***	2.06
	(6.81)	(2.98)	(2.98)	(1.99)	(2.94)
ReposGR	0.06	-0.02	0.04	-0.00	0.03
	(0.07)	(0.03)	(0.03)	(0.02)	(0.03)
Q4*ReposGR	0.45	0.05	-0.07	0.09	-1.28
	(0.64)	(0.23)	(0.36)	(0.16)	(0.95)
GSIBS*ReposGR	31.71	20.52**	7.08	1.71	-1.09
	(21.84)	(9.53)	(5.21)	(2.00)	(2.83)
Q4*GSIBS*ReposGR	13.92	-8.29	-24.74**	-12.27	-9.92
	(49.23)	(20.18)	(12.00)	(8.58)	(10.57)
2017	-4.15	-1.96	-3.15*	-2.94***	-3.85**
	(3.65)	(1.54)	(1.68)	(0.95)	(1.93)
2018	-3.49	-0.98	-2.41*	-0.72	-3.53**
	(3.71)	(1.31)	(1.29)	(0.60)	(1.72)
2019	-2.47	-1.52	-0.15	-0.20	-2.28
	(3.94)	(1.26)	(1.24)	(0.54)	(1.81)
CET1	120.46	54.04	123.27	-7.78	45.64
	(241.14)	(93.19)	(104.63)	(36.55)	(70.70)
Obs	280.00	280.00	280.00	280.00	280.00
R_Squared	0.29	0.29	0.15	0.26	0.12
TimeFE	Yes	Yes	Yes	Yes	Yes
BankFE	Yes	Yes	Yes	Yes	Yes
BankNumber	20.00	20.00	20.00	20.00	20.00

Table 3.23: Category scores: effects of total repos activity and G-SIBs. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of the specification (3.5). Wells Fargo is omitted during the regression. The two banks that are not part of this analysis are Discover Financial and Regions bank. The effective sample size is 19. The period of the sample is 2016Q3-2019Q4.

3.7.2 Appendix B: Method 2 Analysis

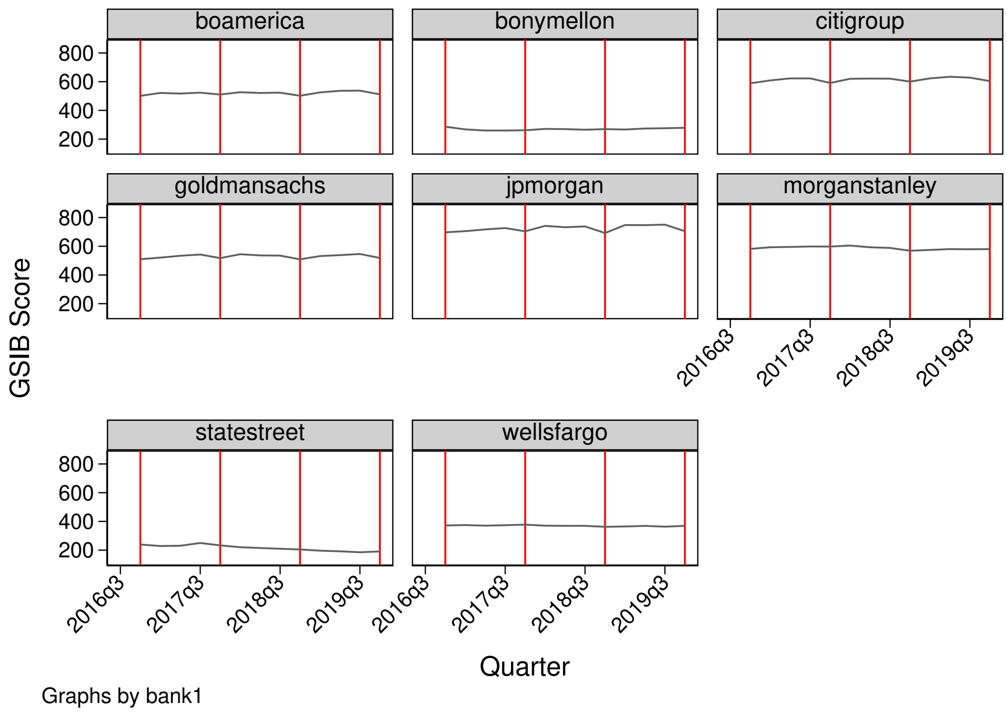

Figure 3.9: Method 2 scores of eight U.S. G-SIBs. Note: The red vertical line represents fourth quarter of a year.

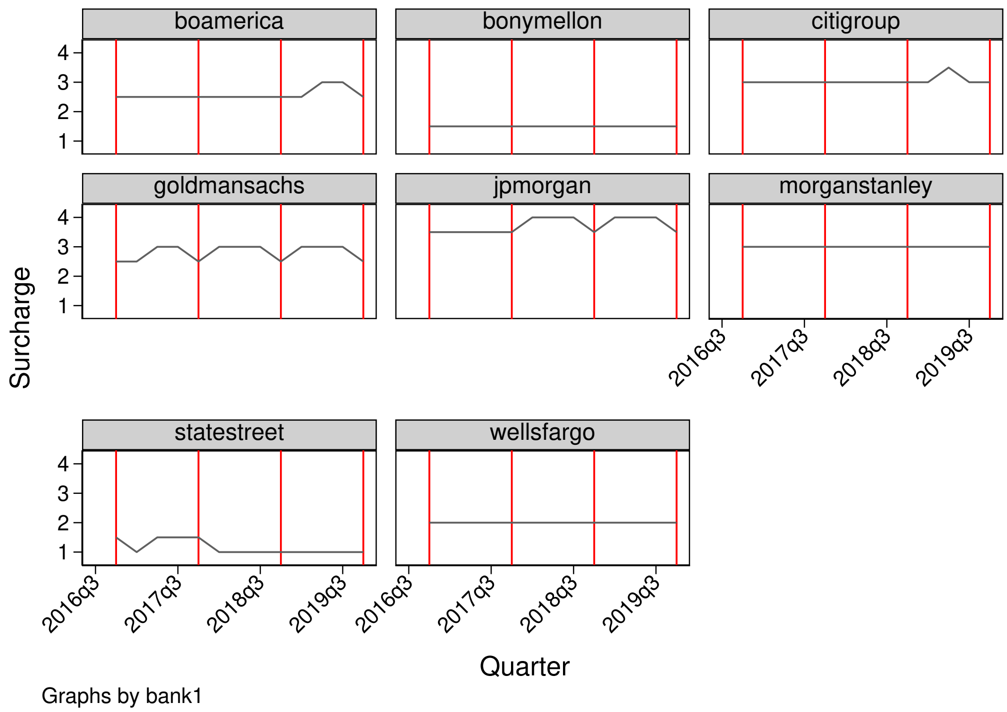

Figure 3.10: Method 2 surcharge of eight U.S. G-SIBs. Note: The period of the sample is 2016Q4-2019Q4, the possible maximum length of period that short-term wholesale funding matrix (STWSFM) is publicly available. Since non G-SIBs have a short period of data of STWSFM available and G-SIBs are the main interest, only the eight U.S. G-SIBs are considered for method 2. The red vertical lines correspond to the fourth quarter of 2016, 2017, 2018, and 2019.

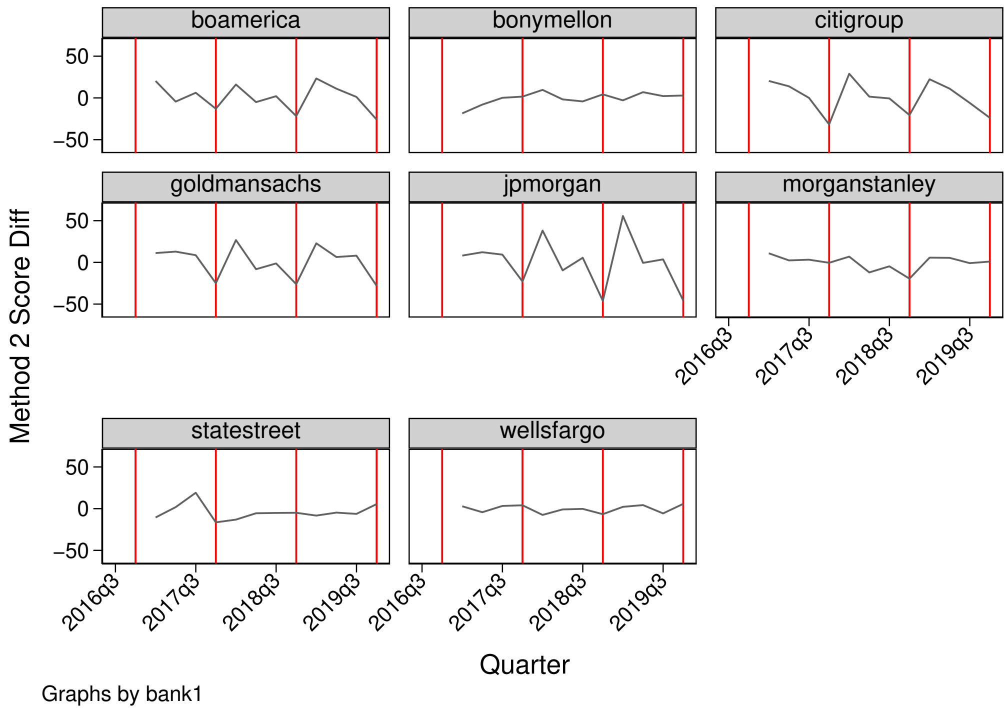

Figure 3.11: Method 2 score quarterly differences. Note: The period of the sample is 2017Q1-2019Q4. The red vertical lines correspond to the fourth quarter of 2016, 2017, 2018, and 2019.

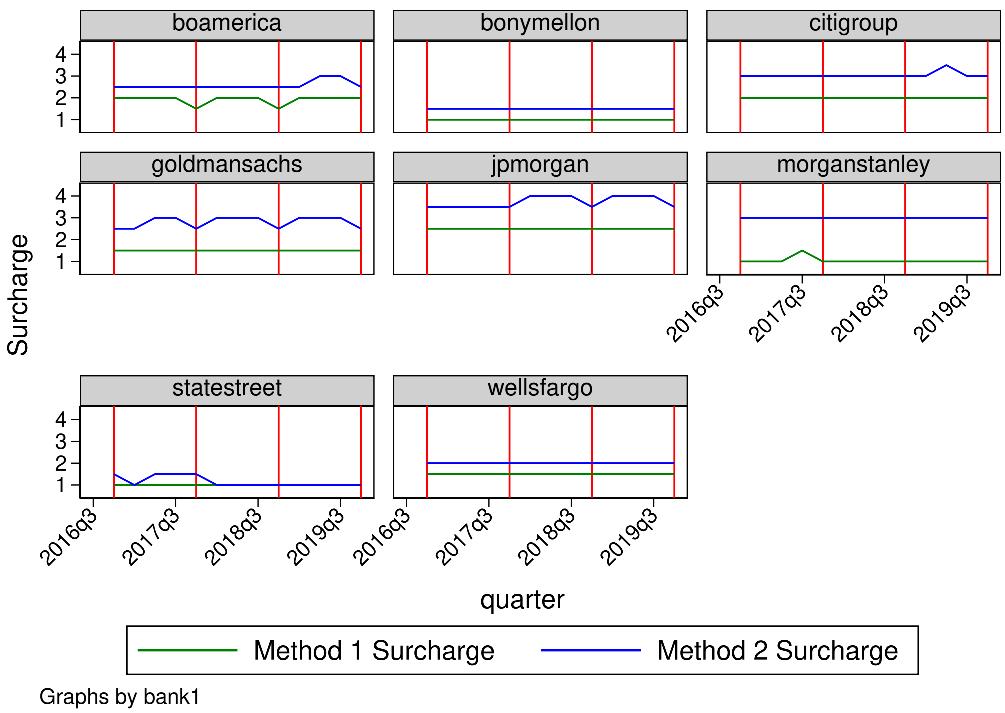

Figure 3.12: Method 1 and 2 surcharge comparison. Note: The period of the sample is 2016Q4-2019Q4. The red vertical lines correspond to the fourth quarter of 2016, 2017, 2018, and 2019. The biggest surcharge of method 1 and 2 are adopted by bank regulators.

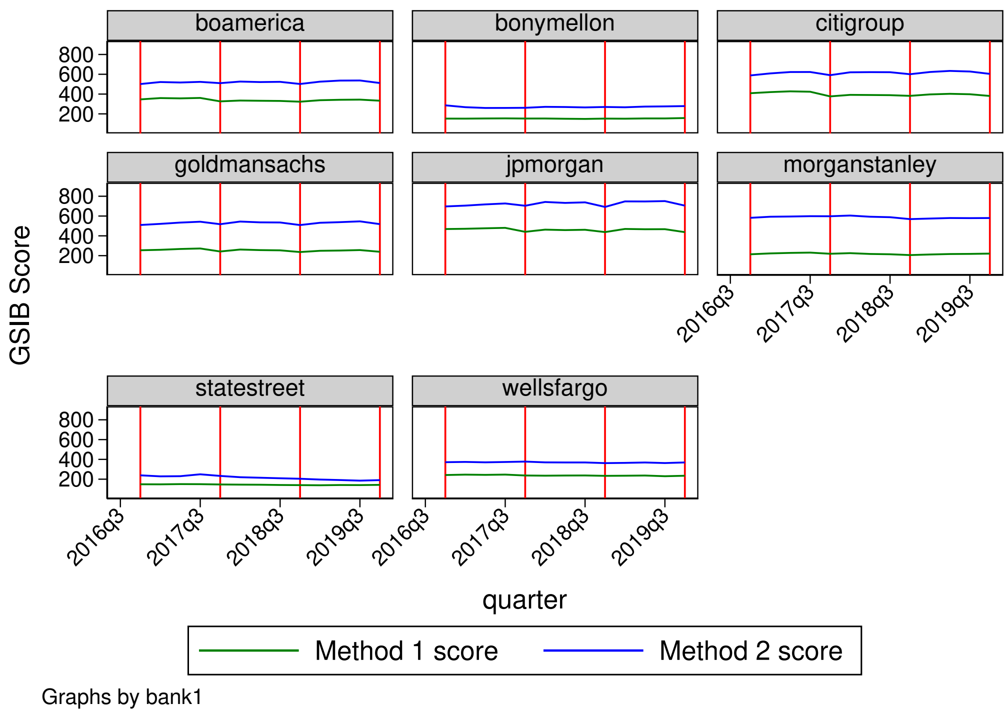

Figure 3.13: Method 1 and 2 score comparison. Note: The period of the sample is 2016Q4-2019Q4. The red vertical lines correspond to the fourth quarter of 2016, 2017, 2018, and 2019.

