Different Aspects of Market Liquidity

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Abstract

This thesis presents three chapters examining different aspects of market liquidity. The first chapter explores whether investor sentiment has the power to forecast stock market liquidity. The chapter employs the Amihud (2002) illiquidity measure as a proxy for price-impact, the bid-ask spread as a transaction cost measure of liquidity, and the individual investor sentiment spread and the Baker and Wurgler (2006) sentiment index to represent investor sentiment. Analysing NYSE stocks from 1994 to 2015 over weekly and monthly out-of-sample forecast horizons, the study finds investor sentiment is a statistically significant predictor of stock market liquidity. The second chapter explores the so-called "presidential gap" in U.S monetary aggregates. By examining monthly data from 1959 to 2017, the study finds a positive and significant Democratic premium in the inflation adjusted growth rates of narrow money, broad money and the money multiplier. The Democratic premium remains statistically significant and economically meaningful in the M1 and M2 growth rates after controlling for autoregressive components and the distributed lags of the federal funds rate. Moreover, the chapter finds a partisan Fed chair is a statistically significant indicator to explain the presidential gap. Finally, the third chapter investigates the transmission of commodity prices to the illiquidity of 22 currencies relative to the U.S dollar. The chapter exploits a new monthly dataset of commodity terms of trade (CTOT) in a GVAR framework over the period between 01/1994 and 12/2016. On the supply side, illiquidity of the currencies of less developed economies experience a significant and persistent fall following a local CTOT shock. On the demand side, the study finds a negative and persistent effect of a local CTOT shock on the illiquidity of most currencies, excluding highly liquid currencies. Finally, illiquidity of the currencies that are considerably exposed to commodity exporting and the currencies of smaller economies are significantly influenced by common commodity price shocks.

Overview

Background and objectives of the study

Liquidity is one of the fundamental building blocks of modern financial markets. It can perhaps be defined as easiness to execute market operations with little transaction cost, short time frame and minimal price impacts. As Easley and O'Hara (2004) explains, liquidity is hard to define but easy to feel, especially during crises.

Market liquidity is not a unique concept for a specific market. It has implications for almost all segments of global financial markets. Understanding the drivers of market liquidity is of interest to investors, portfolio managers and policymakers. Especially in the recession period, market liquidity can dry up very quickly and cost financial institutions and tax payers much more than expected. Additionally, the theoretical models show that market liquidity can evaporate very quickly during a crisis through the interaction effects between lower prices and higher volatility as financial agents faces losses and higher margins (Brunnermeier and Pederson, 2009). Given the existence of leverage and moral hazard, liquidity can be insufficient when it is needed most (Acharya and Viswanathan, 2011). Therefore, understanding areas of market liquidity is of the utmost importance not just because of the interest of market players, but also to stabilize negative future outcomes by revealing the interactions of market liquidity.

This thesis studies three aspects of market liquidity, namely, forecasting stock market liquidity, exploring the US monetary aggregates under different political regimes and the transmission of commodity price to FX liquidity.

Examining the stock market, I investigate whether investor sentiment has a statistical power to forecast market liquidity. Investor sentiment is linked with market liquidity by direct volume channels (Baker and Wurgler, 2006; Baker and Wurgler, 2007; Baker and Stein, 2004) as well as indirect behavioural channels (DeLong et al., 1990; Liu, 2015; Kahneman and Riepe, 1998; Gervais and Odean, 2001). However, none of these papers attempts to assess whether investor sentiment can forecast stock market liquidity. On the other hand, the existing studies in liquidity forecasting are bounded by either short-term quote predictability (Hardle, Hautsch and Mihoci, 2012) or focus on modelling liquidity risk (Weiß and Supper, 2013) rather than liquidity itself. NYSE liquidity is characterized by employing transaction cost, price-impact measures, and investor sentiment using sentiment spread from the American Association of Individual Investor and the Baker and Wurgler (2006) sentiment index. By examining more than 2000 NYSE stocks from 1994 to 2016 in a weekly and monthly out-of-sample forecasting framework, I show that investor sentiment can be a useful indicator to forecast the NYSE liquidity 1-4 steps ahead in the weekly and 1-2 steps ahead in the monthly estimations.

From the aspect of monetary liquidity, I investigate U.S. monetary aggregates within different political regimes in the second chapter. Previous studies document a striking phenomenon in U.S. political-economy cycles. The U.S. economy (Blinder and Watson, 2016) and stock markets (Santa-Clara and Valkanov, 2003; Pastor and Veronesi, 2017) perform significantly better under Democrat presidencies than Republican presidencies. Despite several attempts (Santa-Clara and Valkanov, 2003; Pastor and Veronesi, 2017; Blinder and Watson, 2016; Sy and Zaman, 2011) to provide explanations of this partisan gap, the phenomenon is still considered as a puzzle. Given the importance of monetary aggregates to the economy and stock markets (Thorbecke, 1997; Chen, 2007), it is surprising that no previous studies consider U.S. monetary aggregates under different political regimes. As the "partisan" model of political business cycles supports the idea that real output may become significantly different under the Democrat and the Republican presidencies, the chapter expects that the money base, M1 and money multiplier may also be in line with the partisan cycles. After defining the main monthly U.S. monetary aggregates from 1959 to 2017, I carry out the diagnostic tests, adjusting the data from inflation, trends, unit roots and seasonality. I find that the partisan gap in narrow and broad money indicators is even more pronounced than GDP growth and stock market performance, while it is less noticeable in the case of the money multiplier. The Democratic premium is found to be 5.15 percent and 9.12 percent for M1 and M2 growth rates, respectively. The Democratic premium remains statistically significant and economically meaningful in M1 and M2 growth rates after controlling for the autoregressive components and the distributed lags of the federal funds rate. Moreover, the chapter finds a partisan FED chair is a statistically significant indicator to explain the presidential gap. In other words, the democratic Fed chair gap is found to be more robust than the democratic presidential gap in the growth rates of the monetary aggregates.

In the final research chapter, examining foreign exchange (FX) market, I investigate the transmission of commodity price movements to the illiquidity of 22 currency pairs relative to the U.S dollar. The foreign exchange market is considered to be highly liquid. As of 2016 data, the average daily market turnover was $5.1 trillion per day (BIS, 2016). In recent years, FX liquidity has received increasing attention. Several studies (Banti et al., 2012; Banti and Phylaktis, 2015; Karnaukh, Ronaldo and Soderlind, 2015; Mancini et al., 2013; Menkhoff et al., 2012) explore the drivers of FX liquidity and find the TED spread, volatility as the main commonality and local money market and capital flows as the main cross-sectional determinants. However, none of these studies considers commodity prices as a determinant of FX liquidity. The linkages between commodity prices and international finance have received more attention in the exchange rate literature. The concept of "commodity currencies" indicates that commodity price is an important driver of the exchange rate movements under the sticky-price model of an open economy with non-traded goods, a portfolio balance model and the terms-of trade hypothesis (Chen and Rogoff, 2003; Chen, 2004). From other way around, similar findings document that exchange rates also influence or Granger-cause commodity prices as they are determined by the net present value of fundamental asset prices (Zhang et al., 2016; Obstfeld and Rogoff, 1996; Engel and West, 2005; Chen at al., 2010; Alquist et al., 2012). Finally, some studies (Ferraro et al., 2015; Chen et al., 2010; Zhang, et al., 2016) document that commodity prices have the power to forecast exchange rates or the other way around, particularly in the case of "commodity currencies". Commodity prices may influence FX liquidity from different channels. From the demand side perspective, commodities are a vital part of international trade flows, hence can be a determinant of FX liquidity. Since commodity prices are one of the factors that link exchange rates and economies each other, it would be a potential driver of FX liquidity from the commonality perspective. Finally, as commodity prices may significantly influence the local funding conditions especially in economies which are significantly exposed to exporting commodities, they affect FX liquidity from the supply side perspective. Considering the above channels that commodity prices may transmit to FX liquidity, it is clearly worthwhile exploring whether commodity prices are a determinant of FX liquidity.

To better estimate local effects of commodity prices shocks, I assemble a new, monthly dataset for commodity terms of trade. The existing dataset has been improved by preparing it at a higher (monthly) frequency, updating trading weights every year in countries' trade composition and extending the data to the end of 2016. By estimating, the transmission of commodity prices to FX liquidity in a rich, GVAR framework, I find that local CTOT shocks have a negative and persistent effect on illiquidity of the currencies of less developed economies in the supply side estimation, all of the currencies excluding highly liquid and some Asian currencies in the demand side estimation, of the commodity and less developed currencies in the estimation expressing commodity prices as commonality factor.

Contributions of the thesis

The thesis can be beneficial to researchers, investors and policymakers. The thesis contributes to the literature in three areas of market liquidity from several aspects. It provides major contributions to the liquidity forecasting, money supply and FX liquidity literature, and other contributions and suggestions relate to the market microstructure, behavioural finance, U.S presidential gap, commodity prices and GVAR areas. The contributions to the literature can be structured as follows.

The thesis contributes to the market microstructure literature in the first chapter. By analysing more than 2000 stocks on the NYSE over more than two decades, the thesis provides new empirical work to forecast stock market liquidity by using investor sentiment indicators. It finds that investor sentiment is a useful indicator to forecast the transaction cost and price-impact measures of stock market liquidity in the weekly and monthly out-of-sample forecast framework. The chapter also contributes to the scarce literature on liquidity forecasting. Additionally, the chapter suggest to the behavioural finance literature that simple survey measures of investor sentiment might become more successful measurements than academic proxies such as Baker and Wurgler (2006).

The thesis makes a significant contribution in the second chapter by exploring the US monetary aggregates under different political regimes from 1959 to 2017. The chapter contributes to the money supply, monetary policy and the U.S presidential puzzle literature by providing empirical evidence that there is a positive and significant Democratic premium in the inflation adjusted growth rates of narrow money, broad money and the money multiplier. The chapter emphasizes that the partisan Fed chair is a statistically significant indicator to explain the presidential gap and the democratic Fed chair gap seems statistically more robust than the democratic presidential gap in the growth rates of the monetary aggregates. By emphasising these findings, the chapter suggests to the U.S. presidential puzzle literature that it might be more worthwhile to focus on the local scale political affiliation rather than the country wide presidential gap. Finally, the chapter suggests to the political theory and all relevant stakeholders that the role of political affiliation in deriving successful economic and financial outcomes is important.

The thesis provides major contributions to international finance literature in the third chapter. First, it provides a new, monthly dataset for commodity terms of trade (CTOT). The chapter improves the current CTOT dataset by constructing at a monthly frequency, updating trade weights of countries' trade composition and extending the dataset to the end of 2016. Second, the chapter provides rich empirical work for the transmission of commodity prices to FX liquidity. The chapter finds that commodity price shocks significantly matter to the cross-sectional illiquidity of most floating exchange rates. Commodity prices are also found as a significant commonality factor of FX liquidity.

