Master's Double Degree Programme in Finance and Financial Risk Management

Final Thesis

The Effect of US Quantitative Easing on US Equity Capital Flows to China

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Section I: Introduction

In response to the economic and financial instability caused by the Global Financial Crisis in late 2008, monetary institutions in developed countries implemented various extraordinary measures to stabilize financial markets and promote economic growth. Whilst there is an ongoing debate about the extent to which these measures achieved their intended goals, extensive literature confirms that these actions had significant spillover effects on global trade, capital markets, and the financial stability of Emerging Market Economies (EMEs). Among the monetary institutions in developed countries, the actions of the Federal Reserve (FED) have been considered most responsible for spillover effects due to the US dollar's status as a global reserve currency and its important role in international trade and the financial sector. Particularly, various pieces of literature found that FED's Quantitative Easing (QE) induced capital outflows from the US toward EMEs, damaging their overall financial stability. On the other hand, despite China having affirmed itself as the world's second-largest economy in terms of GDP, it is still consensually considered an Emerging Market Economy with tight capital controls for foreign investors.

Hence, in this study, we investigate the effects of FED's extraordinary monetary policy and its tapering on bilateral Equity Capital Flows from the US to China. We observe whether Chinese Equities were primary targets of Capital Flows from the US caused by the QE programme. Particularly, we aim to study how QE impacts the US to China Equity Flows compared to the flows to a Global Equities Portfolio and a Portfolio of Asian Emerging Markets Economies (AEMEs). Our objective is to understand if China saw similar behaviours in Equity Capital Flows as happened in other emerging countries or if there is evidence that China, with its capital frictions and PBOC countermeasures to QE, is not considered similar to other AEMEs by US investors.

The primary role of US monetary policy in driving the Global Financial Cyle was confirmed by the influential research of Miranda-Agrippino and Rey (2020) on the factors driving the Global Financial Cycle. They determined that the FED's monetary policies significantly contributed to fluctuations in the Global Financial Cycle and cross-border capital flows due to their impact on aggregate risk aversion and global volatility indicators. Moreover, Park Donghyun et al. (2014) demonstrated through a balanced panel dynamic regression that the Quantitative Easing employed by the FED after the global financial crisis substantially boosted capital flows towards Emerging Market Economies. This led to asset and currency appreciation under the QE programs, followed by rapid depreciation, declines in equity prices, and overall financial instability in AEMEs as QE tapering talks started in mid-2013. Similar findings were found by Moez et al. (2021). More importantly, both studies highlighted varying behaviours of EMEs in managing the financial inflows caused by QE, affecting their ability to mitigate subsequent financial instability following QE tapering. Moez et al. (2021) revealed that a country's degree of openness and the presence of capital controls reduced the impact of QE-induced capital inflows in EMEs. Similarly, Park et al. (2014) found that AEMEs that actively defended their domestic currency exchange rates against the USD were comparatively less affected by the tapering.

Regrettably, Park et al. (2014) excluded China from their EMEs panel data, reasoning that China was considered a high-income financial centre. As mentioned, this dissertation aims to conduct a comparative analysis of Equity Capital Flows between the US and China under the FED's QE programs and QE tapering. The choice of Equity Flows was due to the data reliability and availability concerning Chinese Equity Securities compared to other instruments and respective metrics (such as credit and foreign direct investments). Unlike Park et al. (2014), this study will not employ panel data analysis. Instead, we will utilize a preliminary normalization of Equity Flow data to examine changes in the Chinese Equity Securities Share within the total US Foreign Equity Securities Portfolio under QE programs and QE tapering. We believe that this approach offers an insightful perspective on results, as it shifts the interpretation of data from a Capital Account (Balance of Payments) framework to an aggregate Portfolio Choice framework. The model's regressors, representing different monetary policy channels, can be easily interpreted as premia or excess returns, as opposed to push or pull factors. Furthermore, in contrast to Park et al. (2014)'s approach of assessing monetary policy through three distinct channels and employing a set of dummy variables to account for the residual effects of extraordinary FED policies, we will incorporate synthetic Monetary Policy Indicators (MPIs) instead of dummies. For the US context, we will primarily utilize the Wu-Xia (2016) FED Shadow Rate. We aim to encapsulate the intricacies of US monetary policy during the period of the zero lower bound. Additionally, to measure Chinese Monetary

Policy, we will use the MPI developed by Girardin Eric et al. (2017). This synthetic indicator will encompass the diverse array of monetary measures and instruments employed by the People's Bank of China (PBOC), including its informal and indirectly observable practices such as window guidance and credit quotas operations. We argue that, with knowledge of the extensive set of Capital Controls as well as different actions of the PBOC to sterilize QE induced Capital Inflows, China was able to contain significantly Capital Inflows from the US, reducing its exposure to QE tapering, compared to an appropriate frame of reference.

The primary findings of our research underscore that, relative to a global portfolio of countries, China was not a primary recipient of QE-induced capital outflows from the US. This contrast becomes even more pronounced when comparing China to other Asian Emerging Market Economies. Conversely, during the QE tapering, China exhibited more pronounced Equity Flow Flights compared to the US Global Foreign Portfolio. However, this result loses robustness when China is compared to a set of AEMEs. This suggests that China is not considered part of either an Emerging Market Economy or a Developed Market Economy by the aggregate US investor. Additionally, the study identified positive effects of increases in the CBOE Implied Volatility Index (VIX) on changes in the Chinese Equity share within the US Foreign Portfolio. This implies, or at least suggests, that these securities offer US investors hedging opportunities against other foreign investments.

Our significant contribution, compared to previous literature, lies in the use of synthetic monetary policy indicators instead of dummies or discrete variables. This approach allows us to incorporate a wider range of continuous variables for capturing US monetary policy indicators. Moreover, the specific study of US-to-China Equity Capital Flows is, by itself, a major contribution to this work since many previous studies tend to avoid including China in their set of countries of interest. We also believe that having structured our work according to a Portfolio Choice framework could be considered a major strength, as we believe that basic knowledge of Modern Portfolio Theory is more widespread and known as well as more intuitive for Finance students and professionals, compared to Balance of Payments Theory. Lastly, we observe that our method to run comparative analysis without recurring to panel data modelling is a major strength of this analysis due to its simple implementation, even though we recognize that this method's efficacy is based on some strong assumptions.

The dissertation's structure is organized as follows: a concise literature review covering prior research on Capital Flows and QE, as well as a brief overview of Chinese Financial Markets. The subsequent section describes the data and necessary adjustments for modelling purposes. The chosen analysis methods are then presented. A dedicated section presents the research results and engages in discussions around those findings. Lastly, a separate section delves into the exploration of interactions within the set of independent variables chosen for the analysis.

Section II: Literature Review and Key Concepts

2.1 Quantitative Easing Description

The Global Financial Crisis (GFC) in 2008 and its damage to the overall stability and solvency of the developed world countries forced central banks to adopt unconventional monetary policy measures to address trembling banking and financial sectors as well as steady low inflation and slowing economy. The Federal Reserve of the United States of America (FED) was the first to act in this sense with the Quantitative Easing Programme (QE). The FED QE mainly consisted of open markets operations that took part in three rounds with three distinct and different securities and objectives. The first round of QE (QE1) started in late 2008 and ended in 2010, this first round aimed to address the Mortgage-Backed Securities Crises (MBS); this round in fact involved purchases by the FED from US banking sectors of 1,25 Trillion USD in MBS as well as 300 billion USD in Treasury Securities. The second round was undergone from November 2010 and June 2011 and was mainly aimed at addressing deflation and stagnating economic conditions; in this round, approximately 600 billion USD in Treasury Securities were purchased. The third round of QE (QE3) was launched at the end of 2012 and ended in early 2014 with the objective of reducing unemployment and stimulating US economic growth with a purchase of 1,25 trillion USD in Treasury Securities and other acquisitions in MBS.

2.2. The Spillover Effects of Quantitative Easing on Emerging Markets, the Asian Case.[1]

Observing that the three rounds of the QE involved different measures and different objectives is important to understand why these three rounds of QE had different spillover effects on the global financial markets. Widespread literature found that QE, particularly QE1, had a significant impact on the capital flows towards Asian Emerging Economies (EMEs) (Cho and Rhee (2013)) and other EMEs (Lim, Mohapatra, and Stocker (2014)). Moreover, the surge in Capital Flows from the US towards Asian EMEs had a significant impact, leading Asian EMEs Asset Prices to grow significantly.

The QE's apparently positively connotated spillover effects on Asian EMEs had however one important key issue, as the QE was tapered, a period of financial instability, dropping asset prices and outflows from EMEs could have followed. Park et al (2014) confirmed

[1] Refer to Park et al. (September 2014)

indeed this hypothesis in their study of QE effects on Asian EMEs. What is concerning is that there is evidence that QE tapering talks held in May 2013, not even the end of QE itself, was sufficient to revert the direction of flows, generating significant capital outflows from EMEs, causing financial instability, domestic depreciation, and a fall in asset prices.

Park et al (2014) moreover find in their study that the effects of QE tapering are not symmetrical across all Asian EMEs; there is evidence that different actions of Asian Central Banks and idiosyncratic characteristics of countries' financial markets and economies can reduce or tame the sudden spillover effects of QE tapering. More specifically, there is evidence that Asian Central Banks' actions aiming at defending exchange rates as well as capital controls have a negative impact on capital inflows. However, these results are not significant, suggesting that these measures may have had a role but with no clear results. The non-significance of Park et al (2014) in this delimited context may have stemmed from the fact the authors did not address heterogeneity in Capital Markets Controls and Frictions properly, since their aim was to observe primarily differences in Capital Flows due to Heterogeneous Macroeconomic Fundamentals, Capital Controls were simply measured with a dummy variable. A more comprehensive approach specifically addressing the matter is proposed by Moez et al (2021) who used several variables (a degree of openness, distance, common language, and the presence of free trade agreements) to proxy the financial integration of EMEs with the United States of America. The results of this work imply that during the pre-QE period (2000-2007) the degree of openness affected significantly and positively Foreign Direct Investment (FDI) whilst it had no significant effect on Portfolio Investment. This relation maintained its sign during the QE period when only portfolio investments were affected. These findings can be explained by the fact that, as reported by Park et al (2014), QE changed significantly also the nature of Capita Flows, moving them from Bank Loans and FDI in the pre-crisis period and QE1 towards bonds and equity investment in QE2 and QE3. More interestingly, Moez et al (2021) also found that capital frictions, measured with distance, free trade agreements and common language, significantly reduced the effects of FED QE on Capital Flows towards EMEs. These results are significant in the scope of this dissertation since, as will be presented later in this section, China has a complex and tight system of capital controls.

The previous literature reported in this paragraph suggests that FED Quantitative Easing had significant positive spillover effects on Capital Flows towards Emerging Markets Economies. The QE changed the extent as well as the nature of Capital Flows, having a more significant effect on Portfolio Investments (Bond and Equity Markets). The FED's unconventional monetary policy was also a factor of financial instability since under the QE programmes the increase in Capital Inflows towards EMEs generated abnormal currency appreciation and a rise in equity returns, that were offset by rapid depreciation and bursts of equity bubbles when the QE tapering caused outflows from EMEs. These effects, however, were found to be tamed and reduced in their extent with the presence of active domestic central banks measures and macroprudential measures as well as the presence of capital controls.

2.3. The Rationale Behind the Transmission of US Monetary Policy onto the Global Financial Capital Flows.[2]

More traditional literature argues that US Monetary Policy has spillover effects internationally due to the role of the US dollar as a Reserve Currency and its primary role in international trade. Dr Yonghong Tu in his participation in the "High-level Seminar on Global Liquidity and Impact of Capital Flows on Exchange Rate in Emerging Asia" argues that US Monetary policy is transmitted to the world through three different channels: trade channel, exchange channel and financial channel. For countries with a pegged currency, the increasing supply of USD depreciates their currency, bolstering imports from the US. Subsequently, this rise in imports pushes up US GDP, that leads necessarily to an increase in domestic demand hence also imports from foreign countries to the US, increasing GDP in foreign countries; at the same time increasing exports towards the US causes rises in foreign reserves, forcing a pegging central bank to expand too its monetary base. On the contrary, countries with a floating regime, under US QE, see a currency appreciation that slowdowns exports and drives up domestic demand and consequently imports, reducing GDP growth in the long run. According to Dr Yonghong the third channel of transmission is imputable to the so-called Hot Money phenomenon; an excess in supply of USD depreciates the value and incomes of USD-denominated securities. To hedge this risk financial intermediaries, sell part of their dollar-denominated positions to exchange dollars for foreign currencies (such as JPY and RMB)

[2] Refer to Miranda-Agrippino & Rey (2020) and Yonghong Tu (2014).

to open positions in non-dollar-denominated securities. This in turn pushes asset prices and generates currency appreciation in foreign economies.

However, the approach proposed by Dr Yonghong seems to be lacking in some ways since the three channels proposed do not capture important and significant findings reported by more recent literature. Miranda-Agrippino and Rey (2020) find important US Monetary policy spillovers on the Global Financial Cycle. These two influential authors find in this work that, using a dynamic model, it is possible to estimate a unique Global Factor describing approximately 20% of the total variability of a wide panel of risky global assets' prices. Moreover, if the panel is restricted to US, European and Japanese assets, as well as commodities, this global factor can explain 60% of the total variability in this restricted sample. More importantly, this Global Factor displays co-movements with US recession periods and with global indices of Implied Volatility (VIX, VSTOXX, VNKY, VFTSE). Miranda-Agrippino and Rey find that their factors' main component is a function of realized volatility and aggregate risk aversion (explaining hence its co-movement with Implied Volatility Indexes). The importance of these findings for this dissertation consists in the fact that the authors then proceed to evaluate how the Global Financial Cycle is affected by the US monetary policy, and the results are remarkable in many senses. First Miranda-Agrippino and Rey find that shocks in US monetary policy impact global markets. Shocks in US monetary policy have significant effects on aggregate risk aversion as well as US domestic risk premia. Contractions in US monetary policy have no significant direct effects on global growth whilst it has significant negative effects on global credit provision, international capital flows, corporate bond spread, and global banks leverage. The authors interpret these results by observing the fact that the major responsible players for International Capital Flows are Global Banks and Asset Managers. The firsts finance their operation approximately at the US risk-free rate and optimize their portfolio on excess returns under the constraint that their VaR cannot exceed the global bank equity. The Asset Managers, on the other hand, optimize their global portfolio using excess returns penalized by a volatility component multiplied by a risk aversion parameter; factors that, as the authors themselves found in their results, are affected by US monetary policy. Finally, in their work, Agrippino and Rey find that US monetary policy has spillover effects also in Floating Regime Economies suggesting, contrary to Yonghong, that exchange rate regimes seem to have a lesser role than expected. However, as reported in the previous paragraph, the authors do not exclude that macroprudential measures may still have a potential role in taming the spillover effects of US monetary policy. A more recent and preliminary work by the two influential authors (Miranda-Agrippino, Nenova, Rey 2022) focused more closely on the transmission channels of US monetary policy compared to Chinese Monetary policy on Global Markets. The results confirm previous authors' work, underlying that Global Indexes are more affected in the short term by US monetary policy due to its influence on risk aversion, private liquidity, credit generation, and VIX. This in turn affects significantly Capital flows in and out of the US and Emerging Economies. On the other hand, the authors underline how Chinese Monetary policy affects global markets in the longer term and via different channels. Particularly, Chinese Monetary Policy affects domestic demand which in turn drives down global economic activity affecting commodity markets particularly, which, with a considerably longer lag, affects asset prices. The interpretation of this latter fact is easily imputable to the major share of commodity global demand taken by the Chinese Real Estate and Durable Consumer Good Markets. Further confirming the relative importance of the financial channel over trade and exchange rate channels for US monetary policy transmission is also the work by Zhang et al (2022). The authors focus on the US monetary policy spillovers transmission channels into China. They underline how FED activity affects significantly financing premia for Chinese Companies as well as expectations on their financial results, confirming at the same time Agrippino & Rey's (2020) results.

2.4. Overview of Chinese Financial Markets[3].

China – despite having gradually affirmed itself as a major economic player – is still consensually regarded as an Emerging Market Economy. Moreover, in spite of its role as a world leader in industrial production, China from early 2000 to today had and still has significant Capital Controls for Foreign as well as domestic Investors and, as it was reported, these may have an important effect on taming capital flights. Hence, understanding the progressive opening of Chinese Mainland Financial Markets could be important. Access to Shanghai and Shenzhen stocks and bonds exchanges from foreign investors can be divided into two types of channels: on-shore access and off-shore access programmes. Before proceeding, two points must be kept in mind: firstly, despite being formally part of the People's Republic of China, Hong Kong has its own financial sectors that are fully integrated with other global financial markets; secondly, Hong Kong has its

[3] Refer to ASIFMA (January 2021).

own currency, rigidly pegged to the USD. On the other hand, China officially has one currency – the Renminbi (RMB), also called Yuan – which has two different markets, with different pricing. Indeed, there is the onshore Yuan traded and used only for transactions in Mainland China and the off-shore Yuan traded on foreign markets such as Hong Kong and Singapore.

2.4.1 Onshore access.[4]

2.4.1.1. QFII

In 2002 China allowed access to its markets to foreign investors under its first programme: the Qualified Foreign Institutional Investors (QFII) scheme. A Foreign Institutional Investor (FII) is an intermediary (Global Banks, Pension Funds, etc) of sufficient size that has been approved by Chinese Financial Authorities to operate in Shanghai and Shenzhen Exchanges. Every FII receives from authorities a quota of allowed investment that is a percentage of the maximum Foreign Investors' Portfolio that could be reached under the programme. Initially, the total foreign portfolio could not exceed 4 billion USD, but this cap was progressively extended in different stages up to 300 billion USD in 2019. Later in 2020, all caps on quotas were abolished. The QFII programme requires FII to convert their USD liquidity into On-Shore Yuan before investing. Under this programme, there were up until 2019 strong limitations in divestments and repatriation of capital as well as other constraints regarding their deposit in China and their relationship with Chinese Brokers and Chinese Clearing Houses. Moreover, under these programmes, there were tight restrictions on securities that could be bought and sold by FIIs, mainly only Stocks and Bonds Traded on the exchanges could be traded, other instruments such as derivatives were initially precluded.

2.4.1.2. RQFII

Despite being the first attempt at opening to foreign capital, QFII was not a successful programme, probably because it required investors to deposit USD into a Mainland Chinese Bank to receive in exchange on-shore Yuan, which – as mentioned before – is traded exclusively domestically in Mainland China. It is likely that investors considered this procedure to be too risky in terms of exchange rate and liquidity risk. Therefore in 2009, to partially solve the issue and more importantly to bolster the role of the RMB as an international currency, Chinese Authorities launched the Renminbi Qualified

[4] Ibidem

Institutional Investor (RQFII) programme. Contrary to QFII investors did not need to deposit USD but instead, they could buy directly offshore yuan in regulated jurisdictions (such as Singapore and Hong Kong). Apart from this difference, RQFII and QFII have similar capital restrictions (quotas), lock-up periods, repatriation restrictions etc.

2.4.2. Offshore access: Stock Connects.[5]

The main issues for FIIs in the onshore programmes are not limited to capital restrictions and other conditions that I have already mentioned. Another important obstacle to the financial integration of Chinese markets with global markets are their idiosyncratic peculiarities. Chinese markets have peculiar sets of rules in various concerns from trading hours to clearing houses procedure, brokers' roles, authorities, complex bond markets, etc. To avoid the large difference between Financial Sector Infrastructure posing a threat to Foreign Capital Investments, Chinese Authorities – first in 2014 for Shanghai and later in 2016 for Shenzhen – developed the Hong Kong Stock-Connect programmes. Under these programmes, it is possible for investors to trade a determined set of stocks from Mainland China Exchanges directly in Hong Kong. This allowed foreign investors to hold their operations in China via Hong Kong, a reputed and well-integrated financial centre with rules and infrastructure like other global financial markets. Under stock connect there are still overall quotas as well as daily trading quotas for investors. Concerning securities traded, there is a list of medium-large cap stocks from the Shanghai Composite Index as well as a set of medium-large cap stocks from the Shenzhen Composite Index. In other terms, Chinese small-medium cap stocks are not tradeable under this programme.

2.5. Gross Flows or Net Flows.[6]

Before proceeding with the dissertation, it is also important to note that studying net capital or gross capital has its consequences in results and findings. As Davis et al (2021) report, before the Global Financial Crisis the focus on literature was centred around net flows since they are the current account of a country. Net flows are defined as the difference between inflows and outflows. Inflows for a given country are the purchases by foreigners of domestic securities net of the repurchases from country citizens of domestic securities. On the other hand, outflows are defined as the purchases by country citizens of foreign securities net of repurchases by foreigners of foreign securities. Finally

[5] Ibidem
[6] Refer to Davis et al (2021)

Gross Flows are defined as the sum of inflows and outflows. Scott Davis et al (2021) found that inflows and outflows since the 1990s, but more prominently after the 2008 global financial crisis, are more volatile, even though they tend to co-move. This in turn means that gross flows display increased volatility whilst net flows remain approximately stable. Hence, given the purposes of this dissertation, only a component of Gross Flows will be analysed. This being the outflows from US to China, this choice stands to avoid eliminating useful variability. Secondly, this component is thought to be more interesting to analyse and more coherent with the objectives of the dissertation.

Section III: Data and Methods

3.1. Approach, Data Collection and Model Specification.

3.1.1 Approach

To study the impact of US monetary policy on the US-China capital flows, we will use an approach inspired by Park et al (2014). The authors used a balanced dynamic panel regression, with three different channels of transmission: Liquidity Channel, Portfolio Balance Channel and Confidence Channel. The extra-ordinary monetary policy will be measured with synthetic Monetary Policy Indicators (MPI). Since this analysis' focus is uniquely on capital flows from the US to China (and not a panel of countries) a multivariate linear regression model will be specified. Moreover, we will model the dynamics of capital flows, not the levels; hence, changes (first differences or percentage changes) are both used for dependent variables and regressors. However, contrary to some of the previous literature that approaches the issue of explaining Capital Flows as the results of Push and Pull factors, the following analysis is meant to move the problem toward a portfolio choice problem.

3.1.2 Data and Data Collection

3.1.2.1 Dependent Variable: Normalized Equity Outflows.

The only data provider that gives access to bilateral data on Capital Flows between the US and other countries is the U.S. Department of the Treasury, under the Treasury International Capital (TIC) System. Within this data programme, financial intermediaries such as banks, funds and insurance companies must record – under specific conditions – their transactions against foreign buyers or sellers. The first TIC data used was under section 2a. "Monthly Transactions in Long-term Securities between U.S. and foreign residents". Under the global data, it is possible to find specific data for US-China transactions since the late 1970s for different long-term securities, including Equity ones (object of this dissertation). It was possible to obtain monthly Equity Inflows and Equity Outflows as well as Gross Equity Flows and Net Equity Flows. However, this dataset, after some trial and preliminary modelling, has not been considered satisfying due to one important reason. As stated in paragraph 2.5., a capital outflow is defined as the purchases by country citizens (in this case US) of foreign securities (Chinese) net of repurchases by foreigners of foreign securities. By cumulating the US to China outflows computed from the database "Monthly Transactions in Long-term Securities between U.S. and foreign residents", it should be possible to compute the US Monthly holdings (stocks) in Chinese Equity Securities. Unfortunately, the results obtained with this method did not match at all the US Monthly holdings in Chinese Equity Securities (accessible in another database of TIC system). The quantities obtained with cumulation differed from the official data in the order of hundreds of billions of dollars. This must be explained by an important problem in the dataset, which does not track transactions by Issuer Nationality but, on the contrary, by the nationality of the counterparty in the transaction (i.e., if a US bank acquires a Chinese Stock via a Luxembourgish Intermediary the transaction will be recorded against Luxembourg and not China). Considering the important role taken by Hong Kong financial centre for China, after the 2014 Shanghai-Hong Kong Stock Connect, it was decided to opt towards another dataset that avoids this bias. The new dataset used is under TIC data section 2.b. "Monthly Holdings of Foreign Long-term Securities at Current Market Value by U.S. Residents". From this dataset, US monthly holdings in Chinese Equity Securities were taken and divided, for normalization purposes, by the US total monthly holding in Foreign Equities. Then the first differences of this ratio were computed and chosen to be dependent variable of our analysis. In this way, we meant to proxy the US-China Equity Capital Outflows. This variable can be alternatively interpreted as the monthly changes of Chinese Equity Securities share in the Total US Foreign Equity Portfolio.

The main issue of this dataset change is that it reduces the time span of analysis from January 2012 when QE1 and QE2 already ended. It is possible to observe only QE3 and QE tapering periods, while the Sars-Cov2 pandemic will be left out of the analysis.

The original series on US Holdings in Chinese Equity and US holdings in Foreign Equity have been seasonally adjusted using the X11 method, and plots on seasonal components are shown in Appendix. Both the series US Chinese Equity Security Holdings as well as US Total Foreign Equity Security Holdings are USD denominated. The acronym for the dependent variable is Y. In Figure 1 it is possible to observe the plot of the series.

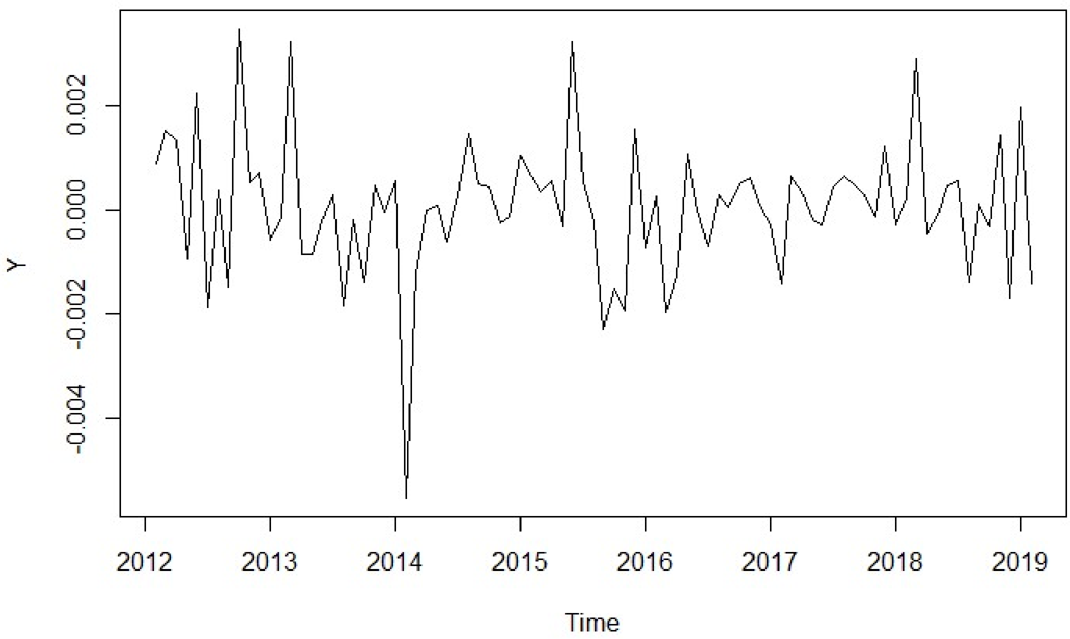

Figure 1; *Y: Chinese Equity Share in US Foreign Portfolio (first differences), from Feb 2012 to February 2019.*

3.1.2.2. Measuring Monetary Policy, Balance Sheet Measures and Synthetic Indicators

Contrary to Park et al. (2014), to measure the unconventional monetary policy two monetary policy measures have been selected. The first is the difference between Federal Reserve Bank (FED) and People Bank of China (PBOC) Total Assets Growth Rate. From both the Central Banks databases monthly Total Assets data have been downloaded, seasonally adjusted with X11 method, and the difference between their respective percentage changes was computed to obtain a spread in monetary balance sheet growth as independent variables. Discussions on the weakness of this approach will be provided in a dedicated paragraph. The acronym for this variable is sTA. A plot of the series is shown in Figure 2.