	$\Delta GSIBScore$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BOA	BONYM	CTG	GS	JPM	MSLY	SS	WF
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Q4	-29.44***	6.08	-32.10***	-36.89***	-53.84***	-6.64	3.20	2.63
	(6.55)	(4.93)	(8.59)	(7.74)	(12.74)	(3.65)	(8.97)	(3.06)
2018	-6.22	6.89	31.83*	-5.88	-36.44*	-12.10***	4.73	-3.53
	(11.21)	(5.59)	(15.79)	(6.79)	(17.05)	(2.89)	(12.53)	(4.55)
2019	-0.73	8.02	39.15*	2.74	-11.23	-1.47	12.89	5.09
	(14.01)	(5.54)	(18.08)	(6.10)	(19.76)	(4.62)	(16.00)	(6.66)
CET1	-231.11	4.06	2401.67	-445.38	-6259.72	-356.75	386.66	385.08
	(2033.78)	(1154.56)	(1894.56)	(716.72)	(3810.03)	(610.16)	(252.48)	(504.68)
Repos	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00
R_Squared	0.67	0.48	0.80	0.79	0.74	0.63	0.14	0.41
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankNumber	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 3.24: Eight U.S. G-SIBs Method 2: baseline regressions. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of eight U.S. G-SIBs' individual method 2 score quarterly differences on the fourth quarter dummy variable and other control variables according to the specification (3.2) but without GSIB dummy variable. The period of the sample is 2017Q1-2019Q4. BOA=Bank of America, BONYM=Bank of New York Mellon, CTG=Citigroup, GS=Goldman Sachs, JPM=JPMorgan Chase, MSLY=Morgan Stanley, SS=State Street, WF=Wells Fargo.

	$\Delta GSIBScore$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BOA	BONYM	CTG	GS	JPM	MSLY	SS	WF
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Q4	-21.50*	1.79	-19.08	-26.85***	-36.82***	-9.33	1.55	-2.68
	(10.33)	(2.23)	(11.24)	(6.85)	(9.65)	(4.86)	(1.90)	(2.03)
2017	-38.58**	5.56	-16.77*	-29.34*	-36.99***	-13.37**	3.86	-4.18
	(13.44)	(3.11)	(8.55)	(12.30)	(8.42)	(5.37)	(2.56)	(2.88)
2018	-33.05**	5.32*	30.35**	-27.23*	-35.78**	-17.28***	5.95	-0.96
	(9.98)	(2.60)	(12.27)	(11.51)	(10.74)	(3.42)	(5.00)	(3.50)
2019	-30.06**	6.51**	38.87**	-25.85*	-35.48**	-10.57	9.21	4.23
	(9.01)	(2.26)	(13.05)	(12.07)	(11.27)	(6.21)	(5.68)	(4.94)
CET1	247.04	119.92	3998.85*	90.17	-841.07	231.79	-48.23	-330.84
	(2409.29)	(289.73)	(1753.09)	(647.94)	(2708.63)	(585.64)	(71.92)	(420.19)
Repos	0.00	-0.00	-0.00	-0.00	0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	13.00	13.00	13.00	13.00	13.00	13.00	13.00	13.00
R_Squared	0.69	0.45	0.83	0.77	0.75	0.57	0.48	0.64
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BankNumber	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 3.25: Eight U.S. G-SIBs Method 1: baseline regressions. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. This table displays regression results of eight U.S. G-SIBs' method 1 score quarterly differences on the fourth quarter dummy variable and other control variables according to the specification (3.2) but without GSIB dummy variable. The period of the sample is 2016Q4-2019Q4. BOA=Bank of America, BONYM=Bank of New York Mellon, CTG=Citigroup, GS=Goldman Sachs, JPM=JPMorgan Chase, MSLY=Morgan Stanley, SS=State Street, WF=Wells Fargo.

3.7.3 Appendix C: Proposed New Approaches

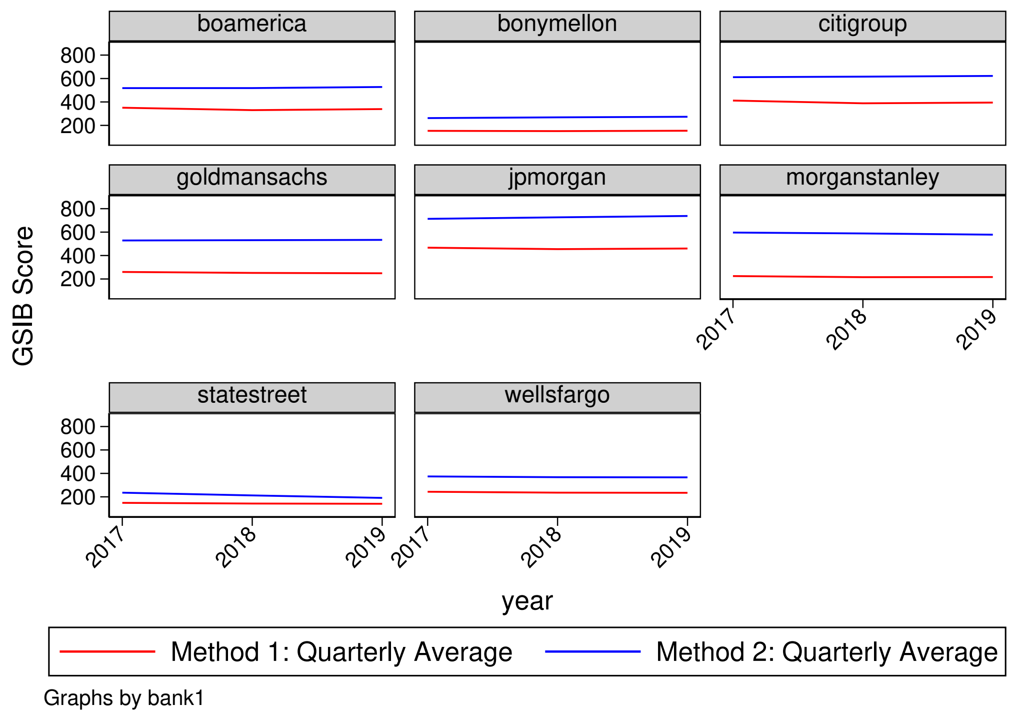

Figure 3.14: Quarterly average systemic importance score. Note: This is the newly proposed systemic indicator score approach for method 1 and method 2 by taking the average of the quarterly data in a year. The years used here are 2017, 2018, and 2019. Only the eight U.S. G-SIBs are studied here since they are likely more affected by this type of new regulation than non G-SIBs.

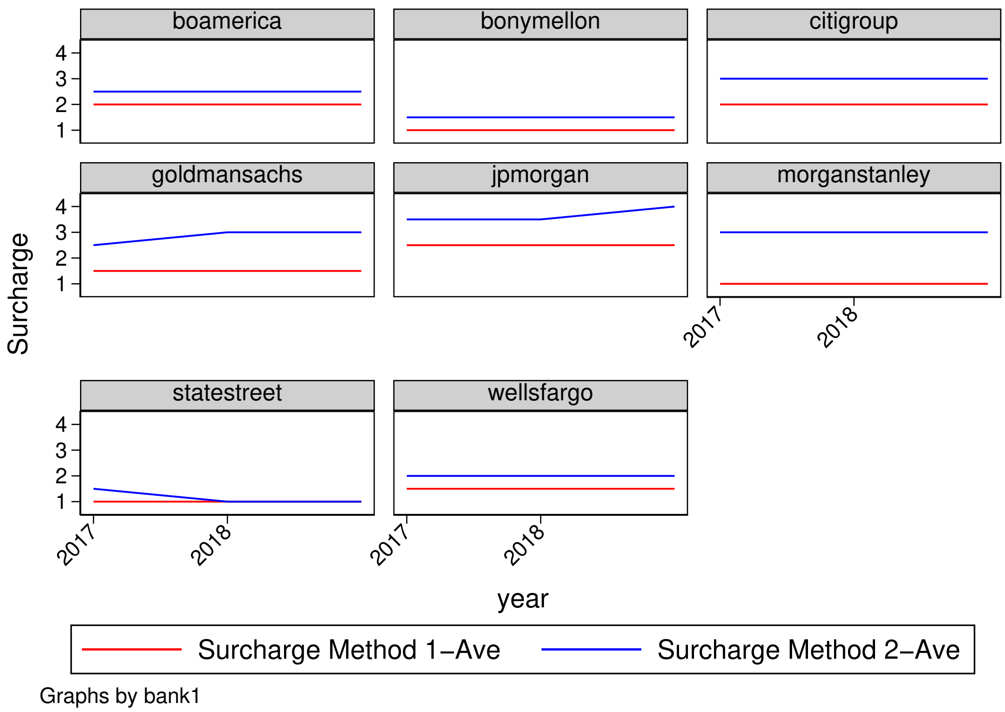

Figure 3.15: Capital surcharge based on newly proposed Quarterly Average method. Note: This figure shows the surcharges assigned to the eight U.S. G-SIBs according to their quarterly average score measured by method 1 and method 2. The years of the sample are 2017, 2018, and 2019.

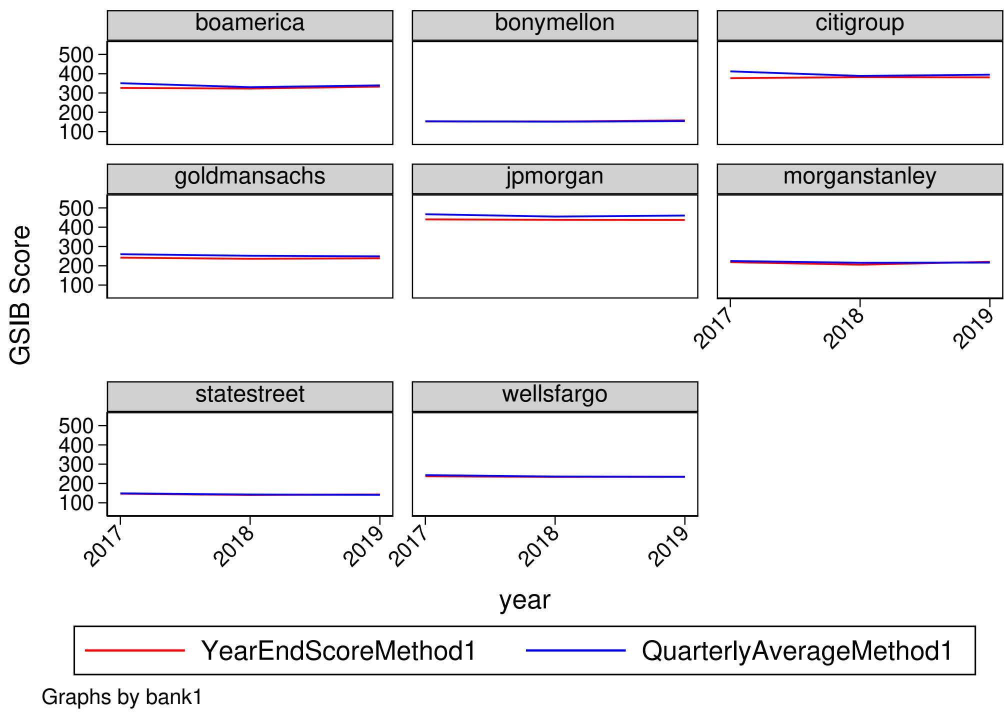

Figure 3.16: Comparison of year-end Method 1 score and Quarterly Average Method 1 score. Note: This figure displays the newly proposed quarterly average method 1 score and currently being implemented year-end method 1 score. The years of the sample are 2017, 2018, and 2019.