The thesis can be useful to investors. In the first chapter, investors can benefit from the results by having a better vision of the future direction of stock market liquidity in a straightforward forecasting framework. Investors specializing in liquidity investing can also benefit from the results of the third paper to better model the illiquidity component of a given currency by using the relevant information on commodity prices. Policymakers and investors can both benefit from the findings of the second chapter: (i) The democratic Fed chair gap seems statistically more robust than the democratic presidential gap in the growth rates of the monetary aggregates. (ii) It might be worthwhile to focus on the local scale political affiliation rather than the country wide presidential gap. (iii) The role of political affiliation in deriving successful economic and financial outcomes is important.

Structure of the thesis

This thesis presents empirical investigations in the stock market, monetary and FX areas of market liquidity. The main body of the thesis is structured in the following three chapters. The chapters are followed by concluding remarks section that summarize the thesis, highlights the limitations and suggests the areas for further research.

The first chapter is an empirical investigation that examines the power of investor sentiment to forecast stock market liquidity at the weekly and monthly horizons from 1994 to 2015. The chapter defines bid-ask spread as a transaction cost measure and Amihud (2002) as a price-impact measure of liquidity. In the meantime, investor sentiment is defined using investor sentiment spread from the American Association Individual Investor and Baker and Wurgler (2006) sentiment index. The chapter applies all common stocks of the NYSE in a straightforward forecasting framework.

The second chapter explores U.S monetary aggregates under different political regimes from 1959 to 2017. The chapter introduces several empirical models to control the main possible drivers of monetary aggregates that could potentially sweep away the effects of the partisan gap. Additionally, the chapter explores the partisan gap in the Fed chairman and model with potential determinants.

The third chapter is an empirical work that investigates the transmission of commodity prices to the illiquidity of 22 currencies relative to the U.S dollar. The chapter exploits a new monthly dataset of commodity terms of trade (CTOT) in the GVAR framework over the period between 1994:01 and 2016:12. The study explores the transmission of commodity prices to FX liquidity in demand side and supply side equations of liquidity as well as in the equation expressing commodity prices as commonality factor.

Chapter 1. Does investor sentiment forecast stock market liquidity?

1.1 Introduction

Forecasting stock market liquidity is of interest to investors, portfolio managers and policy makers. Particularly in the recession period, market liquidity can evaporate very quickly and cost financial markets much more than anticipated. Therefore, modelling and forecasting liquidity is important not just because of the interest of the market players but also to stabilize negative future outcomes that arise from liquidity shortages in the markets.

Nevertheless, a few natural and practical challenges remain in the existing literature that prevent sophisticated liquidity modelling and forecasting framework. The first challenge is the fact that unfortunately, market liquidity is an unobservable phenomenon as the market data cannot directly reveal the liquidity component. Since the first ever comprehensive attempt by Roll (1984) to extract the liquidity component from the data, several metrics have been suggested to adopt a proxy for the liquidity component. As this paper does not aim to test the validity of the existing measurements, we focus on comparative studies (Goyenko, Holden and Trzcinka, 2009) to adopt appropriate liquidity metrics. The second shortcoming is practical limitations of current studies. In other words, existing studies either are constrained by short term quote predictability (Härdle, Hautsch and Mihoci, 2012) or focusing on modelling liquidity risk (Weiß and Supper, 2013) rather than liquidity itself.

Investor sentiment as a concept is considered as an important contribution in behavioural finance theory. Investor sentiment, in a broad sense, can be defined as investors' optimistic and pessimistic biases while investing in the financial markets (Baker and Wurgler, 2006). Although, several proxies are suggested to capture different aspects of investor sentiment, Baker and Wurgler (2006), Baker and Wurgler (2007) develop a conceptual proxy for investor sentiment designed to capture possible deriving factors under an umbrella. Investor sentiment is linked with market liquidity with direct volume channels (Baker and Wurgler, 2006; Baker and Wurgler, 2007; Baker and Stein, 2004) as well as indirect behavioural channels (DeLong et al., 1990; Liu (2015); Kahneman and Riepe, 1998; Gervais and Odean, 2001). However, none of these papers attempts to assess whether investor sentiment can forecast stock market liquidity.

In this study, we aim to test whether stock market liquidity can be forecasted by using investor sentiment indicator. In other words, the paper assesses whether investor sentiment has the power to forecast stock market liquidity over the weekly and monthly horizons. To maintain the validity of the results, we apply both transaction cost and price-impact measures of liquidity. Regarding investor sentiment, we utilize a survey measure as well as abovementioned academic proxy.

After carrying out the cross-metrics empirical analysis in the weekly and monthly out-of-sample forecasting framework, we find that investor sentiment as a behavioural proxy can become a useful indicator to forecast stock market liquidity. The forecast performance is found to be better in the weekly estimations with the survey-based sentiment measure rather than the monthly estimation with the academic proxy. By contrast, the survey measure can forecast the NYSE liquidity better than the Baker and Wurgler (2006) sentiment index in monthly frequency, as well.

This chapter contributes to the liquidity forecasting literature by finding a statistically significant predictor (i.e investor sentiment) which can successfully forecast stock market liquidity at the weekly and monthly frequencies. Additionally, the forecasting work does not require on heavy computational burden as it is merely carried out in the OLS framework.

Therefore, investors can benefit it and easily use publicly available investor sentiment indicators to have a vision on the future direction of stock market liquidity. The chapter also contributes to the scarce literature on the linkage between investor sentiment and market liquidity.

The rest of this chapter is organized as follows. The second section reviews the literature on the theoretical link between market liquidity and investor sentiment as well as featured works on liquidity forecasting and well-known academic liquidity metrics. In the third section, we describe applied liquidity and investor sentiment indicators in detail, present the forecasting methodologies and the forecasting performance measurements. The fifth section outlines the results and the forecasting power of the model relative to the benchmark. In the last section, we emphasize the major findings and summarize the paper with concluding remarks.

1.2 Literature review and theoretical underpinnings

A wide range of the market liquidity measures are applied in the academic literature. For instance, in the context of the price-impact relationship, market liquidity has been defined as the inverse of the price sensitivity to order flows (Kyle, 1985). In his effective bid-ask spread setup, Roll (1984) defines liquidity as the negative serial dependency between successive price changes. In the transaction cost view, a variety of spread measures are available in market microstructure works. Meanwhile, investor sentiment as a conceptual framework is proposed by Baker and Wurgler (2006) to characterize optimism or pessimism about the future stock market performance. Nevertheless, some survey-based sentiment measures, of which one is applied here, are available designed to capture direct investor opinions.

1.2.1 Market liquidity and investor sentiment

Investor sentiment may influence to market liquidity through three distinct channels:

1.2.1.1 Noise trading

In the context of illiquidity, Kyle (1985) classifies market participants into three groups: noise trader, the insider and market makers. As any of these traders are affected by investor sentiment, market liquidity will be affected as well. When noise trading is larger, the market makers believe that the proportion of the insider trading is lower. This belief subsequently induces market makers to adjust the price by a smaller amount which means the price impact caused the order flow is lower and liquidity increases.

Moreover, DeLong et al. (1990) show that noise traders aggressively short sell stocks if their sentiment is high (bullish) or low (bearish) by means of overvaluation or undervaluation of the stock price. As noise traders misperceive the future market prices, higher sentiment induces noise trading to sell or buy aggressively. In addition, Liu (2015) emphasizes real world short sale constraints and claims that the noise traders can only trade when their sentiment is high. Consequently, the higher sentiment induces noise traders to trade more aggressively. Thus, the synthesized results from these two studies stimulates the conclusion that higher investor sentiment generates larger noise trading which in turn stimulates lower price impact of order flow.

1.2.1.2 Inefficient market

Baker and Stein (2004) differentiate market makers into rational and irrational categories. In this framework, rational market makers correctly infer the insider information whereas irrational market makers underreact to insider information as they are biased by overconfidence. If the proportion of irrational market makers is higher relative to the rational group, a lower price impact will be observed in the market, as the underreaction bias does not stimulate the correction of prices inflated by insiders.

On the other hand, irrational market makers only exist if investor sentiment is higher and constantly overvalues the intrinsic value of the stock. Consequently, as investor sentiment induces higher irrational market makers, the market will be less efficient, the lower price impact will be observed which in turn stimulates more market liquidity.

1.2.1.3 Overconfidence

The Kahneman and Riepe (1998) research on investor psychology reveals that investment decision making process can be mostly affected by sentiment and overconfidence biases. From the psychological perspectives, optimistic investors are more likely to be overconfident which induces more aggressive trading, provides more market liquidity. Moreover, Gervais and Odean (2001) argue that past investment success generates additional overconfidence and make noise traders excessively bullish in the following investment cycles.

In summary, the literature reveals investor sentiment may increase stock market liquidity through the channel that irrational market makers psychologically biased by overconfidence trade more aggressively in the inefficient markets. However, the reverse causality relationship, more clearly, market liquidity increasing investor sentiment might exist, although there is no empirical work to support it.

1.2.2 Liquidity forecasting

The liquidity forecasting literature is mostly bounded by forecasting monetary aggregates. Central Banks are closely interested in making strong projections on the expected amount of the money aggregates to make policy decisions on interest rates and financial stability.

However, published literature on forecasting market liquidity is limited by a few papers which attempted to model the dynamics of bid and ask curves.

Weiß and Supper (2013) is one of the pronounced papers in the liquidity forecasting literature which attempts to model the joint distribution of bid-ask spread and log returns of a stock portfolio by using Autoregressive Conditional Double Poisson and GARCH processes for the marginals and vine copulas for the dependence structure. This paper finds evidence for strong co-movements in liquidity and strong tail dependence between bid-ask spreads and log returns from intraday data. Afterwards, they forecast three types of liquidity-adjusted intraday Value-at-Risk measurement by incorporating commonalities in liquidity and co-movements of stocks and bid-ask spreads. They find from the backtesting results that the proposed models perform well in forecasting liquidity-adjusted intraday portfolio profits and losses.

A few papers (for example, Härdle, Hautsch and Mihoci, 2012) attempt to model the dynamics of ask and bid curves in a limit order book market applying a dynamic semiparametric factor model. Best bid and best ask quotes are modelled with appropriate factor loading using vector error correction specification. By using a sample from the Australian Stock Exchange, they find that the model can capture the spatial and temporal dependencies of the limit order book. A noteworthy contribution of the paper is finding evidence for short-term quote predictability. Moreover, they show that recent liquidity demand has the strongest impact on the pattern of the variable reflecting the current state of the market.

1.2.3 Liquidity measures

Liquidity is an unobservable variable as the market data cannot explicitly reveal the liquidity of a security. However, a number of liquidity measures have been suggested in the academic literature to capture different aspects of liquidity. We discuss some of them which are considered robust relative to the benchmark spreads (Goyenko, Holden and Trzcinka, 2009).

Roll (1984) develops an effective bid-ask spread measure based on the efficient market hypothesis. Within the efficient market, they assume the fundamental price fluctuates randomly while trading cost negative serial dependency in successive market price changes. Let denote V_t be the unobservable fundamental value of the stock on day t. Assume that it evolves as

$$V_t = V_{t-1} + e_t \tag{1.1}$$

Where e_t is the mean-zero, serially uncorrelated public information shock on day t.