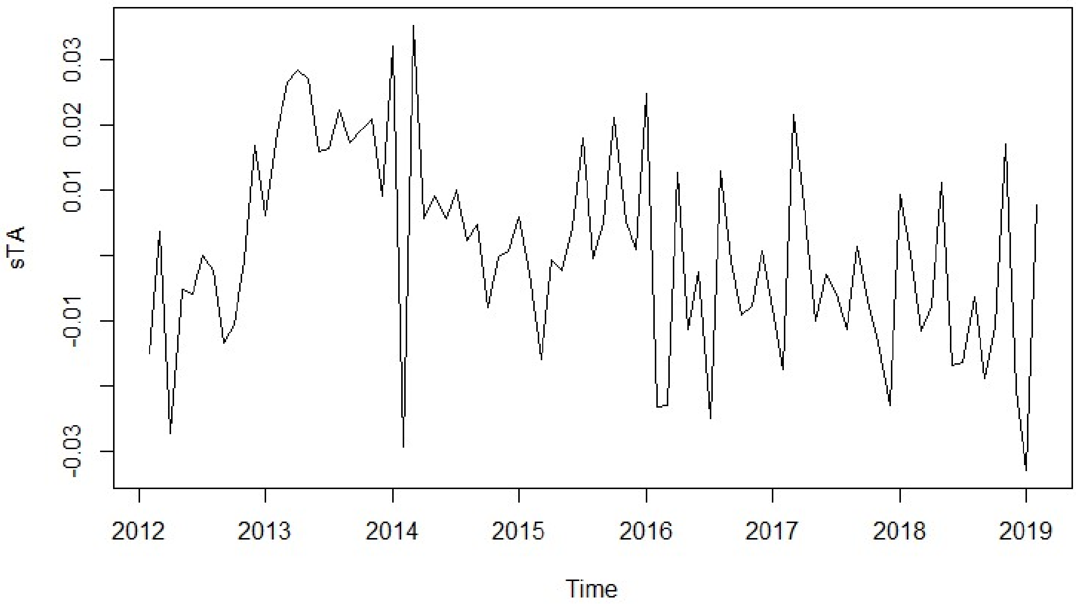

Figure 2; sTA: Differential in Total Assets growth (Percentage Changes)

The second monetary policy measure proposed is the difference in two different synthetic monetary policy indicators, for the US and for China. For FED, the Wu-Xia (2016) Federal Funds Shadow Rate have been chosen and downloaded from the Federal Reserve Bank of Atlanta data download section. On the other hand, as a measure of Chinese monetary policy, the composite monetary policy index (MPI) computed by Girardin et al (2017) will be used to measure PBOC monetary policy. We consider these monetary policy measures to be more precise in capturing the policies by FED and PBOC. Wu-Xia Federal Funds Shadow Rate captures the extraordinary quantitative monetary policy conducted by the FED when the zero lower bound for FED Effective funds rate has been reached. On the other hand, the MPI set up by Girardin et al (2017) is a synthetic measure that captures and synthetizes a unique rate summarizing the behaviour of different monetary policy instruments utilized by PBOC. The MPI is also computed considering informal credit quotas and window guidance operations, measures taken by Chinese authorities in response of Quantitative Easing[7]. Due to these reasons, employing the MPI is considered a much more refined and comprehensive way to introduce Chinese Monetary policy in the analysis compared to other measures. Data of Girardin et al (2017) stops at 2013, but an extension of the data obtained with the same method was kindly provided by Professor Girardin himself. The spread between the two measures was taken to obtain a Monetary Policy Indicator Spread, and then the first difference of this spread was taken as a variable of interest for the subsequent models. The acronym for this variable is dMIS. A plot of the series is shown in Figure 3.

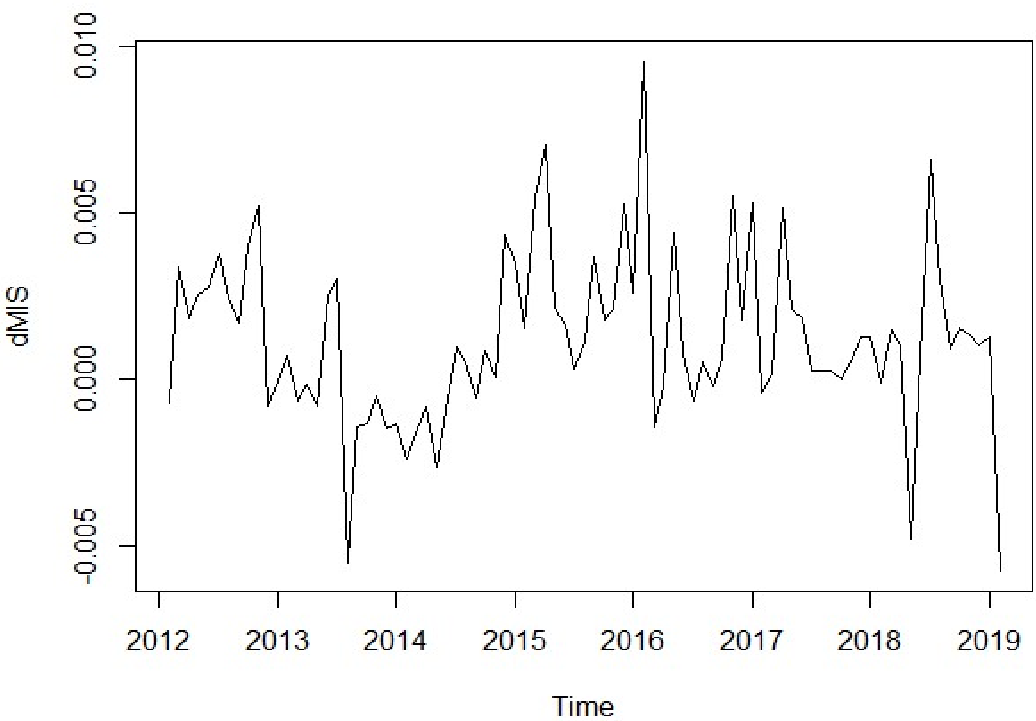

Figure 3; dMIS: US-China Monetary Policy Indicator Spread (first difference)

[7] For a more comprehensive and thorough analysis refer to Girardin et al (2017), we mention also that MPI also removes the temporary liquidity injection of Chinese New Year.

3.1.2.3. Other Monetary Policy Transmission Channels (Controls).

Understanding that monetary policy has different Transmission Channels, some key control variables have been elected to capture each one of those channels. For the Confidence Channel the Chicago Board Options Exchange Implied Volatility Index (VIX) monthly average has been downloaded from Federal Reserve Economic Data (FRED) of the Federal Reserve St. Luis Department. The data was seasonally adjusted with the X11 method. The percentage changes of VIX have been chosen as control variable.

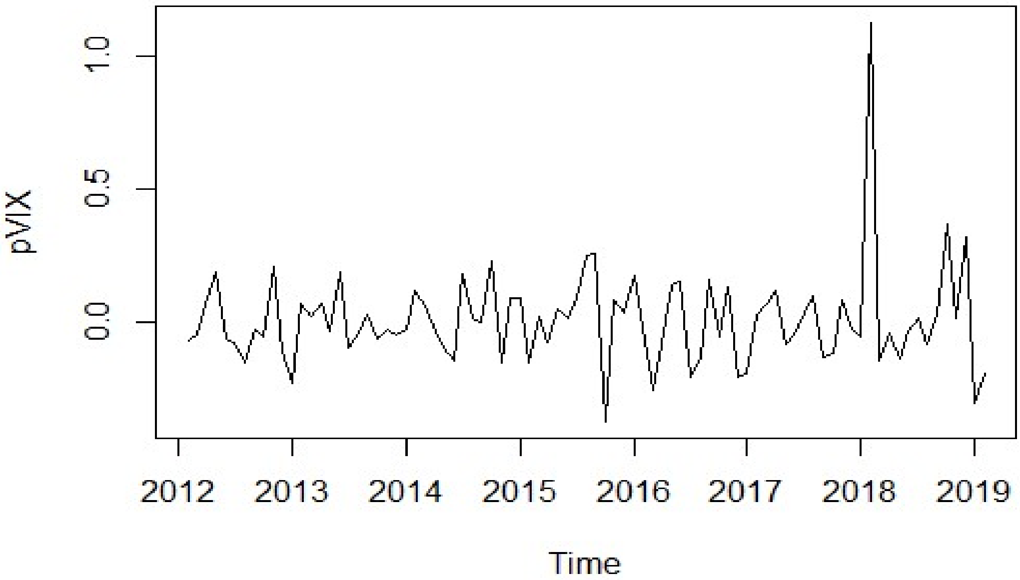

Figure 4;pVIX: CBOE VIX (percentage changes)

The same procedure was held for the exchange rate channel with the average monthly exchange rate RMB/USD downloaded on the FRED site. A plot of the series is available in Figure 5. The acronym of this variable is pDEX.

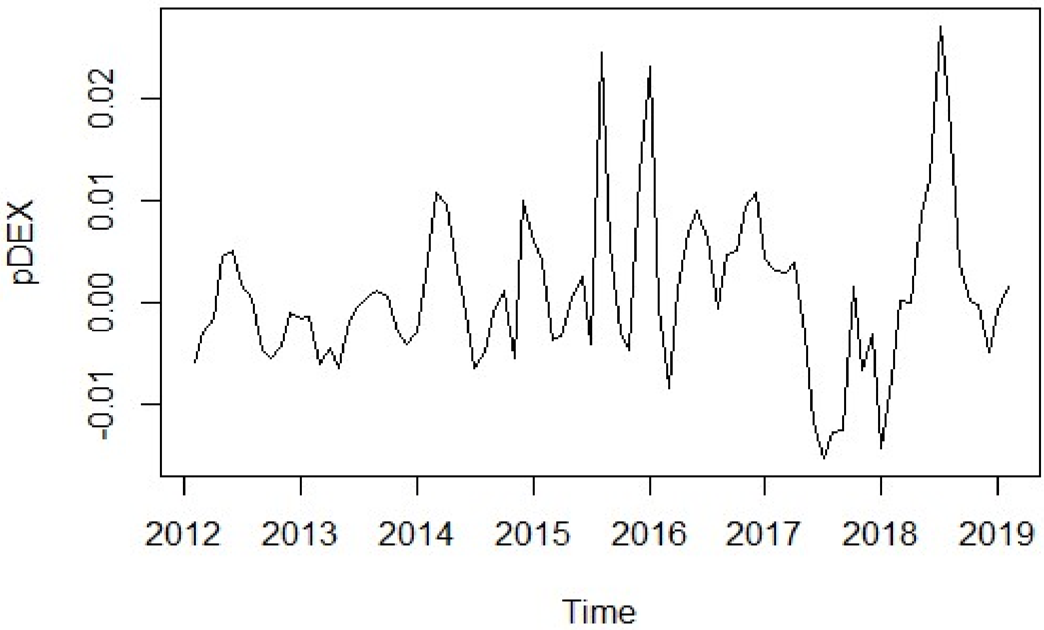

Figure 5; pDEX: RMB per USD (percentage changes)

For the liquidity channel the spread between short-term US and China rates was taken. US short-term rates used were the 4-week monthly average T-bills downloaded from FRED (to proxy 1 month Libor rate), whilst for China Shibor 1 monthly average was downloaded from Eikon Refinitiv data provider. X11 method did not suggest any need of seasonal adjustment for 4Week T-Bills Rate.

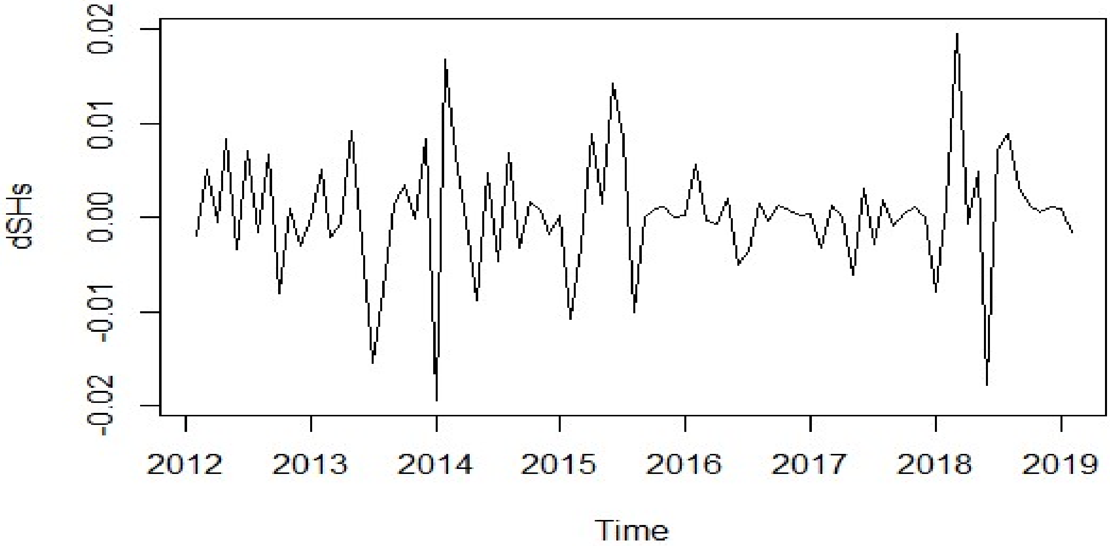

Figure 6; dSHs; Short Term Interbank Rates Spread 1-month (first differences)

Besides a Medium-Short Term spread between the US and China was taken too. For the US, the 3-month monthly average Libor rate downloaded from FRED was taken, and for China the 3-month monthly average Shibor Rate was downloaded from the Refinitiv data provider.

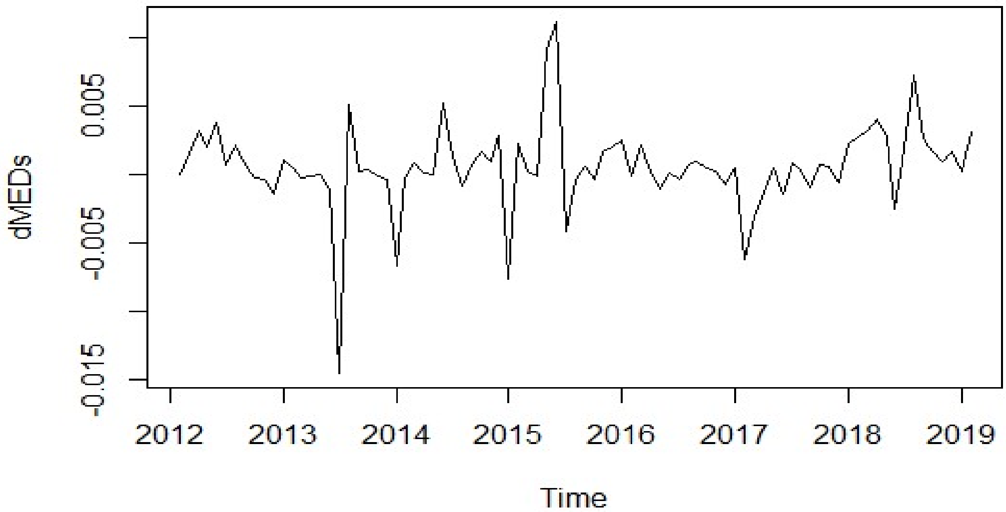

Figure 7; dMEDs: Medium Term Interbank Rates Spread 3-month (first differences)

Both spreads were taken in first difference and the acronyms for the respective liquidity channel variables are “dSHs” and “dMEDs”.

Since the dependent variable concerns Chinese Equity Securities normalized for a Global Portfolio (without US Securities), it was decided to introduce as a control variable the Excess Returns of the Shanghai Composite Index (SSE) against a benchmark index called MSCI ACWI ex-US, where the benchmark represent a Global Portfolio without US equities. The Shanghai Composite daily adjusted Index was downloaded from Yahoo Finance and its monthly average simple returns were computed. Unfortunately, for the benchmark such procedure was not possible: since only month-to-month data was available on the Refinitiv data provider, so simple month-to-month returns were computed. Note also that SSE Composite Index is RMB denominated and the MSCI ACWI ex-US index is USD denominated. The acronym for this variable is dEQ. Plot shown in Figure 8.

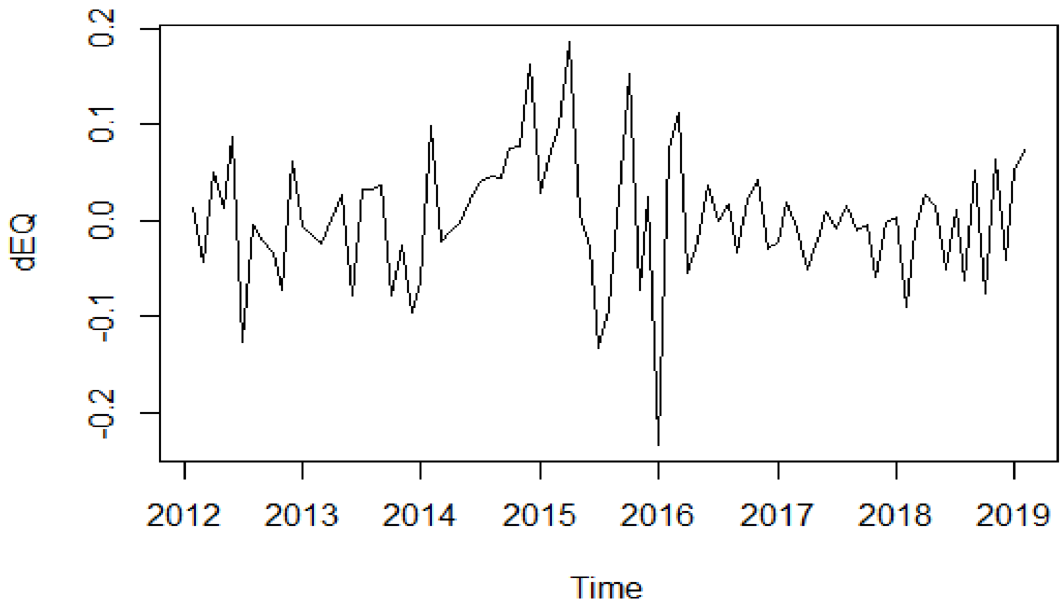

Figure 8; dEQ: SSE Composite Index extra returns on MSCI ACWI ex-US.

Although the dissertation is focused on equity securities, a control variable was introduced to capture possible flight-to-quality effects. The differentials between 10-1-year Government Bond Yields Spreads between US and China were introduced. US data was downloaded from FRED whilst Chinese data was taken from Refinitiv. The acronym for this variable is dsSL. Plot shown in Figure 9.

The SSE Composite Index excess-returns on the Benchmark (dEQ) jointly with the US-China 10-1-year Sovereign Bond Yields spread differential are considered a measure of Portfolio Balance.

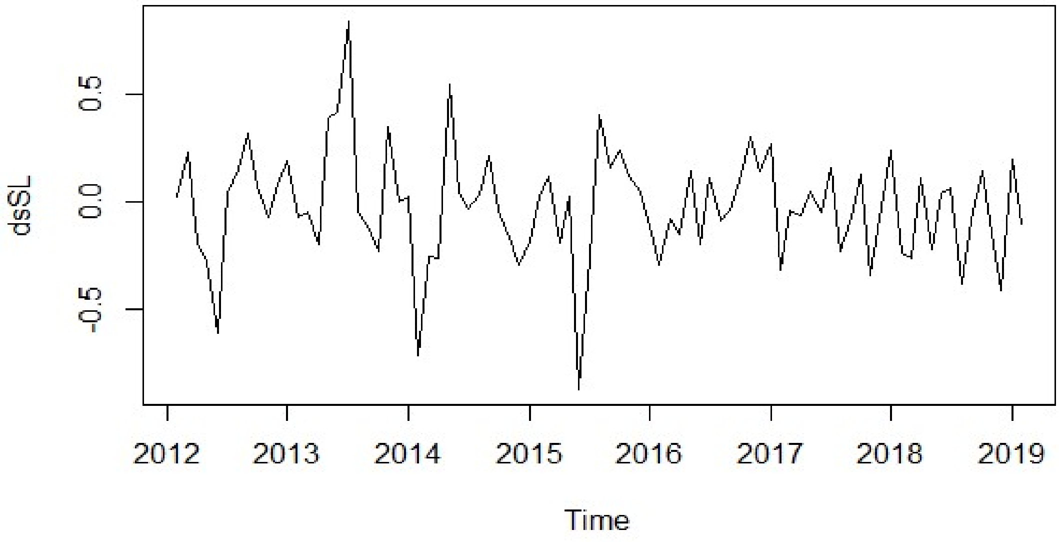

Figure 9; dsSL: US-China 10-1-year Sovereign Bond Yields spread differential (first differences)

3.2. Methods

To conduct the quantitative analysis, the methodological approach proposed by Shrestha and Bhatta (2018) has been conducted.

3.2.1 Stationarity of variables

All series reported in paragraph 3.1. were tested using the Phillips-Perron Test. A summary table is provided below.

Variable		Integration order	Phillips-Perron Test p-value
Chinese Equity share in US Foreign Portfolio	Y	1	<0.01
Total Assets Growth Spread	sTA	1	<0.01
Differential in Monetary Policy Indicator	dMIS	1	<0.01
CBOE VIX	pVIX	1	<0.01
RMB/USD exchange rate	pDEX	1	<0.01
Short Term Intebank Spread Rates 1-month	dSHs	1	<0.01
Medium Term Interbank Spread Rates 3-month	dMEDs	1	<0.01
SSE Composite Index Extra Returns on MSCI ACWI ex-US	dEQ	1	<0.01
10-1year Sovereign Bond Yields Spread Differential	dsSL	1	<0.01

Table 1; Phillips-Perron Test p-value, Null Hypothesis is series is nonstationary, note that dEQ is of integration of order one since returns are obtained from indexes prices.

3.2.2. Breakpoint test on a dependent variable

Using the R package “strucchange” a “breakpoints” test has been run on the dependent variable searching for structural changes in the series. “Breakpoints” implements Bai and Perron’s (2003) algorithm; further information on the test is available on the documentation of the R package as well as in Zeileis et al. (2003). Results on the breakpoints suggest that there are no structural breaks in the series using the BIC criterion. However, looking at the second and third-best BIC, it is possible to notice that the difference in BIC scores is comparatively small. Moreover, the test’s date breaks are interesting from an interpretation standpoint and may be significant for useful subsamples. The dates March 2013 and March 2014 are important since they are related with talks and effective QE3 tapering and announcement of Hong-Kong Shanghai Stock Connect (April 2014). The summary Table is Table 2.

Number of breaks	RSS	BIC	Break date
0	1,437E-04	-8,796E+02	NA
1	1,375E-04	-8,745E+02	March 2013
2	1,278E-04	-8,718E+02	March 2014

Table 2; Breakpoints Test Output on Y (changes in Chinese Equity Securities Share in US Foreign Equity Portfolio).

3.2.3. Models Specification.

As mentioned in the beginning of this section, it has been decided to proceed with the analysis using a multivariate linear regression model with different specifications that will be reported below.

Model A.1

$$Y_t = \alpha + \beta Y_{t-1} + \beta_1(sTA_{t-i}) + \beta_2(pVIX_{t-j}) + \beta_3(pDEX_{t-h}) + \beta_4(dEQ_{t-g})$$

Model A.2

$$Y_t = \alpha + \beta Y_{t-1} + \beta_1(sTA_{t-i}) + \beta_2(pVIX_{t-j}) + \beta_3(pDEX_{t-h})\beta_4(dEQ_{t-g}) + \beta_5(dSHs_{t-l})$$

Model A.3

$$Y_t = \alpha + \beta Y_{t-1} + \beta_1(sTA_{t-i}) + \beta_2(pVIX_{t-j}) + \beta_3(pDEX_{t-h}) + \beta_4(dEQ_{t-g}) + \beta_5(dSHs_{t-l}) + \beta_6(dMEDs_{t-k})$$

Model A.4

$$Y_t = \alpha + \beta Y_{t-1} + \beta_1(sTA_{t-i}) + \beta_2(pVIX_{t-j}) + \beta_3(pDEX_{t-h}) + \beta_4(dEQ_{t-g}) + \beta_5(dSHs_{t-l}) + \beta_6(dMEDs_{t-k}) + \beta_7(dsSL_{t-m})$$

Subsequently, similar models have been specified. However, in the following the differential in growth rate in central banks total assets (sTA) has been substituted with first differences in monetary policy indicators spread (dMIS).

Model B.1

$$Y_t = \alpha + \beta Y_{t-1} + \beta_1(dMIS_{t-i}) + \beta_2(pVIX_{t-j}) + \beta_3(pDEX_{t-h}) + \beta_4(dEQ_{t-g})$$

Model B.2

$$Y_t = \alpha + \beta Y_{t-1} + \beta_1(dMIS_{t-i}) + \beta_2(pVIX_{t-j}) + \beta_3(pDEX_{t-h}) + \beta_4(dEQ_{t-g}) + \beta_5(dSHs_{t-l})$$

Model B.3

$$Y_t = \alpha + \beta Y_{t-1} + \beta_1(dMIS_{t-i}) + \beta_2\left(pVIX_{t-j}\right) + \beta_3(pDEX_{t-h}) + \beta_4\left(dEQ_{t-g}\right) + \beta_5(dSHs_{t-l}) + \beta_6(dMEDs_{t-k})$$

Model B.4

$$Y_t = \alpha + \beta Y_{t-1} + \beta_1(dMIS_{t-i}) + \beta_2(pVIX_{t-j}) + \beta_3(pDEX_{t-h}) + \beta_4(dEQ_{t-g}) + \beta_5(dSHs_{t-l}) + \beta_6(dMEDs_{t-k}) + \beta_7(dsSL_{t-m})$$

The different specification between models B.2., B.3, and B.4 – as well as A.2., A.3., A.4 – is due to the willingness to understand whether adding more than one regressors for Liquidity and Portfolio Balance channel each improves reasonably the estimation of the models. Model A.1. and B.1., on the contrary, have been specified as control models, since it was feared that Liquidity Channel, measured with the 1-month Interbank spread changes (dSHs), may have unexpected relations with monetary policy measures. The letters i, j, h, g, l, k stand for the optimal lags to be selected for each variable. The lag selection procedure is explained in next paragraph.

3.2.4. Model Estimation: an ARDL estimation with stationary and same-order variables.

According to Shrestha and Bhatta (2018), having both dependent and independent variables stationary, to estimate the models specified in the previous paragraph it would be logical to just run an OLS to estimate the linear model. However, to simplify greatly the optimal lag selection for each variable (in the models denoted with the letters i, j, h, g, l, k) an ARDL algorithm has been used to find optimal lag for each regressor. It must be reported that "ardlDlm" function in the R package "vars" was used. This function estimates coefficients via OLS. The model estimation proceeded as follows: an ARDL estimation was launched on the regressors with maximum lag for exogenous regressors of 3 months and 1 month for the endogenous regressor, and then less significant lags were included in a list. The model was then estimated again with "ardlDlm" and the remove lists to obtain the model estimates that, after the removal of all non-significant lags for each regressors, became a multivariate dynamic linear regression model.

3.2.5. Diagnostics on Residuals

After models' estimations were run, different diagnostics tests were performed on estimated residuals. Diagnostics include:

- Autocorrelation and Partial Autocorrelation of residuals graphical analysis.
- Phillips-Perron test on Residuals.
- Ljung-Box and Box-Pierce Tests on Residuals.
- McLeod-Li test to evaluate volatility clustering.
- Breusch-Pagan Test for Heteroskedasticity in Residuals.
- Jarque-Bera Test for Normality in Residuals.
- Breakpoint test on residuals (Bai-Perron methodology, refer to paragraph 3.2.2.)

In the case of heteroskedasticity detected, the Correction for the Covariance Matrix of Residuals was computed using the Eicker-Huber-White sandwich estimator[8].

[8] No model reported in the dissertation needed the procedure except for some estimation with Two Stage Regressions found in the appendix, not reported in the main text.

3.2.6. Testing Multicollinearity, Granger Casualty, Orthogonal Impulse Response on Regressors, Forward Error Variance Decomposition.

To test for multicollinearity in the dataset, a correlation matrix was firstly computed on non-lagged regressors and then on lagged regressors. Then, a Variance Inflation Factor (VIF) test was launched on non-lagged regressors matrix and on the estimated lagged regressors. The VIF test has been chosen for its easy implementation and interpretation in OLS estimations (refer to Fox & Monette (1992) for in depth description of the test). We remind briefly that the VIF score for the i^{th} independent variable is calculated as the inverse of the Tolerance[9] of the OLS regression of the i^{th} independent variable on the others.

Consequently, Granger Causality Tests from orders 1 to 8 were run for each regressor on the Monetary Policy Indicator Spread (dMIS) to observe whether monetary policy indicators were causing any of the other regressors (as it is theoretically plausible). Finally, to better capture possible long-lagged relations between the variable of interests and the other regressors, a VAR model was estimated on the regressors matrix, and an Impulse Response Analysis was run on the model to observe whether Orthogonal Shocks in Monetary Policy Indicator Spread (dMIS) and Differential in Central Banks' Total Assets Growth rate were having effects on the behaviour of the other regressors. The order of the VAR model has been chosen as high as the sample dimension allowed estimation[10]. On the same VAR model then a Forecast Error Variance Decomposition (FEVD) was computed and analysed.

3.2.7. Transforming a regressor to better capture liquidity channel: 3-1 Month Interbank rates spread.

Similarly, it has been noted by preliminary results obtained with the previous methodology that there might be a possible collinearity problem between Interbank Spreads (1 Month and 3 Month maturity). The potential multicollinearity issue was opted out by subtracting the 3 Month Interbank Spread (dMEDs) for the 1 Month Interbank Spread (dSHs). The new regressor is called 3-1 Month Interbank Rates Spread, whose acronym is "dSIRS". Subsequently a Phillips Perron Test was implemented on the new regressor. It has been found to be stationarity. The 3-1 Month Interbank Rates Spread

[9] The Tolerance is defined as $1-R^2$, with R^2 being the unadjusted coefficient of determination.
[10] Best AIC value suggested high order VAR model, on the contrary, BIC values suggested a VAR of order 1.

(dSIRS) was used to measure the liquidity channel and the procedure conducted in the previous paragraph was run again. The new model specification will be called B.4.Adj.

Model B.4.Adj.

$$Y = \alpha + \beta Y_{t-1} + \beta_1(dMIS_{t-i}) + \beta_2(pVIX_{t-j}) + \beta_3(pDEX_{t-h}) + \beta_4(dEQ_{t-g}) + \beta_5(dSIRS_{t-l}) + \beta_6(dsSL_{t-m})$$

3.2.8. Focus on QE tapering, abandoning the difference in FED and PBOC Total Assets growth (sTA) as a regressor.

After the corrections to the data reported in the previous paragraphs, it was decided to specifically study the behaviour of the model in the subsample starting in March 2014 and ending in February 2019; moreover, the differential in FED and PBOC Total Assets Growth was dropped as independent variable since (as shown in the following section) this monetary policy measure is Granger causing other regressors, and models using only Monetary Policy Indicators Spread have been kept for the analysis. However, this variable is kept for modelling purposes as shown in next paragraph.