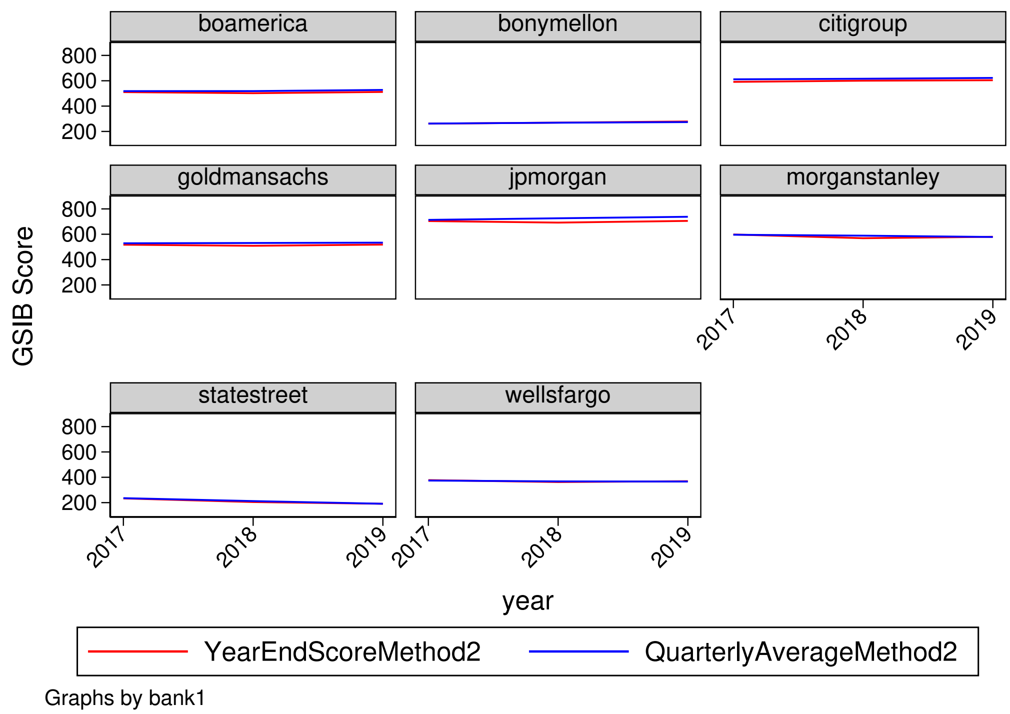

Figure 3.17: Comparison of year-end Method 2 score and Quarterly Average Method 2 score. Note: This figure displays the newly proposed quarterly average method 2 score and currently being implemented year-end method 2 score. The years of the sample are 2017, 2018, and 2019.

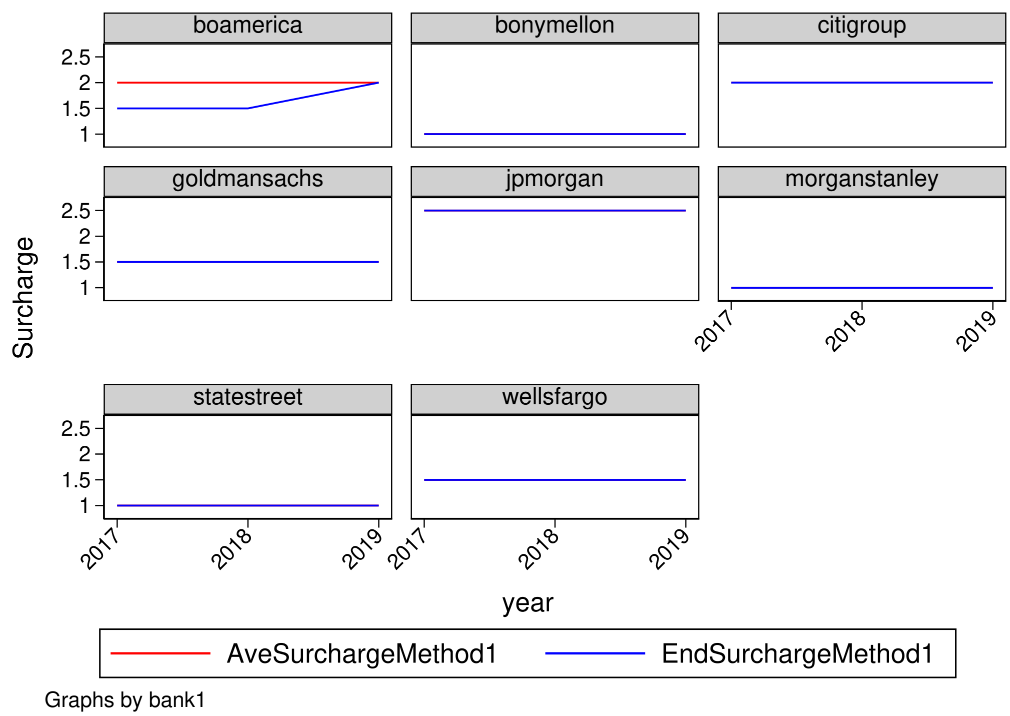

Figure 3.18: Comparison of surcharges based on year-end and Quarterly Average Method 1 score. Note: This figure displays the capital surcharges assigned to those eight U.S. G-SIB banks according to the systemic importance score calculated by using the proposed quarterly average method 1 score and year-end method 1 score. The years of the sample are 2017, 2018, and 2019.

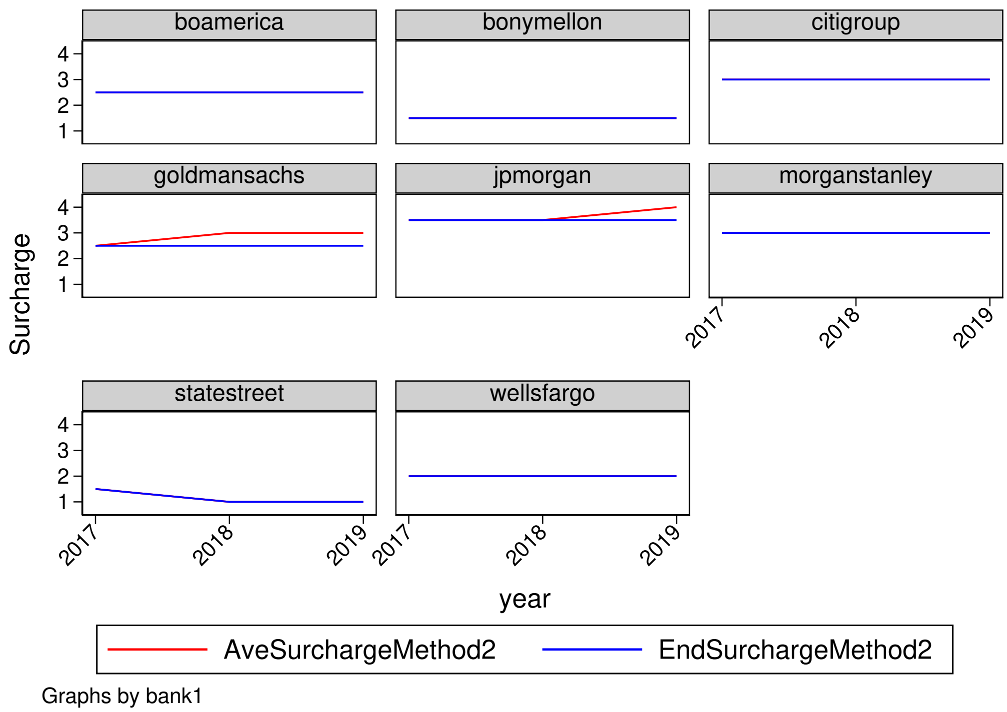

Figure 3.19: Comparison of surcharges based on year-end and Quarterly Average Method 2 score. Note: This figure displays the capital surcharges assigned to those eight U.S. G-SIB banks according to the systemic importance score calculated by using the proposed quarterly average method 2 score and year-end method 2 score. The years of the sample are 2017, 2018, and 2019.

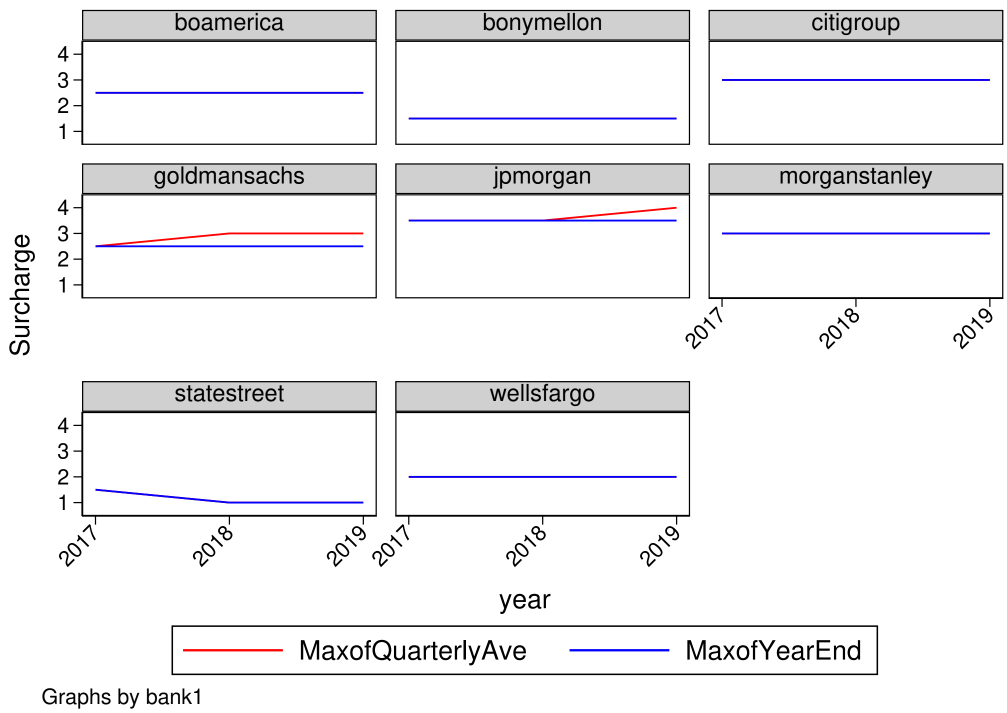

Figure 3.20: Comparison of maximum surcharges of Method 1 and Method 2. Note: This figure displays the highest capital surcharges assigned to those eight U.S. G-SIB banks according to the systemic importance score calculated by using the proposed quarterly average method and year-end method. They are called "MaxofYearAve" and "MaxofYearEnd" respectively in the legend box. For the U.S. BHCs, the highest surcharge calculated according to the method 1 and method 2 is implemented. The years of the sample are 2017, 2018, and 2019.

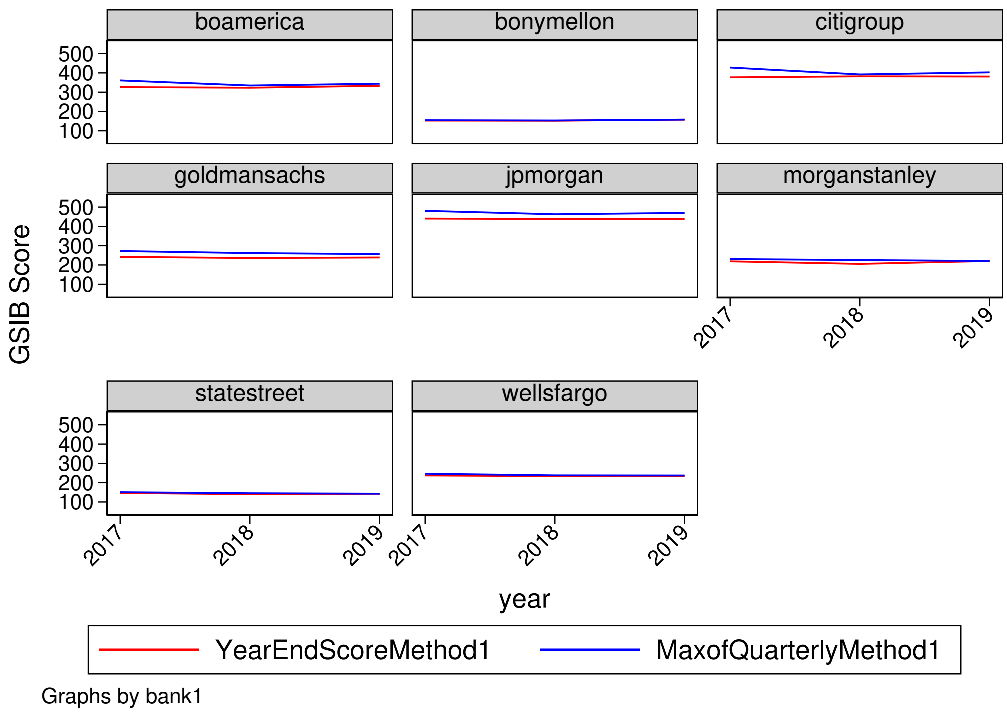

Figure 3.21: Comparison of year-end and Quarterly Maximum Method 1 score. Note: It is proposed to assign the capital surcharges based on the maximum of systemic importance score according to method 1. This figure shows the newly proposed “MaxofQuarterly” score with the currently being implemented “YearEndScore”. The years of the sample are 2017, 2018, and 2019.