Afterwards, let P_t be the last observed trade price on day t. Assume it is determined by

$$P_t = V_t + \frac{1}{2} S Q_t \tag{1.2}$$

Where S is the effective spread and Q_t is a buy/sell indicator for the last trade that equals +1 for a buy and -1 for a sell. Assume that Q_t is equally likely to be +1 or -1, is serially uncorrelated and is independent of e_t. Taking the first difference in the equation (1.2) and combining it with equation (1.1) yields

$$\Delta P_t = \frac{1}{2} S \Delta Q_t + e_t \tag{1.3}$$

where Δ is the change operator. Roll (1984) shows that the serial covariance is

$$Cov(\Delta P_t, \Delta P_{t-1}) = \frac{1}{4} S^2 \tag{1.4}$$

Or equivalently

$$S = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})} \tag{1.5}$$

Lesmond, Ogden and Trzcinka (1999) develop a liquidity measure called LOT which is an estimator of the effective spread based on the assumption of informed trading on non-zero-return days and the absence of informed trading on zero-return days. The LOT model assumes that the unobserved "true return" R_{jt}^* of a stock j on day t is given by

$$R_{jt}^* = \beta_j R_{mt} + \varepsilon_{Jt} \tag{1.6}$$

Where $\beta_j$is the sensitivity of stock j to the market is return R_{mt} on day t and ε_{Jt} is a public information shock on day t. It is assumed that ε_{Jt} is normally distributed with mean zero and variance σ_j^2. Let $\alpha_{1j} \leq 0$ be the percent transaction cost of selling stock j and $\alpha_{2j} \geq 0$ be the percent cost of buying stock j. The observed return R_{jt} on stock j given by

$R_{jt} = R_{jt}^* - \alpha_{1j}$ when $R_{jt}^* < \alpha_{1j}$

$R_{jt} = R_{jt}^*$ when $\alpha_{1j} < R_{jt}^* < \alpha_{2j}$

$R_{jt} = R_{jt}^* - \alpha_{2j}$ when $\alpha_{2j} < R_{jt}^*$

The LOT measure is found by getting the difference between the percent buying cost and the percent selling cost:

$$LOT = \alpha_{j2} - \alpha_{j1} \tag{1.7}$$

Another well-known and extensively used liquidity measure is a price-impact indicator developed by Amihud (2002). The author assumes it captures the daily response associated with one dollar of trading volume. In this paper, it is one of two liquidity measures we used to forecast. The equations and the formulas are discussed in the third section.

Pastor and Stambaugh (2003) develop a gamma which is considered another robust price-impact measure (Goyenko, Holden and Trzcinka, 2009). They get a gamma by running the following regression:

$$r_{t+1}^e = \theta + \varphi r_t + (Gamma) sign(r_t^e)(Volume_t) + \varepsilon_t \tag{1.8}$$

Where r_t^e is the stock's excess return above the CRSP value-weighted market return on day t and $Volume_t$ is the dollar volume of on day t. Gamma should have a negative sign (Goyenko, Holden and Trzcinka, 2009) as it measures the reverse of the previous day's order flow shock. Thus, the larger the absolute value of the Gamma, the larger price impact that will be observed.

1.3 Data and Methodology

In this paper, we utilize two different liquidity and investor sentiment measures to capture size and cost dimensions across the weekly and monthly analysis to match the frequency of the investor sentiment data.

1.3.1 Liquidity measures

Our data set for the liquidity measures encompasses all common stocks on the NYSE. The reason for choosing NYSE rather than NASDAQ, as emphasized in Amihud (2002), is the differences of microstructure between the NASDAQ and the NYSE stock returns. Another distinguishing feature of the markets is the reported volume figures. Trading is done via market makers in the NASDAQ operations which cause the artificial high volumes in the data whereas NYSE is operated by directly seller-buyer principle. The daily data covering the period between 01/1994 and 12/2015 has been collected from CRSP. The main reason for the chosen period is to follow the findings in the literature that the stock market has become relatively more liquid in last two decades.

On average year, around 2000 stocks were traded during the period studied. However, not all stocks are traded every day. To clean the data, we follow Chordia et al. (2000). Firstly, to avoid any influence of the minimum tick size, we delete a stock on a day its average price falls below \$2. Chordia et al. (2000) include all the stocks traded at least once in ten trading days. However, since our analysis covers a bigger data set and following Amihud (2002), we impose more stringent requirements, at least 200 out of 252, for the trading days of stocks to make sure that the empirical analysis represents the market characteristics as much as possible. After cleaning, we still have more than 1900 stocks of the NYSE in the data set.

The first liquidity measure used in this paper is the well-known price-impact measure proposed by Amihud (2002). This metric is considered an illiquidity measure that originates from the idea in Kyle (1985) that the price responses to order flows. Goyenko, Holden and Trzcinka (2009) demonstrate that the Amihud (2002) illiquidity measure is highly correlated with TAQ-based price impact measures. The measure is obtained as the absolute price change per dollar of daily trading volume for each stock each day. If we denote λ as the Amihud measure, then the metric is computed as follows:

$$\lambda_{td}^{i} = \frac{|R_{td}^{i}|}{\$Vol_{td}^{i}} \tag{1.9}$$

Where R_{td}^{i} is stock i's return on day d of week t and $\$Vol_{td}^{i}$ is the same day dollar trading volume (measured in millions of dollars) of this stock. The weekly and monthly illiquidity measures for each stock are computed by averaging the daily measures within each week and month, respectively.

$$\lambda_{t}^{iA} = \frac{1}{D_{t}^{i}} \sum_{d=1}^{D_{t}^{i}} \frac{|R_{td}^{i}|}{\$Vol_{td}^{i}} \tag{1.10}$$

Where D_{t}^{i} is the number of days in the week/month t for which data are available for the stock i. It aggregates the daily measures over weekly and monthly. The market illiquidity is subsequently calculated as the cross-sectional equal-weighted average of the individual stock illiquidity in that week/month. To adjust the inflation effect on the dollar volume of trading, we scale the market illiquidity by Consumer Price Index. We also take the logarithmic transformation of market illiquidity following Amihud (2002).

TABLE 1. 1 SUMMARY STATISTICS OF THE LIQUIDITY AND INVESTOR SENTIMENT MEASURES

Measure	Horizon	Mean	Median	Std Dev	Min	Max	Skewness	Kurtosis
Amihud (2002)	Weekly	-7.17	-7.01	1.12	-13.54	-4.27	-1.28	3.14
	Monthly	-6.79	-6.84	0.57	-8.08	-4.18	1.03	3.36
Bid-Ask spread	Weekly	-3.64	-3.63	0.09	-3.93	-1.69	9.47	18.4
	Monthly	-3.64	-3.64	0.07	-3.81	-3.21	0.69	4.88
Sentiment Survey	Weekly	0.11	0.11	0.18	-0.51	0.63	0.05	-0.05
Baker and Wurgler (2006)	Monthly	0.15	0.02	-0.91	2.49	0.56	1.79	3.92

The first two rows of Table 1.1 present the descriptive statistics of the log transformation of the Amihud (2002) illiquidity measure across the weekly and monthly horizons during 1994 and 2015. The table reveals that the weekly and monthly data share similar patterns for all metrics but skewness which is negatively biased in the weekly data whereas being positively skewed in the monthly frequency.

FIGURE 1. 1 LOG TRANSFORMATION OF AMIHUD (2002) ILLIQUIDITY

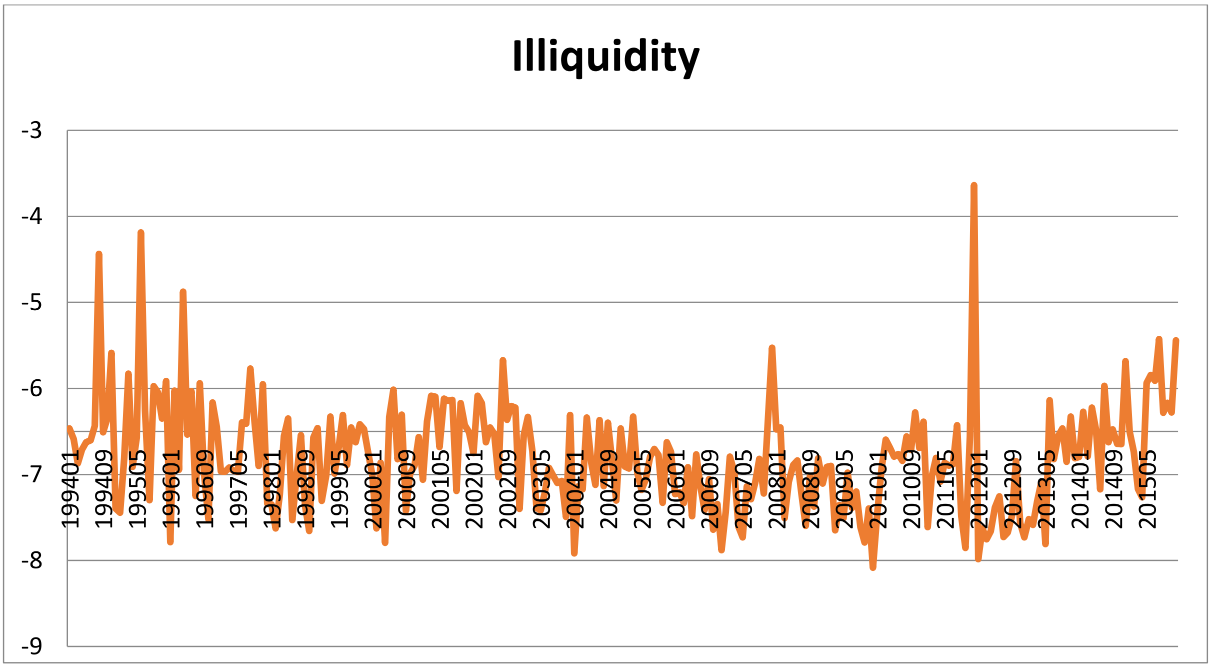


Figure 1.1 presents the time series pattern of the monthly averages of the weekly logarithmic transformation of the market illiquidity from 1994 to 2015. Although the extreme spikes associated with more liquid market can only be explained by their outlier nature, the general pattern of the graph is in line with major historically important, financial events. For instance, 9/11 terror event, recent financial crisis is associated with high illiquidity. We also conduct Augmented Dickey Fuller (ADF) test to check the stationarity. We allow at least 12 lags for performing ADF tests.