3.2.9. Two-Stage Regression, Total Asset Growth Rates as Instrument.

By observing Granger Causality tests and Impulse Response functions, we tried a two-stage regression approach from regressors that are Granger caused by the difference in FED and PBOC Total Assets Growth, since it is feared that omitting this variable may cause endogeneity problems in the regressors matrix. Hence this variable was taken as an instrument and preliminary regressions were run on the changes in VIX, 3-Month Interbank Spreads, SSE Composite Excess Returns and differences in 10-1-year sovereign bond yield spreads. The preliminary regressions were run utilizing ARDL models of orders p=k and q=1. Here p stands for the lag order taken by the difference in Total Assets Growth Rate and its k value was taken by maximizing the Adjusted R Squared of each preliminary regression. Besides q is the order of the autoregressive endogenous component of each variable that was instrumentalized. The residuals of each preliminary regression were taken as new variable in the second stage regression. In the case of heteroskedastic errors in the second stage regression the correction for the covariance Matrix of Residuals was computed using the Eicker-Huber-White sandwich estimator. The second stage regression approach was performed both in the full sample and the sub-sample estimation. Note that in sub-sample estimation the new liquidity regressor (dSIRS) was used instead of the interbank rate spread.

3.2.10. Comparative Analysis

To run a comparative analysis a similar, however less through analysis, was performed. Particularly Model B.4.Adj. was estimated again. However, in this set-up, the US Equity Outflows to China were normalized with the US Equity Outflows to Asian Emerging Markets Economies (AEMEs), including China. In this way is it possible to observe the comparative effects of US monetary policy on US to China equity outflows standardized for the other AEMEs. The US monthly holdings in AEMEs were downloaded from TIC section 2.b. and they were seasonally adjusted utilizing the X11 method and then used for normalization purposes. Regarding the regressors matrix the SSE Composite Returns were computed against the benchmark MSCI Asian Emerging Markets index; this index tracks mid-large cap equity securities in eight Asian Emerging Countries: China, India, Indonesia, Korea, Malaysia, the Philippines, Taiwan, and Thailand. Figures reporting these variables are available in the Appendix. Subsequently the B.4.Adj. coefficients estimation diagnostics on residuals were run. The same procedure was run for Model B.4.Adj. in the subsample starting in March 2014 and ending in February 2019. The two-stage regression approach was not performed for the robustness analysis considering two-stage regression preliminary results.

Section IV: The effects of US QE on US equity outflows to China

4.1. Models A and B full-sample estimates, unexpected signs, mixed result, unclear dynamics.

The coefficients estimate on Models A.1., A.2., A.3, A.4 display intriguing and not completely intuitive results (refer to Table 3 for estimation output). First, apparently, the difference in the Growth Rate of FED and PBOC central Banks' Total Assets has a negative effect on changes in Chinese Equity Securities share in US total Foreign Equity Portfolio. More interestingly, it is possible to note that the significance of these results tends to fall as other interest rates spread variables are introduced. Equally counterintuitive is the positive coefficient found for changes in VIX, suggesting that an increase in VIX raises the share of Chinese Equities in the US Foreign Equity Portfolio. Interestingly, this coefficient is stable with the addition of new variables. Surprisingly, different signs were observed for the 1-month interbank rate spread (dSHs) and 3-month interbank rate spread (dMEDs) in model A.3. More in line with common sense is the positive sign of SSE Composite extra returns against the MSCI ACWI ex-US benchmark and the positive effect registered for the RMB/USD rate. Another point to remark is that SSE Composite extra returns against the benchmark are the only regressor that has been found to significantly influence the dependent variable at a lag greater than 1. Flight to quality effects, which should be captured by the difference in 10-1-year Sovereign Bond Yield between US and China, seem not relevant in the analysis.

Looking instead at the diagnostic summarized in Table 4, the models do not display problems of autocorrelation or heteroskedasticity (except for two lags in Ljung Box Tests that are however insignificant in the Box-Pierce Test). The residuals are stationary, but they are not normal. Nonetheless, from analysing the qqplot of the residuals and their pdf, it is possible that there may be some outliers in residuals that are affecting the behaviour of the Jarque-Bera test. Figures on qq-plots are available in the Appendix and, in fact, if some outliers are taken out, the qq-plot approximately follows the qq-line.

In terms of goodness of fit, it seems, by observing the Adjusted R2, that these models have explanatory capacities of the data structure.

	lag	Model [A.1]		lag	Model [A.2]		lag	Model [A.3]		lag	Model [A.4]	
	/	0,0000		/	0,0000		/	0,0000		/	0,0000	
sTA	1	-0,0165	*	1	-0,0176	*	1	-0,0132	°	1	-0,0137	°
pVIX	1	0,0025	***	1	0,0028	***	1	0,0028	***	1	0,0028	***
pDEX	0	-0,0275	°	0	-0,0280	*	1	-0,0311	*	1	-0,0306	*
dEQ	2	0,0115	***	2	0,0115	***	2	0,0095	***	2	0,0097	***
dSHs		/		0	-0,0442	*	0	-0,0587	**	1	-0,0533	**
dMEDs		/			/		1	0,1078	**	1	0,1090	**
dsSLs		/			/			/		1	0,0003	
dcQ	1	0,0231		1	0,0247		1	0,0035		1	0,0091	
R^2		45,2%			49,4%			54,9%			55,2%	
R^2-Adj		41,7%			45,4%			50,7%			50,4%	

*Table 3; Models A. Coefficients estimates, complete summary in Appendix A. Significance levels ° 90%, *95%, **99%, *** 99,9%. Sample: February 2012-February 2019.*

February 2012-February 2019	Model [A.1]	Model [A.2]	Model [A.3]	Model [A.4]
Test on Residuals	p-value(result)	p-value(result)	p-value(result)	p-value(results)
Philipps Perron Test	0,01	0,01	0,01	0,01
Ljung-Box Test	no critical lag	no critical lag at	lag 19 and 20	no critical lag
Box-Pierce Test	no critical lag	no critical lag at	no critical lag at	no critical lag
Breusch-Pagan Test	0,74147	0,9118	0,8244	0,8088
Jarque-Bera Test	3,13E-11	1,62E-04	6,50E-05	2,79E-05
McLeod-Li test	no critical lag	no critical lag	no critical lag	no critical lag
Breakpoint Test (Bai-Perron)	no break	no break	no break	no break

Table 4; Results of diagnostics on residuals for each model.

Similar results have been found in coefficient estimates for models B that can be observed in Table 5. Apparently, the monetary policy indicator spread has a positive effect on the changes in Chinese Equity Share in the total foreign portfolio. Changes in VIX, RMB/USD exchange rate, SSE Excess Returns maintain their sign, their module (approximately), and significance. More interestingly, the interbank rates spread in these models assume equal signs and the same lag despite a weaker significance. Finally, flight to quality effects captured by the difference in sovereign bond yield 10-1 year spread display a weak level of significance. Results suggest that the monetary policy indicators' spread affects the changes in the share of Chinese Equity Securities in the US Foreign Equity portfolio without a lagged effect.

Similarly, the diagnostics for each model of type B do not produce evidence to refute Gauss-Markov hypothesis on spherical errors. In fact, residuals are homoscedastic across all model's specification and are generally not autocorrelated. Particularly, the only model specification potentially displaying autocorrelation in residuals is model B.3., where two critical lags at lag 19 and 20 in the Ljung Box are detected. However, this autocorrelation is not detected by the Box-Pierce Test and more importantly is ruled out when sovereign bond yields spreads are introduced in the model (model B.4.). (Reference on Table 6).

In terms of goodness of fit, the behaviour of models B and A is similar. The adjusted R^2 improves as new regressors are introduced in the model, suggesting a correct approach in explaining dependent variable variability.

	lag	Model [B.1]		lag	Model [B.2]		lag	Model [B.3]		lag	Model [B.4.]	
	/	-0,0001		/	-0,0001		/	-0,0001		/	-0,0001	
dMIS	0	0,0797		0	0,0869	°	0	0,0801	°	0	0,0760	°
pVIX	1	0,0023	***	1	0,0023	***	1	0,0022	***	1	0,0025	***
pDEX	1	-0,0343	*	1	-0,0346	*	1	-0,0363	*	1	-0,0351	*
dEQ	2	0,0092	***	2	0,0089	***	2	0,0085	***	2	0,0087	***
dSHs	1	/		1	-0,0491	**	1	-0,0395	*	1	-0,0517	**
dMEDs	1	/		1	/		1	-0,0487		1	-0,0637	°
dsSLs	1	/		1	/		1	/		1	0,0008	°
dcQ	1	0.00602476		1	0.0167890		1	0.0060405		1	0,0116	
R^2		43,8%			49,3%			50,4%			52,5%	
R^2-Adj		40,1%			45,3%			45,8%			47,3%	

*Table 5; Models B. Coefficients estimates, complete summary in Appendix A. Significance levels ° 90%, *95%, **99%, *** 99,9%. Sample: February 2012-February 2019.*

February 2012-February 2019	Model [B.1]	Model [B.2]	Model [B.3]	Model [B.4]
Test on Residuals	p-value(result)	p-value(result)	p-value(result)	p-value(results)
Philipps Perron Test	0,01	0,01	0,01	0,01
Ljung-Box Test	no critical lag	no critical lag at	lag 19 and 20	no critical lag
Box-Pierce Test	no critical lag	no critical lag at	no critical lag at	no critical lag
Breusch-Pagan Test	0,8384	0,678	0,6735	0,475
Jarque-Bera Test	2,2*E-16	1,071*E-5	3,09*E-06	1,0*E-03
McLeod-Li test	no critical lag	no critical lag	no critical lag	no critical lag
Breakpoint Test (Bai-Perron)	no break	no break	no break	no break

Table 6; Results of diagnostics on residuals for each model.

4.2. QE tapering and Capital Flights, clearer dynamics in Sub-Sample estimates.

As mentioned in data collection paragraph 3.1.2.1. the dependent variable in the models displays a possible breakpoint in early-mid 2013 and March 2014. Due to the sample size and relevant information connected to Quantitative Easing, it has been decided to break up the sample in analysis in March 2014. Jointly the liquidity channel regressors (dSHs and dMEDs) were combined taking their difference. The new liquidity regressors, called dSIRS, was introduced in model B.4. obtaining the model specification B.4.Adj. (refer to paragraph 3.2.7. Results of the estimation are provided in Table 7; diagnostic of the model is reported in Table 8. Note that a Shapiro-Wilk Test for Normality has been added to the diagnostics test because it performs better with smaller samples than the Jarque Bera Test.

We can observe from the results in Table 7 that all the regressors, except for the endogenous one, are significant (at different confidence levels). The monetary policy indicators spread (dMIS) displays a negative sign with a weak significance; interestingly its lag order has moved from 0 to 2. Changes in VIX, pDEX and dsSL maintain in this model their sign and approximately their module that was estimated in the previous specifications of model B.4. in full sample estimates. Interestingly it is possible to notice a positive sign for the liquidity channel measured with the new regressor dSIRS.

Looking at diagnostics results in Table 8 it is possible to notice that there is no evidence to refute the Gauss-Markov hypothesis on spherical errors (homoscedasticity and no-autocorrelation) in the model. There is also no evidence to refute the hypothesis of normal residuals, contrary to the estimation in previous models; it is likely that regression outliers were removed when reducing the sample. This suggests that OLS is Best Unbiased Estimator (BUE). No breakpoints have been detected on residuals by the Bai-Perron test.

March 2014-February 2019			Model [B.4.Adj.]	
Coefficients		lag		
Intercept		/	0,0001	
Δ differential Wu-Xia Rates and MPI (Girardin et. Al)	dMIS	2	-0,0700	°
%change VIX	pVIX	1	0,0020	***
%change RMB/USD	pDEX	1	-0,0275	*
Δ Extra returns SSE Composite Index and MSCI ACWI ex-US	dEQ	2	0,0096	***
Δ differential 3-1 Moth Interbank Spreads ((3mLib-1mLib)-(3mShi-1mShi)	dSIRS	1	0,0355	*
Δ differential 10-1 year Sovereign Bond Yield spread (US-China)	dsSL	1	-0,0012	**
endogenous regressors dcQ	dcQ	1	0,0483	
R^2	R^2		72,2%	
R^2 Adjusted	R^2-Adj		68,2%	

*Table 7: Models B.4. adjusted with dSIRS, Coefficients estimates. Significance levels ° 90%, *95%, **99%, *** 99,9%. Sample: March 2014-February 2019.*

March 2014-February 2019	Model [B.4.Adj.]
Test on Residuals	p-value(result)
Philipps Perron Test	0,01
Ljung-Box Test	no critical lag
Box-Pierce Test	no critical lag
Breusch-Pagan Test	0,207
Jarque-Bera Test	0,665
Shapiro-Wilk Test	0,08576
McLeod-Li test	no critical lag
Breakpoint Test (Bai-Perron)	no break

Table 8; Diagnostic on Model B.4.Adj.

4.3. Comparative Analysis Results: QE effects on US-China Equity Flows compared to US-Asian Emerging Markets Economies Flows.

February 2012-February 2019			Model/Robusteness [B.4.Adj.]	
Coefficients		lag		
Intercept		/	-0,0017	
Δ differential Wu-Xia Rates and MPI (Girardin et. Al)	dMIS	0	1,3810	*
%change VIX	pVIX	1	0,0279	***
%change RMB/USD	pDEX	1	-0,3737	*
Δ Extra returns SSE Composite Index and MSCI AEMEs	dEQ	2	0,0952	***
Δ differential 3-1 Moth Interbank Spreads ((3mLib-1mLib)-(3mShi-1mShi)	dSIRS	1	0,6639	*
Δ differential 10-1 year Sovereign Bond Yield spread (US-China)	dsSL	2	0,0032	**
endogenous regressors dcQE	dcQE	1	-0,0085	
	R^2		48,4%	
	R^2-Adj		43,5%	

*Table 9: Models B.4. Adjusted with dSIRS, Dependent Variable are changes in Chinese Equity Securities share in US Asian Emerging Markets Total Portfolio. Coefficients estimates. Significance levels ° 90%, *95%, **99%, *** 99,9%. Sample: February 2012-February 2019.*

February 2012-February 2019	Model/Robusteness [B.4.Adj.]
Test on Residuals	p-value(result)
Philipps Perron Test	0,01
Ljung-Box Test	no critical lag
Box-Pierce Test	no critical lag
Breusch-Pagan Test	0,55
Jarque-Bera Test	0,019
Shapiro-Wilk Test	0,0208
McLeod-Li test	no critical lag
Breakpoint Test (Bai-Perron)	no break

Table 10: Diagnostic on Model B.4.Adj., Full Sample, Robustness Analysis.

Notable results of this section for the full sample estimation are the positive sign in the differential of Monetary Policy indicator spread, that also displays a relatively high coefficient compared to the previous estimations of the models, and the positive sign and significance of the 10-1-year Sovereign Bond Yield Spread differential.

March 2014-February 2019			Model/Robusteness [B.4.Adj.]	
Coefficients		lag		
Intercept		/	-0,0017	
Δ differential Wu-Xia Rates and MPI (Girardin et. Al)	dMIS	3	0,8209	
%change VIX	pVIX	1	0,0260	***
%change RMB/USD	pDEX	1	-0,1432	
Δ Extra returns SSE Composite Index and MSCI AEMEs	dEQ	2	0,1128	***
Δ differential 3-1 Moth Interbank Spreads ((3mLib-1mLib)-(3mShi-1mShi)	dSIRS	0	-0,2585	
Δ differential 10-1 year Sovereign Bond Yield spread (US-China)	dsSL	2	-0,0096	
endogenous regressors dcQE	dcQE	1	0,1158	
	R^2		61,8%	
	R^2-Adj		56,1%	

*Table 11: Models B.4. Adjusted with dSIRS, Dependent Variable are changes in Chinese Equity Securities share in US Asian Emerging Markets Total Portfolio. Coefficients estimates. Significance levels ° 90%, *95%, **99%, *** 99,9%. Sample: March 2014-February 2019.*

March 2014-February 2019	Model/Robusteness [B.4.Adj.]
Test on Residuals	p-value(result)
Philipps Perron Test	0,01
Ljung-Box Test	no critical lag
Box-Pierce Test	no critical lag
Breusch-Pagan Test	0,749
Jarque-Bera Test	0,3157
Shapiro-Wilk Test	0,4348
McLeod-Li test	no critical lag
Breakpoint Test (Bai-Perron)	no break

Table 12: Diagnostic on Model B.4.Adj., Subsample from March 2014 to February 2019, Robustness Analysis.

Notable results of this section for the sub sample estimation are the positive sign in the Monetary Policy Indicator Spread (dMIS) at lag 3, that also displays a relatively high coefficient compared to the previous estimations (however not significant). More notably as shown in Table 11 and Table 12, residuals turn from non-normal to normal residuals in sub-sample model estimation, as it had happened for the previous estimations under different model specification.

4.4. Discussion and Interpretation on Model Coefficients Estimates.

4.4.1 Capital Flows or Aggregate Portfolio Allocation

Before starting to discuss the results reported in the previous paragraphs, it is important to reflect upon how the construction of the dependent variable subject of this analysis impact interpretation. The variable of interest in this dissertation is the Equity Capital Outflows from the US towards China computed from US Chinese Equities holdings (or rather stocks) normalized for all US holdings in foreign equities. Hence, the variable can be more easily thought of as the changes in the Chinese Equity Securities' share in the US Foreign Portfolio. This interpretation opens the analysis towards a more similar theoretical framework of Capital Allocation at the aggregate level for the US investors, or more specifically to a Portfolio Choice interpretation. This approach was also proposed by Miranda-Agrippino & Rey (2020) when interpreting their results of their studies. The authors in fact suggest that major players in determining Capital Flows are Global Banks and Fund/Portfolio Managers. Therefore, we believe that adopting this line of interpretation greatly simplifies the interpretation of results.

4.4.2. Building Evidence that China is Not an Emerging Market Economy.

4.4.2.1. Monetary Policy Measures Unexpected Signs: US-China Flows are comparatively less affected by QE in respect to other Equities.

As shown in Tables 3 and 5 the monetary policy variables display an opposite sign as expected from previous literature. We should expect a positive effect for the difference in Central Banks' Total Assets Growth (sTA); as the QE programmes developed, FED Total Assets increased inducing more foreign investments, and, as reported by Park et al (2014), this should be particularly true for Equity Securities during QE3 programme. In Table 3 it is possible to notice an inverse sign. However, this is not probably the case since as mentioned in previous paragraph the dependent variable can be thought as the changes of Chinese Equities share in US foreign portfolio. So, the negative sign of sTA may mean that US quantitative easing may have reduced US Outflows to Chinese Equity Securities, compared to all other Foreign Equity Securities present in US Foreign Portfolio. This in turn suggest that other countries were primary targets of Financial Outflows from the US, not China. The same interpretation can be given for the difference between the Wu Xia Shadow Rates and the Chinese MPI by Girardin et al. (2017) (dMIS). We should expect a negative sign. Indeed, as the US Wu Xia shadow rates become more negative, net of Chinese Monetary Policy Indicators, we expect an opposite sign change in Chinese Equity Securities shares in the US Foreign portfolio. This interpretation is supported by the results obtained in the comparative analysis that shows that, when comparing China with other Asian Emerging Economies, the coefficient of Monetary Policy Indicators Spread (dMIS) remains positive, but its module becomes much higher compared to the previous models. This suggests indeed that US monetary policy affected more other Asian Emerging Markets Economies compared to China.

4.4.2.2. Confidence Channel, counterintuitive but consistent effects, Chinese Equity may be a hedging instrument within the US foreign portfolio.

Among all the regressors the one that maintains consistently across all model's specifications its optimal lag, sign and approximately its module is the percentage change in VIX, measuring the confidence channel. This channel as shown by Park et al (2014) and Miranda-Agrippino & Rey (2020) usually displays significant results, as it was also obtained in our analysis (coefficients significantly different from zero with 99,9% confidence). However contrary to Park et al (2014), who found that the confidence channel usually has negative effects on capital flows toward emerging markets, the results of our analysis seem to suggest the opposite. Still, as stated in the previous paragraph, it must be noticed that the dependent variable in this analysis is US-to-China Equity Outflows normalized for US Foreign Equity Outflows. Hence two lines of interpretation are possible to explain the positive sign obtained for the changes in VIX: Chinese Equity Securities may be considered as not properly Emerging Markets Securities but more like Developed Market securities; alternatively, it is possible that Chinese securities provide US investors hedging opportunities compared to other foreign equity securities; hence, when VIX increases, Chinese Equities' Share in US Foreign Equity Portfolio increases comparatively to the rest of the US foreign portfolio. The first of the two hypotheses may be predominant since the robustness analysis confirms these results, finding that changes in VIX maintain their sign in affecting US to China Equity Outflows even when normalizing for the other Asian Emerging Markets Economies. These results combined indeed suggest that China is not (anymore) considered by US investors as an emerging market economy.

4.4.2.3. Exchange rate channel, evidence for currency returns as a driver of the US to China Equity Capital Flows.

All the models estimated over the full sample suggest that the exchange rate channel is significant in explaining Equity Capital Flows from the US to China. What is not clear however is why in models A.1 and A.2, the best explanatory lag of percentage changes in RMB/USD is zero whilst for all the other models estimated on the full sample the lag is one. Nonetheless the interpretation of these results is in a way simple and extremely intuitive: monthly percentage changes in RMB/USD exchange are indeed, within a portfolio allocation context, monthly simple currency returns. Hence the interpretation of the negative sign in RMB/USD is clear: as the Renminbi appreciates (less RMB per dollar) we see a push in the Equity flows towards China from the US.

4.4.2.4. SSE Composite Index Excess Returns against MSCI ACWI ex-US: A lagged effect, likely evidence towards capital controls affecting investors' expectations.

The SSE Composite Index excess returns against the benchmark is the regressor that, together with VIX, maintains sign, optimal lag and approximately module all along the models' specifications. In particular, the regressor displays a positive sign and a lagged effect of two months. The positive sign could be explained by interpreting the regressor in a portfolio allocation context, as Chinese Equities outperforms the benchmak in terms of returns, we could expect an increase in US Equity Capital Flows towards China, an effect of portfolio balance. On the other hand, the fact that SSE Composite excess returns affect US Capital Outflows with a lag of two months could be explained by capital controls and lock-up periods under RQFII and QFII, as well as stock connects restrictions; having a lock-up period of three months US Qualified Investors model their expectations for the following month observing excess-returns in the previous two months.

4.4.2.5. Liquidity Channel Regressors, unclear results.

The Interbank spreads in the model's specifications A display significant results with, however unclear interpretation. More specifically the 1-Month Interbank Spread and the 3-Month Interbank spread differ in lag and sign affecting the capital flows from the US to China, when the differential in Sovereign Bond 10-1-year spread is not included in the model. A similar sign was expected for the two regressors since the closeness of 1-month and 3-month maturity should make them behave similarly. On the other hand, looking at the results of the model's specifications B.3, we see that the two interbank spreads behave more coherently with equal negative signs and a lag of 1, suggesting that a comparatively more liquid market in the US can be seen as a push factor towards Chinese Equity Markets, as the US interbank rates become smaller relatively to Chinese interbank rates. Moreover, in model B.4, when the differential in Sovereign Bond 10-1-year spread is included, the 3-month Interbank Spread does change its sign, becoming positive and at the same time losing its significance. These mixed results could be explained by multicollinearity between 1-month and 3-month Interbank Rates Spreads, as reported in the correlation matrix (Table 7), as well as with Sovereign Bond 10-1-year spread. Other two important factors may be the proxy used to measure 1-month Libor (it was used for the 4-week T-bills) and the fact that SHIBOR and LIBOR are not two variables that are truly comparable in their meaning, especially if we include in the period of analysis late 2012 and 2014 when Chinese Credit and Banking sectors saw significant changes and a liquidity crisis that however are not reflected in the sample. Moreover, another significant problem for the analysis in this approach is the zero lower bound on interest rate for US Interbank Sectors in the period from 2012-2016 which is almost reached in different points of the series. Further discussion on the limits of these variables will be addressed in the conclusion of the dissertation. All in whole, these reasons were the rationales for conducting the later analysis with 3-1-month Interbank Spread differential (dSIRS) instead of using two variables for the liquidity channel.

4.4.3. Focus on QE tapering: monetary policy tightening affects significantly interested variables; Building evidence that China is neither a developed nor an emerging market.

When ruling out from the sample the initial part of the third-round quantitative easing (QE3) and the very beginning of the QE tapering, when analysing the behaviour of the US Chinese Equity Securities' share in the total foreign portfolio, it is possible to find more results in line with previous literature. More precisely we notice that Model B.4.Adj. estimates reveal that Wu-Xia Shadow Rates, net of the Chinese MPI from Girardin et al (2017), have a negative effect on the dependent variable, suggesting a more accentuated flight from Chinese Equity Markets as the QE tapering proceeds and as FED interests rates turn from negative to positive. The effect however is weakly significant. As mentioned in paragraph 4.2. it is also interesting that in the subsample the monetary policy indicator spread affects the dependent variable at lag two. It is possible that this result is a further confirmation of the effects of lock-up periods and capital controls since investors must form their expectations for the current month based on their observations of the last two months (in line with the same reasoning for SSE Composite Excess Returns).

Alternatively, remembering that both Wu-Xia Shadow Rates and the Chinese Monetary Policy Indicator by Girardin et al. (2017) are ex-post synthetic measures to study the behaviour of respectively FED and PBOC, it is possible to assume also that financial intermediaries are less efficient in interpreting and computing their own measures of monetary policy impacts in their portfolios, hence the requirement of an extra lag compared to other variables to impact portfolio choices. However, another interpretation is possible. It is worth noting that the negative sign of these regressors is not maintained in the comparative analysis. When normalizing Chinese Equity Outflows for other Asian Emerging Markets Economies, in the subsample starting in March 2014, the US monetary policy, net of Chinese measures, becomes positive with a much higher module (compared to model B.4.Adj in the previous analysis). These changes in sign may well be explained by the fact that China, if compared with a Global Portfolio, is more affected by QE tapering, since the US aggregate investor dimmish its share of Chinese Equities in its total Foreign Portfolio. However, if China is compared to a portfolio of Asian Emerging Market Economies (AMES), it is found that China is less affected compared to these. This suggests that China may be considered by US investors neither as a Developed market and nor as an Emerging one. This last interpretation may be confirmed by the steady significance and positive sign of changes in VIX that are maintained across model specifications, full and sub-sample as well as in the robustness analysis.

Behaviours of the RMB/USD exchange as SSE Composite Index excess returns on the MSCI ACWI do not significantly change in the subsample, compared to the full sample. However, it is worth noting that RMB/USD exchange displays a negative (as expected) but not significant effect in the sub-sample robustness analysis. This fact is not clear in interpretation, it could be advanced that probably currency channels affected homogeneously all the Asian Emerging Markets. However, from these models and these results we cannot be reasonably proposing this conclusion without prejudice.

Besides the role of the liquidity channel, now measured with the differential in 3-1-month Interbank Spreads in US and China, is unclear in its interpretation. It displays significant positive effects, suggesting that when the 3-1-month Libor Rate Spread is higher in the US compared to the 3-1-month Shibor Rate Spread, the share of Chinese Equity Securities in the US Total Foreign Portfolio increases. It can be hypothesized that the closer to zero is 3-1-month Interbank Rates Spread differential, the more liquid is considered that market. This interpretation could be supported by the fact that banking intermediaries operating in the interbank market do not foresee liquidity crunches in the short-medium term. Based on this theoretical assumption, we can better comprehend why the 3-1 Month Interbank Rate Spread differential shows a positive trend. Essentially, this could be because when the US market is less liquid (causing the 3-1 Month Libor spread to increase) compared to the Chinese markets (leading to a higher 3-1 Month Shibor spread), the share of Chinese Equity Securities within the overall US Foreign portfolio tends to rise, and vice versa.

Finally, it seems in the Sub-Sample estimation of Model B.4.Adj. that the Flight to Quality effect regressors assume significant and negative coefficients, suggesting that when developed markets' (proxied via the US alone) sovereign bond long term yield spread (10-1 year) is comparatively greater than the Chinese counterpart, there is a reduction in the share of Chinese Equity Securities in US Foreign Portfolio, suggesting that there might be flight to quality effects.