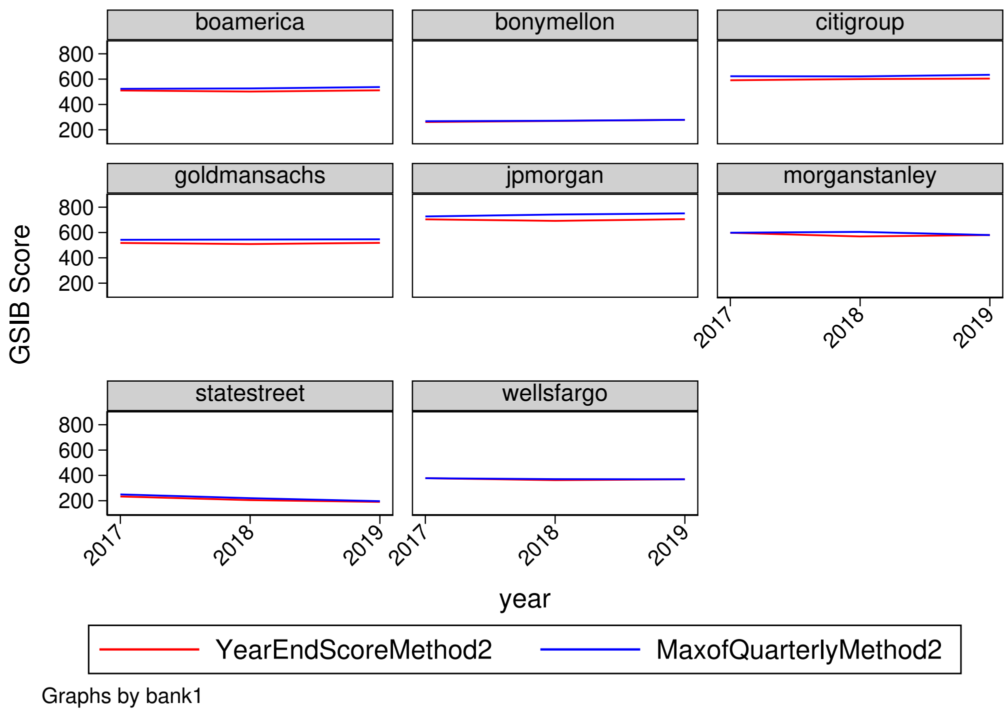

Figure 3.22: Comparison of year-end and Quarterly Maximum Method 2 score. Note: It is proposed to assign the capital surcharges based on the maximum of systemic importance score according to method 2. This figure shows the newly proposed "MaxofQuarterly" score with the currently being implemented "YearEndScore". The years of the sample are 2017, 2018, and 2019.

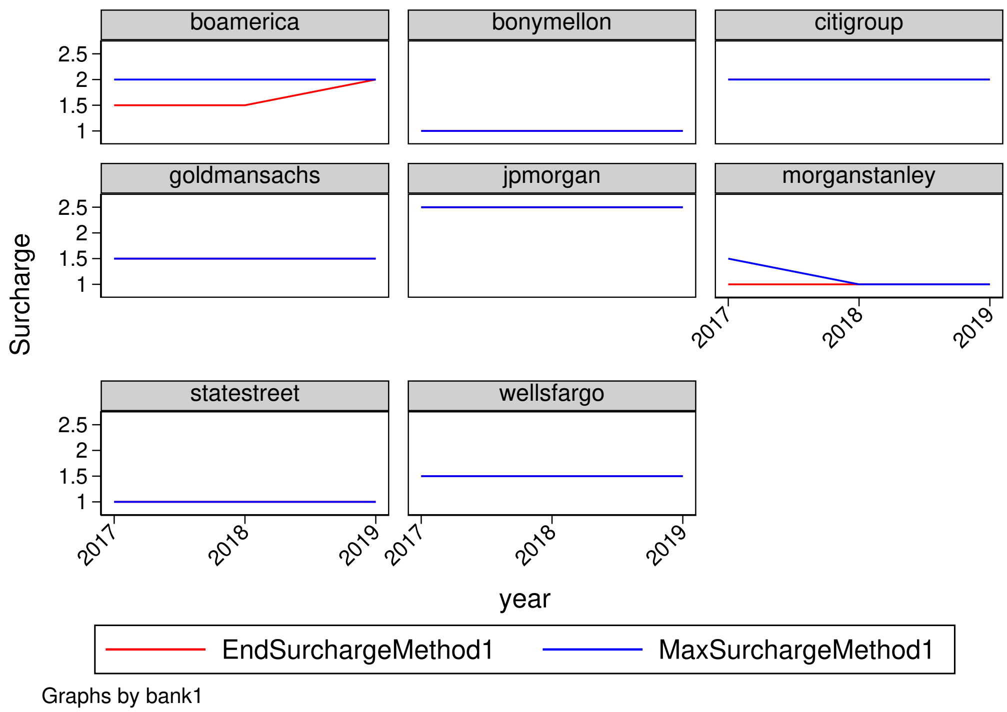

Figure 3.23: Comparison of surcharges based on year-end and Quarterly Maximum Method 1 score. Note: This figure displays the capital surcharges assigned to those eight U.S. G-SIB banks according to the systemic importance score calculated by using the proposed quarterly maximum method 1 score and year-end method 1 score. The years of the sample are 2017, 2018, and 2019.

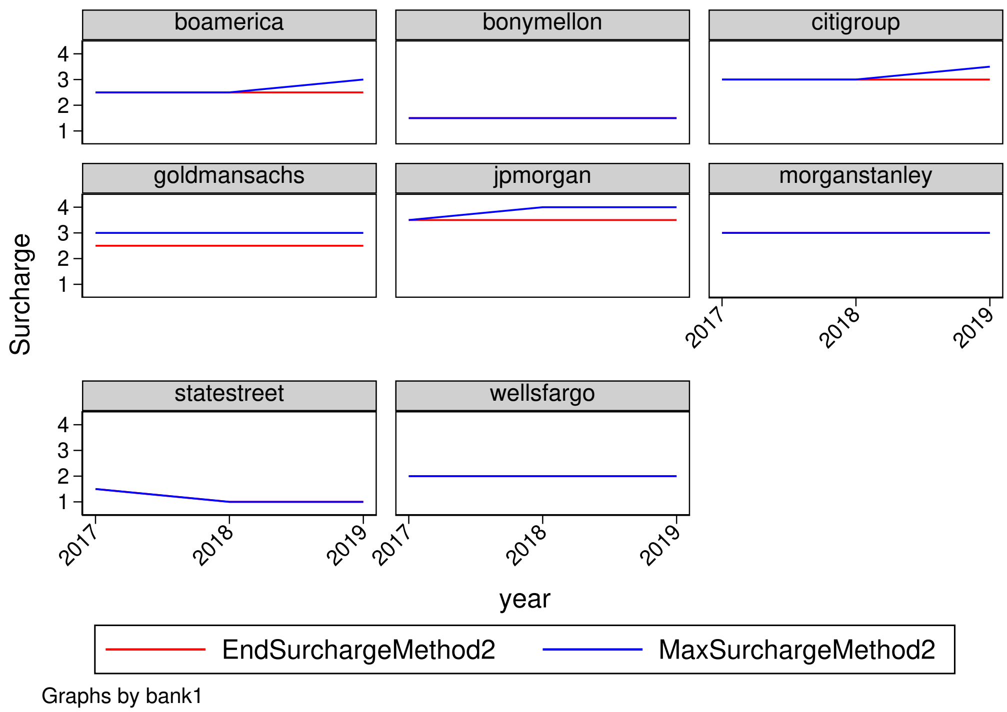

Figure 3.24: Comparison of surcharges based on year-end and Quarterly Maximum Method 2 score. Note: This figure displays the capital surcharges assigned to those eight U.S. G-SIB banks according to the systemic importance score calculated by using the proposed quarterly maximum method 2 score and year-end method 2 score. The years of the sample are 2017, 2018, and 2019.

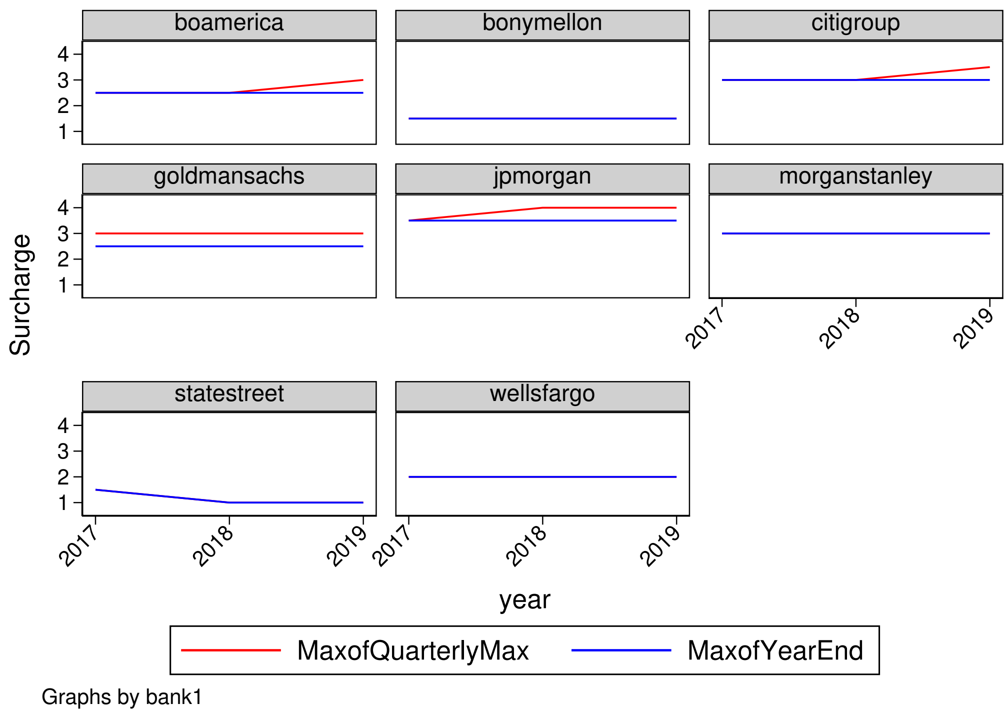

Figure 3.25: Comparison of maximum surcharges of Method 1 and Method 2. Note: This figure displays the highest capital surcharges assigned to those eight U.S. G-SIB banks according to the systemic importance score calculated by using the proposed quarterly maximum method and year-end method. They are called "MaxofYearMax" and "MaxofYearEnd" respectively in the legend box. For the U.S. BHCs, the highest surcharge calculated according to method 1 and method 2 is implemented. The years of the sample are 2017, 2018, and 2019.

Chapter 4

Modernizing Taylor Rule with Time-Varying Inflation Target and Natural Rate of Interest

Traditional linear Taylor rule based on several assumptions like fixed natural rate of interest and inflation target is widely used as a monetary policy rule. However, the U.S. economy has changed significantly since the 2008 Financial crisis, and the effectiveness of the linear Taylor rule has been subject to criticism. This paper examines the effectiveness of a linear Taylor rule in which both the natural rate of interest and the inflation target is time-varying. The time-varying variables are estimated with two different methods: a multi-step Maximum-Likelihood approach and a standard New-Keynesian framework. I find that applying time-varying estimates to the original Taylor rule (1993) slightly increases the accuracy of the policy rate for the post-1993 period, but the differences are significant. However, applying the same data to the inertial Taylor rule, the prescribed policy rate is highly consistent with actual data for the overall sample period (1965Q1-2019Q1), especially for the post-2008 period. The results suggest that the market-determined natural rate of interest and implicit inflation target may be more useful in determining the policy rate.

4.1 Introduction

Federal Funds Rate (FFR) is one of the most important rates used by central banks to influence economic activity. Using a simple monetary policy rule may not be able to capture all the related variables to the policy rate. However, it is convenient for the public to predict the policy rule, which is further very important to achieve the central bank's goal of influencing economic activity.

[30] put forward a simple linear policy rule, which is then generally called as "Taylor rule" or "1993 Taylor rule". In the 1993 Taylor rule, the FFR is a function of the rate of inflation, 2 percent inflation target, percent deviation of output from its potential out level, and inflation deviation from its previous four quarters summation. The coefficients for both the output gap and inflation gap are 0.5 while both the target inflation rate and the natural rate of interest are assumed to be 2 percent according to the long-term trend of historical data. Policy rates gained by deploying the Taylor rule manage to capture the basic trend for the sample period of 1987-1992 successfully.

Figure (4.1) shows the real time prediction of the FFR for the period of 1985Q2-2019Q1 by employing the Taylor rule and the actual FFR. Taylor rule is relatively successful in capturing the basic trend with a small difference till 1993Q2 as it did in [30]. What is more, the predicted policy rate deviates far away from the actual FFR for the post-1993 period while loosely following the trend of actual FFR except for the period of 1993-1999. Even though the actual FFR is nearly zero after the Great Recession in 2008, the policy rate prescriptions are above one percent for the whole post-2008 period. Therefore, why does the same Taylor rule that worked effectively for the pre-1993 period fail to work for the post-1993 period? Do we need improvement of the 1993 Taylor rule or just simply stop using it? Are there any fundamental changes in the U.S. economy?

Ever since the introduction of the Taylor policy rule, it has been widely used in academia and other related areas. As a simple linear policy rule, it has several advantages and shortcomings. Being a useful benchmark for both policymakers, financial market participants, and good channel for communication between policymakers and the general public are advantages of Taylor rule while different measurements of inflation, not the availability of real time potential output, limited variables consideration, and not consideration of risk management are shortcomings of a simple linear rule ([19]). Besides, the natural rate of interest and inflation target is assumed to be 2 percent even though the Federal Reserve did not announce its target inflation rate until 2012 and the FFR stays near Zero Lower Bound (ZLB) till recently. [30] chose the "equilibrium" interest rate of 2 percent because of its closeness to the assumed steady-state real GDP growth rate of 2.2 percent. The natural rate of interest or equilibrium interest rate is not directly observable. Therefore, it needs to be estimated by using different approaches. There are different definitions of the natural rate of interest. As [1] points out, the notion of the natural rate of interest is not static all the time. The recent ones, for example, [22] state that the "natural rate of interest is the real fed funds rate consistent with stable inflation absent shocks to demand and supply". [16] points out that the natural rate of interest is the FFR that is consistent with neither accommodative nor restrictive monetary policy. The short term feature of the equilibrium interest rate makes the assumption of a fixed natural rate of interest made in [30] hard to convince.