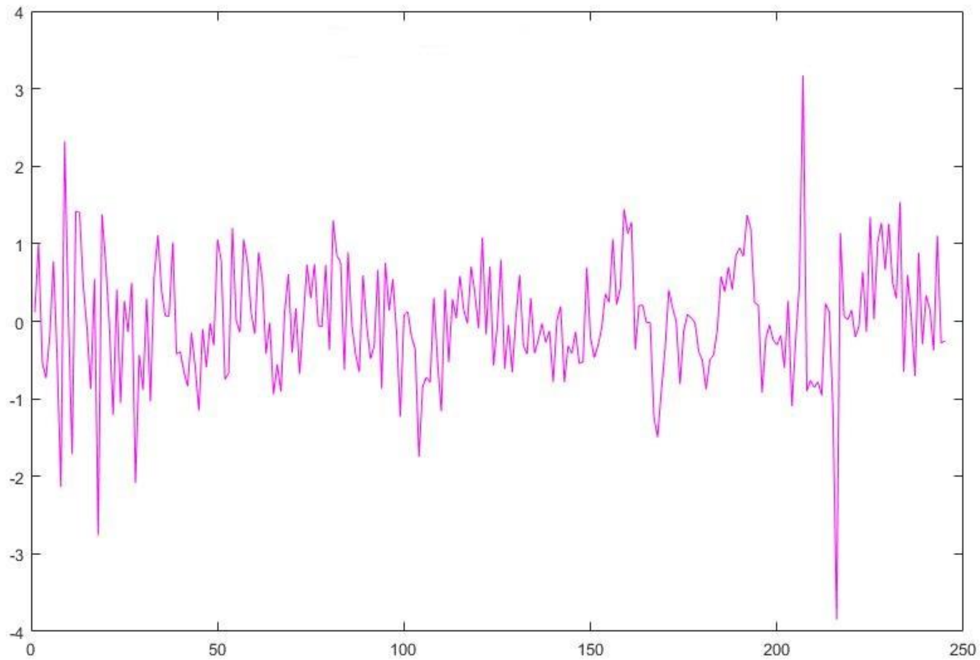
Table 1. 2 ADF test for the liquidity and investor sentiment measures

Measure	Horizon	H_0: unit root	P value
Amihud (2002)	Weekly raw data	Rejected	0.001
	Monthly raw data	Failed to reject	0.3756
	Monthly filtered	Rejected	0.000
Bid-Ask spreads	Weekly raw data	Failed to reject	0.2134
	Weekly filtered	Reject	0.0000
	Monthly raw data	Failed to reject	0.3781
	Monthly filtered	Reject	0.0000
Sentiment Survey	Weekly, Monthly	Rejected	0.001
Baker and Wurgler (2006)	Monthly	Rejected	0.001

We find that for the weekly data, the null hypothesis of unit root is rejected in favour of stationary with and without drift for any chosen lags. However, the stationarity condition for the monthly data above is violated after 9th lags which might be explained by the data aggregation carried out by averaging 5 daily data for the weekly figures, subsequently computing the averages of 4 weekly data for the monthly series.

Therefore, we perform diagnostic checks of monthly data, find the appropriate polynomials and filter the data. Afterwards, we get the following graph which is stationary and free of any trend and seasonal components.

Figure 1. 2 Adjusted monthly Amihud (2002) measure



The second liquidity measure is the traditional bid-ask spread calculated as the difference between the closing values of the bid and ask prices divided by mid-price for scaling and comparability across the stocks.

$$S_{td}^{i} = \frac{P_{td}^{Ask} - P_{td}^{Bid}}{P_{td}^{Mid}} \tag{1.11}$$

The bid-ask spread is also computed across the weekly and monthly horizons.

The second two rows of Table 1.1 reports the descriptive statistics of the log transformation of the bid-ask spread across the weekly and monthly horizons from 1994 to 2015. The table suggests that weekly data is fatter tailed and more positively skewed than the monthly averages which might be explained by noisier nature of higher frequency data.

FIGURE 1. 3 LOG OF MONTHLY BID-ASK SPREADS

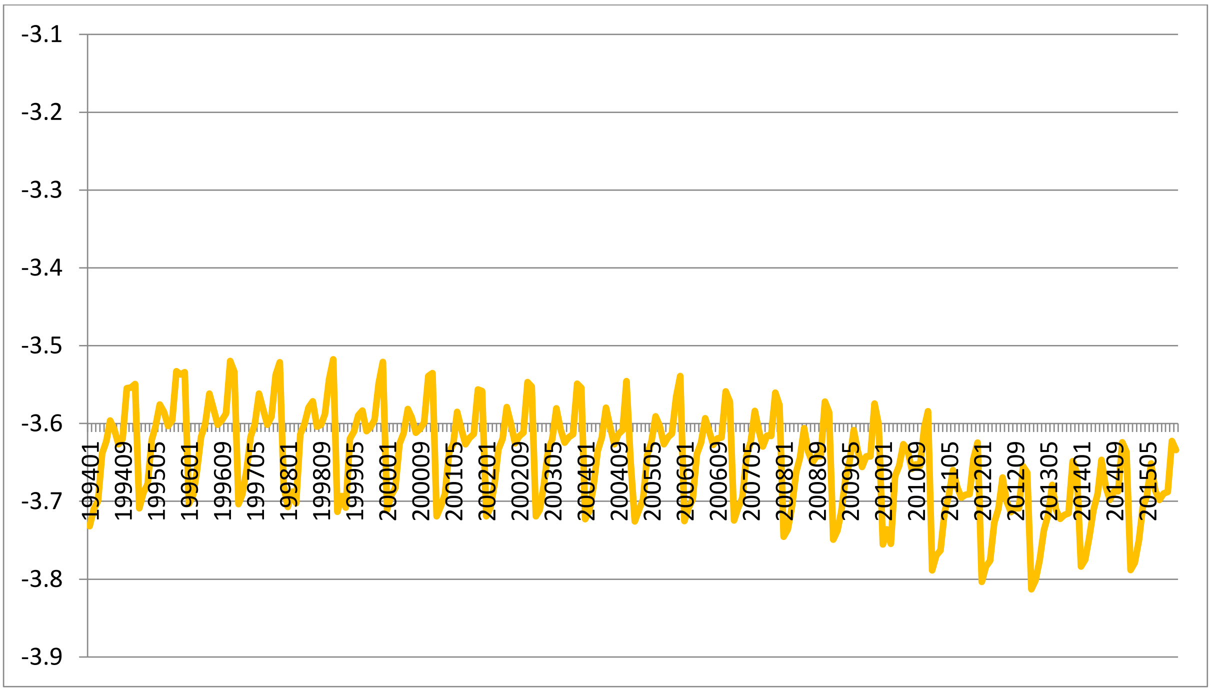
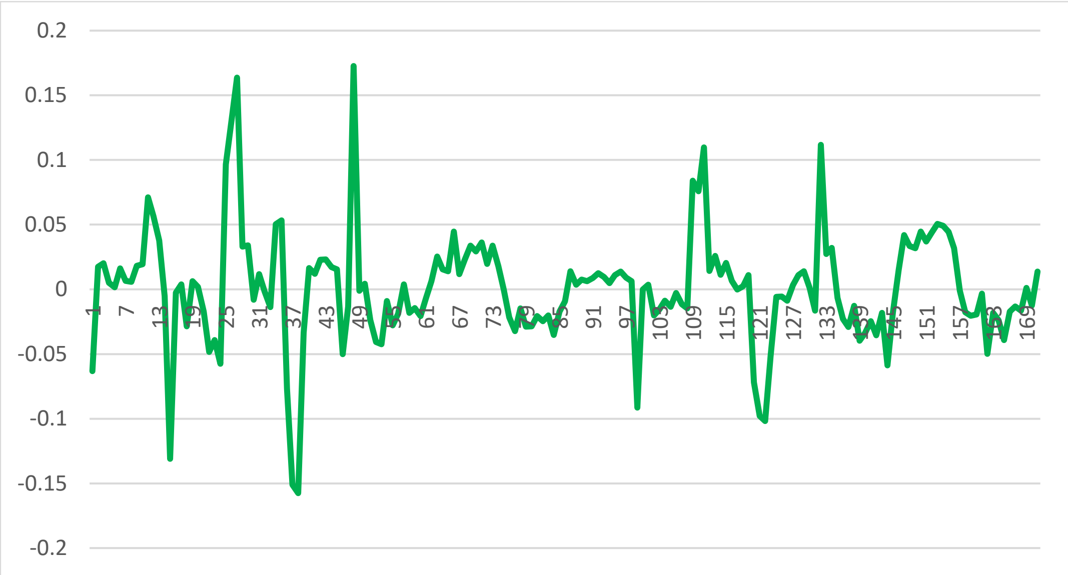


Figure 1.3 demonstrates the time series pattern of the monthly averages of the weekly logarithmic transformation of the market illiquidity from 1994 to 2015. The diagnostic checks reveal that the monthly data above contain trends and cyclical components after 9th lags. We conduct Augmented Dickey Fuller (ADF) test for the weekly and monthly bid-ask spread series to check the stationarity.

We find that the weekly bid-ask spread does not contain unit root in the Autoregressive Model with Drift whereas found as non-stationary in the pure Autoregressive framework. Therefore, we find the first difference which is stationary in any selected models. Regarding the monthly data, we get appropriate polynomial by applying 10^{th}, 11^{th}, 12^{th} lap operators simultaneously and subsequently filtering from the original data. Afterwards, we get the graph in the Figure 1.4 which is stationary in any selected models and free of trends, seasonal components.

FIGURE 1. 4 ADJUSTED MONTHLY BID-ASK SPREADS



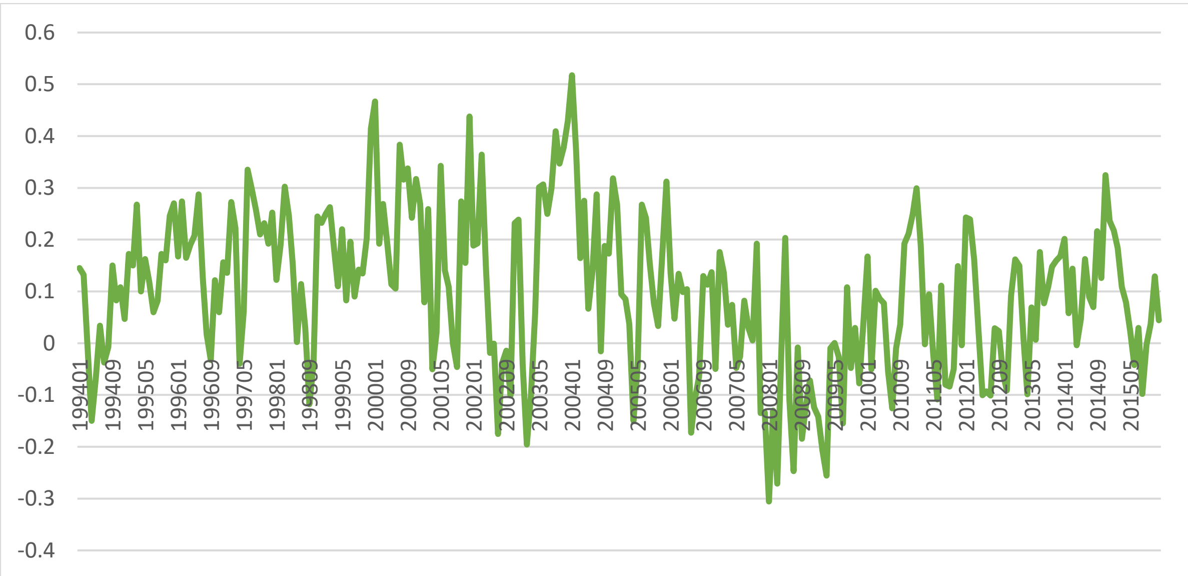
It is worth to discuss the possible correlation between two liquidity measures. Although, Amihud (2002) and bid-ask spread measure two different types of liquidity, it makes sense thinking about their possible co-direction as they are originated from the same market movement. We find them positively correlated indeed. The correlation coefficient is found to be 0.4. Consequently, we can argue that although, Amihud (2002) and Bid-Ask Spread measure two distinct liquidity definitions, their movements have been found to be in the same direction, possibly due to the fact that they measure the same underlying concept.