Section V: Regressors Matrix analysis and testing

5.1 OLS validation, non-collinearity hypothesis, Summary Paragraph.

All coefficients' estimates reported and discussed in section 4 were obtained utilizing OLS. In the previous paragraph, other diagnostic tests were already reported, mainly regarding residuals. These were found to be non-autocorrelated and homoscedastic. Moreover, the series of residuals were found without any structural breakpoints, suggesting a conditional (to time) and unconditional mean not significantly different from zero. Additionally, each regressor has been found to be second-order stationary. To validate the OLS estimation, two hypotheses must still be tested: exogeneity and non-collinearity in the Regression Matrix. As mentioned in Section 3, the first hypothesis was tested by utilizing the variable sTA, which represents the difference in Central Banks' Total Assets growth, as an instrument to be used in a two-stage least square approach (2SLS). The non-collinearity hypothesis was mainly tested using the correlation matrix and the VIF test, as well as Granger Causality Effects, IRF and FEVD. In summary, the subsequent paragraphs report that there is no significant evidence to refute the non-collinearity hypothesis of the Gauss-Markov theorem. Regarding the results obtained from 2SLS, nonsensical coefficients were obtained, suggesting that this approach may have introduced more endogeneity in the regressors, implying that sTA is a weak instrument or possibly even a bad instrument. Finally, Impulse Response Functions (IRF) were computed between monetary policy variables of interest and other regressors to possibly capture long-term relations between them. However, the results were mostly insignificant for long lagged effects. For a more comprehensive approach, a Forecast Error Variance Decomposition (FEVD) has been performed on the regressors Matrix. It was found that monetary policy variables are in the long run responsible for an extensive share of variability of some regressors. This fact should not produce bias in coefficient estimates in the model specifications (since the lags between different regressors do not vary significantly), however, it is worth noting that these interactions should be better addressed with quantitative modelling and a more thorough analysis. More detailed results can be found in the subsequent paragraphs, as well as in the Appendix.

5.1.1. Diagnostics on Full-Sample.

To assess possible multicollinearity problems, the Correlation Matrix of Regressors and a Variance Inflation Factor (VIF) test on non-lagged regressors are presented in Table 13 and Table 14. Correlations reported in Table 13 are in absolute value since the extent of multicollinearity is of interest and not its sign.

	dMIS	sTA	pVIX	pDEX	dEQ	dSHs	dMEDs	dsSL
dMIS	diag							
sTA	0,305363	diag						
pVIX	0,116181	0,006095	diag					
pDEX	0,188251	0,019873	0,033936	diag				
dEQ	0,05221	0,224993	0,31506	0,147625	diag			
dSHs	0,103175	0,117691	0,047271	0,002903	0,013197	diag		
dMEDs	0,054952	0,15375	0,035514	0,099351	0,040178	0,385506	diag	
dsSL	0,08389	0,148235	0,186139	0,049483	0,074532	0,444023	0,371042	diag

Table 13; Correlation Matrix of Regressors (without lag), all correlations are in absolute values.

dMIS	MTAS	pVIX	pDEX	dEQ	dSHs	dMEDs	dsSL
1,2618	1,2135	1,2133	1,0983	1,2346	1,4047	1,2936	1,4668

Table 14: Variance Inflation Factor (VIF), test scores for each non-lagged regressor.

From the correlation matrix (Table 13) it is possible to observe that the variables of interest, Monetary Policy Indicator Spread (dMIS) and Differential in Central banks' Total Assets Growth Rates (sTA), seem uncorrelated with any other regressor (all correlations below 30%). As it could be expected, Interbank Rates Spreads (dSHs and dMEDs) display higher correlations between themselves and with Differential in Sovereign Bond Yield 10-1 year spread (dsSL). These results are indeed confirmed by the VIF where dSHs, dMEDs and dsSL render the highest VIF score although none of them seem to be significant. All VIF scores in fact are above 1, which could suggest a moderate correlation between regressors. However, none of them exceeds 1.5. Considering that important thresholds for the VIF test are 5 and 10, it is considered that, from this test, multicollinearity problems seem to be limited and not extensive in the non-lagged regressor matrix.

The correlation matrix was also run for the regressors with their corresponding lag used in the model. From a graphical point, it is possible to note that there might be some correlation between the 1-month Interbank Rates Spread with the 3-month Interbank Spreads and the 10-1 Year Sovereign Bond Yield Differential. The VIF test suggests however that there is no significant multicollinearity issue.

	dMIS	pVIX.1	pDEX.1	dEQ.2	dSHs.1	dMEDs.1	dsSL.1
dMIS	diag						
pVIX.1	0,106097583	diag					
pDEX.1	0,275840886	0,031071588	diag				
dEQ.2	0,289155906	0,015542557	0,077846127	diag			
dSHs.1	0,05087121	0,020253226	0,031940622	0,091250264	diag		
dMEDs.1	0,153367687	0,069302424	0,109389058	0,150532589	0,332387642	diag	
dsSL.1	0,022902886	0,191300055	0,044961098	0,103999677	0,434620743	0,370305166	diag

Table 15; Correlation Matrix of Regressors, the number after "." indicates the lag of each regressors, all correlations are in absolute values.

MTAS.1	dMIS	pVIX.1	pDEX.1	dEQ.2	dSHs.1	dMEDs.1	dsSL.1
1,0761	1,2667	1,0571	1,1278	1,1963	1,3149	1,2683	1,3970

Table 16: Variance Inflation Factor (VIF), the number after "."indicates the lag of each regressor.

To run a more thorough analysis, and to possibly isolate better the role of monetary policy, we run Granger Causality Tests on each regressor against variables of interest. Results are available in Appendix. None of the regressors is Granger-caused by the Monetary Policy Indicator Spread (dMIS). On the other hand, results on the difference in Central Banks' Total Assets growth rate seem to Granger-cause at lag 3 significantly, with a confidence of at least 95%, the differential in Sovereign Bond 10-1-year Yields. Moreover, the same variable appears to Granger Cause, at lag 3 with a confidence of 90% percentage, changes in VIX.

To investigate further and understand possible long-term relations in the regressors matrices for both models A and B, VAR models were run on regressors, and Orthogonal

Impulse functions have been produced. The results are reported in Appendix. The VAR order was taken as the highest possible order to be run on the dataset of the regressor. Due to the sample size and number of regressors, the order is equal to 9, the ahead forward period is of 10 months. The IRF estimation however did not produce any significant results, suggesting that orthogonal shocks in monetary policy measures (both sTA and dMIS) have no long-term significant effects on the other regressors. However, a more thorough analysis utilizing a Forecast Variance Error Analysis (FEVD) suggest indeed that some long-term relationships between monetary policy and other regressors are present. Particularly the FEVD displays that the changes in the Currency Channel are significantly affected by changes in Monetary Policy Indicator Spread (dMIS). Secondarily, troubling is the FEVD for 10-1-year Sovereign Bond Yield spread (dsSL) and 1-Month Interbank Rates Spread (dSHs), in fact their respective forecast error variance is largely a combination of the other variables. Refer to figure 10 for the plot, alternatively a more zoomed plot is available in appendix.

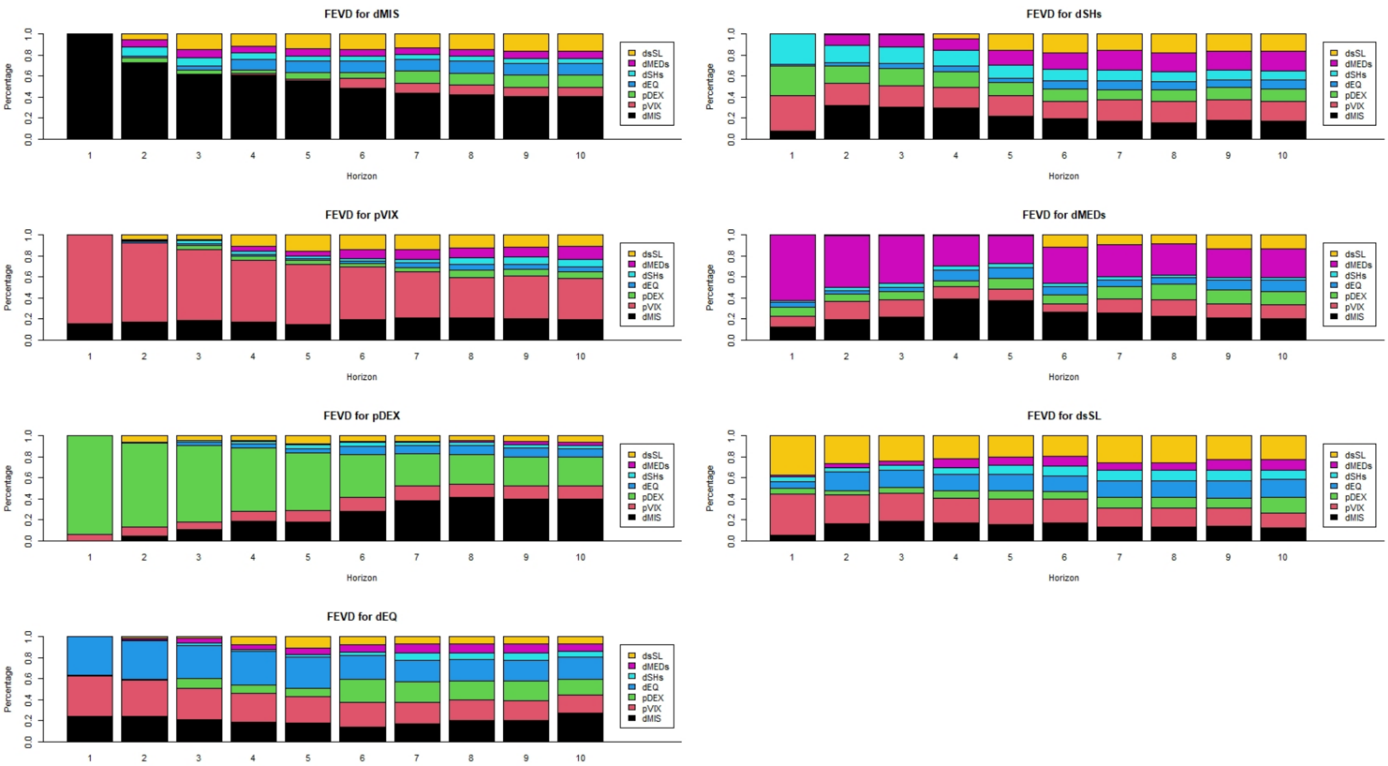

Figure 10; Forecast Error Variance Decomposition (FVED); Full-Sample Analysis, Regression Matrix with dMIS.

5.1.2 Testing Regressors Matrix with the new liquidity channel variable (dSIRS).

From the correlation matrix in previous paragraph, it is possible to note that the two liquidity channel measures (the two Interbank Bank Rates Spreads) dSHs and dMEDs were displaying multicollinearity between themselves and with the Sovereign Bond 10-1 year spread differential. Therefore, we decided to unite these two regressors into a unique new variable to capture the liquidity channel in monetary policy transmission without introducing multicollinearity or causality effects**.** The new regressor is simply the difference between the 3-1-month Libor spread and the 3-1-month Shibor spread. That algebraically can be seen as the difference between the 3-month interbank spread with the 1-month interbank spread. In this way, intuitively, it should be possible to eliminate the common variation between these two regressors that could be expected or at least guessed to be caused by monetary policy shocks. The new regressor, whose acronym is dSIRS, has been tested as well with Philips-Perron Tests and has been found to be stationary and to not be Granger Caused by either the Monetary Policy Indicators Spread or Central Banks' Total Assets growth rates. Moreover, an impulse response analysis has been conducted. Results are reported Appendix. The IRF in the regressors matrix with dSIRS instead of the two former regressors does not produce significant results suggesting preliminarily no long-term relations between the Monetary Policy Indicator Spread shocks and the other regressors. Moreover, the FEVD analysis, reported in appendix suggests that the new regressor matrix with the new liquidity channel displays comparatively minor issues of long-term relations between regressors.

5.1.3. Diagnostics in Sub-Sample.

As observed from Table 17, the correlation matrix shows how in the sub sample March 2014-February 2019 the 1-Month Interbank Rate Spread (dSHs) would have displayed high correlation with both the 10-1-year Sovereign Bond Yield (dsSL) spread differential, and with the 3-Month Interbank Rate Spread (dMEDs) and the Monetary Policy Indicator differential (dMIS). On the contrary, it is possible to notice that the correlation with the new liquidity channel regressor is more contained, suggesting that the approach to create a new liquidity variable was indeed correct. From Table 18, it is possible to note the VIF scores do not reach significant threshold of 5 or 10. Suggesting that there is no multicollinearity between non-lagged regressors matrix.

	dMIS	pVIX	pDEX	dEQ	dSHs	dMEDs	dSIRS	dsSL
dMIS	diag							
pVIX	0,104	diag						
pDEX	0,237	0,021	diag					
dEQ	0,131	0,383	0,242	diag				
dSHs	0,260	0,027	0,010	0,068	diag			
dMEDs	0,098	0,033	0,077	0,006	0,290	diag		
dSIRS	0,317	0,046	0,032	0,072	not of interest	not of interest	diag	
dsSL	0,007	0,167	0,091	0,045	0,505	0,265	0,355	diag

Table 17; Correlation Matrix of Regressors (Sub-Sample March 2014-February 2019, all correlations are in absolute values).

dMIS	pVIX	pDEX	dEQ	dSIRS	dsSL
1,3881	1,3379	1,2142	1,4227	1,4183	1,2360

Table 18: Variance Inflation Matrix (VIF), test scores for each regressor (Sub-sample March 2014-Fevrruary 2019).

The lagged regressors correlation matrix (Table 19) indicates no particularly extended correlations between lagged regressors, except for the 3-1 Interbank rates Spread Differential (dSIRS) with the 10-1-year Sovereign Bond Yield Spread Differential (dsSL). From VIF test results reported in Table 20 we observe that none of the regressors is adding significant multicollinearity in the model. Granger Causality Tests have been run between the Monetary Policy Indicator spread (dMIS) and the other regression variables. None of the variables seems to be Granger Caused by the differential in Monetary Policy Indicators in the Sub-Sample. Subsequently, an Impulse Response Reaction has been run on the regressors matrix, observing the effects of orthogonal shocks in Monetary Policy Indicators on the other regressors. Results are shown in Appendix. The results produced are largely insignificant, suggesting no long-term interactions between shocks in the independent variable of interests and controls.

	dMIS2	pVIX1	pDEX1	dEQ2	dSIRS1	dsSL.1
dMIS2	diag					
pVIX1	0,128669793	diag				
pDEX1	0,009195772	0,020546825	diag			
dEQ2	0,176130979	0,011255893	0,150959135	diag		
dSIRS1	0,00436335	0,037579794	0,018565395	0,101183195	diag	
dsSL.1	0,072007448	0,18098386	0,053154577	0,018768514	0,45102116	diag

Table 19; Correlation Matrix of Regressors, the number indicates the lag of each regressors, all correlations are in absolute values (Sub-Sample March 2014-February 2019).

dMIS2	pVIX1	pDEX1	dEQ2	dSIRS1	dsSL.1
1,0615	1,0791	1,0276	1,0713	1,3019	1,3458

Table 20: Variance Inflation Factor (VIF), the number after indicates the lag of each regressor. (Sub-Sample March 2014-February 2019).

Lastly the FEVD for the Sub-Sample Regressors Matrix was computed. As could be seen from figure 11, introducing the new Liquidity Regressor dSIRS may have tamed interactions between different regressors.

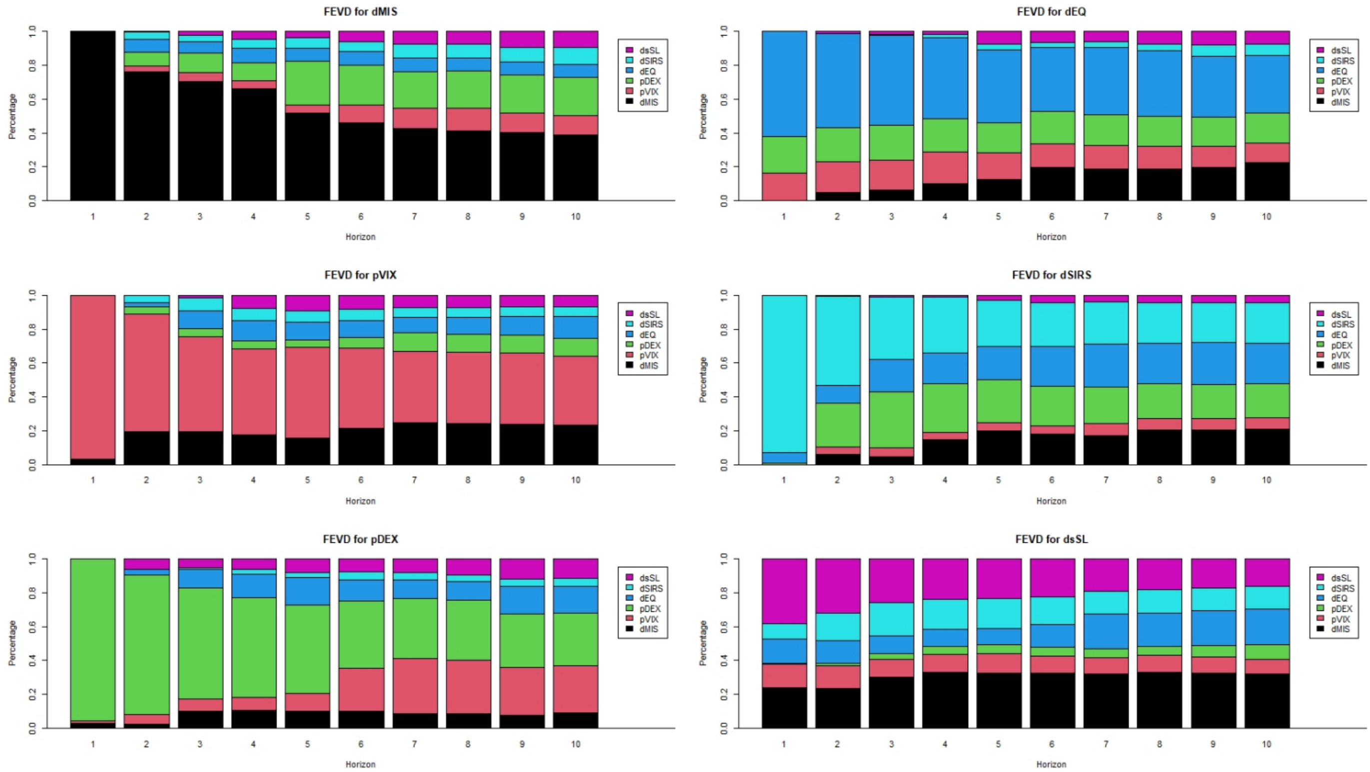

Figure 11; Forecast Error Variance Decomposition (FVED); Sub-Sample Analysis, Regression Matrix with dMIS and new liquidity regressors dSIRS.

5.2. Discussion on Multicollinearity and Long-Term Relations in Regressors.

The results obtained in previous subparagraph suggests no evidence against the Gauss-Markov hypothesis on non-collinearity for our data. These results jointly with diagnostic in section 5 suggests that OLS produced unbiased estimation of coefficients. However due to the FEVD analysis and the relatively low significance in Full-Sample estimation, the introduction difference in 10-1-year Sovereign Bond Yield spread could be omitted. Suggesting that model specification B.3. is overall more appropriate in full-sample analysis.

5.3. Abandoning the Two Stage Regression approach.

The result obtained from two stage regression, utilizing central banks' total assets growth rate differential as instruments, are reported in the Appendix. Their relevance is dubious since they produced unclear and, in some way, non-sensical results. More precisely the sub-sample model estimation suggested a time trend in the dependent variable. This result is not possible considering both stationary test and a model ARIMA estimation performed as diagnostic on the dependent variable. Summary Tables and a brief discussion are available in the Appendix.

Section VI: Conclusions

6.1. Major Findings

Major findings of our research pertain to the comparative behaviour exhibited by Chinese Equities during the Quantitative Easing period in US Foreign Portfolio. We observed that in our comprehensive analysis (encompassing QE3), China did not emerge as a primary target for equity capital outflows induced by the Federal Reserve's QE, within the United States' foreign portfolio. This outcome is supported by a comparative analysis that underscores China's marked divergence in behaviour from other Asian Emerging Market Economies (AEMEs). As previously mentioned, these results appear to support credence to the effectiveness of capital controls enforced by Chinese Financial Authorities, along with the countermeasures implemented by the People's Bank of China (PBOC).

However, when we narrow our focus to QE tapering, a distinct pattern emerges: China experiences more pronounced instances of equity capital flight when compared to the US foreign portfolio. Nonetheless, these findings do not exhibit robustness when contrasted with the group of AEMEs. This in turn implies that aggregate US investors do not perceive Chinese Equity Securities as fitting within the categorization of either a Developed Market Security or an Emerging Market Security.

Another significant result we found pertains to the influence of changes in the VIX on US-China Equity Flows. Remarkably, irrespective of the chosen set of comparisons, alterations in the VIX consistently exerted a positive impact on these flows. This implies that Chinese equities might serve as hedging opportunities for US investors against other securities in their global portfolios. As could have been expected, we also identified that Chinese Equity excess returns in relation to a benchmark play a role in driving the overall foreign portfolio allocation of US investors. A similar but less significant effect was registered also for currency returns.

6.2. Strengths and weaknesses of this analysis.

The major strength of this analysis is most likely the interpretational point of the results. The construction of the dependent variables, as normalizations of US to China equity outflows from the US to a portfolio of countries, allows us to evaluate the effects of US monetary policy in terms of aggregate portfolio allocation without using panel data analysis (as Park et al 2014). Another major strength of this analysis is the use of synthetic measures of monetary policy that can capture better extraordinary monetary measures in a more continuous manner than utilizing raw data of Large-Scale Assets Purchases and their changes.

However, with this strength also comes weaknesses, proxying the Equity Capital Outflows from the US to China by taking the changes in the US holdings in Chinese Equity Securities also carries imprecisions and assumptions, particularly we assume the changes in dependent variable are due to transactions and not just to changes in the value of the securities held in the US foreign portfolio. However, as argued in the introductory paragraphs, using direct US to China Transactions in long-term securities had its own biases that were considered worse in terms of both quantitative analysis and interpretation purposes. Finally, the model has been specified with regressors that usually are constructed by subtracting the US monetary policy variable of interest minus a corresponding Chinese variable of interest. However, the dependent variable has been normalized with a global portfolio, suggesting that for the analysis we should expect to include regressors including also non-US and non-Chinese monetary policy variables. These have been omitted in light of the results of Miranda-Agrippino & Rey's (2020) work on the Global Financial Cycle, in which the authors conclude that US monetary policy alone is responsible for a great part of the variability in their global financial cycle factor.

6.3. Possible further research

Possible further expansions of this analysis would be to construct a factor for Chinese financial integration using a dynamic model. In this way, it would be possible to directly measure the efficacy of the Chinese Financial Markets frictions and Capital Controls in limiting capital flight. Moreover, it would be interesting to include in the model a regressor to measure Hedging Opportunities provided to US investors by investing in Chinese Markets. Alternatively, it would be also a good idea to divide the SSE Composite Excess Returns against MSCI ACWI ex-US for some measure of realized volatility or other volatility measures, since as it is known from modern portfolio theory, excess returns against a benchmark should be weighed against some form of volatility measure or risk.

Another noteworthy constraint of the conducted analysis pertains to the quality of liquidity metrics in proxying effectively the level of liquidity in Chinese Markets. China particularly has indeed a predominant shadow banking sector that has an important role in providing liquidity and credit to the overall Chinese economy. Utilizing Shibor rates as liquidity proxies may indeed be a limiting factor of this analysis since non-captured liquidity changes in China may be a source of endogeneity in the models. This fact may be particularly true for the first part of the full sample in our analysis, since China in the 2013 and 2014 suffered some liquidity crunches. Excluding partially these two years from the sub-sample analysis may have reduced the effects of this issue. Introducing a new and more appropriate measure for liquidity could be a further development of our study. Finally, it would be interesting to study separately the two different monetary policy indicators, trying to observe if they jointly influence capital flows or if only one of them influences capital flows (as proposed by Miranda-Agrippino & Rey 2020). However, it is believed that the current set up for the model, being simply multivariate linear models with lagged regressors may have its limitations in studying furtherly this topic.

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Data sources:

Treasury International Capital (TIC) System: home.treasury.gov

Federal Reserve Bank Data Download Programme: www.federalreserve.gov

People Bank of China, data section: www.pbc.gov.cn

Federal Reserve Bank Department of Atlanta: www.atlantafed.org

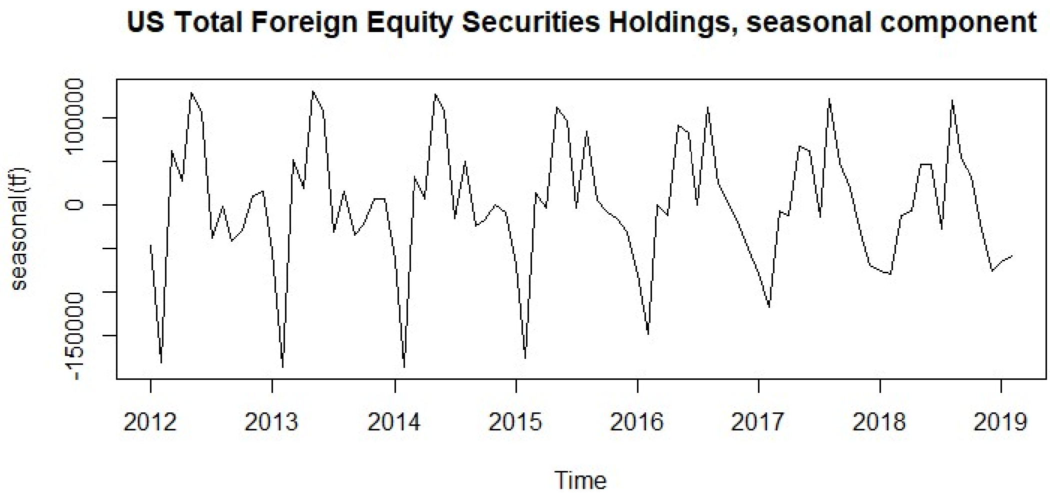
Federal Reserve Bank of St. Louis, Economic Research (FRED): fred.stlouisfed.org

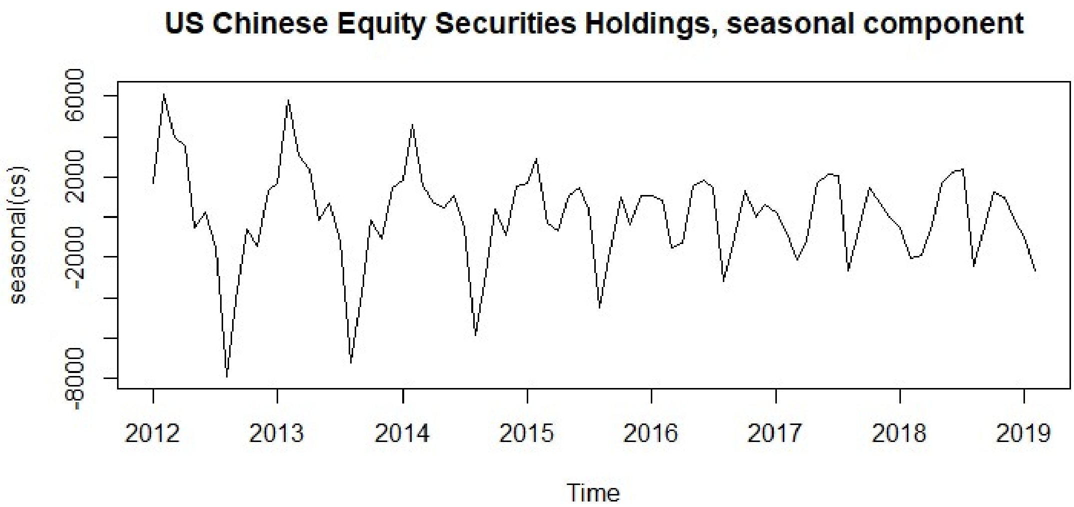
Yahoo finance: finance.yahoo.com

Refinitiv Eikon: www.refinitiv.com

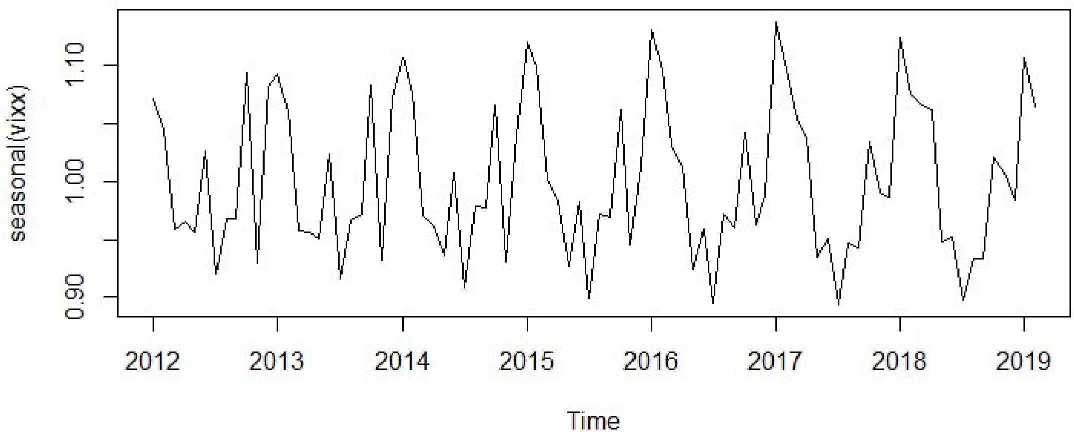
Appendix:

A.1. Seasonal Adjustments Reports

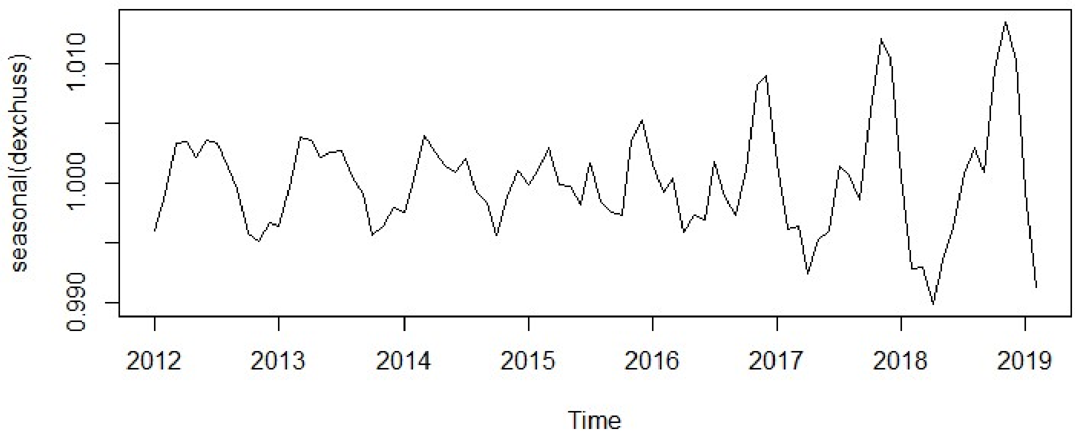




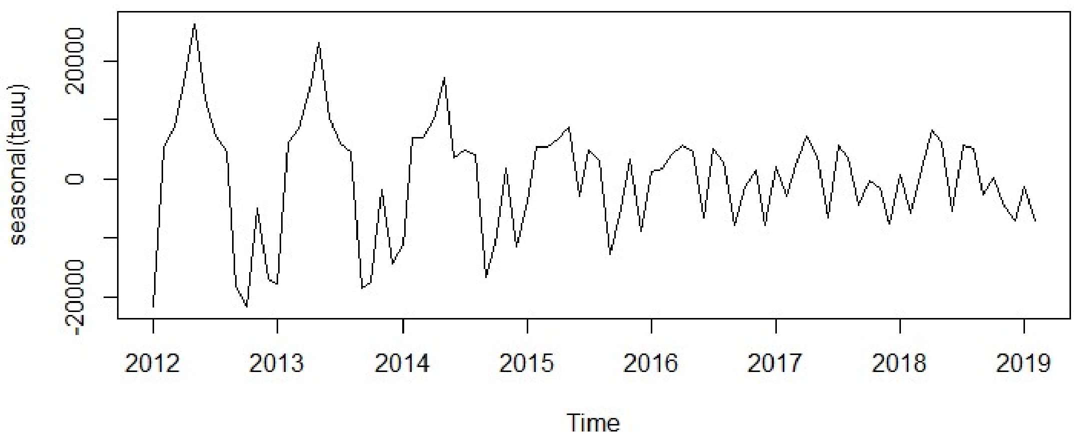
CBOE VIX, seasonal component

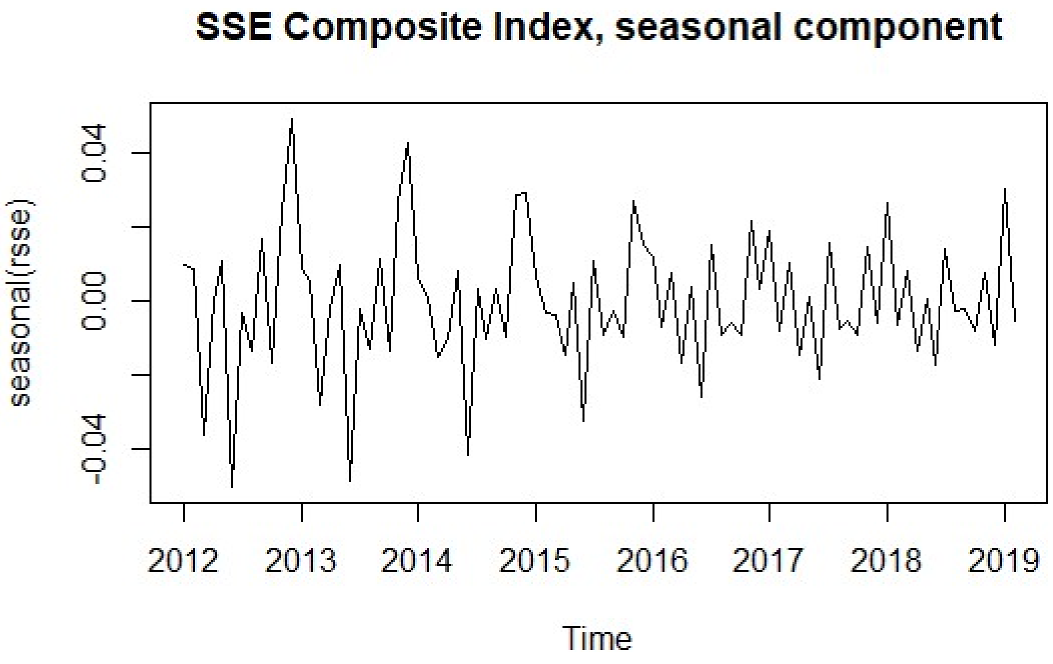


RMB/USD exchange, seasonal component

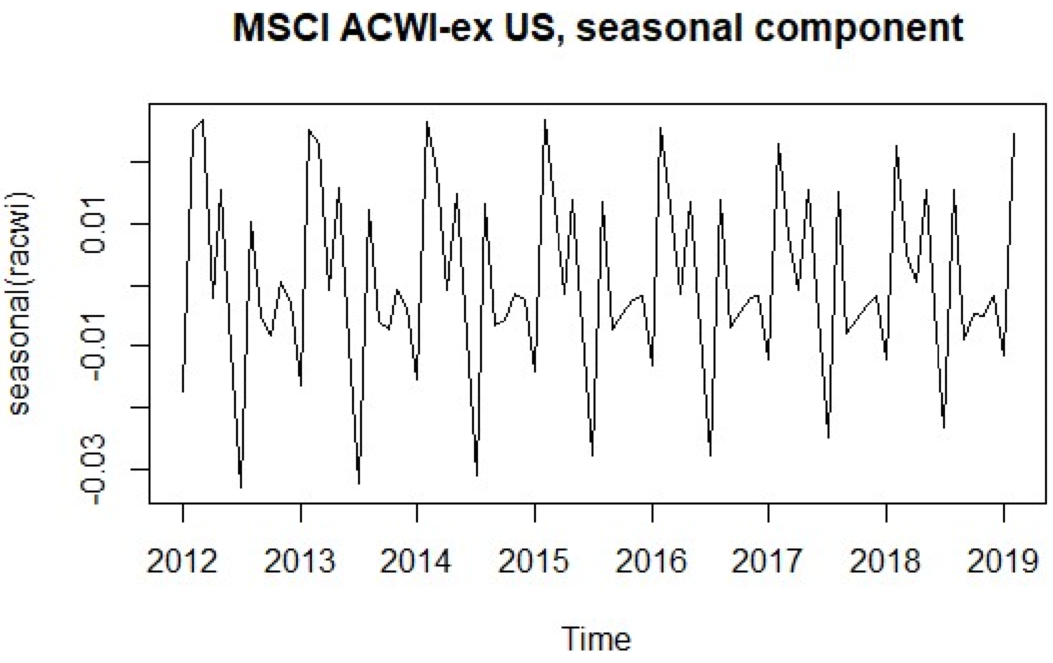


FED Total Assets, seasonal component



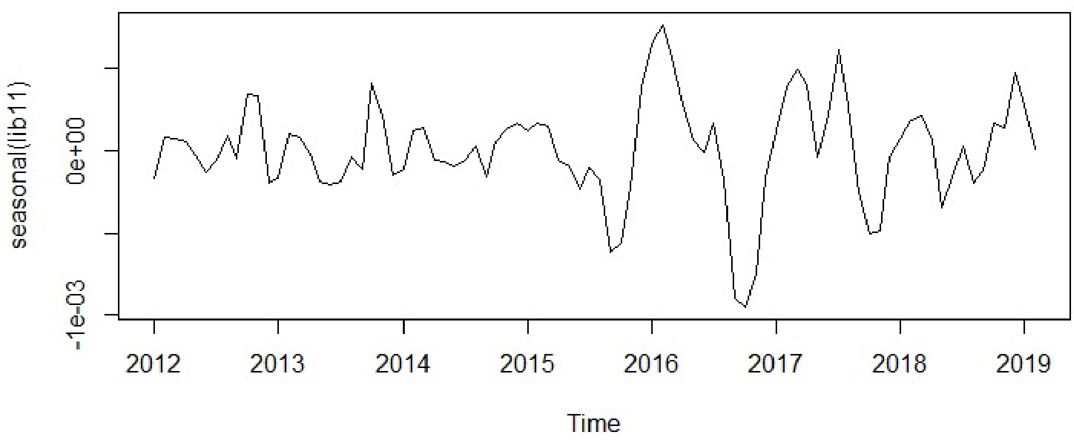


SSE Composite Index, seasonal component
seasonal(rsse)
0.04
0.00
-0.04
2012
2013
2014
2015
2016
2017
2018
2019
Time

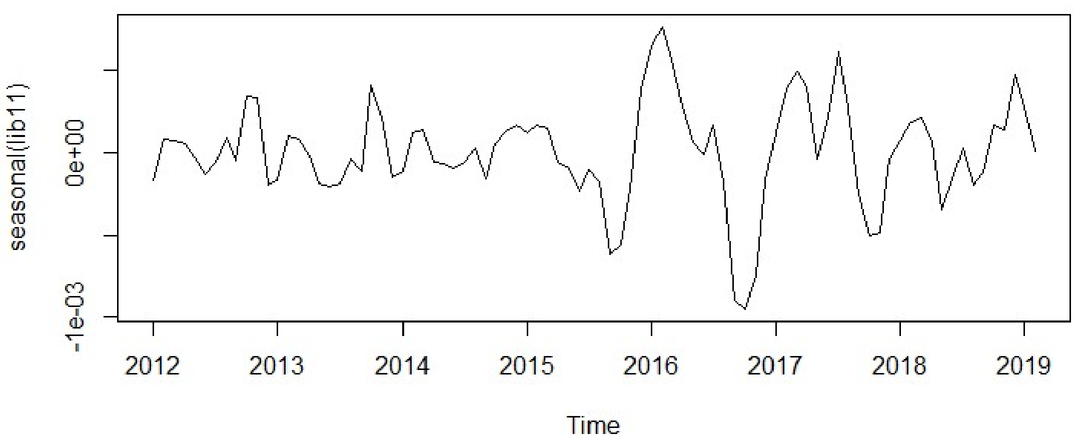


MSCI ACWI-ex US, seasonal component
seasonal(racwi)
0.01
-0.01
-0.03
2012
2013
2014
2015
2016
2017
2018
2019
Time

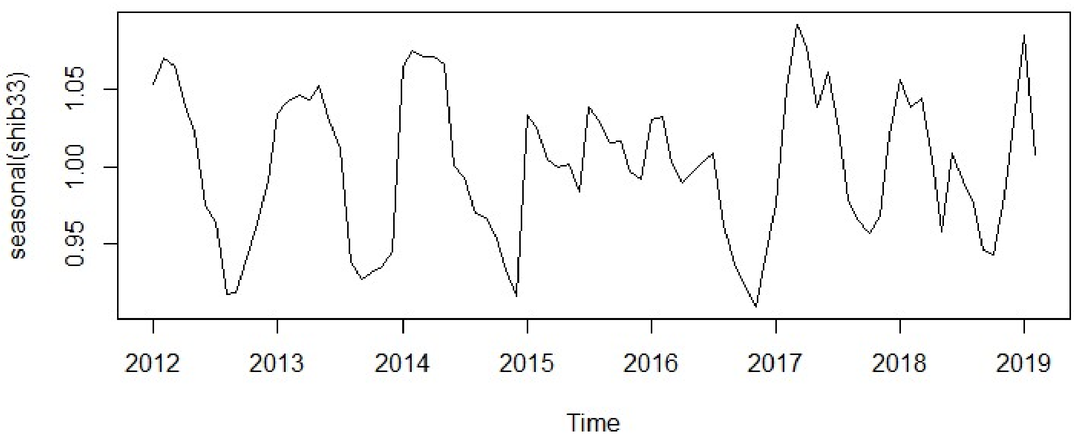
SHIBOR 1-Month, seasonal component



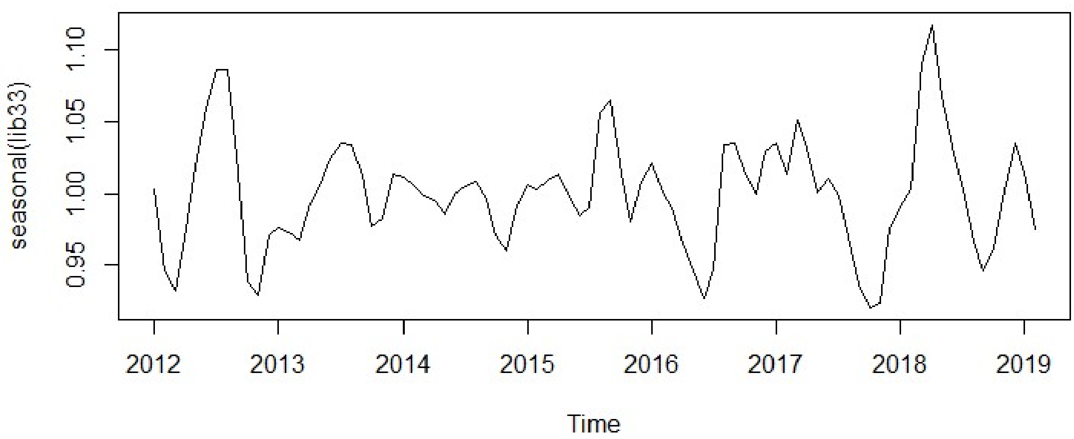
Libor 1-Month, seasonal component



SHIBOR 3-Month, seasonal component

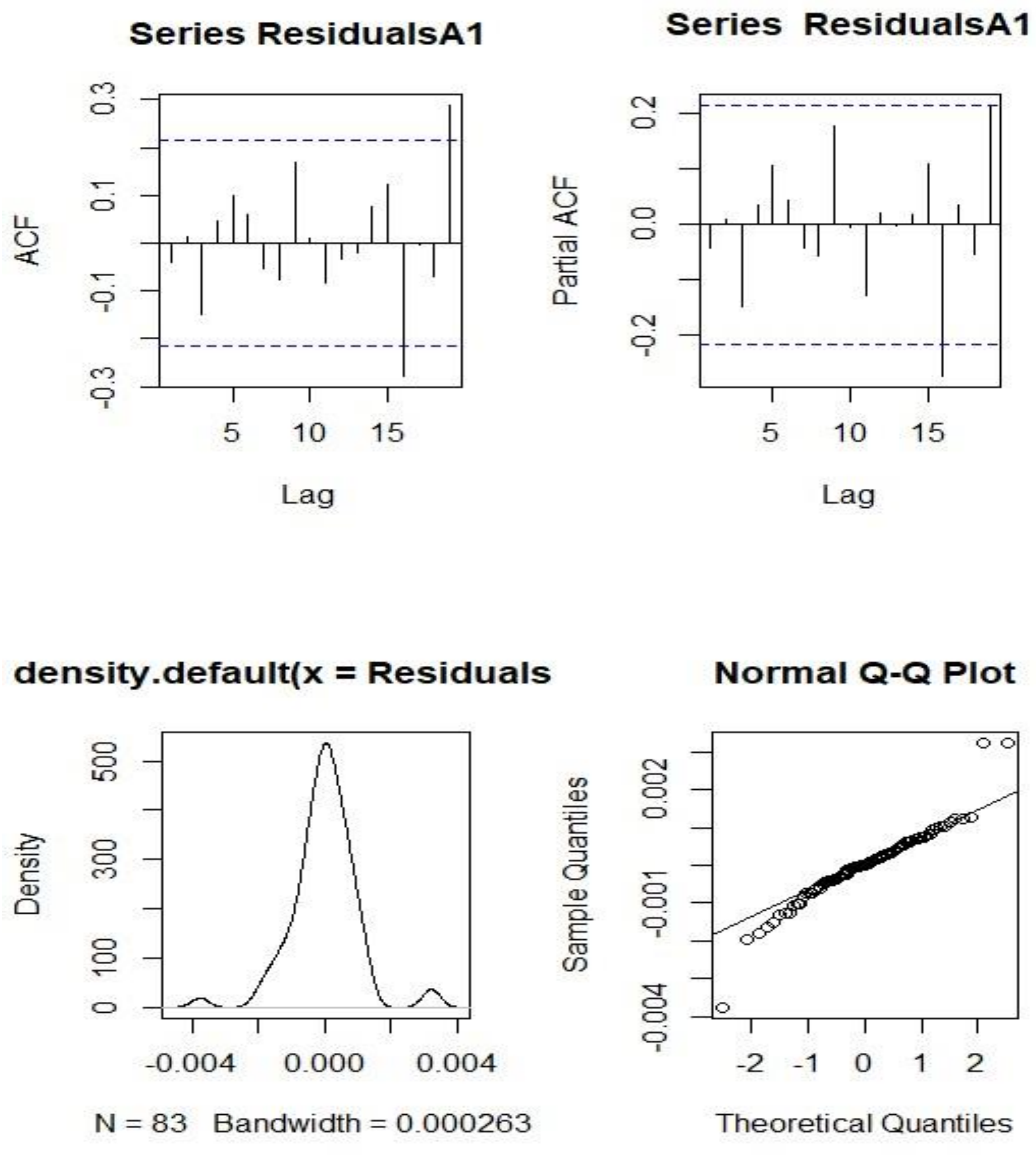


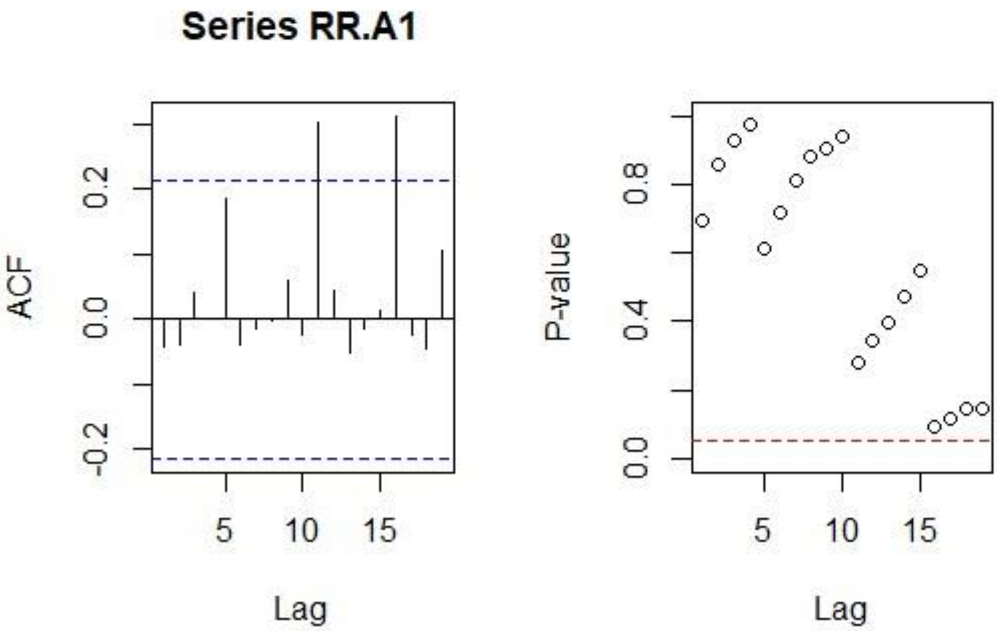
Libor 3-Month, seasonal component



A.2. Model Estimations Diagnostics

Model A.1. Diagnostics Results. In order: Autocorrelation Function of Residuals and Partial Autocorrelation Function of Residuals. Estimated pdf of Residuals and QQ-Plot with QQ-Line of residuals. On next page Autocorrelation of Squared Residuals as well as McLeod-Li test results (maximum lag= 20).

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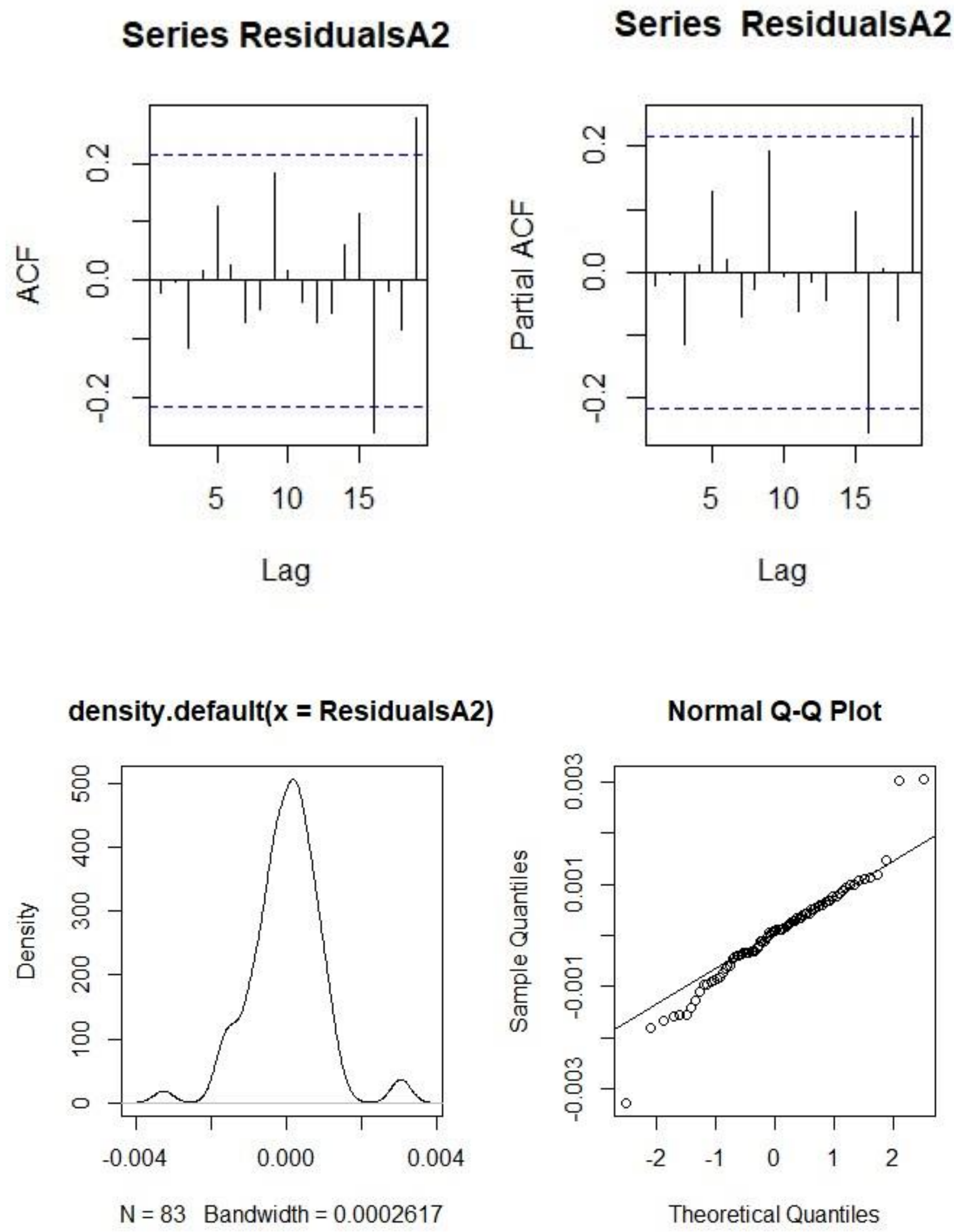
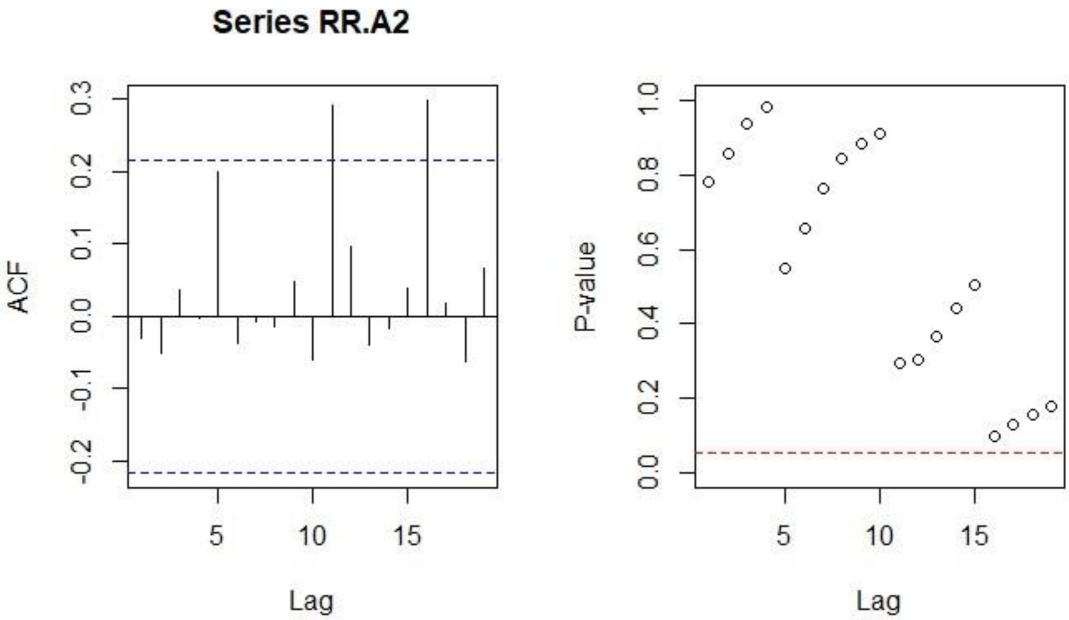
0.2
0.0
-0.2
5
10
15
Lag
P-value
0.8
0.4
0.0
5
10
15
Lag

Model A.2. Diagnostics Results. In order: Autocorrelation Function of Residuals and Partial Autocorrelation Function of Residuals. Estimated pdf of Residuals and QQ-Plot with QQ-Line of residuals. On next page Autocorrelation of Squared Residuals as well as McLeod-Li test results (maximum lag= 20).

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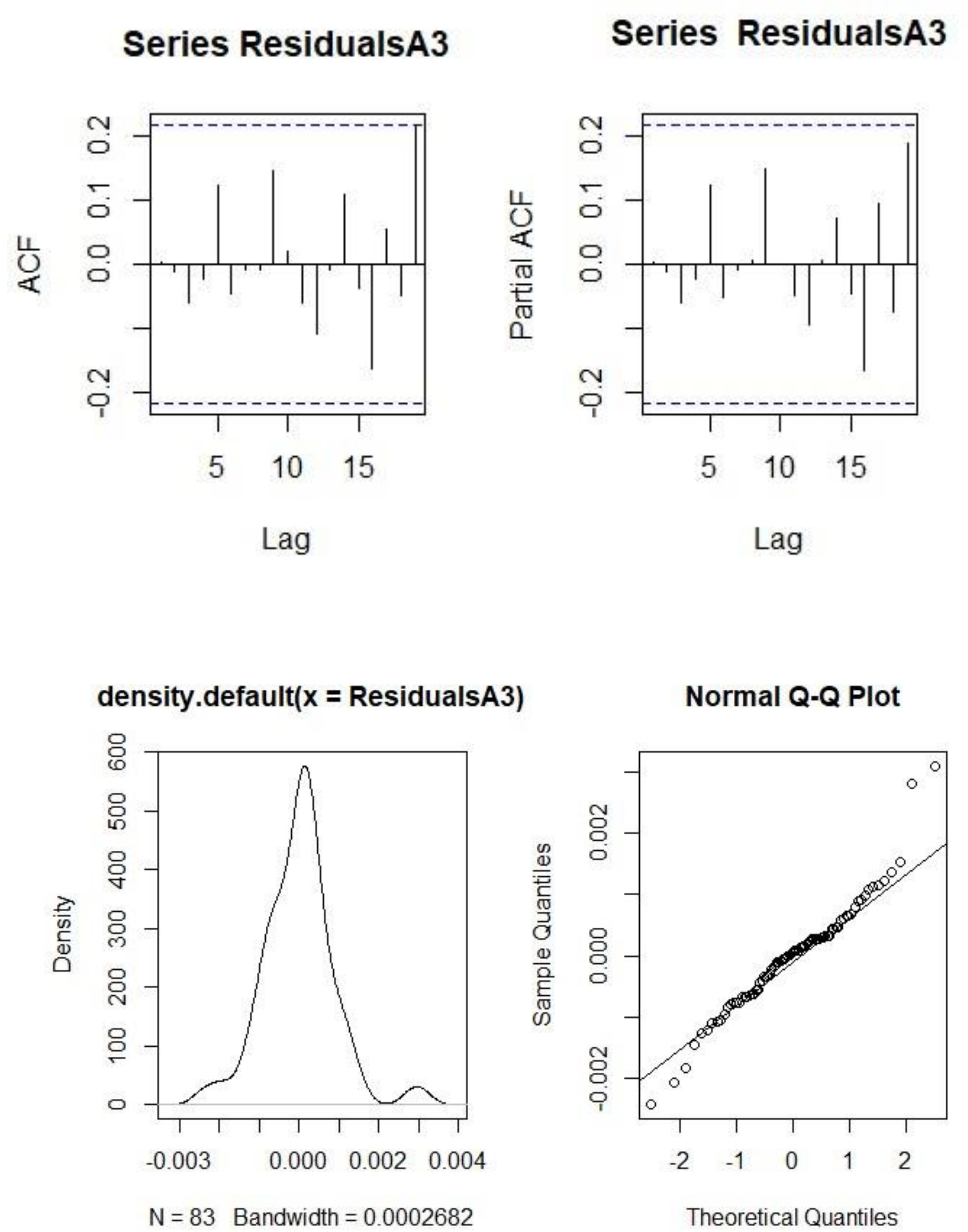
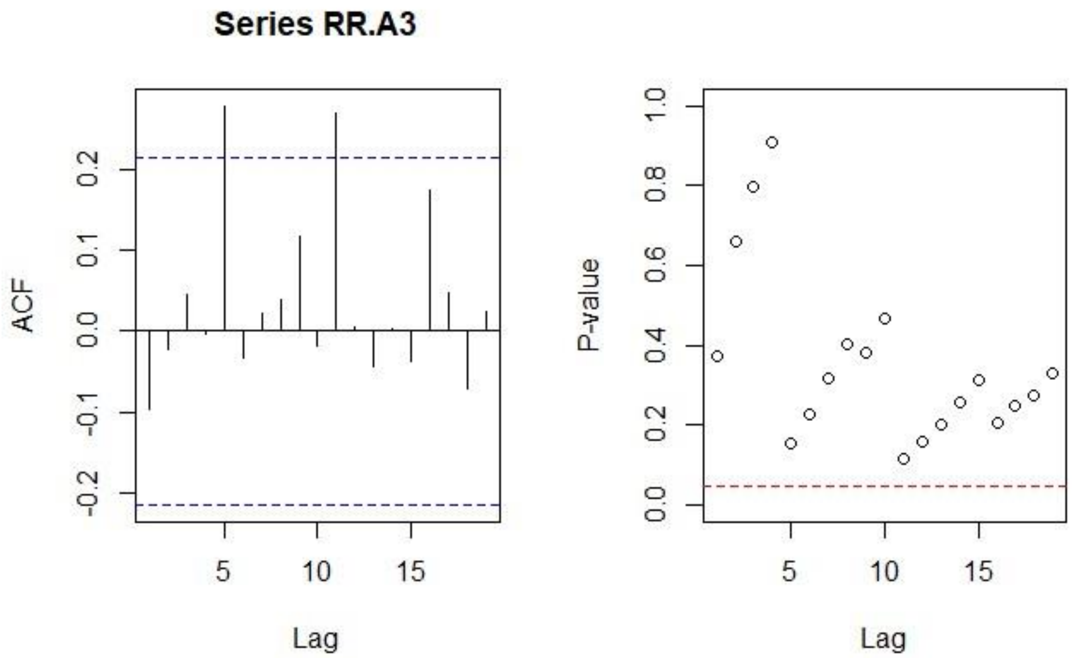
ACF
Lag
P-value
Lag

Model A.3. Diagnostics Results. In order: Autocorrelation Function of Residuals and Partial Autocorrelation Function of Residuals. Estimated pdf of Residuals and QQ-Plot with QQ-Line of residuals. On next page Autocorrelation of Squared Residuals as well as McLeod-Li test results (maximum lag= 20).