Most of the researchers automatically take the fixed inflation target of 2 percent, which is consistent with the long-term price stability, as given. Federal Reserve Board first time announced its official inflation target in 2012 by stating "the Committee judges that inflation at the rate of 2 percent, as measured by the annual change in the price index for personal consumption expenditures, is most consistent over the longer run with the Federal Reserve's statutory mandate" ([5]). [7] reaffirms a 2% symmetric inflation target, which is measured as the annual change of Personal Consumption Expenditure Price Index (PCE price index). Thus, it is reasonable to question whether the inflation target has always been 2% since the mid-1980s. [9] suggests that the U.S. has an implicit inflation target of 2% after 1995, which is the inflation targeting era, because of stabilized U.S. inflation expectations near this value. [28] analyze the sentiment expressed by the participants of internal meetings of the Federal Open Market Committee (FOMC) and estimate that the Federal Reserve inflation target rate was about 1.5 percent over the 2000-2013 period. [15] also estimates the unknown Federal Reserve inflation target by using a New Keynesian Model and estimated inflation target rates were 8 percent in the late to mid-1970s and below 2.5 percent around 2004. Therefore, there is a possible large degree of variations in the assumed to be a constant implicit inflation target rate. [27] examines the impact of the time-varying implicit inflation target and the equilibrium interest rate on the hypothesized asymmetric preference of the U.S. monetary policy and points out that assumptions made regarding the monetary policy rules may have a significant effect on the monetary policy behavior. Overall, all evidence above implies that a possible time-varying inflation target may have been neglected for a long time. Therefore, it is of great importance to understand how the Taylor rule behaves if the assumption of a fixed inflation target is relaxed.

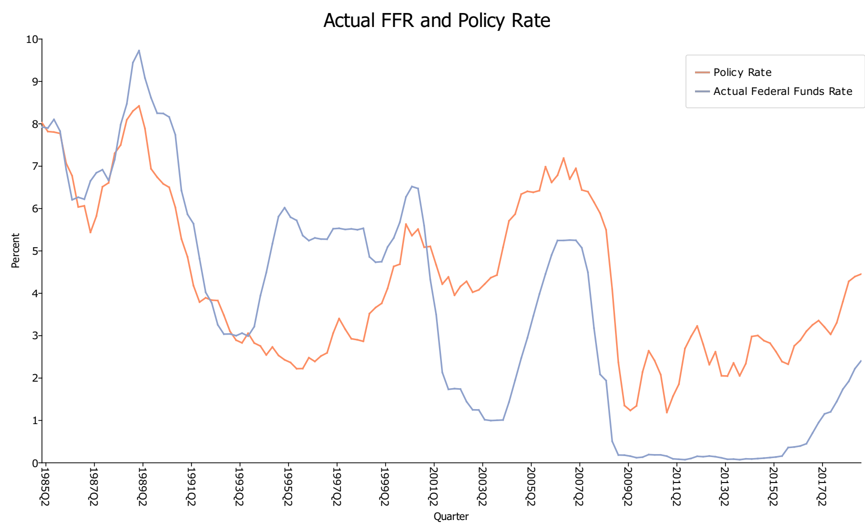

Figure 4.1: The 1993 Taylor rule suggested policy rate and the actual FFR. Note: The prescribed policy rates are estimated by following [30]. Inflation over the previous four quarters is used and it is the summation of the previous four quarters of inflation. The frequency of data is quarterly and for the period of 1985Q2-2019Q1.

After observing a relatively long period of low inflation and interest rate following the Financial crisis, more economists began to question the accuracy and effectiveness of 2% fixed inflation target rate used in the Taylor rule and came up with new proposals. [3] proposes that central banks can perform better by targeting 4% inflation rate by lessening the negative impact of monetary policy constraints caused by near ZLB interest rates. [29] review the history of 2% inflation target rate and state that one possible alternative for Federal Reserve to improve the current monetary policy is increasing the inflation target rate to 3% or 4%. While others propose an inflation target range rather than a precise rate. [26] proposes an adjustable inflation target, which he defines as “a range of inflation rates acceptable to policymakers across many economic circumstances, and a medium-term goal within that range policymakers would set depending on the current circumstance", to avoid extended low interest rate period in the future. [11] also expresses his intention of evaluating the possibility of targeting an inflation range, probably between 1.5% to 2.5%. Even though targeting an inflation range is a good idea, it also creates policy uncertainty and hinders the relatively efficient communication between policymakers and the general public.

The Taylor rule was introduced nearly three decades ago and there have been many significant changes ever since that can affect the monetary policy rule, especially following the Financial crisis in 2008. [8] points out three major changes in the U.S. economy since the 1980s. First, the natural rate of interest has been decreasing. Second, the slope of the Phillips curve, which was negative, has been steadily decreasing and trending to zero since the mid-1990s. Third, the real-time forecasting of inflation has been improved significantly. [31] also examine different measures of U.S. inflation dynamics in the past half century with the latest methods and conclude that inflation persistence has been decreasing significantly over the low inflation period. Therefore, there is a possibility that the 1993 Taylor rule is not flexible enough in capturing the changes since 1993. Those changes can be caused by structural breaks, preference, the priority of policymakers, and sudden shocks to the economy. Therefore, one can express those changes in the Taylor rule by including non-linear features, time-varying response coefficients, time-varying target rates, more accurate estimates, or different measures of variables.

However, considering the simple and easy to form expectation nature of the linear policy rule, I will examine a simple linear Taylor rule with two adjustments. First, the assumption of a central bank fixed inflation target is relaxed and replaced with time-varying inflation targets. Second, a time-varying natural rate of interest, which is also called "rstar" in the literature, will be employed. Time-varying response coefficients are also likely to improve the linear Taylor rule by capturing the priority and preference of policymakers at different times. Examining a linear Taylor rule with the time-varying inflation target, natural rate of interest, and response coefficients is an interesting direction for future research.

To the best of my knowledge, this study is the first of its kind that modernizes the Taylor rule with the new features of both time-varying inflation target and equilibrium interest rate since the 2008 Financial crisis, and thus extends the literature on modernizing the linear Taylor rule. It also contributes to the literature that addresses the importance of interest rate lags in the policy rules. Our findings highlight the importance of relaxing both the fixed implicit inflation target rate and the natural rate of interest assumptions to improve the accuracy of policy rules.

The paper uses sample data of the U.S. from 1965Q1 to 2019Q1. There are several novel findings. First, The estimated implicit inflation target dropped to 0.554 % in 2008Q3 and has stayed very close to 1% till 2019Q1, which is a significant deviation from the official 2% inflation target rate. Second, just a simple balanced linear Taylor rule with time-varying inflation target and the natural rate of interest can not precisely capture the movement of FFR for the whole sample period. Third, the inertial Taylor rule with time-varying inflation target rates and natural interest rates well captures the trend of FFR with a very small difference, even for the post-2008 period. These findings have important implications for policymakers. It stresses the importance of inertia of FFR and provides support for the long-time neglected dynamic nature of implicit inflation target rate and the natural rate of interest.

The rest of the paper is organized as follows. Section (4.2) discusses related previous literature. Section (4.3) briefly describes the empirical methods of [15] and [22] that are used to extract time-varying implicit inflation target and equilibrium interest rate. Section (4.4) analyzes the accuracy and efficiency of linear Taylor rule by employing estimated values. Section (4.5) concludes the paper.

4.2 Literature Review

There is a large number of literature about the Taylor rule with different modifications. The policy rule stated in [30] has the following form:

$$r = p + 0.5y + 0.5(p - 2) + 2 \tag{4.1}$$

where r is the nominal FFR, y is the output gap in percentage and p denotes the inflation rate over the previous four quarters. However, as we discussed earlier, the inflation target rate and equilibrium interest rate are both assumed to be 2 percent. The 1993 Taylor rule can be generalized as:

$$R_t = r_t^* + \pi_t + \alpha(\pi_t - \pi_t^*) + \beta(y_t - y_t^*) \tag{4.2}$$

where R_t is the policy rule suggested FFR, r_t^* is the equilibrium interest rate, π_t^* is the inflation target rate, and α, β are corresponding coefficients, which are both 0.5 in the specification (4.1). The idea of incorporating a time-varying natural rate of interest or time-varying implicit inflation target rate in a Taylor rule is recent. As far as I know, [23] is the only paper that examines a linear Taylor rule with both time-varying inflation target and the natural rate of interest. [23] relaxes the assumption of the constant inflation target rate and the natural rate of interest by assuming them following a random walk process. [23] employs [22] (LW Approach) method to extract the natural rate of interest and then gains the time-varying inflation target rate from an assumed random walk process. The prescribed policy rate in [23] captures the actual path of the FFR relatively better for the whole sample period of 1979-2004. However, the methodology used to estimate the time-varying inflation target rate in [23] is different from the approach I will use in this paper.

There have been several directions in improving the Taylor rule such as considering the asymmetric preference of a central bank, time-varying parameters, including more variables, or nonlinear-Taylor rule. [24] modernize the Taylor rule by accounting for the characters of non-linearity (asymmetric preference of policymakers), time-varying parameters, real-time data, and heteroskedasticity over a long period starting from 1965. [24] find that the Federal Reserve conducted monetary policy like having asymmetric preference in the pre-Volcker period while showed signs of symmetric preference in the post-Volcker period and dynamics of monetary policy are very rich since 1965 considering the Federal Reserve's response to inflation and real output. [10] examines the linearity of the Taylor rule employed by the European Central Bank, Bank of England, and U.S. Federal Reserve with a sample period of 1999-2007 and concludes that a linear Taylor rule can well represent the U.S. monetary policy.

Another way of modernizing the Taylor rule is taking the recent changes in the U.S. economy into account or using a different measure of variables. [8] modernizes the inertial Taylor rule, which includes one quarter lag of FFR with a persistence parameter, by considering three major changes as we mentioned earlier. The forecast result of improved Taylor rule by [8] points to a 2 percent policy rate while the unmodernized Taylor rule suggests a 4 to 6 percent policy rate just for four days of December 2018. [17] also notes the inconsistency between the Taylor rule indicated policy rate and actual FFR since 2010. Thus, [18] follows [8] and modernizes the inertial Taylor rule with different measures of the output gap, inflation gap, Hodrick-Prescott filtered time-varying natural rate of interest, 2 percent inflation target, and updated coefficients. [18] applies the U.S. data of the post-Financial crisis to this new version of Taylor rule and the policy rate is highly consistent with the actual data during the ZLB period while the 1993 Taylor rule still implies at least one percent policy rate over the period of 2010-2016.

[25] propose three important criteria that a successful policy rule should satisfy for the post-2008 era and examine the balanced, output gap tilting, and inflation gap tilting Taylor rules with a fixed or time-varying natural rate of interest. After comparing the results, [25] point out the advantages of inflation tilting rules over others and conclude that inflation gap tilting with the LW approach estimated time-varying natural rate of interest works better than the one with the fixed natural rate of interest. [2] examine the

relationship between the steady-state natural rate of interest and optimal inflation target in a New-Keynesian Dynamic Stochastic General Equilibrium (DSGE) model that is subject to a zero lower bound and find that they have a negative relationship and the slope is -0.9. This finding has important implications since our economy is dynamic and just having a time-varying inflation target or natural rate of interest is ignoring the chain reaction caused by a single important change.

4.3 Empirical Frameworks

In this section, I will briefly describe related empirical frameworks of extracting time-varying natural rate of interest and time-varying implicit inflation target from two different papers. For the detailed description of those two frameworks, please check [15] and [22].

4.3.1 Measuring Natural Rate of Interest r_t^*

I will follow [22] to measure the natural rate of interest from the baseline model.[1] I define the natural rate of interest as "the real interest rate consistent with output equaling its natural rate and stable inflation" as in [22]. The equation (4.3) that describes the link between the real interest rate and growth rate of consumption can be gained by the

[1] I sincerely appreciate Thomas Laubach for sharing the Gauss code of original paper with me. I only worked on the code of processing raw data. If there is any error, it will be mine. The latest updated values of r_t^* and R code is also available on the Federal Reserve Bank of New York website: `https://www.newyorkfed.org/research/policy/rstar`

household's intertemporal utility maximization problem.

$$r = \frac{1}{\sigma} g_c + \theta \tag{4.3}$$

where r, σ, g_c, and θ stand for the real interest rate, intertemporal elasticity of substitution in consumption, growth rate of per capita consumption, and rate of time preference respectively. According to the above relationship, the law of motion is simply can be written as in equation (4.4) for the natural rate of interest, which is r^*.

$$r_t^* = cg_t + z_t \tag{4.4}$$

where g_t and z_t denote the trend growth rate of the natural rate of output and other determinants of the natural rate of interest respectively. Since r_t^* is not observed, the natural rate of interest, output, and trend growth can be jointly estimated by using the Kalman filter. A simple reduced-form IS equation (4.5) is used to identify the natural rate of interest.

$$\tilde{y_t} = a_{y1} \tilde{y_{t-1}} + a_{y2} \tilde{y_{t-2}} + \frac{a_r}{2} \sum_{j=1}^{2} (r_{t-j} - r_{t-j}^*) + \varepsilon_{1t} \tag{4.5}$$

where $\tilde{y_t} = 100 * (ln^{y_t} - ln^{y_t^*})$, r_t, and ε_t denote the difference between real GDP and unobserved natural rate of output, ex ante real FFR, and serially uncorrelated error. Besides, the core PCE inflation (π_t), core import (excluding petroleum, computers, and semiconductors) price inflation (π_t^I), and crude imported oil price inflation (π_t^o) are assumed to follow the relationship as shown in equation (4.6):

$$\pi_t = B_\pi(L)\pi_{t-1} + b_y \tilde{y_{t-1}} + b_i(\pi_t^I - \pi_t) + b_o(\pi_{t-1}^o - \pi_{t-1}) + \varepsilon_{2t} \tag{4.6}$$

where ε_{2t} is a serially uncorrelated error and $B_\pi(L)$ is the lag operation such that summation of coefficients of 8 lags it operates is equal to one.