1.3.2 Investor sentiment

We apply two investor sentiment proxies across the weekly and monthly horizons.

The first metric is a survey measure which is supposed to reflect the investors' expectations on the future performance of the stock market. Following Liu (2015), we calculated the difference between the percentages of the investors' bullish and bearish sentiments reported by American Association of Individual Investors (AAII) to adopt an investor sentiment proxy. AAII conducts weekly survey by polling random samples of its members and ask participants their expectation on the market direction of up, down or the same. Afterwards, the responses are labelled as bullish, bearish or neutral, respectively. The data set is adjusted to the time frame of liquidity measures which are available from 1994 and 2015.

FIGURE 1. 5 INVESTOR SENTIMENT SPREAD



The graph suggests that the general pattern of the sentiment data is in line with the global financial cycles. The lowest sentiment spreads are observed around the peak of dotcom and credit crisis while the highest spreads are found just before the bursts of the bubbles.

The third raw of table 1.1 demonstrates the descriptive statistics of the individual sentiment spreads across the given period. The results reveal that overall distribution of the data is close to the normality, although the sentiment spreads can be thought positively biased as the highest spreads can be found more than 60% whereas the lowest spreads are never found below -60%. This fact confirms the overconfidence theory and the noise trading behaviour. The equality of the mean and the median confirms that the data does not contain too many outliers.

We also conduct ADF tests to check the stationarity and find that the data does not contain unit root in the 1 percent significance level. The second sentiment metric is considered an academic measure proposed by Baker and Wurgler (2006) and Baker and Wurgler (2007) which is a more comprehensive version of the closed end fund discount paradigm. They form a composite index that captures the common sentiment component in the six proxies. They define SENTIMENT as the first principal component of the correlation matrix of six variables and rescaling the coefficients so that the index has unit variance.

$$SENTIMENT_t = -0.241CEFD_t + 0.242TURN_{t-1} + 0.253NIPO_t + 0.257RIPO_{t-1} + 0.112S_t - 0.283P_{t-1}^{D-ND} \tag{1.12}$$

Where *CEFD* is the closed-end fund discount is the average difference between the net asset values (*NAV*) of closed-end stock fund shares and their market prices. It was traditionally supposed to be an investor sentiment indicator and was used to forecast reversion in Dow Jones stocks. *TURN* is the *NYSE* share turnover is based on the ratio of reported share volume to average shares listed from the *NYSE* Fact Book. They define *TURN* as the natural log of the raw turnover ratio, detrended by 5 year moving average. *NIPO* and *RIPO* are considered as the number and the average first day returns on the *IPO* market, respectively. *S* shows the share of equity issues in total equity and debt issues as high values of the equity share predict low market return (Baker and Wurgler, 2006). Last sentiment proxy is dividend computed as the log difference of the average market-to-book ratios of payers and non-payers.

FIGURE 1. 6 INVESTOR SENTIMENT INDEX

The data covers the period between 01/1994 and 09/2015 collected from Wurgler's website[1]. The graph shows that the composite sentiment index is in line with global financial cycles. The data reveals that the sentiment is the highest just before dotcom bubble, found as the lowest in the peak of the dotcom bubble, the credit crisis of 2008-2009.

The last row of table 1.1 summarizes the descriptive statistics of the sentiment index during 01/1994 and 09/2015. Unlike the previous sentiment data, the index contains excess kurtosis and positively skewed. However, as in the survey data, the index is observed as the positively biased since the number of extreme bullish points are higher than the extreme bearish points. We also conduct ADF test to test stationarity of the data and find that the null hypothesis of series contain unit root is significantly rejected.

[1] http://people.stern.nyu.edu/jwurgler/

1.3.3 Forecasting

We employ unconditional out-of-sample forecasting for 1, 2, 3, 4 steps ahead for the weekly analysis, 1, 2 steps ahead for the monthly analysis. To get an unconditional, h step ahead forecast from a regression model, we should get the following regression equation:

$$y_{T+h} = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{1.13}$$

Where the dependent variables in our case are liquidity measures, λ_{td}^{i} and S_{td}^{i} , and the respective investor sentiment indicators are considered as the independent variables.

The in-sample estimations are carried out in the rolling window, as investor sentiment data is quickly digested in financial markets, including liquidity. Therefore, constantly allowing data older data within recursive estimations may introduce “ghost effect” to the liquidity data. The sample is chosen by using one third of total data for the weekly estimation, half of the data for the monthly estimations. The first reason is the more data points in weekly data than monthly data. The second is in line “ghost effect” argument that to eliminate unnecessary effects of older data in quickly updated data environment.

The forecast accuracy is measured by Root Mean Squared Forecasting Error (RMSFE) which is calculated as:

$$RMSFE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e_{t+h,t}^{2}} \tag{1.14}$$

where

$$e_{t+h,t} = y_{t+h} - \widehat{y_{t+h}} \tag{1.15}$$

y_{t+h} shows the actual value of the logarithmic transformation of the market illiquidity while $\widehat{y_{t+h}}$ indicates h period ahead forecasts.

The relative forecasting strength of the model for h period is measured based on the relative RMSFE using Random Walk without drift as the baseline model:

$$RMSFE_h^{REL} = \frac{RMSFE_{m,h}}{RMSFE_{b,h}} \tag{1.16}$$

where b denotes the baseline model. The model with more forecasting power than the baseline model should satisfy $RMSFE_h^{REL}$ less than 1.

We also apply Diebold and Mariano (1995) test to check the significance of the forecasting accuracy. The test statistic defines loss between the two forecasts by

$$d_t = g(e_{1t}) - g(e_{2t}) \tag{1.17}$$

where $g(e_{it})$ are the squared errors of the forecasting models:

$$e_{it} = \widehat{y_{it}} - y_t, \;\; i = 1,2 \tag{1.18}$$

The test statistic is based on the null hypothesis that

$$H_0 \colon E(d_t) = 0 \qquad \forall t$$

versus the alternative hypothesis

$$H_1 \colon E(d_t) \neq 0$$

The null hypothesis is that the two forecasts have the same accuracy. The alternative hypothesis is that the two forecasts have different level of accuracy.

We also consider alternative forecasting comparison methods. As we do not have an empirical evidence for the structural break in the estimations, Clark and McCracken (2005) is not appropriate for the forecasting comparison. Additionally, due to the forecasting works based on a single, a rolling, non-nested model, Clark and West (2007), Hansen (2005), Clark and

McCracken (2009) are not suitable, as well. Finally, Rogoff and Stavrakeva (2008) show that Clark and West (2006) does not always test for minimum mean square forecast error.

Thus, we apply log predictive as a third, alternative forecasting accuracy method. The metric compares the equality of probabilistic forecasts by giving a numerical value for the whole predictive distribution. The formula is based on the joint predictive density function of $y_{t+1}, y_{t+2}, \dots, y_{T+h}$ can be expressed as follows:

$$S(h,m) = \sum_{t=T}^{T+N_h-1} logp(y_{t+1}, \dots, y_{t+h} | Y_t, m) \quad (1.19)$$

We report the difference the log score of the model m and the selected benchmark model. The model is considered as superior to the benchmark model if the difference in the log scores is positive which implies that the model m outperforms the benchmark model in term of predictive density accuracy.

1.4 Empirical results

We conduct the weekly and monthly analysis based on two liquidity and sentiment indicators. We conduct estimations after filtering seasonality and trends from the liquidity data. Two liquidity measures aim to capture price-impact and transactions cost aspects of market liquidity. In the main estimations, we apply the sentiment survey for the weekly estimations while Baker and Wurgler (2006) sentiment index is used for the monthly forecasts. Afterwards, we introduce monthly estimations with sentiment survey spread, as well.

TABLE 1. 3 WEEKLY OUT-OF-SAMPLE FORECAST WITH AMIHUD (2002) AND SENTIMENT SPREAD

Metrics	h=1	h=2	h=3	h=4
RMSFE	0.7215	0.7340	0.7456	0.7781
Log Score	0.9234	0.6723	0.7844	0.3756
DM test	(***)	(***)	(***)	(***)

Notes: Amihud (2002) and Sentiment Survey Spread are used as the liquidity and the investor sentiment indicators, respectively. The dependent variable (the illiquidity measure) is used as the log transformation of Amihud (2002) measure. The stars, *, **, *** indicate the significance of Diebold and Mariano (1995) test in the 10%,5% and 1% significance levels, respectively.

Table 1.3 suggests that the investor sentiment survey spread is a powerful indicator to forecast the NYSE stocks' illiquidity 1, 2,3 and 4 weeks ahead. The sentiment spread obviously outperforms the Random Walk model in the RMSFE and log score measures. Moreover, Diebold and Mariano (1995) test shows that the predictive accuracy of the models is significantly different from each other in the 1 percent significance level.

TABLE 1. 4 MONTHLY OUT-OF-SAMPLE FORECAST WITH AMIHUD (2002) AND SENTIMENT INDEX

Metrics	h=1	h=2
RMSFE	0.9434	0.9549
Log score	0.4234	0.2673
DM test	(*)	(*)

Notes: Amihud (2002) illiquidity and Baker and Wurgler (2006) sentiment index are used as the liquidity and the investor sentiment indicators, respectively. The dependent variable (the illiquidity measure) is used as the log transformation of Amihud (2002) measure. The stars *, **, *** indicate the significance of Diebold and Mariano (1995) test in the 10%, 5% and 1% significance levels, respectively.

Table 1.4 reports the monthly forecasting results. We here employ the academic sentiment proxy which is designed to capture 6 candidate proxies for the investor sentiment. Although the sentiment indicator is still better than random walk to forecast the price-impact measure of the market liquidity, it performs relatively worse than the survey indicator used for the weekly forecast carried out by sentiment spread. The table shows that the sentiment index is able to forecast the market liquidity 1 and 2 month ahead and performs better than the benchmark model. The Diebold and Mariano (1995) test shows that the predictive accuracy of the models is different from each other in the 10 percent significance level while less significant than the weekly forecast with sentiment spread.

To test the validity of the results above, we estimate and forecast the model by applying another liquidity measure, well-known bid-ask spread calculated as the difference between ask price and bid price scaled by the mid-price for comparability. Similar to the Amihud (2002) measure, we get the log transformation of the spread ratio before estimating in the regression. We estimate the weekly analysis with the sentiment spread of the survey data and monthly analysis with the sentiment index.