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5
10
15
Lag
P-value
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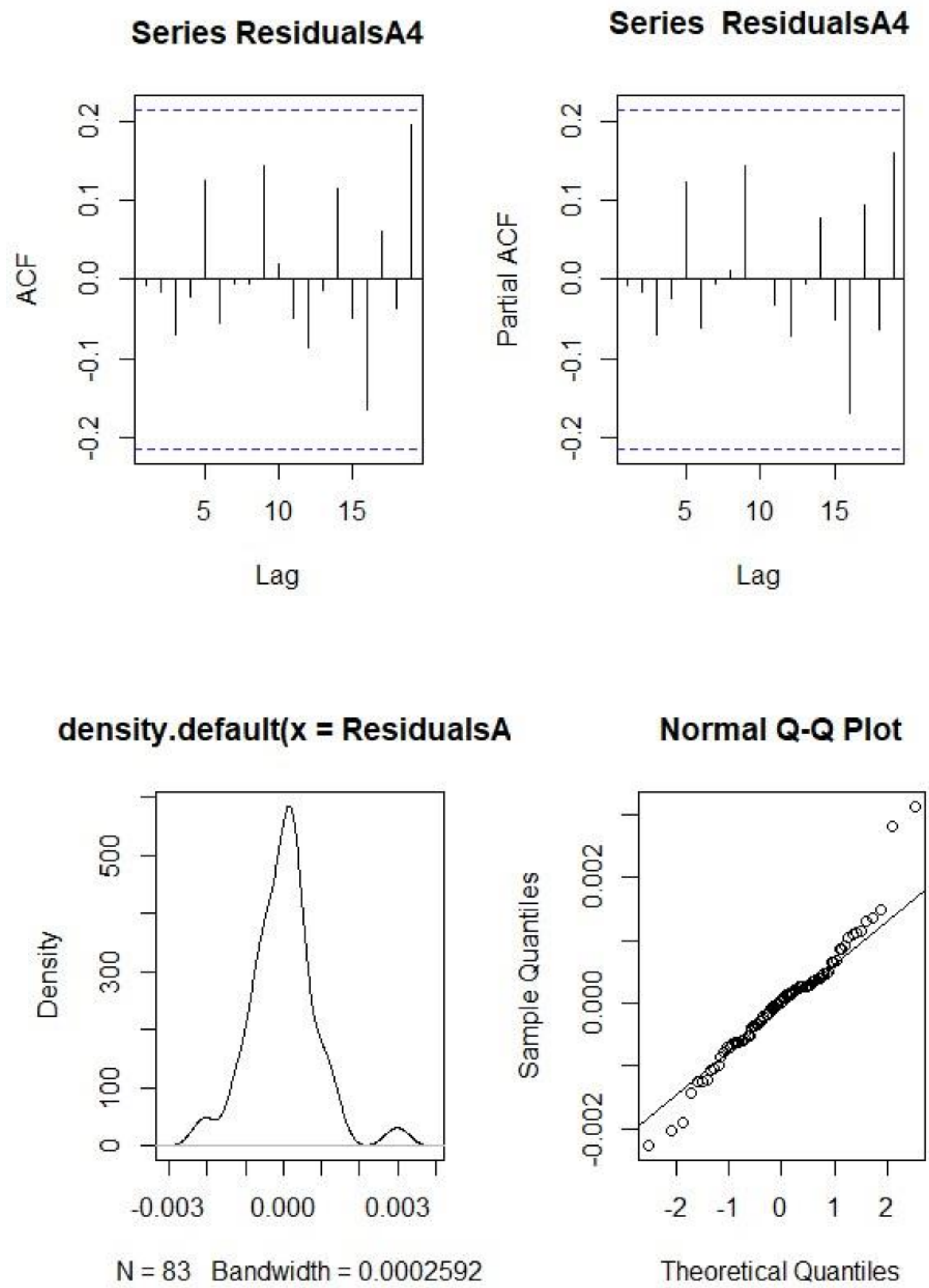
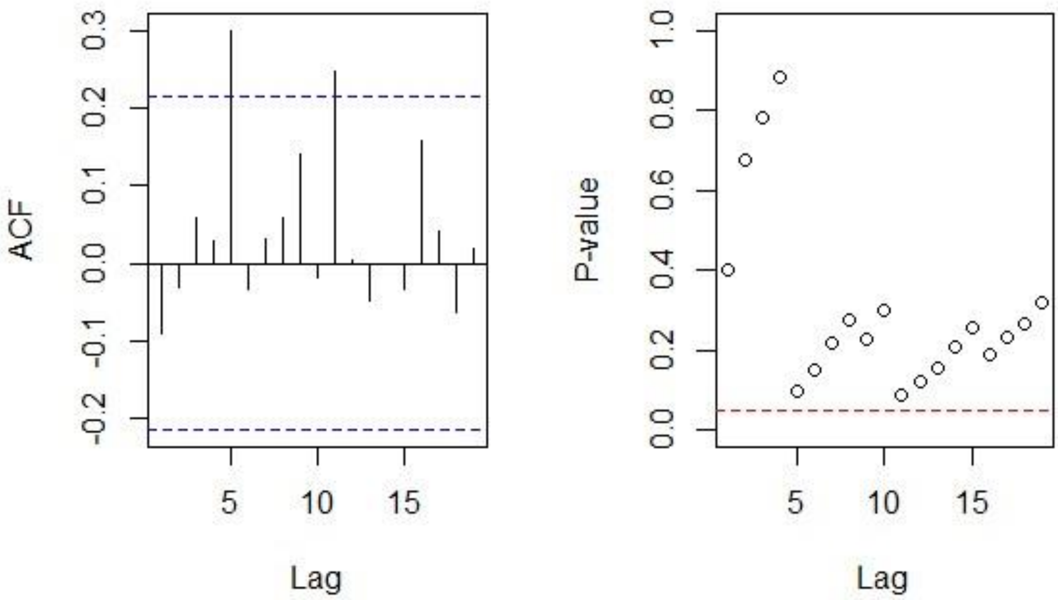
0.8
0.6
0.4
0.2
0.0
5
10
15
Lag

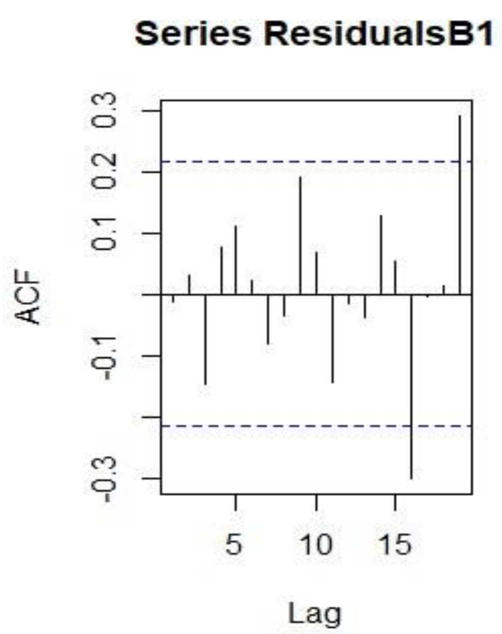
Model A.4. Diagnostics Results. In order: Autocorrelation Function of Residuals and Partial Autocorrelation Function of Residuals. Estimated pdf of Residuals and QQ-Plot with QQ-Line of residuals. On next page Autocorrelation of Squared Residuals as well as McLeod-Li test results (maximum lag= 20).

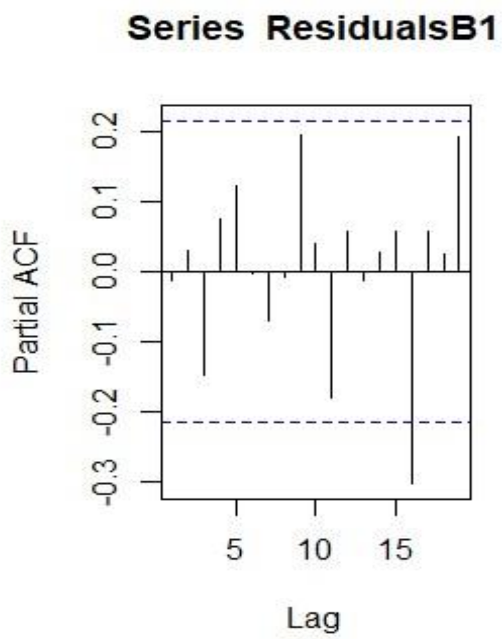


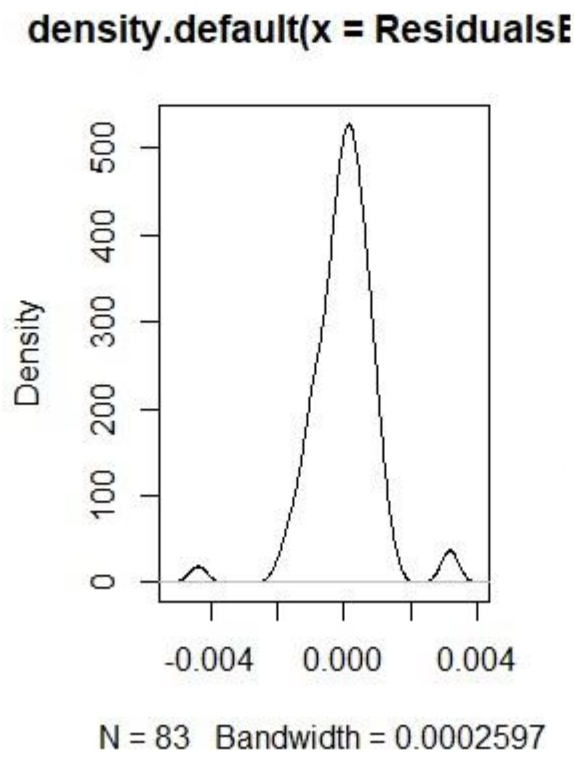
Series RR.A4

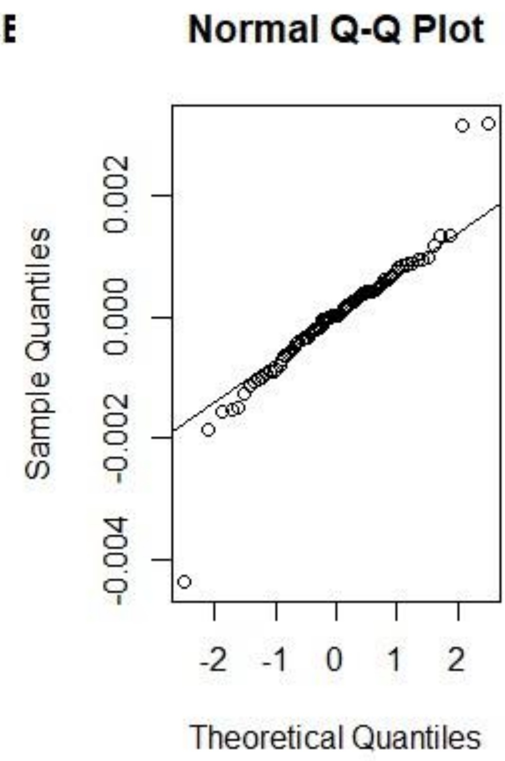


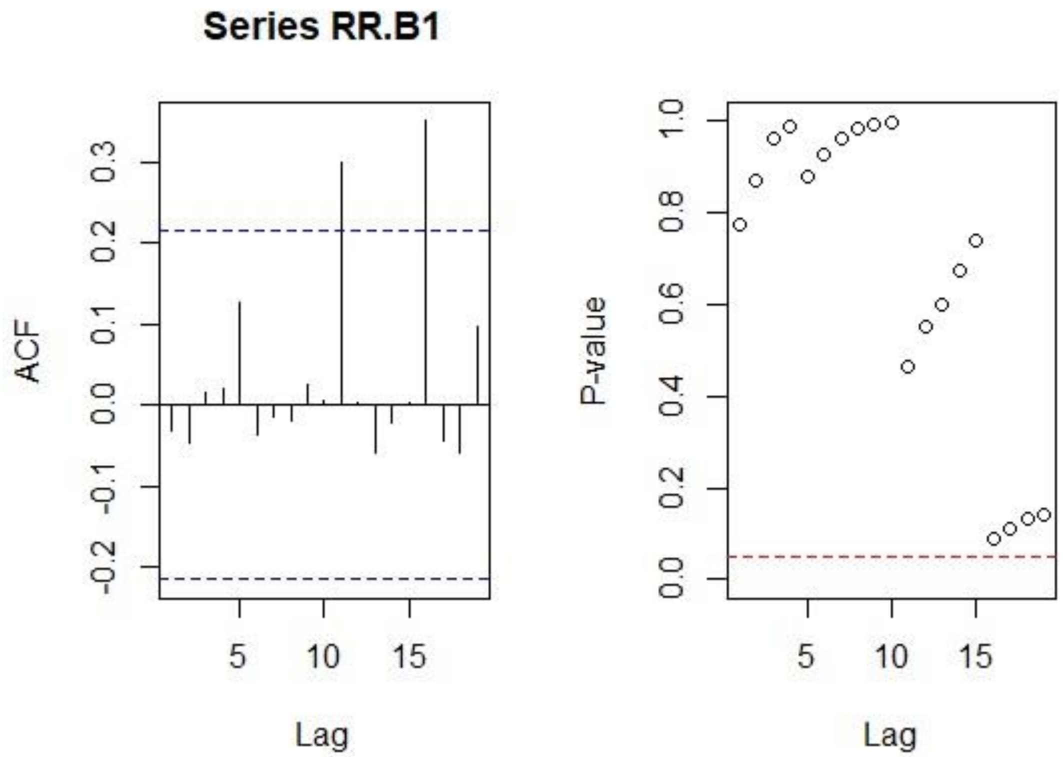
Model B.1. Diagnostics Results. In order: Autocorrelation Function of Residuals and Partial Autocorrelation Function of Residuals. Estimated pdf of Residuals and QQ-Plot with QQ-Line of residuals. On next page Autocorrelation of Squared Residuals as well as McLeod-Li test results (maximum lag= 20).











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10
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Lag
P-value
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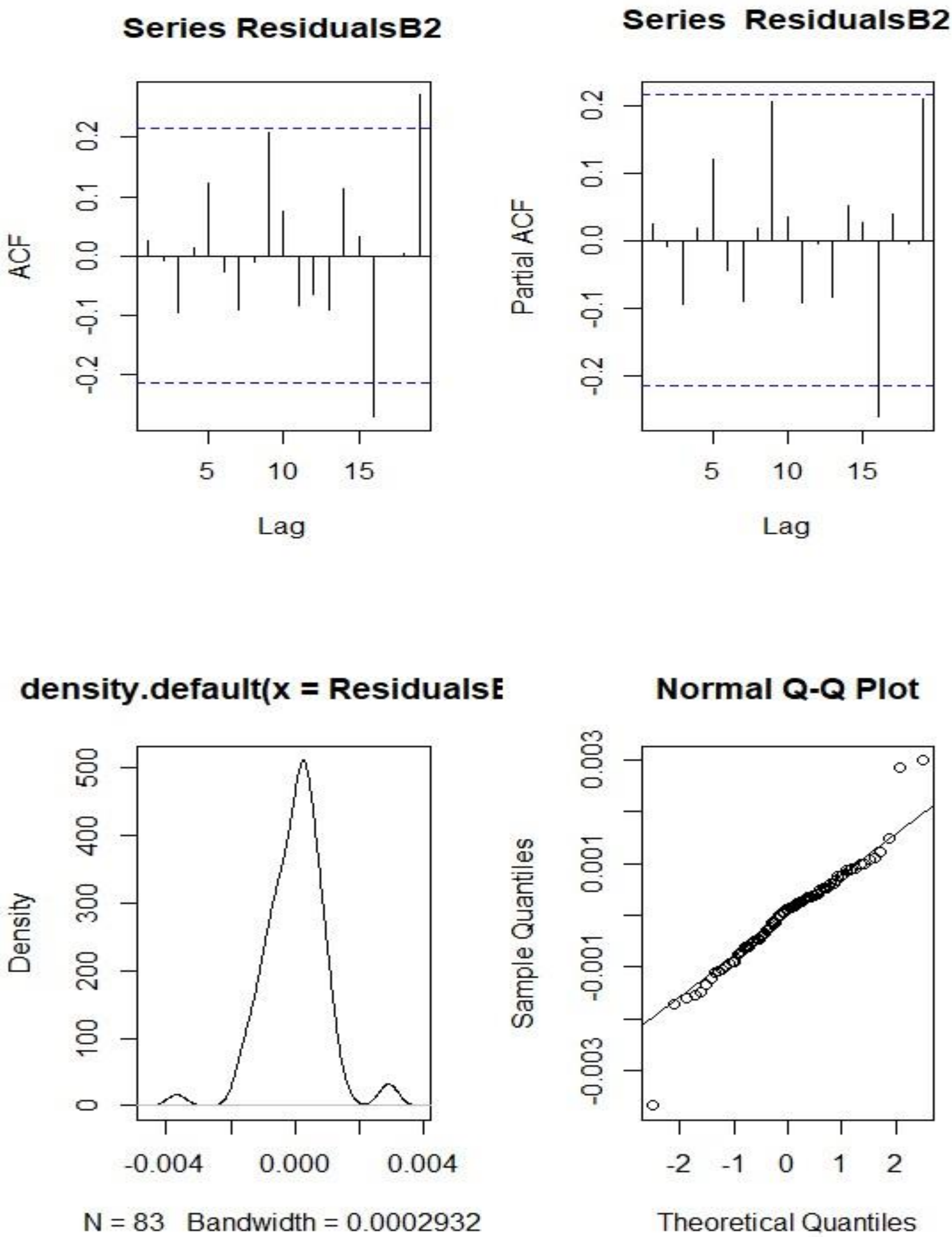
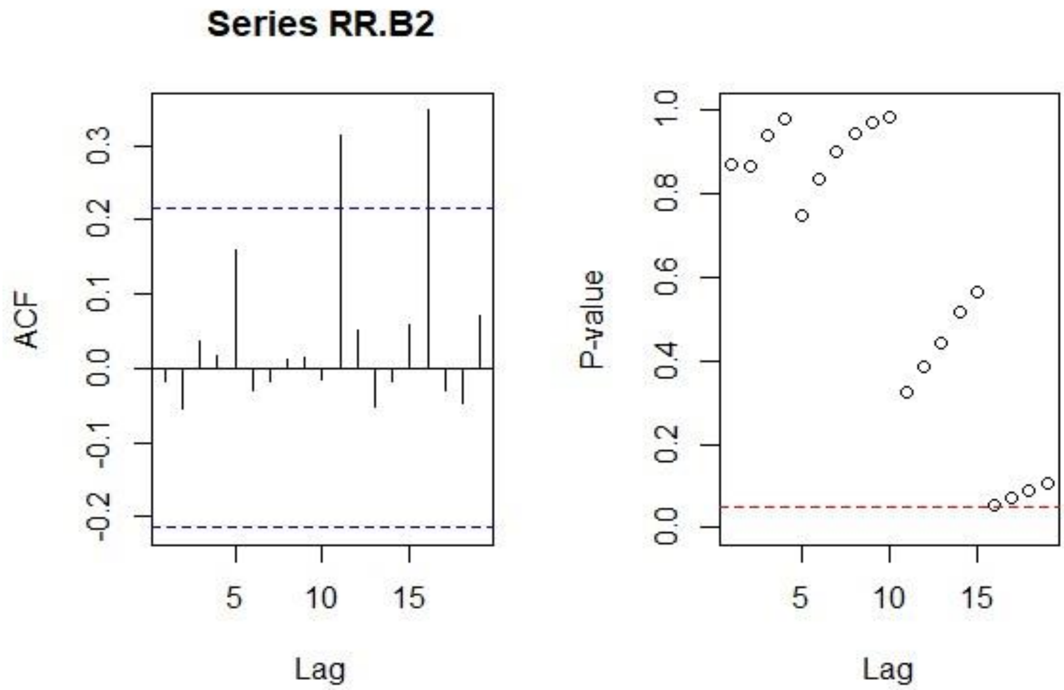
0.8
0.6
0.4
0.2
0.0
5
10
15
Lag

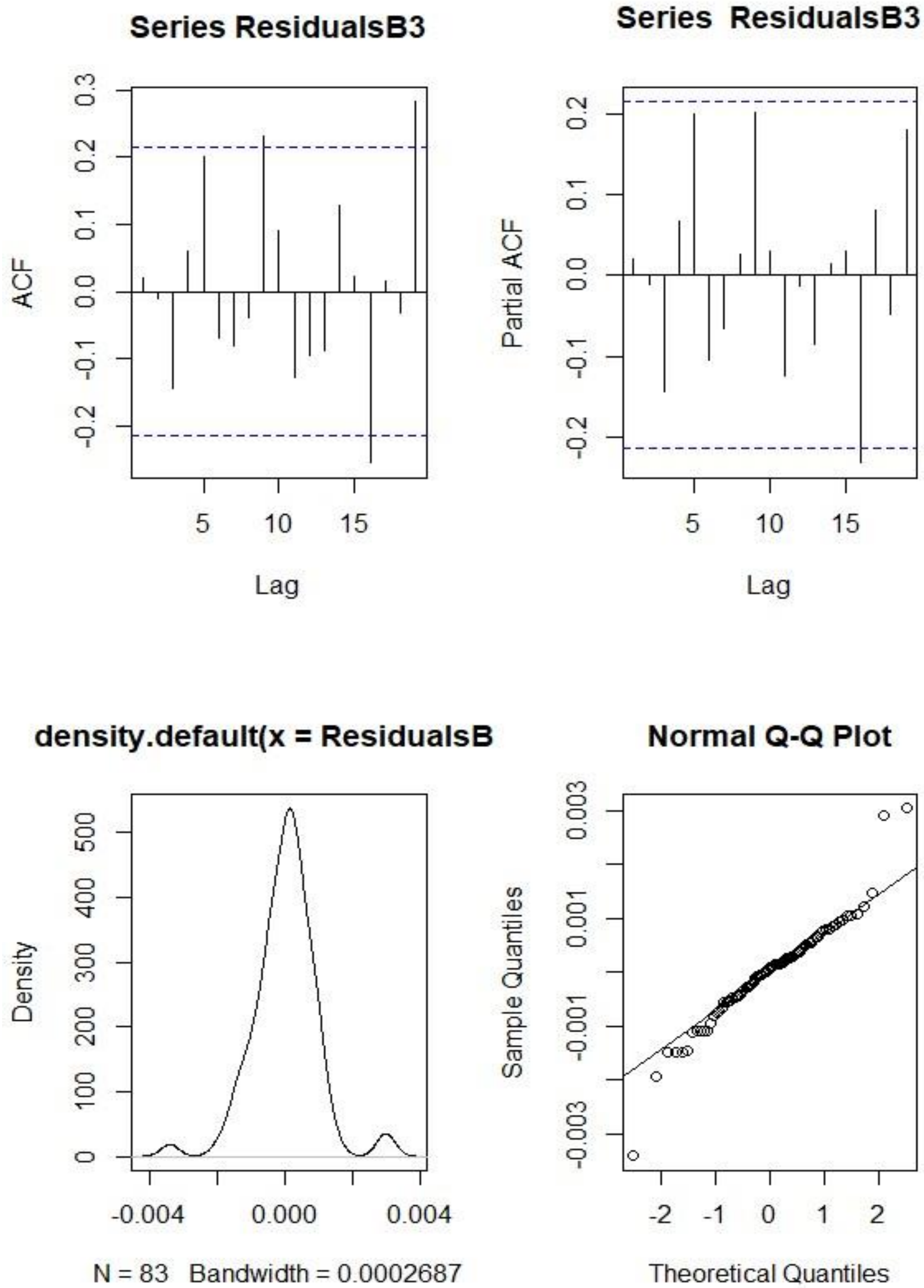
Model B.2. Diagnostics Results. In order: Autocorrelation Function of Residuals and Partial Autocorrelation Function of Residuals. Estimated pdf of Residuals and QQ-Plot with QQ-Line of residuals. On next page Autocorrelation of Squared Residuals as well as McLeod-Li test results (maximum lag= 20).

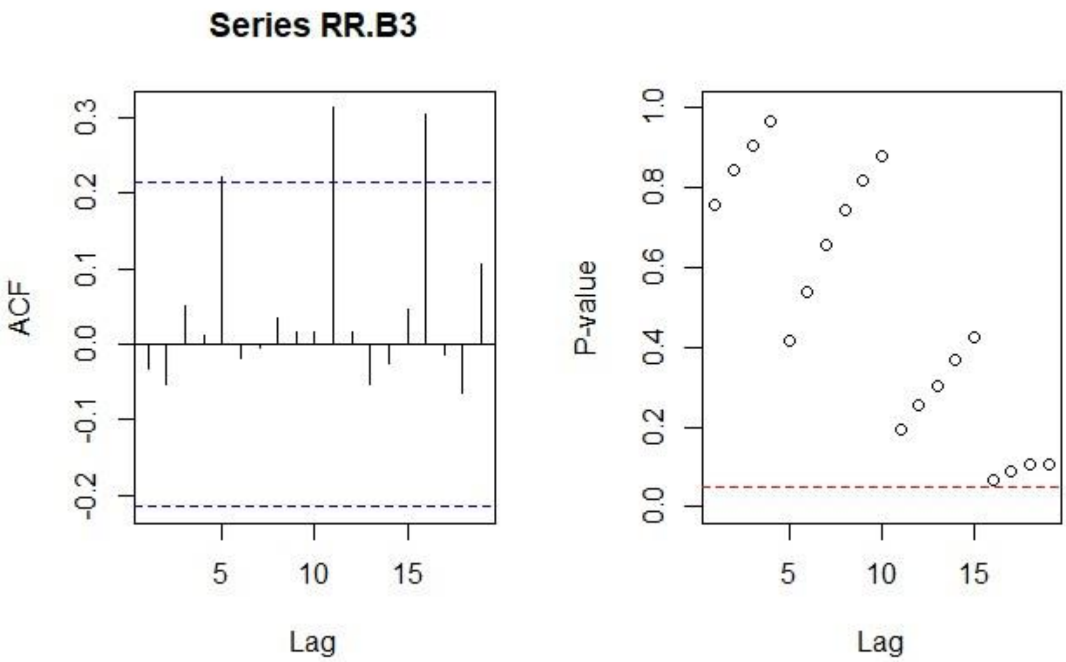




Series RR.B2
ACF
Lag
P-value
Lag

Model B.3. Diagnostics Results. In order: Autocorrelation Function of Residuals and Partial Autocorrelation Function of Residuals. Estimated pdf of Residuals and QQ-Plot with QQ-Line of residuals. On next page Autocorrelation of Squared Residuals as well as McLeod-Li test results (maximum lag= 20).