The variable z in the equation (4.4) also follows an autoregressive process:

$$z_t = D_z(L)z_{t-1} + \varepsilon_{3t} \tag{4.7}$$

For the baseline model of [22], z_t is assumed to follow a random walk process. Additional assumptions are also made about the level of natural rate of output and its trend growth rate.

$$y_t^* = y_{t-1}^* + g_{t-1} + \varepsilon_{4t} \tag{4.8}$$

$$g_t = g_{t-1} + \varepsilon_{5t} \tag{4.9}$$

where ε_{3t}, ε_{4t}, and ε_{5t} are assumed to be serially uncorrelated and contemporaneously uncorrelated innovation.

Equation (4.5) and (4.6) are the components of the measurement equation while equation (4.7), (4.8) and (4.9) constitute transition equation of the state-space model. As shown in [20], the state-space model can be expressed as:

$$y_t = A'x_t + H'\xi_t + v_t \tag{4.10}$$

$$\xi_t = F\xi_{t-1} + c + \varepsilon_t \tag{4.11}$$

where y_t, x_t, and ξ_t denote the vector of contemporaneous endogenous variables, vector of exogenous and lagged exogenous variables, and vector of unobserved variables respectively. The estimation process includes three steps and details of the estimation process can be found at [20].

4.3.2 Measuring the Inflation Target

I will follow [15] to measure the implicit inflation target π_t^* of the Federal Reserve.[2] Here, I will briefly discuss the important empirical parts of [15] that are relevant to extracting the unobserved implicit inflation target rate from a theoretical model. The detailed empirical framework of [15] is available in [14].

[15] develops a New Keynesian model to investigate the patterns, causes, and consequences of changes in the Federal Reserve's implicit inflation target rate. The model has four players: a representative household, a representative final good producer, a continuum of intermediate good producers, and a central bank. The central bank employs linear modified Taylor rule, which is given by:

$$\ln(R_t) = \ln(R_{t-1}) + \rho_\pi \ln(\frac{\Pi_t}{\Pi_t^*}) + \rho_{gy} \ln(\frac{g_t^y}{g^y}) + \ln(\nu_t) \tag{4.12}$$

where R_t, $\Pi_t = \frac{P_t}{P_{t-1}}$, and g_t^y stand for the short-term nominal interest rate, gross inflation rate, and the growth rate of output at time t respectively. Besides, coefficients $\rho_\pi > 0$

[2] All the codes and note for the [15] are available on Peter N. Ireland's website: `https://www2.bc.edu/peter-ireland/programs.html`. I sincerely appreciate Peter N. Ireland for his clarification of some confusion regarding the Matlab code through emails.

and $\rho_{gy} \geq 0$ are determined by the central bank. What is more, the transitory monetary shocks ν_t follows a simple stationary autoregressive AR(1) process with persistence ρ_ν. The implicit inflation target Π_t^* is assumed to evolve according to the following rule:

$$\ln(\Pi_t^*) = \ln(\Pi_{t-1}^*) - \delta_\theta \varepsilon_{\theta t} - \delta_z \varepsilon_{zt} + \sigma_\pi \varepsilon_{\pi t}, \quad \sigma_\pi \geq 0, \quad , t = 0, 1, 2, ... \tag{4.13}$$

where $\varepsilon_{\theta t}$, ε_{zt}, and $\varepsilon_{\pi t}$ denote for the serially uncorrelated innovation to the intermediate good producer's desired markup of price over marginal cost, innovation to the technology, and inflation respectively. The central bank determines coefficients $\delta_\theta \geq 0$, and $\delta_z \geq 0$. One point that needs to be addressed is that potential output is gained by solving the social planner's maximization problem.

After solving the model, linearization, and simplifying, there are a total of 17 parameters to be estimated and three of them are determined in advance. Therefore, 14 of them are left to be estimated by applying the Kalman filter to the maximum likelihood estimation. After simplification, the measurement equation of the state-space model can be written as:

$$s_{t+1} = As_t + B\varepsilon_{t+1} \tag{4.14}$$

where

$$s_t = [\tilde{y_{t-1}}, \tilde{\pi_{t-1}}, \tilde{r_{t-1}}, \tilde{q_{t-1}}, \tilde{a}_t, \tilde{e}_t, \tilde{z}_t, \tilde{\nu}_t, \tilde{\pi_t^*}]' \tag{4.15}$$

where $\tilde{y}_t$ is the percentage deviation of each stationary variable y_t from its steady state level, which can be expressed as $\tilde{y}_t = \ln(\frac{y_t}{y})$. What is more, the similar principle is applied to other variables in the s_t vector. The y_t, c_t, and q_t are the technology adjusted real GDP, real consumption, and real efficient level of GDP while r_t is the ratio of gross nominal interest rates over the inflation target at time t. Besides, a_t, z_t, and ν_t denote the consumer's preference shock, aggregate technology shocks to the intermediate good producer, and transitory monetary policy shocks respectively. Other variables are defined as following: $\pi_t = \frac{\Pi_t}{\Pi_t^*}$, $\pi_t^* = \frac{\Pi_t^*}{\Pi_{t-1}^*}$, and $\tilde{e_t} = \frac{1}{\phi}\tilde{\theta}_t$, where ϕ is a parameter needs to be estimated.

The transition equation can be expressed as:

$$d_t = Cs_t \tag{4.16}$$

where $d_t|_{t=1}^{T}$ is a vector of three observable variables, which are the logarithmic deviation of the growth rate of output, logarithmic deviation of the growth rate of inflation, and the logarithmic deviation of the ratio of nominal interest rate to the inflation rate from their respective steady-state values. The exact expression for the d_t is given as:

$$d_t = \begin{bmatrix} \tilde{g_t}^y \\ \tilde{g_t}^\pi \\ \tilde{r_t}^{r\pi} \end{bmatrix} = \begin{bmatrix} \ln Y_t - \ln Y_{t-1} - \ln z \\ \ln P_t - 2\ln P_{t-1} + \ln P_{t-2} \\ \ln R_t - \ln P_t + \ln P_{t-1} - \ln z + \ln \beta \end{bmatrix} \tag{4.17}$$

where β is the consumer's discount factor and P_t is the nominal price charged by the final good producer. Besides, $z_t = \frac{Z_t}{Z_{t-1}}$ and Z_t is the aggregate technology shock to the intermediate good producer. Therefore, z is the steady-state value of z_t. It is worth noting that eq (4.17) is the core equation used in the estimation process and the real GDP per capita, GDP deflator, and gross nominal interest rate on three-month U.S. treasury bill are used for Y_t, P_t and R_t in the original paper.

C in the transition equation (4.16) is a vector of coefficients and it is given as:

$$C = \begin{bmatrix} U_1 \\ U_2 \\ U_3 \end{bmatrix} \tag{4.18}$$

where U_1, U_2, and U_3 are the corresponding values from the already extracted matrix. What is more, serially uncorrelated shock ε_{t+1} in eq (4.14) is assumed to be normally distributed with vector of zero mean and diagonal covariance matrix V.

4.4 Estimation and Analysis

4.4.1 Data Collections

Three steps are used to measure the natural rate of interest and output gap by using the Kalman smoothing and maximum likelihood estimation as described in [20] and [21], which are the same except the programming tools used. To construct the raw data set, the U.S. real GDP, personal consumption expenditures price index, personal consumption expenditures price index excluding food and energy (Core PCE), core import (excluding petroleum, computers, and semiconductors) price inflation, crude imported oil price inflation, FFR, and Federal Reserve Bank of New York discount rate are needed. The period of sample is from 1947Q1 to 2019Q1. The U.S. real GDP, PCE price index, core PCE, and FFR data are compiled from the Economic Data of the Federal Reserve Bank of St.Louis (FRED). While already spliced and annualized data of core import price inflation, crude imported oil price inflation, and New York Federal Reserve discount rate are extracted from

[13]. The discount rate is used to increase the measurement accuracy of the FFR before 1965. Therefore, the effective sample for the Taylor rule analysis in this paper starts from 1965Q1. Gauss is used for the programming and the frequency of all the data is quarterly.

To estimate the time-varying inflation target rate, real gross domestic product, GDP implicit price deflator, civilian non-institutionalized population are used in the [15]. I will replace GDP deflator with core PCE inflation as the measure of inflation. Besides, I will also replace the three-month U.S. treasury bill rate in a secondary market with the FFR to keep the variables both in [22] and [15] consistent. All of my data is from the FRED. The duration of the sample is from 1947Q1 to 2019Q1 and the frequency is quarterly. The effective sample used for the estimation is starting from 1959Q1. [15] uses the Kalman smoothing to get the implicit inflation target rate.

Once estimating the natural rate of interest, output gap, and implicit inflation target rate by using the Kalman smoothing, I apply estimated values from 1965Q1 to 2019Q1 to the linear Taylor rule.

4.4.2 Result Analysis

The one-sided (filtered) and two-sided (smoothed) estimated values of the natural rate of interest and output gap from 1961Q1 to 2019Q1 are plotted in Figure (4.2) and (4.3). What is more, Kalman smoothing estimates of the inflation target rate are depicted in Figure (4.4).

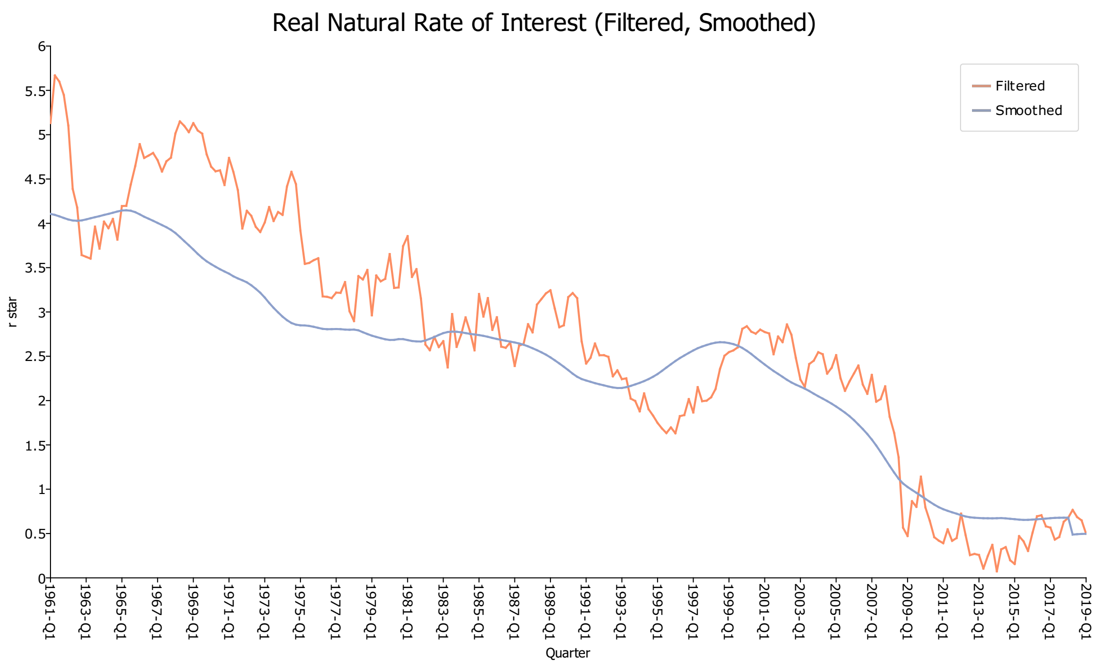

Figure 4.2: Time-varying natural rate of interest. Note: This figure depicts extracted natural rate of interest by using methods described in Section (4.3.1). Filtered stands for the Kalman Filtering approach while Smoothed stands for the Kalman Smoothing approach. The frequency of the data is quarterly and for the period of 1961Q1-2019Q1.

In Figure (4.2), even if there is a relative difference between smoothed and filtered rate of interest, both of them follow a similar trend. The overall trend of the filtered natural rate of interest is decreasing except for several short periods. The maximum natural interest rate was 5.66 percent in 1961Q2 and the minimum rate reached 0.0739 around 2013. It is very obvious from the Figure (4.2) that the equilibrium interest rates were around 0.5 percent during the post-2008 period even if [30] assumes a constant 2 percent natural rate of interest. It is also not hard to find that r^* reaches 2 percent level several times during the sample period, for example, around 1993Q1.