TABLE 1. 5 WEEKLY OUT OF SAMPLE FORECAST WITH BID-ASK SPREAD AND SENTIMENT SPREAD

Metrics	h=1	h=2	h=3	h=4
RMSFE	0.7215	0.7340	0.7456	0.7781
Log score	0.5487	0.4912	0.2876	0.2567
DM test	(***)	(***)	(***)	(***)

Notes: Bid-ask Spread and the sentiment spread are used as the liquidity and the investor sentiment indicators, respectively. The dependent variable (the illiquidity measure) is used as the log transformation of the original bid-ask spread ratio. The stars *,**,*** indicate the significance of the Diebold and Mariano (1995) test in the 10%,5% and 1% significance levels, respectively.

The results reveal that the sentiment survey spread is a statistically powerful indicator to forecast the bid-ask spread for 1, 2, 3, 4 weeks ahead. The sentiment spread obviously outperforms the Random Walk model in forecasting the bid-ask spread. Additionally, Diebold and Mariano (1995) test confirms the significance of the difference between the predictive accuracy of the models.

TABLE 1. 6 MONTHLY OUT-OF-SAMPLE FORECAST WITH BID-ASK SPREAD AND SENTIMENT INDEX

Metrics	h=1	h=2
RMSFE	0.9434	0.9549
Log score	0.9778	0.9907
DM test	(*)	(*)

Notes: Bid-ask Spread and the Baker and Wurgler (2006) sentiment index are used as the liquidity and the investor sentiment indicators, respectively. The dependent variable (the illiquidity measure) is used as the log transformation of the original bid-ask spread ratio. The stars, *, **, *** indicate the significance of the Diebold and Mariano (1995) test in the 10%,5% and 1% significance levels, respectively.

The monthly estimation results are in line with the weekly analysis, albeit being less significant. The Baker and Wurgler (2006) sentiment index is also found as a successful indicator to forecast the spread 1 and 2 months ahead. The sentiment index forecasts the monthly spread better than Random Walk. The test reveals the predictive accuracy of the models is significantly different in 5 percent significance level.

So far, we have carried out the monthly estimations with the Baker and Wurgler (2006) sentiment index. For robustness check, we redo the monthly forecasts with the investor sentiment spread.

TABLE 1. 7 MONTHLY OUT-OF-SAMPLE FORECAST WITH AMIHUD (2002) AND SENTIMENT SPREAD

Metrics	h=1	h=2
RMSFE	0.8356	0.8423
Log score	0.7644	0.3412
DM test	(**)	(**)

Notes: Amihud (2002) illiquidity and the sentiment survey spread are used as the liquidity and the investor sentiment indicators, respectively. The dependent variable (the illiquidity measure) is used as the log transformation of the original spread ratio. The stars *, **, *** indicate the significance of the Diebold and Mariano (1995) test in the 10%,5% and 1% significance levels, respectively.

Table 1.7 shows that the monthly survey spread has better forecasting performance than the Baker and Wurgler (2006) sentiment index in forecasting Amihud (2002) liquidity. It performed better in terms of exposing a lower relative RMSFE, positive log score and more significant Diebold and Mariano (1995) test results. The survey directly asks investors' opinions on the future direction of market rather than extracting sentiment from the market-based data. This fact could be an explanation for relatively better performance of the sentiment survey spread over Baker and Wurgler (2006).

TABLE 1. 8 MONTHLY OUT-OF-SAMPLE FORECAST WITH BID-ASK SPREAD AND SENTIMENT SPREAD

Metrics	h=1	h=2
RMSFE	0.8578	0.8876
Log score	0.9123	0.8221
DM test	(***)	(***)

Notes: Bid-ask Spread and the sentiment survey spread are used as the liquidity and the investor sentiment indicators, respectively. The dependent variable (the illiquidity measure) is used as the log transformation of the original bid-ask spread ratio. The stars *, **, *** indicate the significance of the Diebold and Mariano (1995) test in the 10%, 5% and 1% significance levels, respectively.

The same result can be found in forecasting the bid-ask spread over the monthly horizon. The survey spread is found to be a better and a more significant predictor than the sentiment index.

1.5 Conclusion

In this paper, we investigate whether investor sentiment has the power to forecast stock market liquidity. Despite the wide range of literature on liquidity estimation and market microstructure, only limited numbers of papers are available in liquidity forecasting. We employ Amihud (2002) for a price-impact measure and bid-ask spread for a transaction cost indicator of liquidity. On the right hand of the equation, we adopt individual investor sentiment survey spread and Baker and Wurgler (2006) sentiment index as the investor sentiment measurements. Our large data set of NYSE covers around 2000 stocks during 1994-2015.

This paper is the first attempt conducting out-of-sample forecasts for stock market liquidity by using investor sentiment data. The weekly forecasts 1 to 4 steps ahead and the monthly forecasts 1 to 2 steps ahead are carried out with Diebold (2006) forecast equations while the forecasts performances are measured with RMSFE, log score and Diebold and Mariano (1995) predictive accuracy tests.

We conclude from the estimation results that investor sentiment is overall a significant indicator to forecast market liquidity. However, the sentiment survey spread is found as a better indicator than the Baker and Wurgler (2006) sentiment index to forecast the NYSE liquidity. The survey spread is found as a statistically and economically significant predictor of market liquidity in the weekly and monthly estimations. Likewise, Baker and Wurgler (2006) sentiment index is also able to forecast market liquidity better than Random Walk model, albeit less significantly. The results might also be explained by the frequency of analysis. Liquidity is better forecasted at the weekly rather than monthly frequencies.

Overall, regardless of being a survey measure or an academic index, the sentiment indicators may become powerful measurements to forecast the NYSE liquidity. However, a relatively higher frequency of data might be preferable to obtain a better forecast performance.

Chapter 2. U.S. Monetary Aggregates and Partisan Political Cycles

2.1 Introduction

There is a striking phenomenon in U.S. political-economy cycles. The U.S. economy (Blinder and Watson, 2016) and stock markets (Santa-Clara and Valkanov, 2003; Pastor and Veronesi, 2017) perform significantly better under Democrat presidencies than Republican presidencies. Although, these empirical findings are strong enough to be able to argue that the U.S. economy favours the Democratic Party, the theoretical implications of the U.S. partisan political cycles are less consistent with these findings. Tax reductions, deregulation and overall right-wing based economic policy should produce growth and therefore favoured the Republican Presidencies, given they are direct signals for less government interventions in the economy. Despite several attempts (Santa-Clara and Valkanov, 2003; Pastor and Veronesi, 2017; Blinder and Watson, 2016; Sy and Zaman, 2011) to suggest explanations for the partisan gap, the phenomenon is still considered as a puzzle. The partisan gap is associated with the findings that the observed significant return differences of stock markets, economic indicators under different political regimes in the U.S. that cannot be explained by rational factors.

In this study, we explore the potential partisan gap in monetary aggregates. To our best of knowledge, it is the first study investigating a potential partisan gap in the monetary aggregates. Plenty of empirical and theoretical literature[2] has suggested significant linkages between economic activity, especially real output, and business cycle related monetary aggregates. As the "partisan" model of the political business cycles supports the idea that real output may

[2] For instance, Freeman and Kydland (2000) found positive linkages between the U.S business cycles variables and monetary aggregates. Beenstock (1989) expressed the similar findings between real output and money multiplier in the UK case.

become significantly different under the Democrat and the Republican presidencies, we might expect the money base, M1 and money multiplier may also be in line with the partisan cycles.

Monetary aggregates can also be linked to political cycles via well-documented partisan gap in stock returns. The U.S partisan gap in stock returns is documented by multiple studies (Santa-Clara and Valkanov, 2003; Sy and Zaman, 2011; Pastor and Veronesi, 2017). In the meantime, Thorbecke (1997) shows a positive linkage between ex-post stock returns and monetary policy. Furthermore, this linkage might be asymmetric as monetary policy has larger effects on stock returns in bear markets than bull market (Chen, 2007). Since, there is a strong evidence for the partisan gap in stock returns, the relationship between monetary policy and stock returns gives an additional stimulus to investigate the hypothesis that monetary aggregates might be also in line with presidential cycles.

The partisan gap in the economy is a specific U.S. phenomenon as there is no evidence to support the puzzle elsewhere. Although the Conservative party positively influence the U.K. stock market performance, the return differences are not significantly associated with changing political cycles (Black et al., 2010). Similar findings are attributed to the German elections (Dobke and Pierdrioch, 2004). In the meantime, panel regression analysis across 15 countries confirms that the partisan political gap in the economy is not a global finding (Bohl and Gottschalk, 2006). We might explain it with the real partisan nature of the U.S. political system. Hence, we examine U.S. monetary aggregates to explore other evidence for the partisan political gap.

Given these findings, it is a surprising fact that monetary aggregates as such important components of business cycles never get attention in the presidential puzzle literature. In particular, huge growth rates are historically observed in the U.S. monetary aggregates. Traditional explanations such as economic output, lagged effects might not be enough to fully capture the huge growth rates of the money supply. Considering significant linkages between monetary aggregates and other economic indicators (stock returns, GDP growth) which are found to have a partisan gap, it is worthwhile to explore a similar phenomenon in monetary aggregates. As a null hypothesis, the partisan gap in the growth rates of the U.S. monetary aggregates is statistically insignificant. In the meantime, if the growth rates of the monetary aggregates are significantly influenced by only its previously explored determinants (lagged values, monetary policy), the partisan gap should become insignificant after controlling for them.

There might be concern about the aim of this study that would potentially question the concept of Central Bank independence. Of course, the Federal Reserve System (hereafter, Fed) operational independence was granted within the famous Treasury-Fed accord of 1951. However, historically, there have been several attempts such as Arthur Burn[3]'s contribution to the Richard Nixon re-election campaign (Abrams, 2006) and Reagan's efforts to remove Paul Volcker (Silber, 2012) that could be argued to be political interventions in monetary policy. Moreover, given presidents have a mandate to appoint the Fed chairperson, this raises concern regarding the extent of institutional independence. The most recent example would be President Trump's appointment of a Republican board member as Fed governor violating the general practice[4] that Presidents usually allow the continuation of the current Fed governor to demonstrate the Fed's institutional independence. The Fed, as any monetary organization, aims to maintain price stability by tracking the equilibrium point of output and inflation in a Taylor framework. As monetary organizations are mainly ex-post decision makers in the economy,

[3] The FED chairman during 1970s

[4] https://www.federalreserve.gov/aboutthefed/bios/board/boardmembership.htm For example, William McChesney Martin was appointed by five different presidents, Alan Greenspan was appointed by four different presidents

Central Bank's independence should be thought as operational independence but not determining the economic outlook of the country which is carried out by governments.

Our monthly empirical estimations from 01/1959 to 09/2017 reveal that the presidential gap in narrow and broad money indicators are even more pronounced than GDP growth and stock market performance, but less notable in the case of money multiplier. The Democratic premium is found to be 5.15 percent and 9.12 percent for the M1 and M2 growth rates, respectively. However, and strikingly we did not find evidence for an economically stronger presidential gap after considering only first presidential terms. It might be explained by the fact that unlike stock markets, monetary aggregates may take more time to digest the information effect of changing a political party.