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10
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Lag
P-value
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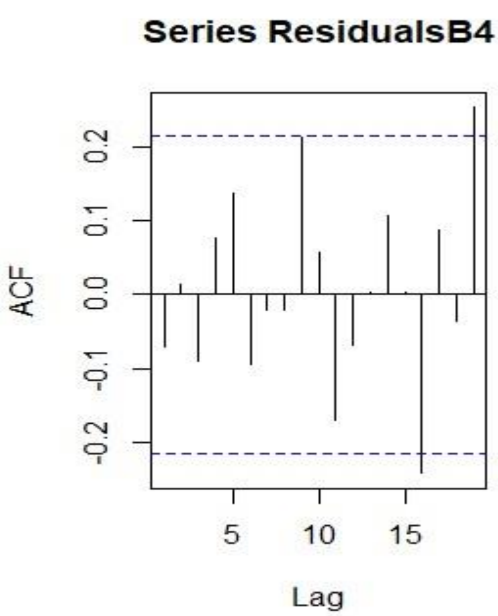
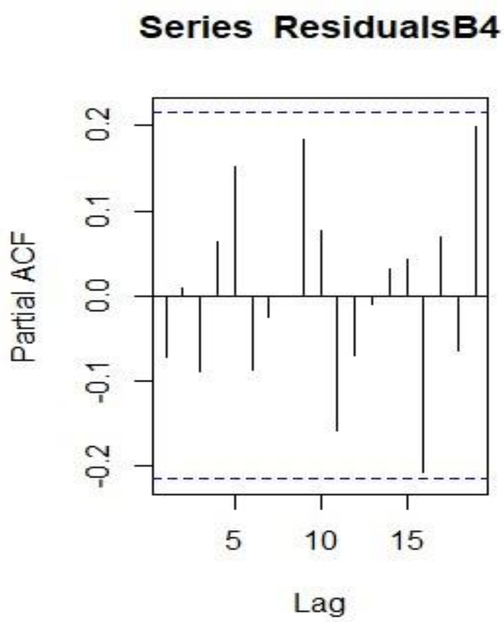
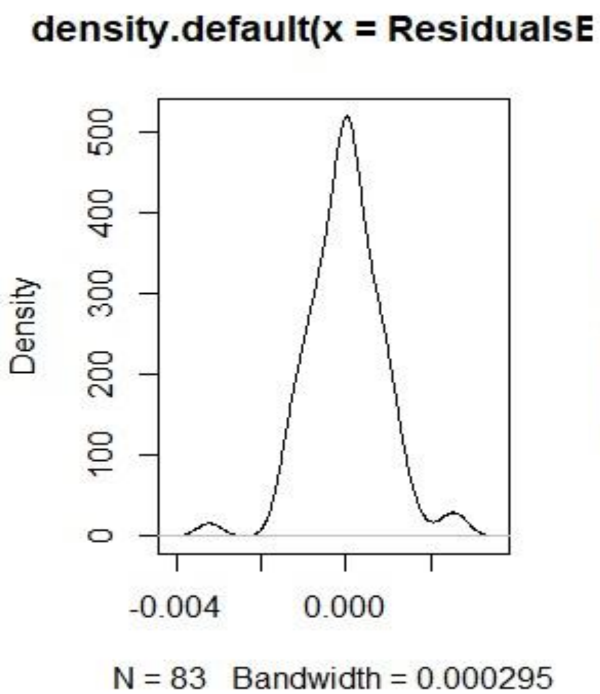
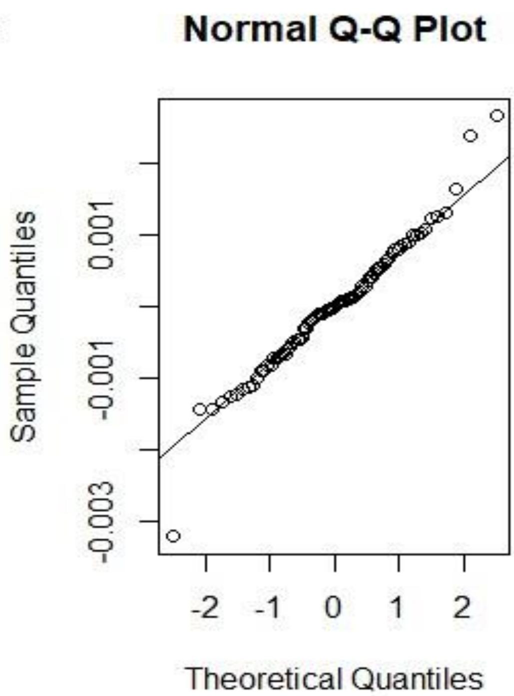
0.0
5
10
15
Lag

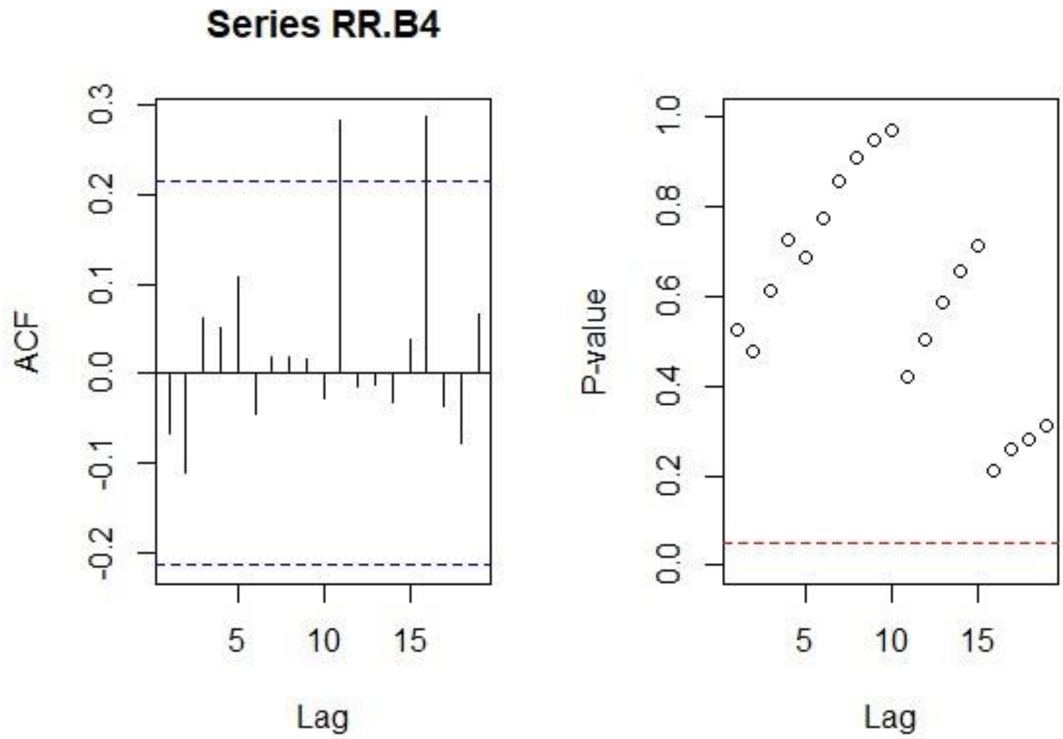
Model B.4. Diagnostics Results. In order: Autocorrelation Function of Residuals and Partial Autocorrelation Function of Residuals. Estimated pdf of Residuals and QQ-Plot with QQ-Line of residuals. On next page Autocorrelation of Squared Residuals as well as McLeod-Li test results (maximum lag= 20).











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-0.2
5
10
15
Lag
P-value
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0.6
0.4
0.2
0.0
5
10
15
Lag

A.3. Diagnostics on Regressors Matrix:

Granger Causality Tests Results

Granger Causality Test, full sample February 2012-February 2019				
Regressor	Lag_Order	Test_Statistic	P_Value	Critical_Lag
pVIX	1	263206189	0.10861174	no evidence
pVIX	2	221170643	0.11633660	no evidence
pVIX	3	240633158	0.07390983	3
pVIX	4	190649017	0.11861694	no evidence
pVIX	5	151396941	0.19681436	no evidence
pVIX	6	126214339	0.28694545	no evidence
pVIX	7	112007857	0.36196155	no evidence
pVIX	8	0.92629862	0.50162684	no evidence
pDEX	1	0.01301986	0.90943722	no evidence
pDEX	2	0.11295715	0.89333477	no evidence
pDEX	3	0.09969737	0.95993900	no evidence
pDEX	4	0.15966901	0.95797813	no evidence
pDEX	5	0.17047714	0.97267514	no evidence
pDEX	6	0.51157997	0.79747899	no evidence
pDEX	7	0.47621703	0.84826307	no evidence
pDEX	8	0.57194935	0.79672675	no evidence
dEQ	1	139226750	0.24147632	no evidence
dEQ	2	114446753	0.32368107	no evidence
dEQ	3	114993231	0.33462628	no evidence
dEQ	4	0.63057041	0.64227288	no evidence
dEQ	5	0.90348302	0.48397121	no evidence
dEQ	6	0.48831308	0.81479537	no evidence
dEQ	7	0.35837189	0.92281171	no evidence
dEQ	8	0.30199510	0.96242399	no evidence
dSHs	1	0.65080136	0.42218871	no evidence
dSHs	2	0.36973515	0.69212166	no evidence
dSHs	3	0.63983496	0.59174233	no evidence
dSHs	4	0.82448303	0.51386774	no evidence
dSHs	5	0.70240661	0.62352081	no evidence
dSHs	6	0.60299100	0.72693927	no evidence
dSHs	7	0.62942824	0.72974494	no evidence
dSHs	8	0.67447972	0.71189601	no evidence
dMEDs	1	175367827	0.18913961	no evidence
dMEDs	2	279210695	0.06742846	2
dMEDs	3	161072053	0.19399769	no evidence
dMEDs	4	134166086	0.26287776	no evidence
dMEDs	5	116941306	0.33310722	no evidence
dMEDs	6	0.62438644	0.71010327	no evidence
dMEDs	7	0.54219144	0.79921891	no evidence
dMEDs	8	0.45147037	0.88482801	no evidence
dsSL	1	0.45364924	0.50252445	no evidence
dsSL	2	435696936	0.01607762	2
dsSL	3	302265403	0.03484885	3
dsSL	4	216880917	0.08108776	4
dsSL	5	174333242	0.13632066	no evidence
dsSL	6	126387087	0.28613315	no evidence
dsSL	7	165600215	0.13636297	no evidence
dsSL	8	191601828	0.07400801	8

Table A.1.; Granger Causality Tests Results of the regressors matrix with cause differential in Central Banks' Total Assets Growth Rates

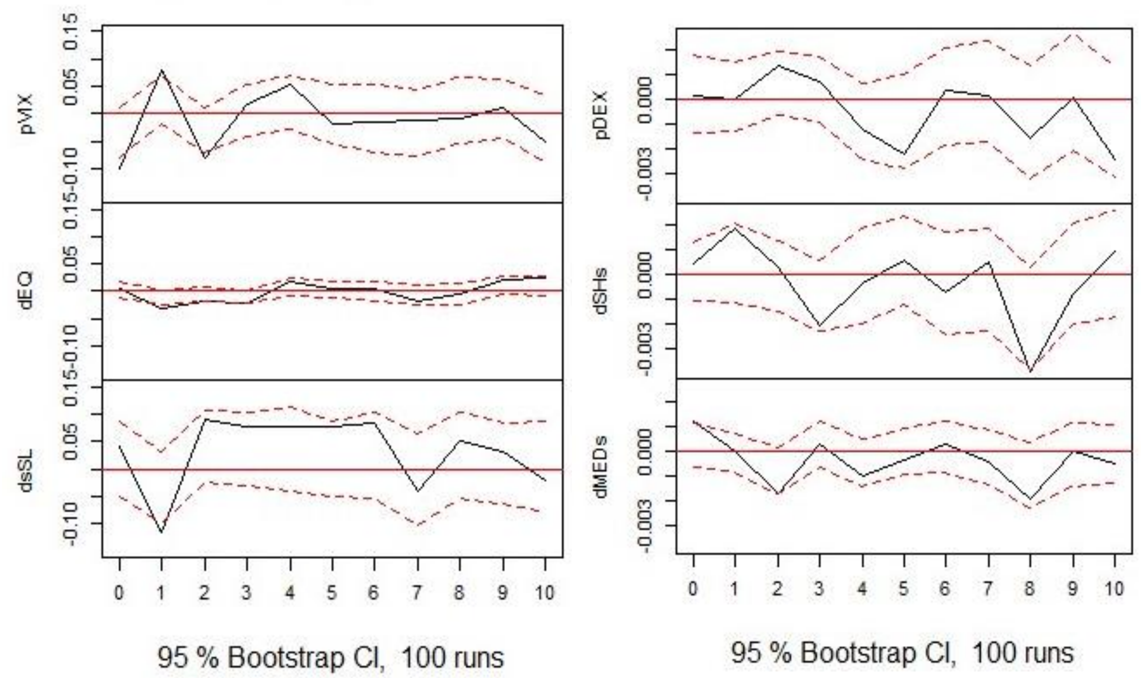
Granger Causality Test, full-sample February 2012-February 2019				
Regressor	Lag_Order	Test_Statistic	P_Value	Causality
pVIX	1	0,72771081	0,396142	no evidence
pVIX	2	0,55568928	0,575931	no evidence
pVIX	3	0,56090978	0,642474	no evidence
pVIX	4	0,95150516	0,439492	no evidence
pVIX	5	0,79123037	0,559619	no evidence
pVIX	6	1,07843051	0,384464	no evidence
pVIX	7	0,80785896	0,583992	no evidence
pVIX	8	0,74006231	0,655895	no evidence
pDEX	1	0,78065242	0,379557	no evidence
pDEX	2	0,6424323	0,528772	no evidence
pDEX	3	0,39158916	0,759396	no evidence
pDEX	4	1,00756524	0,409353	no evidence
pDEX	5	0,88440303	0,496368	no evidence
pDEX	6	0,7097928	0,642862	no evidence
pDEX	7	0,64114389	0,720183	no evidence
pDEX	8	0,5199352	0,83685	no evidence
dEQ	1	1,56453632	0,214603	no evidence
dEQ	2	0,90428236	0,409034	no evidence
dEQ	3	1,07458769	0,365095	no evidence
dEQ	4	1,61094961	0,180822	no evidence
dEQ	5	1,05838384	0,391021	no evidence
dEQ	6	0,9233579	0,48407	no evidence
dEQ	7	0,95081288	0,47463	no evidence
dEQ	8	0,81788405	0,589853	no evidence
dSHs	1	0,07561454	0,784031	no evidence
dSHs	2	0,09836116	0,906434	no evidence
dSHs	3	0,35299	0,787094	no evidence
dSHs	4	0,3488748	0,84399	no evidence
dSHs	5	0,29771197	0,912559	no evidence
dSHs	6	0,30154657	0,933948	no evidence
dSHs	7	0,38053063	0,910395	no evidence
dSHs	8	0,37657153	0,928989	no evidence
dMEDs	1	1,67155655	0,199726	no evidence
dMEDs	2	1,58205025	0,212077	no evidence
dMEDs	3	1,2032056	0,314497	no evidence
dMEDs	4	0,84576273	0,500829	no evidence
dMEDs	5	0,93027634	0,466903	no evidence
dMEDs	6	0,64669969	0,692505	no evidence
dMEDs	7	0,60992019	0,74558	no evidence
dMEDs	8	0,59904553	0,77489	no evidence
dsSL	1	0,56124131	0,455931	no evidence
dsSL	2	0,43548037	0,648517	no evidence
dsSL	3	0,48107172	0,696427	no evidence
dsSL	4	0,35746623	0,838028	no evidence
dsSL	5	0,29536922	0,913909	no evidence
dsSL	6	0,48715485	0,815648	no evidence
dsSL	7	0,84607882	0,553731	no evidence
dsSL	8	1,18266737	0,324595	no evidence

Table A.2.; Granger Causality Tests Results of the regressors matrix with cause differential in Monetary Policy Indicators Spreads (dMIS).

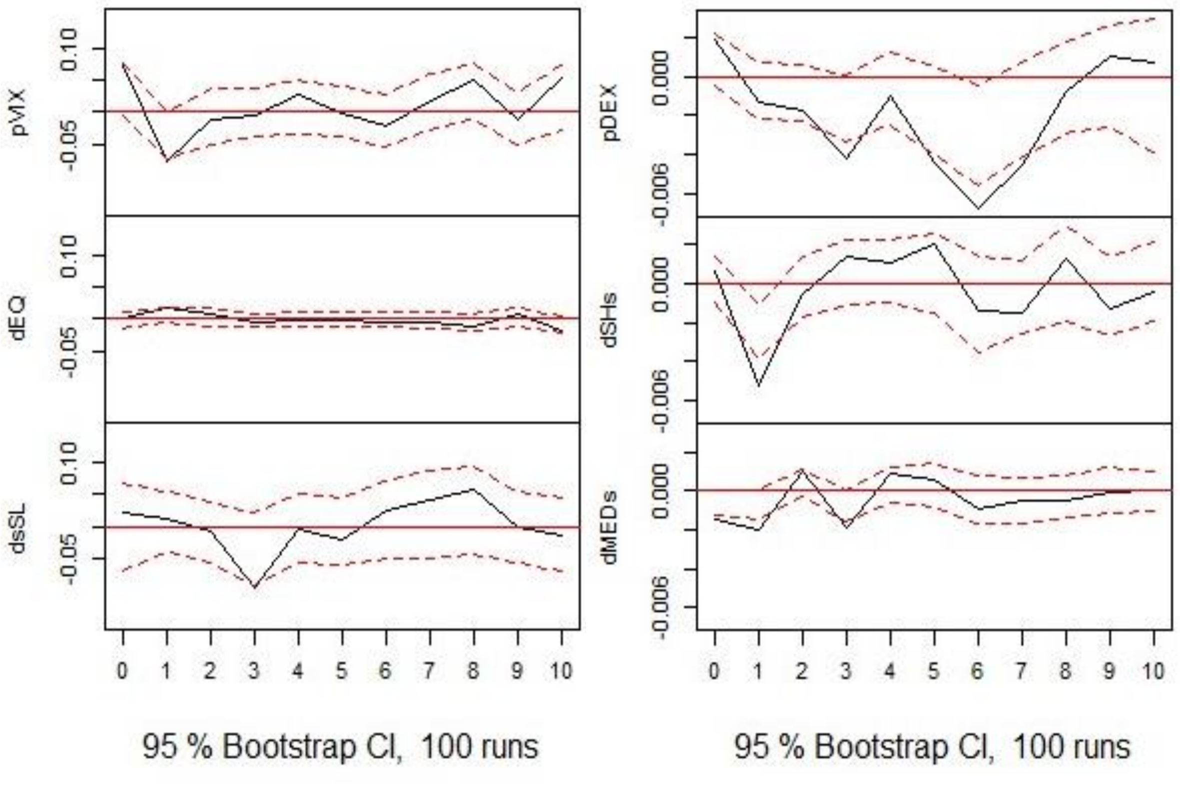
Granger Causality Test, sub-sample March 2014-February 2019				
Regressor	Lag_Order	Test_Statistic	P_Value	Causality
pVIX	1	0,886033	35%	no evidence
pVIX	2	0,957067	39%	no evidence
pVIX	3	0,6907344	56%	no evidence
pVIX	4	0,8983434	47%	no evidence
pVIX	5	0,8210058	54%	no evidence
pVIX	6	0,8850073	52%	no evidence
pVIX	7	0,7843231	60%	no evidence
pVIX	8	0,6776749	71%	no evidence
pVIX	9	0,801046	62%	no evidence
pVIX	10	0,5458923	84%	no evidence
pDEX	1	0,5470055	46%	no evidence
pDEX	2	0,8769842	42%	no evidence
pDEX	3	0,9912249	40%	no evidence
pDEX	4	1,5543688	20%	no evidence
pDEX	5	1,1902095	33%	no evidence
pDEX	6	0,8445712	54%	no evidence
pDEX	7	0,8571284	55%	no evidence
pDEX	8	0,6685014	72%	no evidence
pDEX	9	0,6333082	76%	no evidence
pDEX	10	0,5652301	83%	no evidence
dEQ	1	0,5407133	47%	no evidence
dEQ	2	0,9751559	38%	no evidence
dEQ	3	1,2305785	31%	no evidence
dEQ	4	1,5280499	21%	no evidence
dEQ	5	1,2100723	32%	no evidence
dEQ	6	0,9488308	47%	no evidence
dEQ	7	0,7819732	61%	no evidence
dEQ	8	0,6316861	75%	no evidence
dEQ	9	0,642111	75%	no evidence
dEQ	10	0,6253161	78%	no evidence
dSIRS	1	1,7709685	19%	no evidence
dSIRS	2	0,8358868	44%	no evidence
dSIRS	3	0,4963844	69%	no evidence
dSIRS	4	0,4286012	79%	no evidence
dSIRS	5	0,2388068	94%	no evidence
dSIRS	6	0,226483	97%	no evidence
dSIRS	7	0,1815745	99%	no evidence
dSIRS	8	0,2819381	97%	no evidence
dSIRS	9	0,2616865	98%	no evidence
dSIRS	10	0,290781	98%	no evidence
dsSL	1	1,2895901	26%	no evidence
dsSL	2	1,3328537	27%	no evidence
dsSL	3	0,8804938	46%	no evidence
dsSL	4	0,867537	49%	no evidence
dsSL	5	0,4503831	81%	no evidence
dsSL	6	0,3459927	91%	no evidence
dsSL	7	0,6612997	70%	no evidence
dsSL	8	0,7717887	63%	no evidence
dsSL	9	0,8375537	59%	no evidence
dsSL	10	0,7518634	67%	no evidence

Table A.3.; Granger Causality Tests Results of the regressors matrix with cause differential in Monetary Policy Indicators Spreads (dMIS).

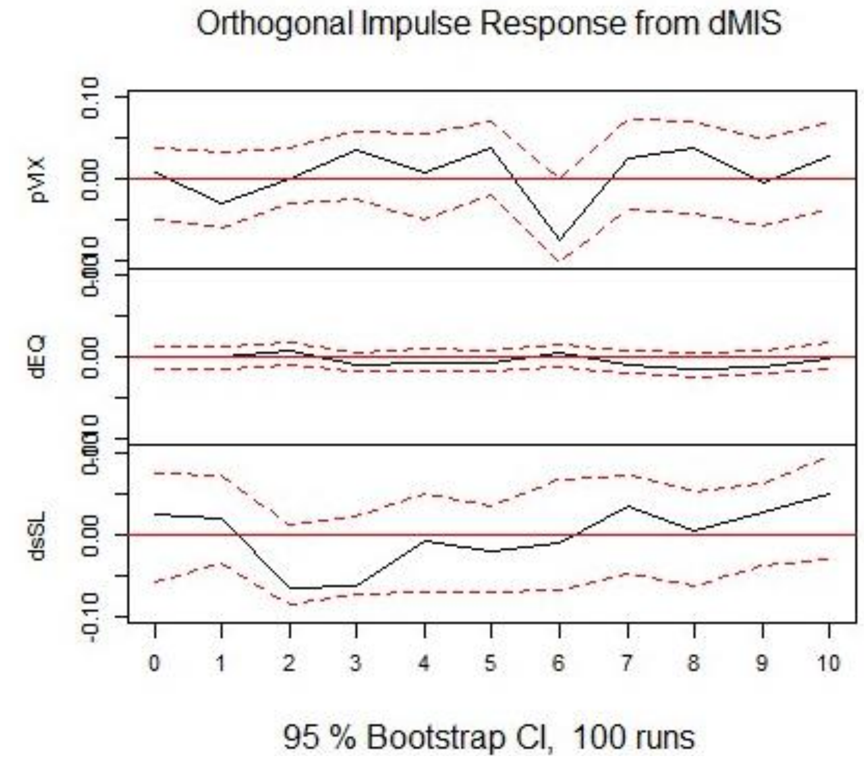
Impulse Response Function (IRF) Analysis:



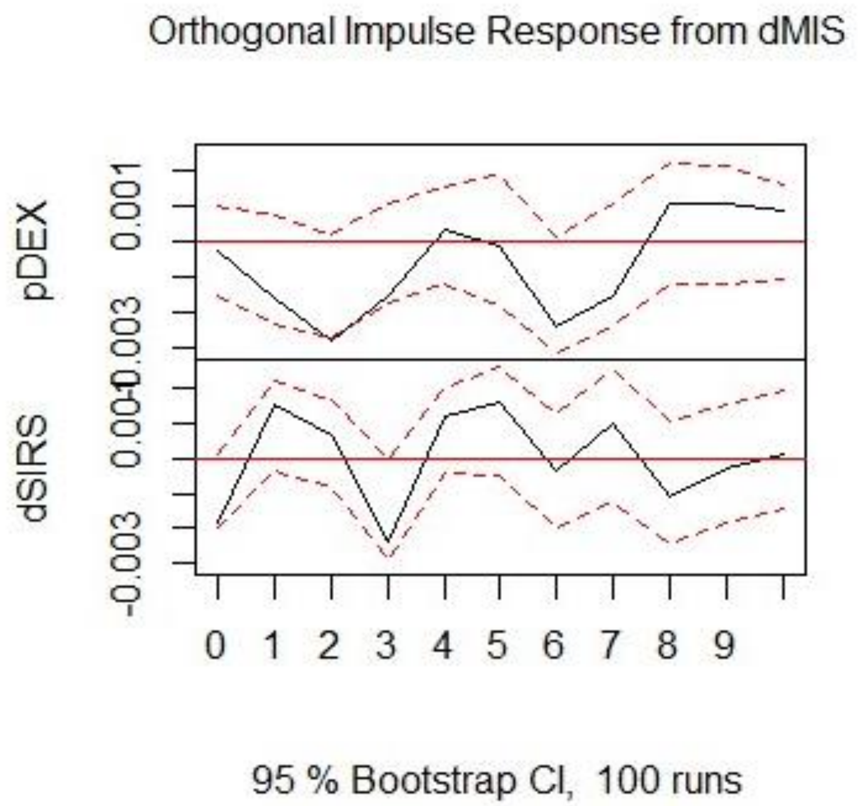
Responses of other regressors from orthogonal shocks in Central Banks' Total Assets growth rate differential (sTA), full sample.



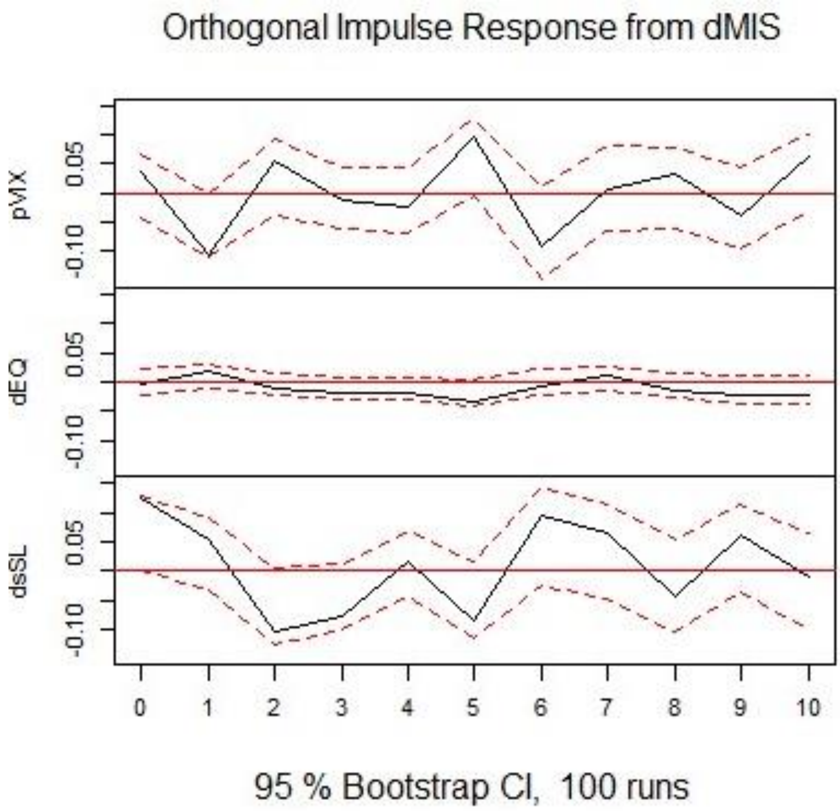
Responses of other regressors from orthogonal shocks in Monetary Policy Indicators spread (dMIS), full sample



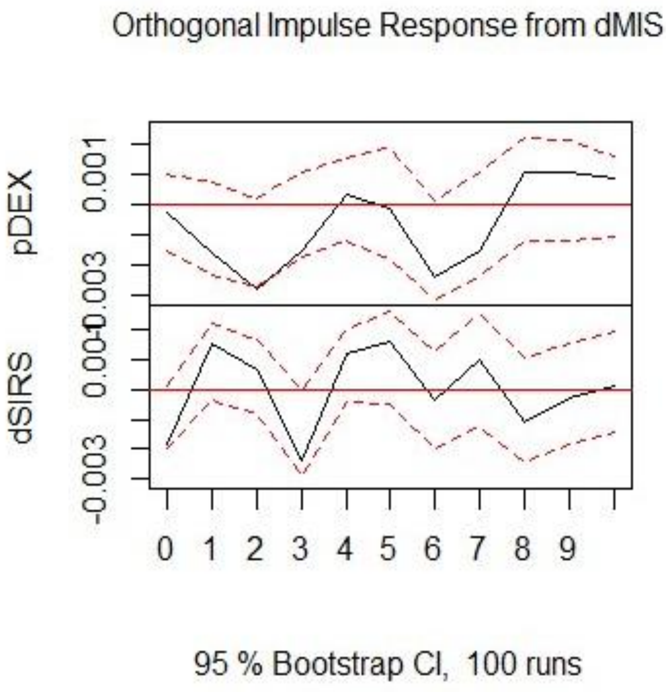
Responses of other regressors from orthogonal shocks in Monetary Policy Indicators spread (dMIS), regressors Matrix with dSIRS, full sample .