The difference between filtered and smoothed output gap, which is the percentage deviation of real GDP from its unobserved natural rate of output or potential output, is

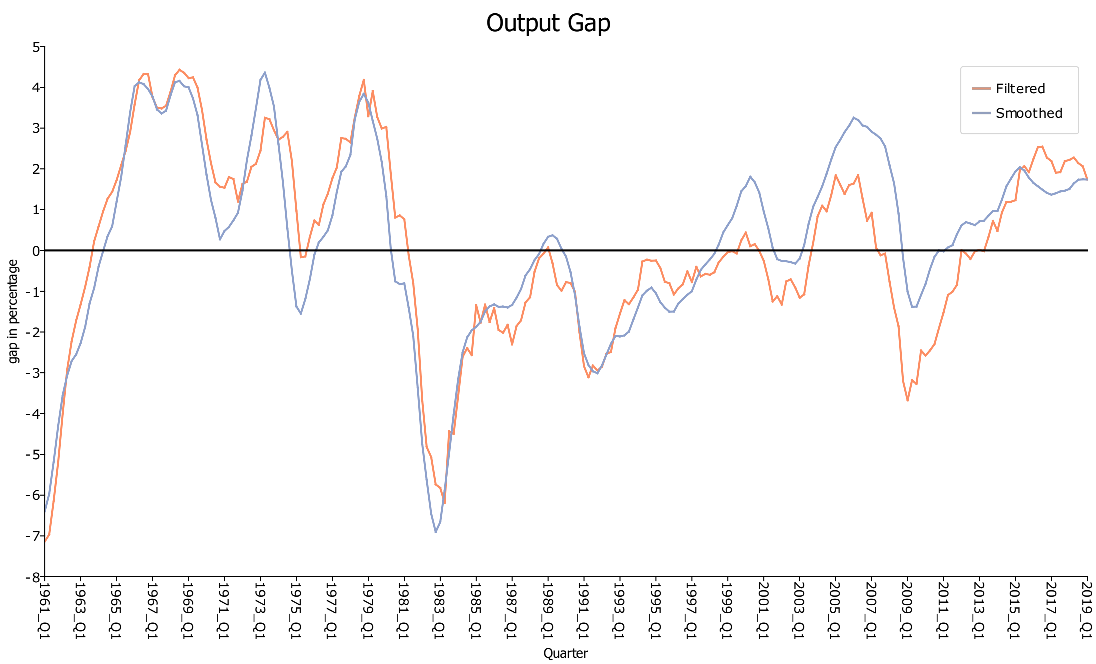

Figure 4.3: Time-varying output gap. Note: This time-varying output gap is estimated by using the LW approach described in Section (4.3.1). Filtered stands for the Kalman filtering while Smoothed stands for the Kalman Smoothing. Frequency is quarterly and the data period is 1961Q1-2019Q1.

Figure 4.4: Time-varying implicit inflation target rate. Note: This figure reports time-varying implicit inflation target rate that is estimated by using the approach described in Section (4.3.2). Data frequency is quarterly and for the period of 1959Q3-2019Q1.

relatively small until the mid-1990s as shown in Figure (4.3). However, there is a significant difference in output gap during the period of the Financial crisis. The U.S. real GDP reached the lowest level in 2019Q2 during the Financial crisis and this is consistent with the smoothing estimate. As the economy is a dynamic system such that there are too many observed and unobserved factors affecting the final outcome, Therefore, filtered or smoothed output gap can improve policy rate accuracy compared to a simple linear detrending one as shown in Figure (4.7) in Appendix.

Figure (4.4) shows the time-varying nature of the implicit inflation target rate, which is assumed to be a constant rate in [30]. The implicit inflation target rate is fluctuating around 1 percent for the post-Financial crisis period, which is lower than the 1.5 percent estimate by [28] and much lower than the 2 percent target rate announced by the Federal Reserve. If we look at the post-1984 period, which is the starting time of the sample used in [30], the overall trend of the π^* has been decreasing with little fluctuations. It is worth noting that the implicit inflation target rate reaches as high as 8.56% in 1974Q1 and 8.46% in 1981Q1. This timing is consistent with the fact that the U.S. economy suffered high inflation during the 1970s. Even if the Federal Reserve announces its target rate of 2 percent in 2012, it is really hard to keep inflation at that fixed level in a dynamic system. But, It is reasonable for economists to assume a time-varying inflation target rate according to the observation in the past several decades.

Employing the natural rates of interest, output gap, and inflation target estimates, I can easily get the prescribed policy rate from the Taylor rule. Figure (4.5) shows actual FFR and 1993 Taylor rule implied policy rates. Compared with the case of both rates

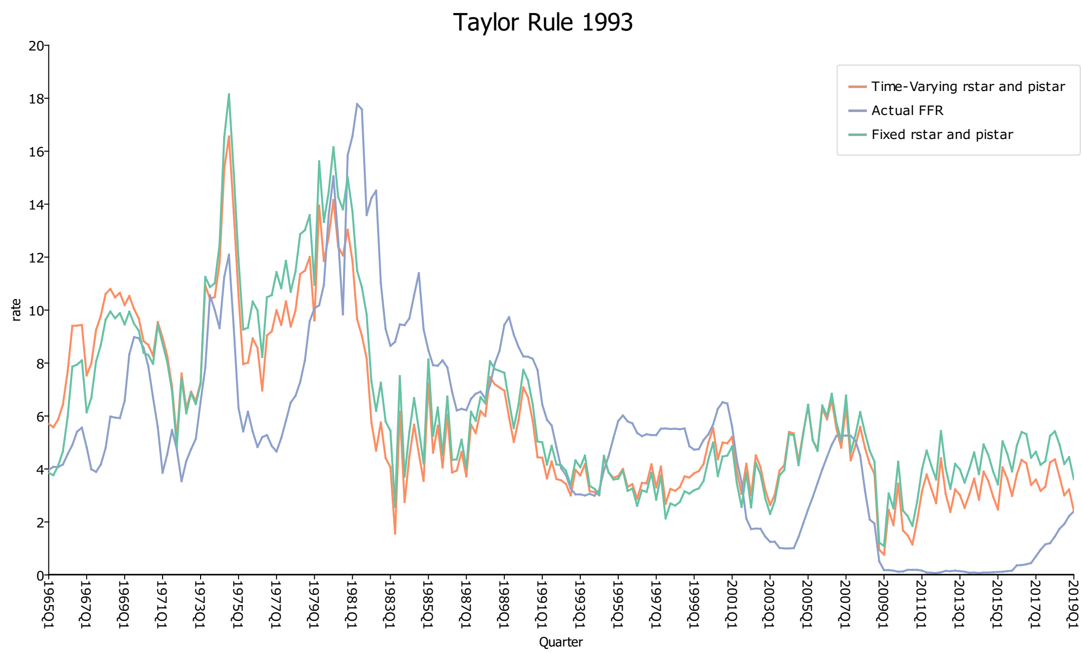

Figure 4.5: 1993 Taylor rule implied policy rate and actual FFR after employing estimated time-varying values. Note: The inflation rate is measured by annualized, quarter-to-quarter percent changes in the core PCE price index. For both time-varying rates, the Kalman smoothed estimates are used. The rstar stands for the equilibrium interest rate r_t^* while pistar stands for the implicit inflation target rate π_t^*. "Fixed rstar and pistar" means both rstar and pistar are fixed at 2% level. Frequency of the data is quarterly and for the period of 1965Q1-2019Q1.

are fixed, employing time-varying rates increases the accuracy of the policy rule for the post-2008 period. However, the Taylor rule with fixed rates performs slightly better than the one with time-varying rates from early 1980 to the early 1990s, which is the period of sample used in [30]. Even though this modernized Taylor rule works slightly better for the post-2008 period compared to the Taylor rule, it is still far away from the actual rates. It is obvious that only using time-varying natural rates and inflation target rates does not increase the quality of the policy rates prescribed by the Taylor rule. As I discussed earlier, our economy is a complicated dynamic system and it is necessary to consider other potential changes and persistency of variables to increase the estimation accuracy and quality of the policy rule. As [4] points out, the central bank's nature of being cautious about the uncertain economic future in a dynamic system and policymakers' strong wish of making monetary policy predictable by the public will contribute the gradual adjustment in economic activity, whether it is because of the gradual approach of policymakers or the gradual changes in underlying economic activities. [12] stress the importance of partial adjustment in the estimated policy rates even with the possibility of serially correlated errors. Considering the gradual adjustment of economic activity and the importance of it to a dynamic FFR, I apply the estimated data on the inertial Taylor rule described by [6]. The inertial Taylor rule has the following form:

$$R_t = 0.85R_{t-1} + 0.15[r_t^* + \pi_t + 0.5(\pi_t - \pi_t^*) + (y_t - y_t^*)] \tag{4.19}$$

Figure (4.6) shows the implied policy rates of the inertial Taylor rule that uses real-time data. The inertial Taylor rule has dramatically increased the accuracy of the prescribed policy rates nearly for the whole sample period. The most notable finding is the capturing of the post-2008 period with high trend consistency with small differences. Compared with those complicated nonlinear Taylor rules or linear Taylor rules that consider many additional critical variables, this finding has important implications for policymakers and the public. Policymakers can use predicted values of relevant variables and inertial Taylor rule to forecast the prescribed policy rate, which would be likely highly consistent with the actual FFR. Therefore, it is recommended for the Federal Reserve to prescribe policy rates by using the approach discussed here. For the public, using the linear Taylor rule is

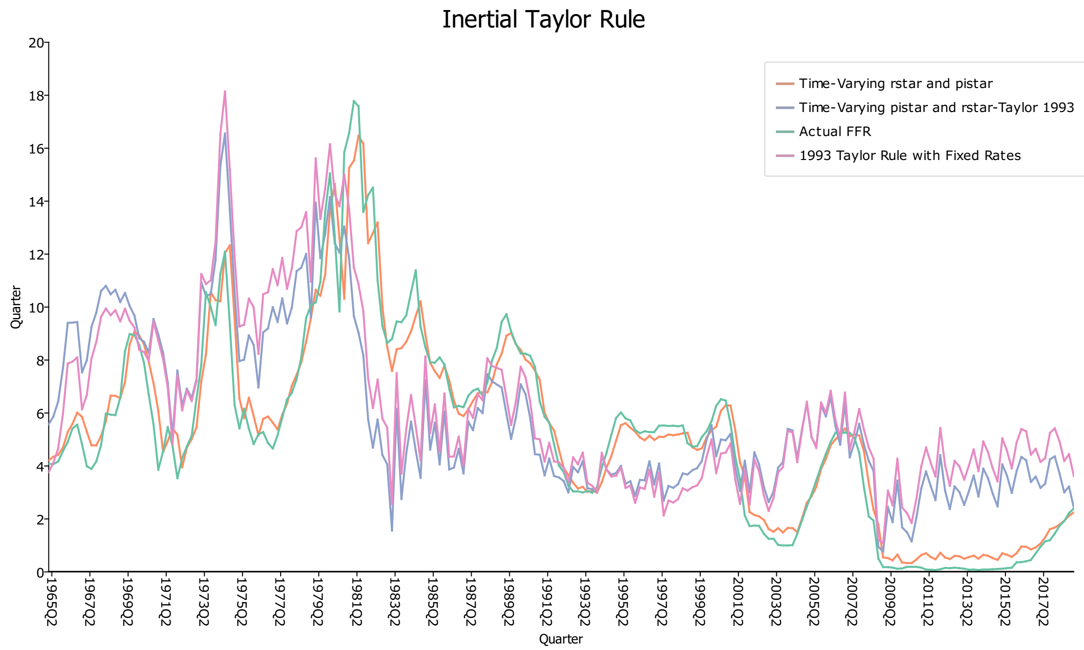

Figure 4.6: Modernized inertial Taylor rule implied policy rates. Note: The inflation rate is measured by annualized, quarter-to-quarter percent changes in the core PCE price index. The "Time-Varying rstar and pistar" refer to the inertial policy rates with rstar and pistar. The "1993 Taylor Rule with Fixed Rates" describes policy rates prescribed by the 1993 Taylor rule with fixed 2 percent rates of both natural rate of interest and inflation target rate. For both time-varying rates, the Kalman smoothed estimates are used. The rstar and pistar stand for the equilibrium interest rate and inflation target rate respectively. The frequency of the data is quarterly and for the period of 1965Q2-2019Q1.

easy and informative. However, they need to be timely informed about the natural rate of interest and implicit inflation target rate, which can be performed by the Federal Reserve or a trusted private firm that specializes in offering financial service.

4.5 Conclusion

The goal of this paper is to examine whether relaxing the assumptions of both constant natural rate of interest and inflation target rate can improve the performance of the linear Taylor rule described in [30], especially for the post-2008 ZLB period. I employ two different methods to extract the unobserved time-varying natural rate of interest and implicit inflation target rate. The two methods are developed by [22] and [15]. The period of the sample used for the analysis is 1965Q1-2019Q1.

There are several notable findings. First, the accuracy of the 1993 linear Taylor rule suffers not only from the constant interest rate and inflation target rate but also from failing to consider the persistence in the FFR. Thus, including the lag of interest rate is of great importance in improving the quality of a linear policy rule. Second, compared with the Taylor rule, the modernized 1993 Taylor rule with both time-varying rates increases the quality of policy rate prescription for the post-2008 ZLB period. However, the effect is not significant. Third, modernized inertial Taylor rule can significantly improve the accuracy of prescribed rates by the policy rule for the whole sample period. Most notably, prescribed policy rates for the ZLB period can capture the trend of the actual rates with very high accuracy and tiny differences.

The findings of this paper highlight the dynamic nature of the economy and the long-time neglected time-varying nature of the implicit inflation target rate. In this paper, I hold the response coefficients of the output gap and the inflation gap constant. Even though it complicates the process for the public to form expectations, time-varying response coefficients can be used in the analysis because of the possible changes in priorities of a central bank. Therefore, examining a linear Taylor rule with the time-varying natural rate of interest, inflation target rate, and response coefficients is a promising avenue for future research.