Afterwards, we estimate several models to check if previously explored determinants[5] of monetary aggregates eliminate the statistical significance of the partisan gap. We start with linear models by jointly estimating determinants of the U.S. monetary aggregates with the partisan gap as an additive dummy. From Autoregressive Distributed Lag (ARDL) model, we find that although contemporaneous and lagged values of the growth rates of monetary aggregates and monetary policy (proxied by the Federal Funds rate) keep the explanatory powers in the variation of the monetary aggregates growth rates, the partisan gap remains statistically significant and economically meaningful. For the first time in the literature, we estimate the effect of the partisan gap in the U.S. monetary aggregates using non-linear estimation. The findings in the Markov switching model are found to be line with the findings of the linear regression analysis. High growth rates of the monetary aggregates associated with

[5] Such as lagged growth rates of monetary aggregates, monetary policy. See for example Freeman and Kydland (2000) and Beenstock (1989)

the Democratic presidential years and low growth rates linked to the Republican presidencies tend to be persistent with more than 90 percent probability in their respective regimes.

Another interesting finding occurs after controlling for the partisan gap in the lagged values of the growth rates of the U.S. monetary aggregates. Apparently, the presidential gap is not only additive to the baseline growth of the monetary aggregates but also multiplicative in the coefficients. Moreover, the multiplicative partisan gap induces the additive partisan gap become less significant. However, this finding might be due to pure econometrical reasons as the multiplicative and additive dummies possibly have multi-collinear relationship.

Finally, we test the role of a partisan Fed chair to explain the presidential gap. First, we find that a statistically significant and economically meaningful partisan Fed chair gap is present in the growth rates of U.S. monetary aggregates. Second, we find that after controlling for the Fed chair gap, the statistical significance of the presidential gap diminishes and becomes insignificant. Finally, the results show that Fed chair gap in the growth rates of the US monetary aggregates remains statistically significant and economically meaningful even after controlling for autoregressive components of the growth rates and monetary policy. Consequently, we argue that the partisan FED cycle is a statistically more powerful than the partisan presidential cycles in the case of the monetary aggregates.

The rest of this chapter is organized as follows. The second section reviews the literature on the U.S. presidential cycles from an economic perspective and also discussed related works on monetary liquidity. In the third section, we present the data and the main empirical models to be applied in the estimations. The fourth section discusses the empirical findings and the additional checks for robustness. In the last section, we discuss the major findings and provide concluding remarks.

2.2 Literature review and theoretical underpinnings

2.2.1 The U.S. political economic cycles

The early literature on the economic models of political cycles, so called "political business cycle" theory describes the U.S. political cycles in the "opportunistic" models where all parties find it optimal to adopt the same policy in order to capture the median voter (Downs, 1957). In addition to the assumption of the opportunistic behaviour of the parties, Nordhaus (1975) and MacRae (1977) contributed two more crucial assumptions and rejected the "partisan" factor. First, they argue that the voters have short term memories and can be systematically fooled. Second, the economy is described by an exploitable Philips curve[6] and the rational expectations critique is not considered. Therefore, the opportunistic models of the "political business cycle" theory could not explain any differences across the Democratic and Republic administrations.

In contrast, originating with Hibbs (1977), the literature has developed "partisan" models of political cycles. Hibbs (1977) shows that lower income and occupational status groups are best served by a relatively low unemployment-high inflation macroeconomic configuration whereas a comparatively high unemployment-low inflation policy package serves the interests and preferences of upper income and occupational status groups. Therefore, the governments in the office pursue macroeconomic policies broadly in accordance with the objective economic interests and subjective preferences of their electoral elites and core political objectives. This pioneering attempt to modelling political business cycles in the context of partisan nature encouraged further researches to examine the structural differences between the political objectives in the macroeconomic policies of the main parties.

[6] An inverse relationship between unemployment rate and wage rises

In particular, Alesina (1987) and Alesina and Sachs (1988) develop a partisan economic model in a two party repeated game. By confirming Hibbs (1977) and Hibbs (1987), they find that partisan politics matters when it comes to the macroeconomic policy and its outcomes in the business cycles. Moreover, they show that the first half of the administration indicates significant differences in output growth whereas the second half does not show a consistent statistically significant difference between the macroeconomic outputs of the economic policies undertaken during the political cycles. Nevertheless, the Nixon (Beck, 1984) and Kennedy (Alesina, 1987) governments are considered exceptions in the "partisan" theory, more in line with the "political business cycle" theory due to political scandals and shorter span of the presidential terms, respectively.

Another striking feature of a partisan economic model originates from the differences in the tax policies. More left-wing governments' (i.e Democrats) periods in office have been marked by higher state tax burdens whereas right wing parties (i.e Republicans) are known as typically being in favour of low tax or small government principles (Reed, 2006). Moreover, left-wing governments across the world tend to expand government revenue and expenses (Cameron, 1978; Tavares, 2004. The US real GDP growth, during 1930 and 2015, is found to be 4.9% under Democratic presidencies, whereas only 1.7% during Republican presidents' periods in the office. The 3.2 % difference is found to be economically and statistically significant (Pastor and Veronesi, 2017).

The discussion above sheds light on the role of the US partisan gap in business cycles, macroeconomic policy, economic growth and the tax burden. The differences in the aspects of the political objectives, historical roots and more importantly, subjective preferences of the electoral crowd may underlie explanations for the existing partisan political economy gap.

Additionally, the partisan gap in the stock market returns remains a puzzle and unresolved despite of several attempts. In a seminal paper, Santa-Clara and Valkanov (2003) demonstrate that stock markets perform significantly better under Democratic rather than Republican presidencies during the period 1927 and 1998. The nine percent difference for the value-weighted portfolios and the sixteen percent difference for the equal-weighted portfolios are found to be statistically and economically significant. Moreover, business cycle variables, announcement effect, risk premium do not explain the return difference. An extended empirical analysis to 2015 by Pastor and Veronesi (2017) show that the evidence of partisan gap is even stronger. Their estimation from 1999 to 2015 reports 17.39 percent for the partisan return gap compared to 9.38 percent in the 1927-1998 period. A striking feature of the presidential stock return gap is its mean reverting characteristics. The Democratic-minus-Republic return gap is found the highest, 36.88 percent per year when averaged over the first year of presidency alone (Pastor and Veronesi, 2017). The gap gradually decreases starting from the second year when the difference is 15.55 percent; it is 12.43 percent over the three years. However, these values are still higher than full term average (10.90 percent) which might be explained by a higher risk premium earlier in the presidential term since there is more uncertainty on political and economic objectives of a new president.

2.2.2 Monetary liquidity

The definition of the monetary aggregates varies across countries and monetary organizations.

For instance, the European Central Bank (ECB) does use M0 but adopts M1 as a narrow money indicator which includes physical currency in circulation as well as balances such as overnight deposits that can immediately be converted to cash or cash equivalents[7]. The ECB defines M2

[7] https://www.ecb.europa.eu/stats/money_credit_banking/monetary_aggregates/html/hist_content.en.html

as “intermediate money” that includes M1 plus deposits with maturity up to 2 years and redeemable deposits up to 3 months. M3 is considered as a broad money measurement that comprises all M2 plus money market fund shares, repurchase agreements and debt securities up to 2 years. Note that the Bank of England[8] accepts the aggregates definitions of the ECB, additionally defines M4 as M3 plus foreign currency deposits held by the private sector in the UK and sterling and foreign currency deposits held by UK public corporations with Monetary Financial Institutions (MFI) in the UK.

US monetary aggregates definitions are slightly different from their European counterparts. Additionally, note that since 2006, the Federal Reserve System has ceased to track M3, large-denomination time deposits, repurchase agreements and Eurodollars. Narrow money is defined[9] as M1 which includes all physical currency outside the U.S Treasury and Federal Reserve, demand deposits and travellers' checks. In the meantime, M2 is accepted as a broader monetary concept encompassing M1 plus saving deposits, small denomination time deposits and balances in retail money market funds. Finally, the money multiplier is calculated as the ratio of M1 to money base which is the sum of currency in circulation plus reserve deposits. In other words, the money multiplier demonstrates how banks can create additional money in the economy by per unit reserve deposits in the Federal Reserve.

A handful of empirical macroeconomic papers have attempted to model money supply employing a wide range of time series models. Nelson (2002) develops a theoretical model of the real money base growth and the real economic activity. The empirical evidence for the UK and the US from 1961 to 1999 shows that the money base growth is a significant determinant of economic activity. As the “partisan” model of the political business cycles supports the idea that the economic activity may become significantly different under the Democrat and the

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[8] http://www.bankofengland.co.uk/statistics/Pages/iadb/notesiadb/m3.aspx

[9] https://fred.stlouisfed.org/series/M1SL

Republican presidencies, we can expect the money base may also be in line with the partisan cycles.

Apart from modelling monetary aggregates separately, Kurita (2011) attempted to model the money multiplier by employing co-integration analysis for the Bank of Japan data. It is a stylised fact that the log of monetary aggregates contains stochastic $I(2)$ trends. The paper shows that constructing linear combinations of logged monetary aggregates with linear combinations of logged prices indices can remove $I(2)$ stochastic trends and leave the data as $I(1)$. Consequently, the paper finds that the main monetary aggregates can be modelled in the light of the $I(2)\ to\ I(1)$ transformation on the money multiplier.

The endogenous nature of monetary aggregates has firstly been explored with the procyclical movement of the nominal money stock by Friedman and Schwartz (1963). Since then, the business cycle literature has attempted to model the money multiplier in the classical business cycle set-up (Freeman and Huffman, 1991) and to calibrate the money aggregates considering a long-run vision for the U.S. economy (Kydland and Prescott, 1982). In contrast to the monetary models, Freeman and Kydland (2000) develop a money-output model using sticky prices or fixed money holdings and assuming all prices and quantities are fully flexible. The paper finds several significant linkages between business-cycle related monetary aggregates and U.S. real output such as a positive correlation between M1 and real output. Additionally, the money multiplier and deposit-to-currency ratios are positively correlated with real output, whilst the price level is negatively correlated with output. Note that the correlation of M1 with contemporaneous prices is substantially weaker than the correlation of M1 with real output and these correlations among real variables are essentially unchanged under different monetary-policy regimes and real money balances are smoother than money-demand equations would predict.

The determinants of the money multiplier have also been explored for UK monetary data. Beenstock (1989) investigates evolutionary of monetary policy in the United Kingdom and concludes that monetary aggregates were endogenously determined until the mid-1970s when sterling was allowed to free float. Specifically, the free float regime of the exchange rate allowed the money supply to become exogenous starting in the 1980s. Consequently, the money multiplier has become more responsive to the interest rates and economic activity. Although, there is no investigation for the existence of the partisan business cycles in the United Kingdom, the findings of the paper provide additional motivation to consider the possible indirect linkages between the monetary aggregates and the political regimes via economic activity and output.

To sum up, monetary aggregates can be significantly different under different political regimes in the U.S. motivating by the economic activity and stock markets channels they are empirically proven to have partisan gap.