Responses of other regressors from orthogonal shocks in Monetary Policy Indicators spread (dMIS) regressors Matrix with dSIRS, full sample .

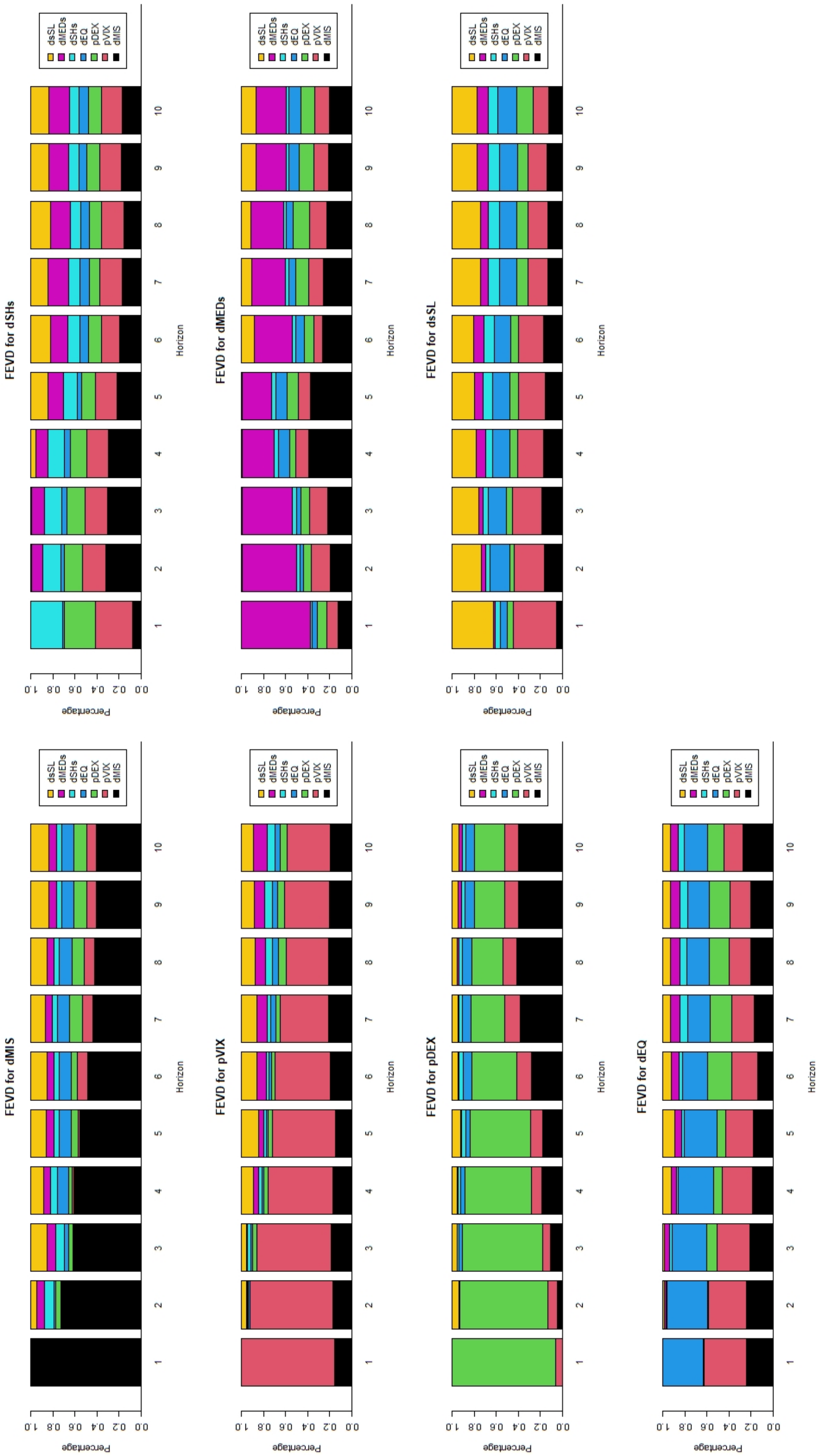


Responses of other regressors from orthogonal shocks in Monetary Policy Indicators spread (dMIS), regressor matrix with dSIRS, Sub-Sample March 2014-February 2019.

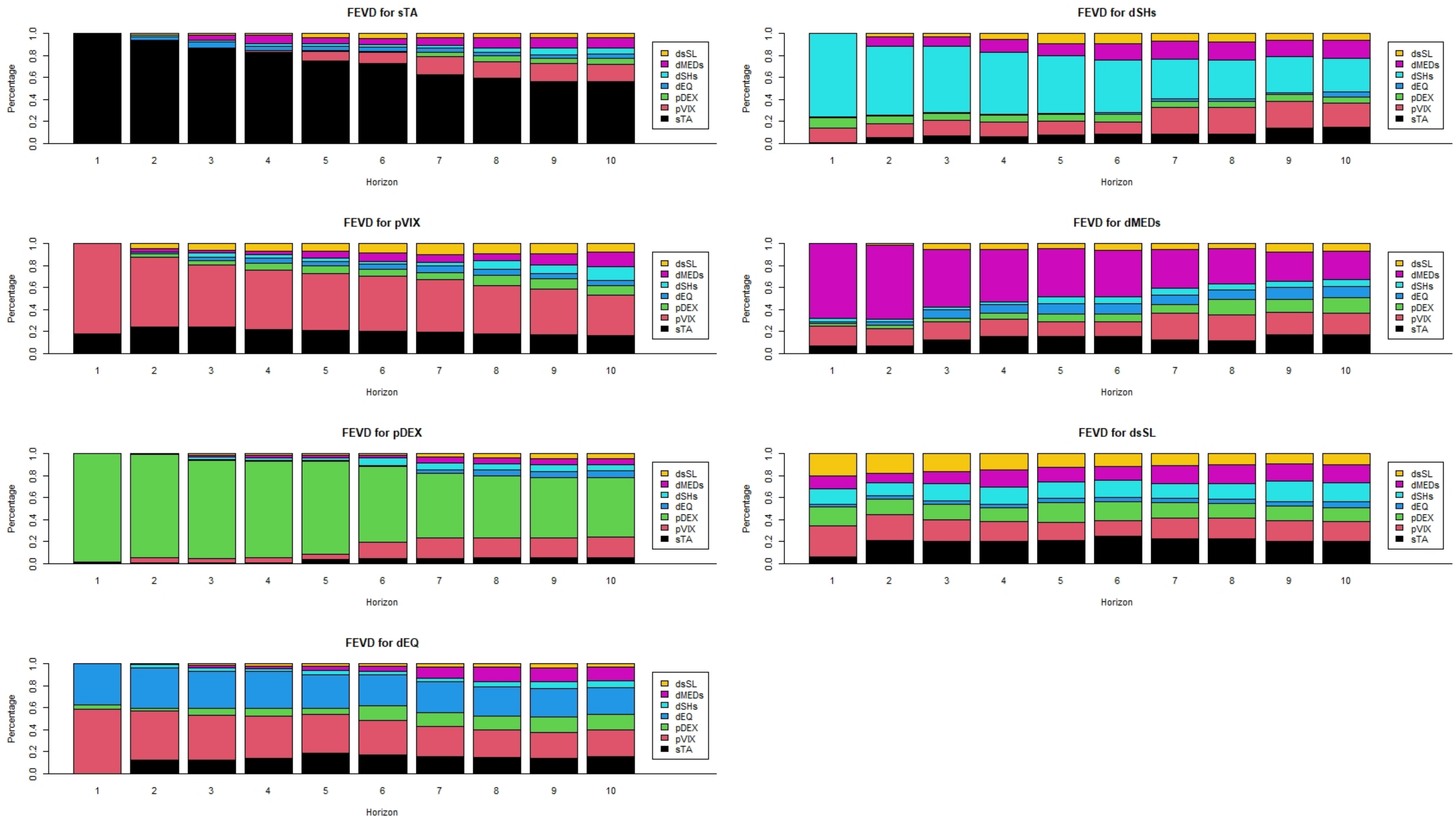


Responses of other regressors from orthogonal shocks in Monetary Policy Indicators spread (dMIS); regressor matrix with dSIRS Sub-Sample March 2014-February 2019

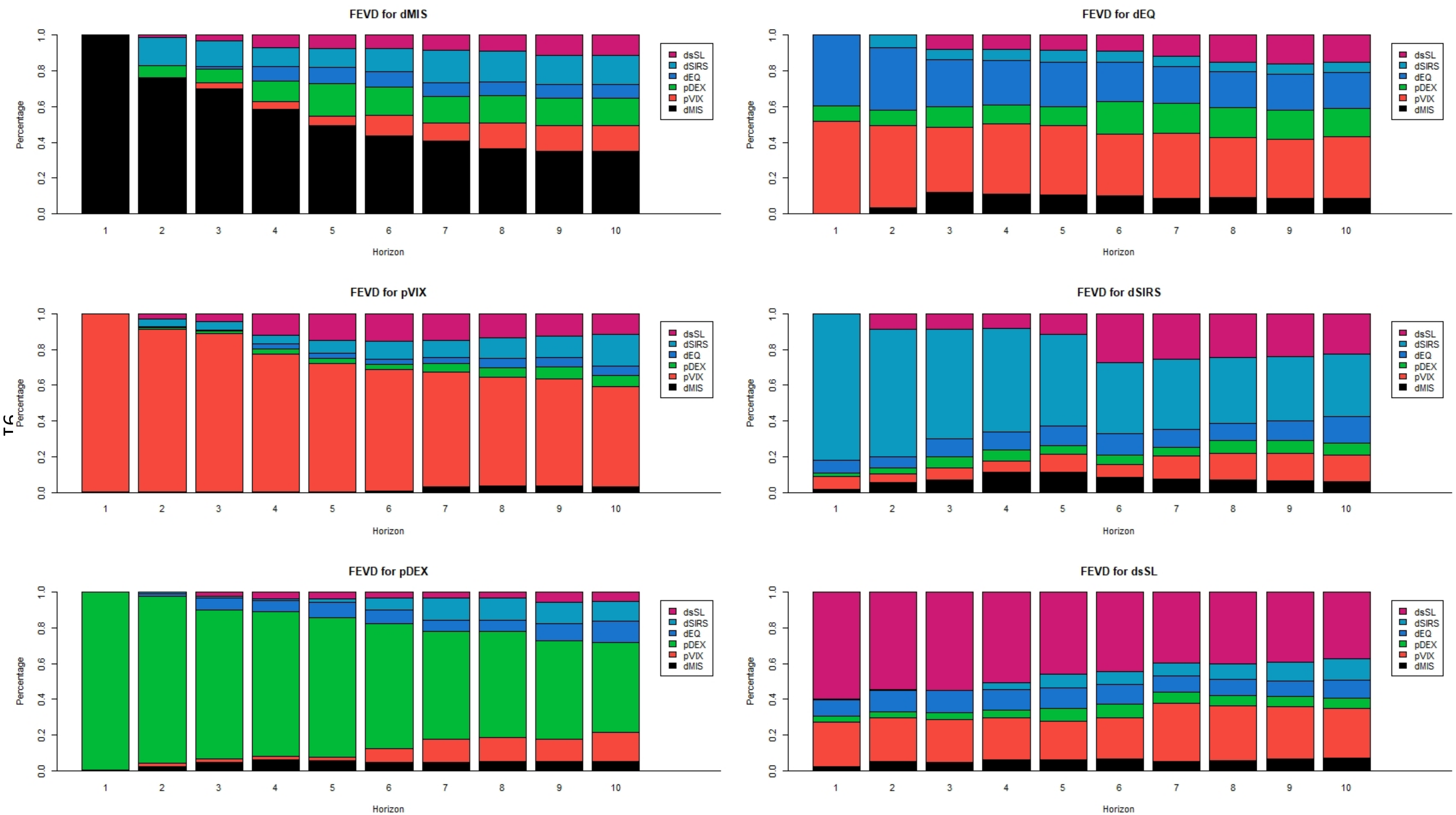
Forecast Error Variance Analysis (FEVD):



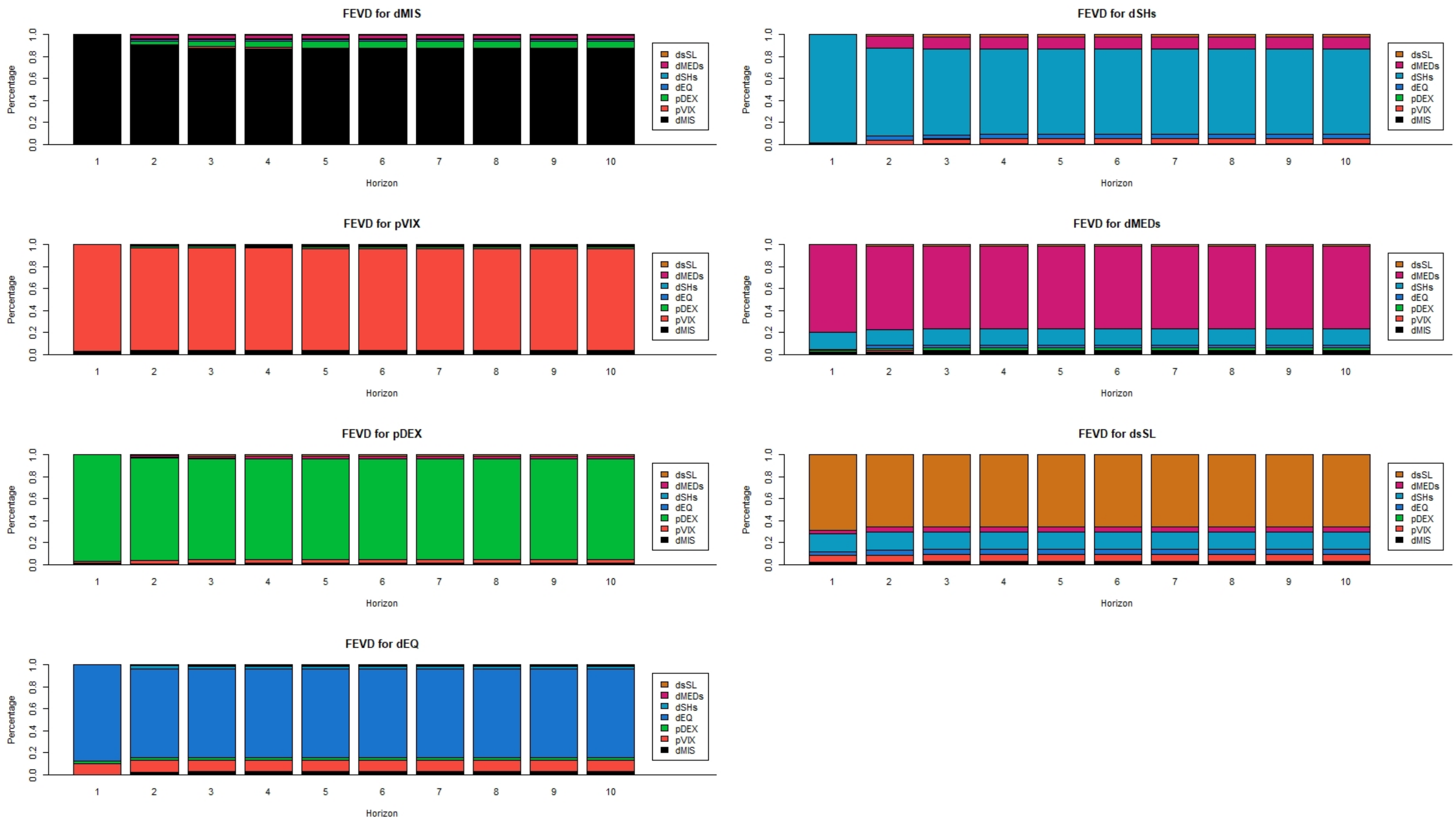
FEVD: Regressor Matrix with dMIS, Full-Sample, VAR order 9



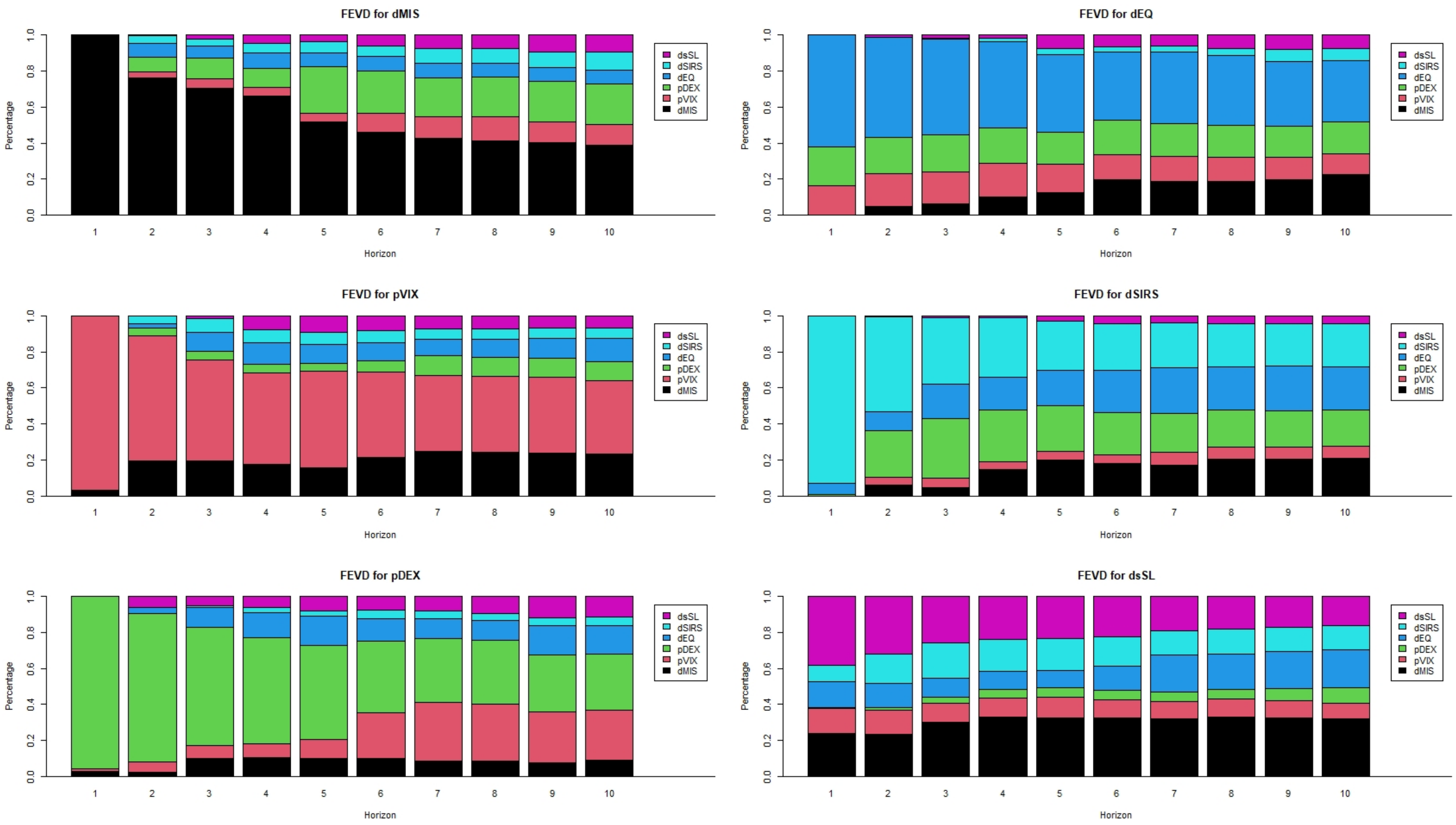
FEVD: Regressor Matrix with sTA, Full-Sample, VAR order 9



FEVD: Regressor Matrix with dMIS and dSIRS, Full-Sample, VAR order 10



FEVD: Regressor Matrix with dMIS, Full-Sample, VAR order 1



FEVD: Regressor Matrix with dMIS and dSIRS, Sub-Sample, VAR order 6

Two Stage Regression Results and Diagnostics

Instrumentalizations Output

First Stage Regressions Results

Summary Output of %Changes of VIX (pVIX) dynamic regression on differential in total asset growth rates (sTA).

```
Call:
dynlm(formula = as.formula(model.text), data = data)

Residuals:
    Min      1Q   Median      3Q     Max
-0.35399 -0.09188 -0.01929  0.05287  0.98882

Coefficients:
              Estimate  Std. Error  t value   Pr(>|t|)
(Intercept)   0.01574   0.02021     0.779     0.4384
sTA.t         1.10332   1.50824     0.732     0.4667
sTA.1         3.13335   1.40472     2.231     0.0287 *
sTA.2         -1.73628  1.45577     -1.193    0.2367
sTA.3         -3.14818  1.56105     -2.017    0.0473 *
pVIX.1        -0.14410  0.11175     -1.289    0.2011
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1811 on 76 degrees of freedom
Multiple R-squared:  0.1151,	Adjusted R-squared:  0.05693
F-statistic: 1.978 on 5 and 76 DF,  p-value: 0.09148
```

Summary Output of first differences in 3-month Interbank Rates Spread (dMEDs) dynamic regression on differential in total asset growth rates (sTA).

```
Call:
dynlm(formula = as.formula(model.text), data = data)

Residuals:
      Min        1Q     Median        3Q       Max
-0.0129187 -0.0011742  0.0002646  0.0015428  0.0103412

Coefficients:
              Estimate     Std. Error  t value   Pr(>|t|)
(Intercept)   0.0006201    0.0003843   1.614     0.1106
sTA.t         -0.0136258   0.0263600  -0.517     0.6067
sTA.1         -0.0212196   0.0260886  -0.813     0.4185
sTA.2         -0.0478094   0.0272714  -1.753     0.0835 .
dMEDs.1       0.0188733    0.1112707   0.170     0.8658
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.003439 on 78 degrees of freedom
Multiple R-squared:  0.07207,	Adjusted R-squared:  0.02449
F-statistic: 1.515 on 4 and 78 DF,  p-value: 0.2061
```

Summary Output of first differences in 10-1-year sovereign bond yield spread differential (dsSL) dynamic regression on differential in total asset growth rates (sTA).

```
Call:
dynlm(formula = as.formula(model.text), data = data)

Residuals:
    Min      1Q   Median      3Q      Max
-0.84433 -0.15627  0.00964  0.17864  0.66738

Coefficients:
            Estimate Std. Error  t value   Pr(>|t|)
(Intercept) -0.02804   0.02781   -1.008    0.3165
sTA.t        1.04351   1.92714    0.541    0.5897
sTA.1        0.35770   1.91089    0.187    0.8520
sTA.2        4.86261   1.98439    2.450    0.0165 *
dsSL.1       0.10934   0.10764    1.016    0.3129
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2514 on 78 degrees of freedom
Multiple R-squared:  0.1121,	Adjusted R-squared:  0.06651
F-statistic: 2.461 on 4 and 78 DF,  p-value: 0.05213
```

Summary Output of SSE Composite Index extra returns on benchmark (dEQ) dynamic regression on differential in total asset growth rates (sTA).

```
Call:
dynlm(formula = as.formula(model.text), data = data)

Residuals:
     Min        1Q    Median        3Q       Max
-0.227431 -0.036152  0.001242  0.039647  0.162770

Coefficients:
                Estimate   Std. Error t value Pr(>|t|)
(Intercept)     0.002499   0.007163   0.349   0.7282
sTA.t          -1.350527   0.543848  -2.483   0.0152 *
sTA.1          -0.710800   0.515496  -1.379   0.1720
sTA.2           0.476812   0.513390   0.929   0.3560
sTA.3           1.034528   0.548299   1.887   0.0630 .
dEQ.1           0.046539   0.114366   0.407   0.6852
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06436 on 76 degrees of freedom
Multiple R-squared:  0.1121,	Adjusted R-squared:  0.05365
F-statistic: 1.918 on 5 and 76 DF,  p-value: 0.101
```

Second Stage Regression output.

Second Stage Regression Full Sample

```
Call:
dynlm(formula = as.formula(model.text), data = data)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0038253 -0.0005246 -0.0000869  0.0005936  0.0035457

Coefficients:
               Estimate      Std. Error t value Pr(>|t|)
(Intercept)    -0.0001738    0.0001436  -1.211  0.23024
dMIS.t          0.2056226    0.0540884   3.802  0.00031 ***
IVIX.1          0.0006493    0.0007686   0.845  0.40122
pDEX.1         -0.0493297    0.0172010  -2.868  0.00550 **
IEQ.2          -0.0046503    0.0021678  -2.145  0.03552 *
dSHs.1          0.0416997    0.0213044   1.957  0.05442 .
IMEDs.1         0.0091999    0.0415082   0.222  0.82526
IsSL.1          0.0003362    0.0005879   0.572  0.56930
dcQ.1          -0.0415981    0.1035012  -0.402  0.68901
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.001156 on 68 degrees of freedom
Multiple R-squared:  0.2866,	Adjusted R-squared:  0.2027
F-statistic: 3.415 on 8 and 68 DF,  p-value: 0.002345
```

The second stage regression full sample gives surprising results suggesting that the variable majorly responsible in changes in Chinese Equity Security share in US total foreign portfolio is given by differential in monetary policy indicators spread (if module of coefficient and significance of coefficient are looked closely).

Second Stage Regression Sub-Sample (March 2014-February 2019), Ordinary Least Square.

```
Call:
dynlm(formula = as.formula(model.text), data = data)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0014574 -0.0003075  0.0001308  0.0004221  0.0020313

Coefficients:
               Estimate      Std. Error  t value   Pr(>|t|)
(Intercept)     0.0002280    0.0001233   1.849     0.070557 .
dMIS.2         -0.0833763    0.0436402  -1.911     0.061924 .
IVIX.1          0.0018961    0.0005306   3.574     0.000802 ***
pDEX.1         -0.0225989    0.0110922  -2.037     0.047033 *
IEQ.2           0.0099291    0.0015812   6.280     8.66e-08 ***
dSIRS.3         0.0116268    0.0178420   0.652     0.517671
IsSL.1         -0.0007239    0.0004688  -1.544     0.128968
dcQ.1          -0.0014118    0.1018895  -0.014     0.989001
---
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0007279 on 49 degrees of freedom
Multiple R-squared: 0.5978,	Adjusted R-squared: 0.5404
F-statistic: 10.41 on 7 and 49 DF, p-value: 6.375e-08

Diagnostics on models have been run to assess goodness of the second stage regressions. The Sub-Sample estimation displayed utilizing a Breusch-Pagan test heteroskedasticity in residuals. The results of the test are reported below.

studentized Breusch-Pagan test

data: IB4$model
BP = 15.925, df = 7, p-value = 0.02581

Second Stage Regression Sub-Sample (March 2014-February 2019), Robust Standard Errors estimated with Huber-White Sandwich Estimator, test t on coefficients.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.00022800	0.00010238	2.2269	0.0305779 *
dMIS.2	-0.08337632	0.05699259	-1.4629	0.1498711
IVIX.1	0.00189608	0.00051401	3.6888	0.0005648 ***
pDEX.1	-0.02259885	0.00964457	-2.3432	0.0232238 *
IEQ.2	0.00992914	0.00193487	5.1317	4.917e-06 ***
dSIRS.3	0.01162676	0.01950724	0.5960	0.5539034
IsSL.1	-0.00072386	0.00042992	-1.6837	0.0985938 .
dcQ.1	-0.00141177	0.10968860	-0.0129	0.9897832

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

A dynamic model with stationary variable having a positive intercept suggests a time trend in the dependent variable. Hence Phillips-Perron Unit Root Test and an Augmented Dickey-Fuller Test together with a ARIMA model estimation according to AIC criterion.

Phillips-Perron Unit Root Test

data: Y
Dickey-Fuller Z(alpha) = -90.4, Truncation lag parameter = 3, p-value = 0.01
alternative hypothesis: stationary

Augmented Dickey-Fuller Test

data: Y
Dickey-Fuller = -3.3482, Lag order = 4, p-value = 0.06963
alternative hypothesis: stationary

Series: Y
ARIMA(0,0,0) with zero mean

sigma^2 = 1.696e-06: log likelihood = 428.43
AIC=-854.86   AICc=-854.81   BIC=-852.45

The diagnostic on dependent variable suggests that the series is stationary, particularly it does seem to take the form of a white noise process. Hence it is concluded that instrumentalizing regressors utilizing ARDL models using differential in Total Assets Growth Rates may have introduced more endogeneity in the model that the one it was removed with the instrumentalization, the effect of this approach is this positive intercept in sub-sample instrumentalized model.