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4.7 Appendix

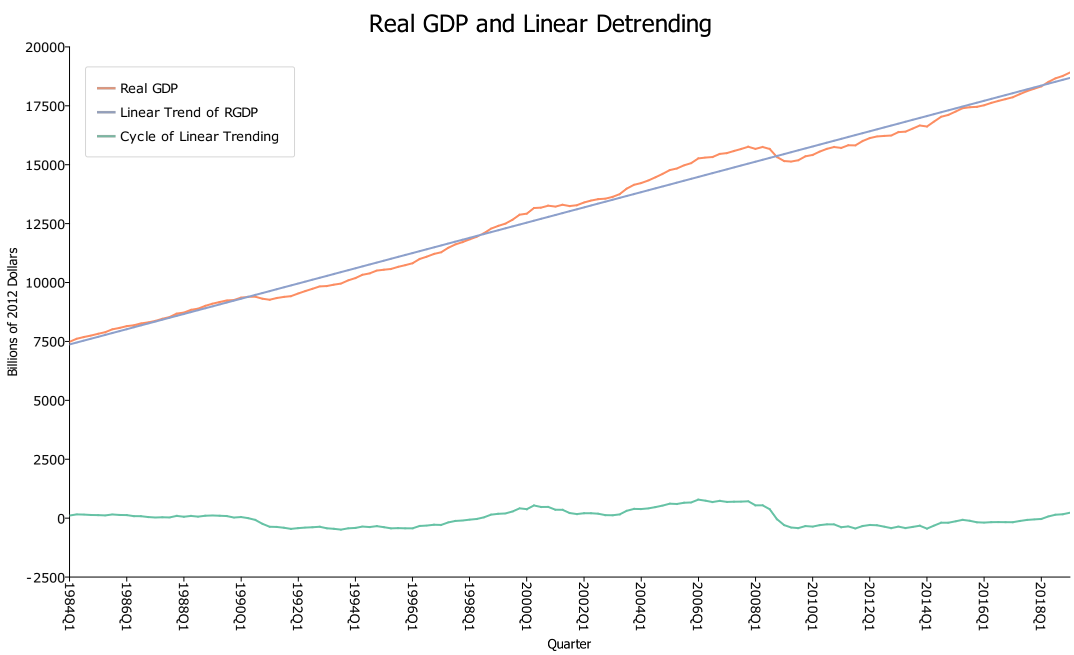

Figure 4.7: Linear detrending of the U.S. real GDP. This figure describes the linear detrending of the U.S. real GDP as in [30]. Frequency of the data is quarterly and for the period of 1984Q1-2019Q1.

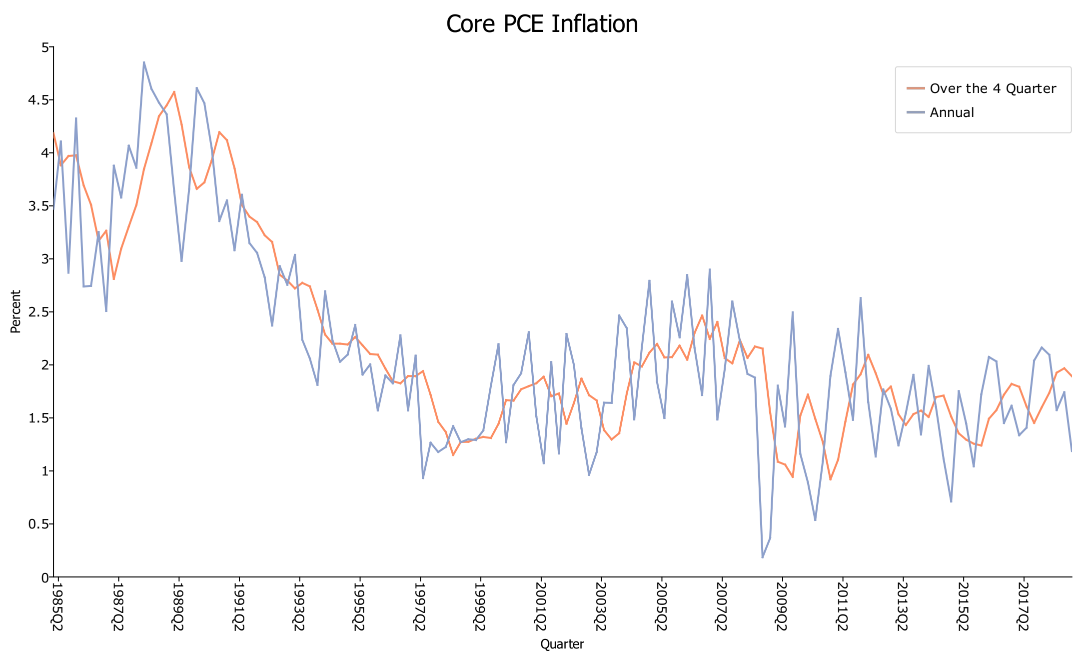

Figure 4.8: Inflation rates. Note: The "Over the 4 Quarter" describes the summation of the core PCE inflation over the previous four quarters. The "Annual" stands for the annualized core PCE inflation rate. Frequency of data is quarterly and for the period of 1985Q2-2019Q1

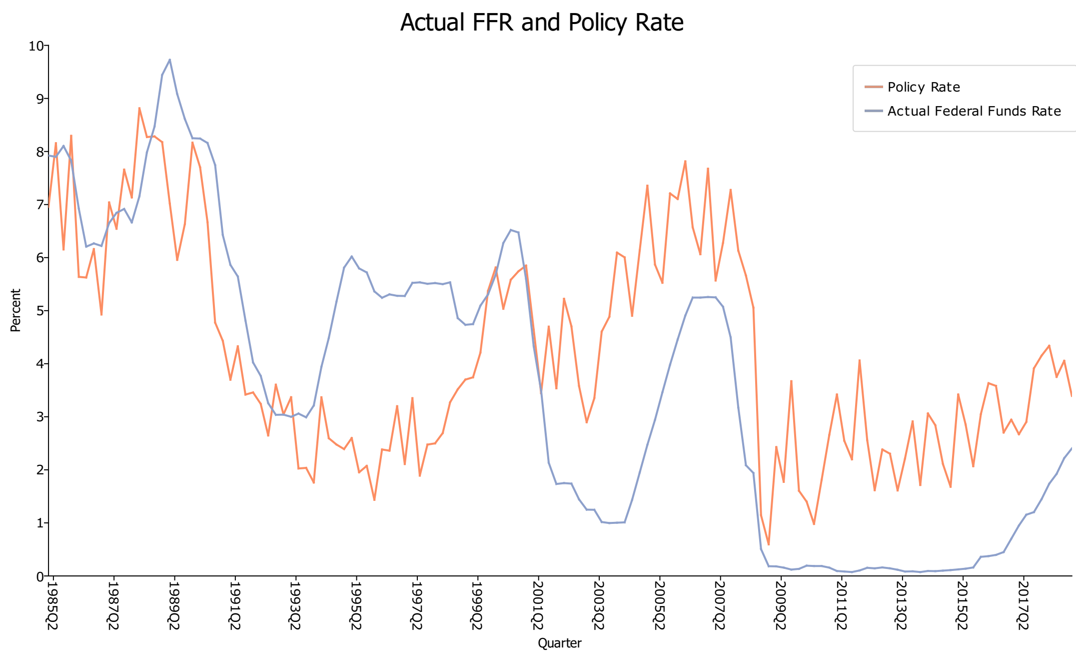

Figure 4.9: Original 1993 Taylor rule implied policy rates by using annualized inflation rates. Note: Annualized core PCE inflation rate is used in the Taylor Rule. Frequency of the data is quarterly and for the period of 1985Q2-2019Q1.

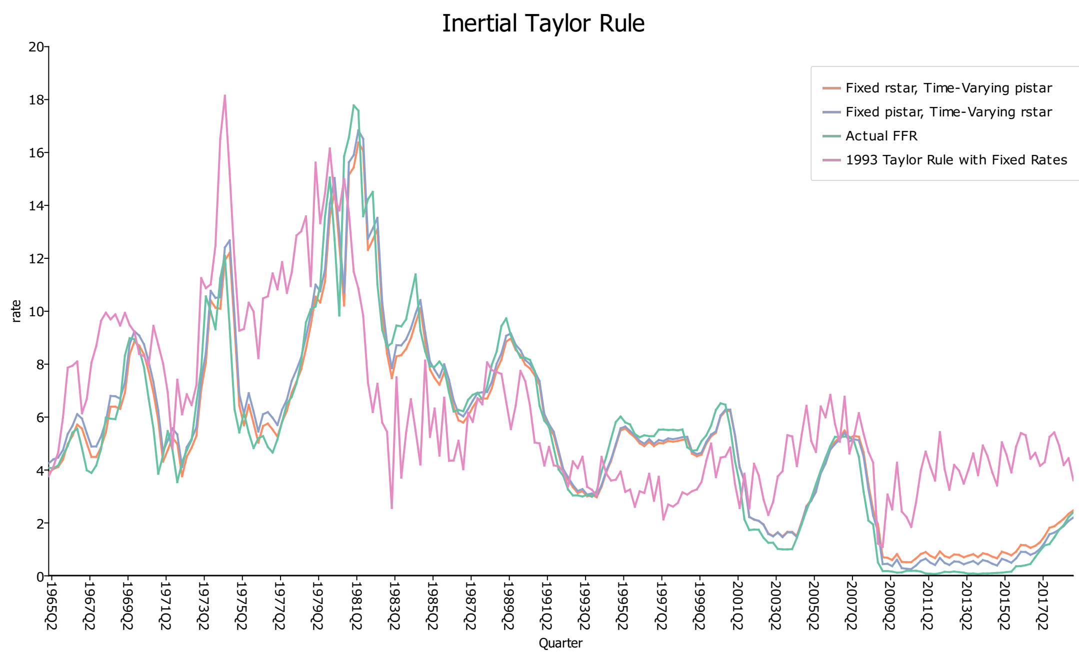

Figure 4.10: Modernized inertial Taylor rule implied policy rates by different combinations. Note: The inflation rate is measured by annualized, quarter-to-quarter percent changes in the core PCE price index. The "1993 Taylor Rule with Fixed Rates" describes policy rates prescribed by the 1993 Taylor rule with fixed 2 percent rates of both natural rate of interest and inflation target rate. "Fixed rstar, Time-Varying pistar" and "Fixed pistar, Time-Varying rstar" refer to policy rates prescribed by the inertial Taylor rule. Fixed implies 2% rate. The rstar is r_t^* and pistar is π_t^*. For both time-varying rates, the Kalman smoothed estimates are used. Frequency of data is quarterly and for the period of 1965Q2-2019Q1.

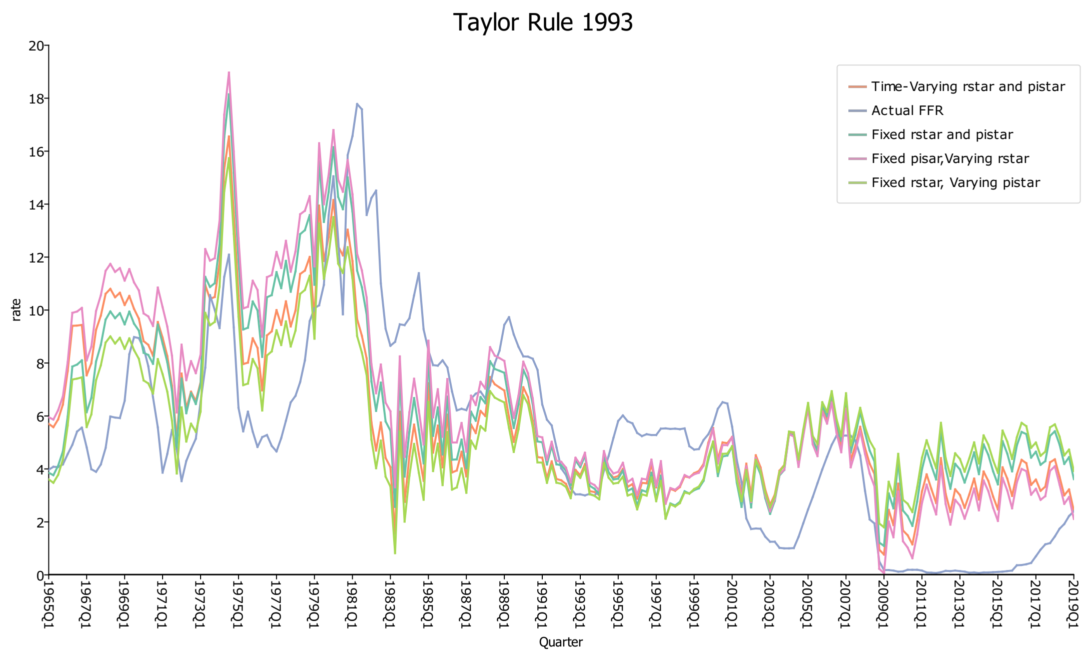

Figure 4.11: Different versions of the 1993 Taylor rule implied policy rates and actual FFR. Note: The inflation rate is measured by annualized, quarter-to-quarter percent changes in the core PCE price index. Fixed implies 2% fixed rate is used for the policy rule. Time-Varying implies estimated r_t^* and π_t^* by following Section (4.3.1) and (4.3.2) are used in Taylor rule. The rstar is r_t^* and pistar is π_t^*. For both time-varying rates, the Kalman smoothed estimates are used. Frequency of data is quarterly and for the period of 1965Q1-2019Q1.