2.3 Data and Methodology

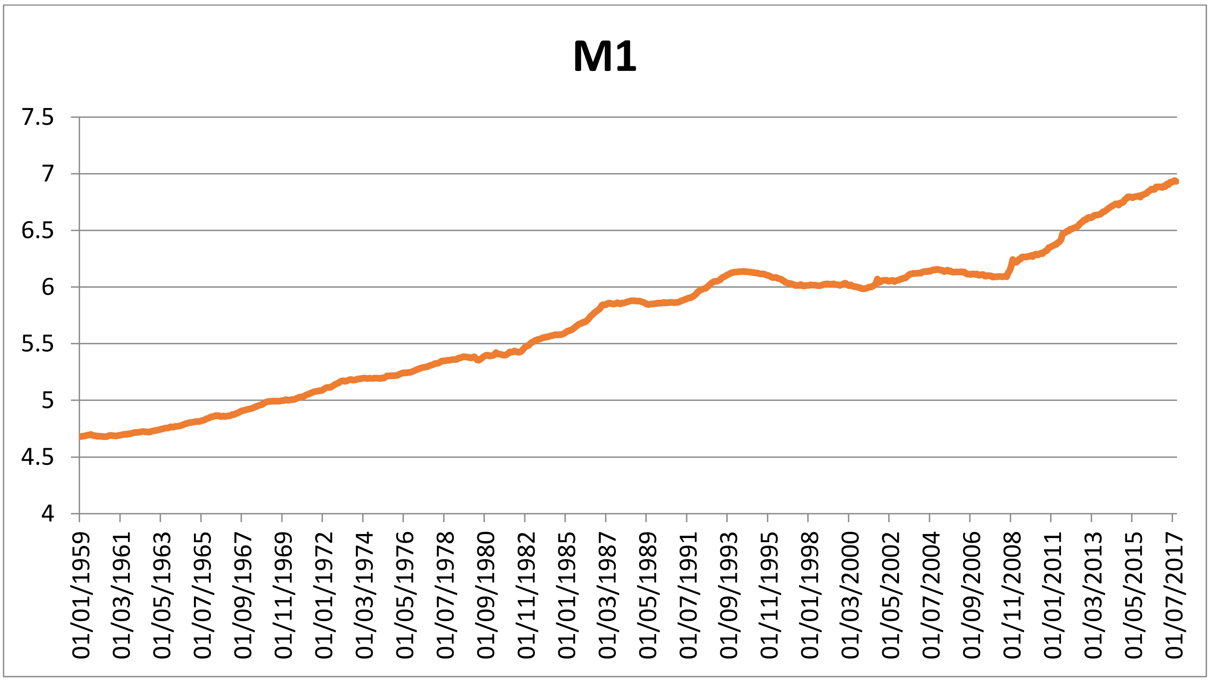
2.3.1 Data

Our monthly data set covering the period between 1959:01 and 2017:09 is available from the of Federal Reserve Bank of St. Louis (FRED). The official definitions of the U.S monetary aggregates have considerably changed over the years before our sample period. Since Federal mandatory reserve requirements were officially imposed in 1914, banks did not differentiate among demand, saving and time deposits (Anderson, 2003). Therefore, it is not possible differentiate between M1 and M2 until 1914 according to the modern definitions. Likewise, U.S. financial institutions did not distinguish between small and large denomination time deposits that are necessary to split M2 from the rest of “higher order” monetary liquidity. More importantly, the Board of Governors of the Federal Reserve System approved the monetary aggregates data from 01/1959, possibly due to the reasons emphasized above.

The first monetary aggregate we employ is M1 which is officially defined[10] as the sum of 1) currency outside the U.S. treasury, Federal Reserve Banks, the vaults of depository institutions 2) traveller's checks of nonbank issuers 3) demand deposits and 4) other checkable deposits.

Figure 2.1 presents the monthly M1 aggregate for the USA from 01/1959 to 09/2017. The seasonally adjusted data is collected from FRED. We subsequently adjusted it for monthly inflation which is available from FRED as Consumer Price Index (CPI) with all items, then take the log value.

FIGURE 2. 1 LOG OF THE U.S M1 INDICATOR ADJUSTED FOR SEASONALITY AND INFLATION



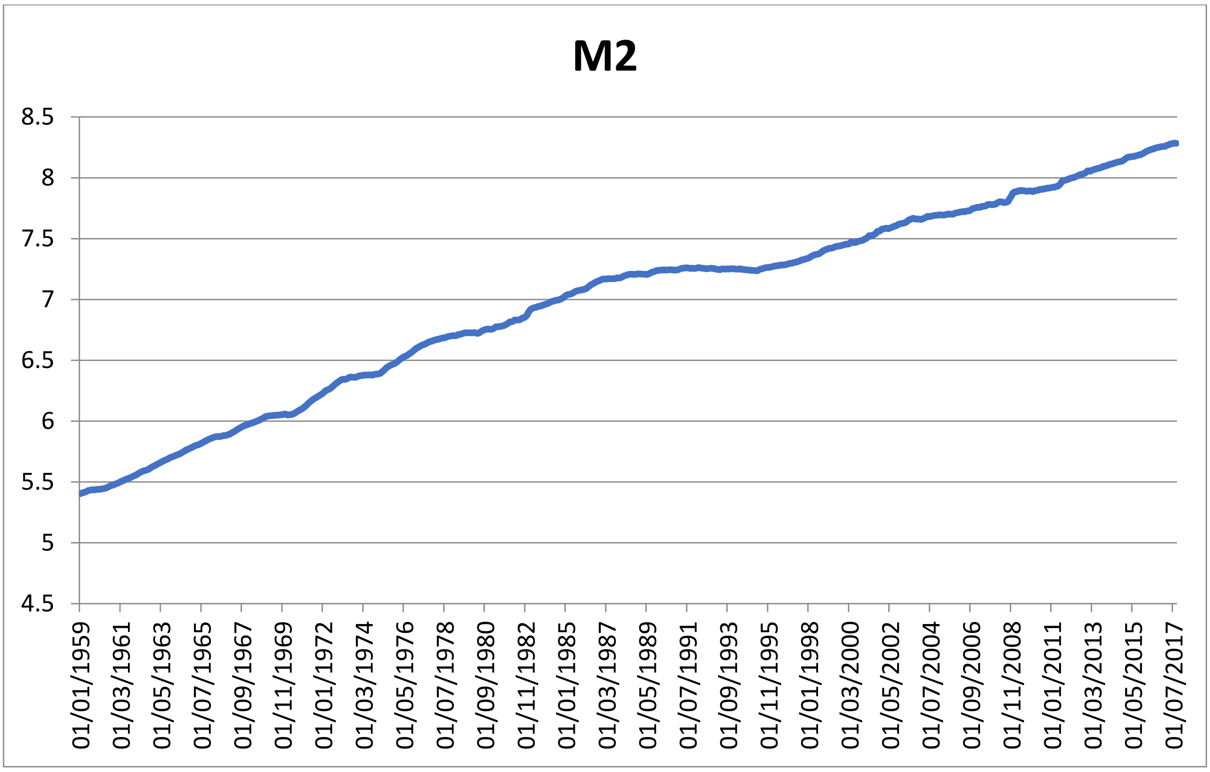
The graph overall suggests a gradual increase in the M1 amount in real terms throughout the sample period. The small fluctuations and the levelling of the trends during the 1990s and 2000s are followed by a sharper increase during the recent years. The latest trend might be

[10] https://fred.stlouisfed.org/series/M1SL

explained by the recent FED interest rate policy which remained historically low since last financial crises due to the fact that expansionary monetary policy increases money circulation in the financial system. The second monetary aggregate we use is U.S. M2 which is officially defined[11] as the sum of all the M1 components, saving deposits, small-denomination time deposits and balances in retail money market mutual funds.

Figure 2.2 demonstrates the monthly U.S. M2 aggregate from 01/1959 to 09/2017. The seasonally adjusted data is collected from FRED and adjusted for the monthly inflation by using Consumer Price Index (all items).

FIGURE 2. 2 LOG OF THE U.S M2 INDICATOR ADJUSTED FOR SEASONALITY AND INFLATION



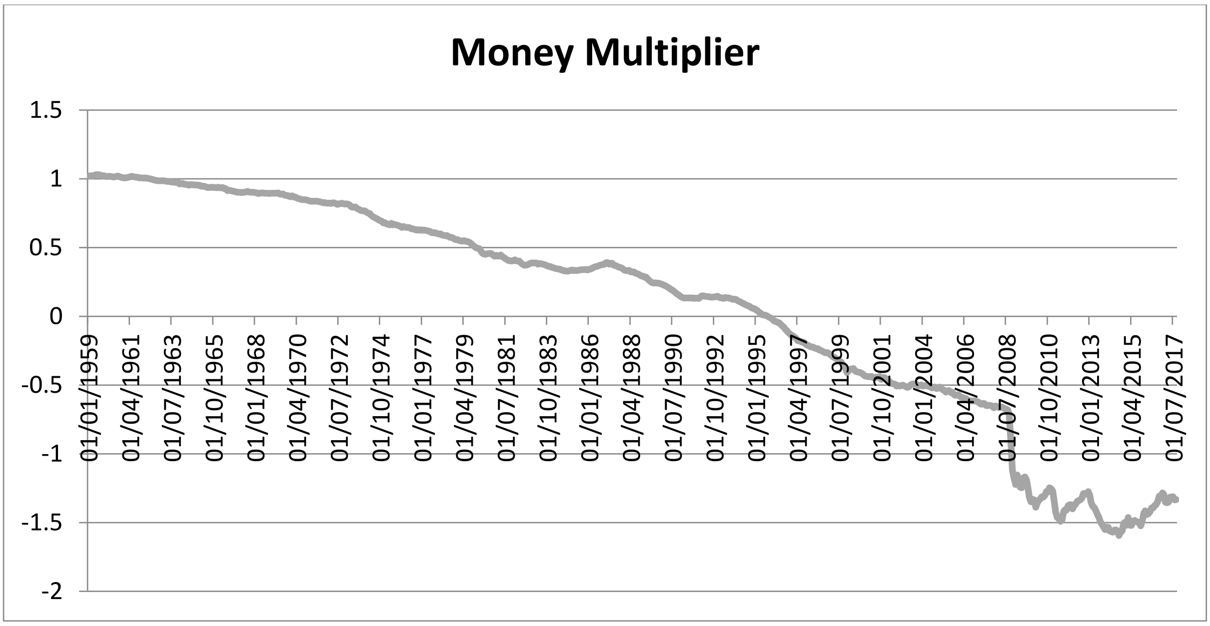
The graph suggests a similar pattern to M1 but with a sharper increase in the M2 amount across the entire sample period. The difference between Figures 2.2 and 2.1 suggests a considerable increase in the saving and small-time deposits and the balances of money market funds after

[11] https://fred.stlouisfed.org/series/M2SL

carrying out the quantitative easing and expansionary monetary policy actions during the 2008/2009 crisis.

The final indicator, we employ is the U.S money multiplier computed as the ratio of M1 to the U.S. monetary base. The ratio literally demonstrates how banks can create additional money in the economy by per unit reserve deposits in the Federal Reserve. The seasonally adjusted monthly data from 01/1959 to 09/2017 for the U.S. money base is collected from FRED[12] , subsequently adjusted for inflation as in the previous aggregates. To get money multiplier, we find the ratio of the previously adjusted M1 to the adjusted monetary base.

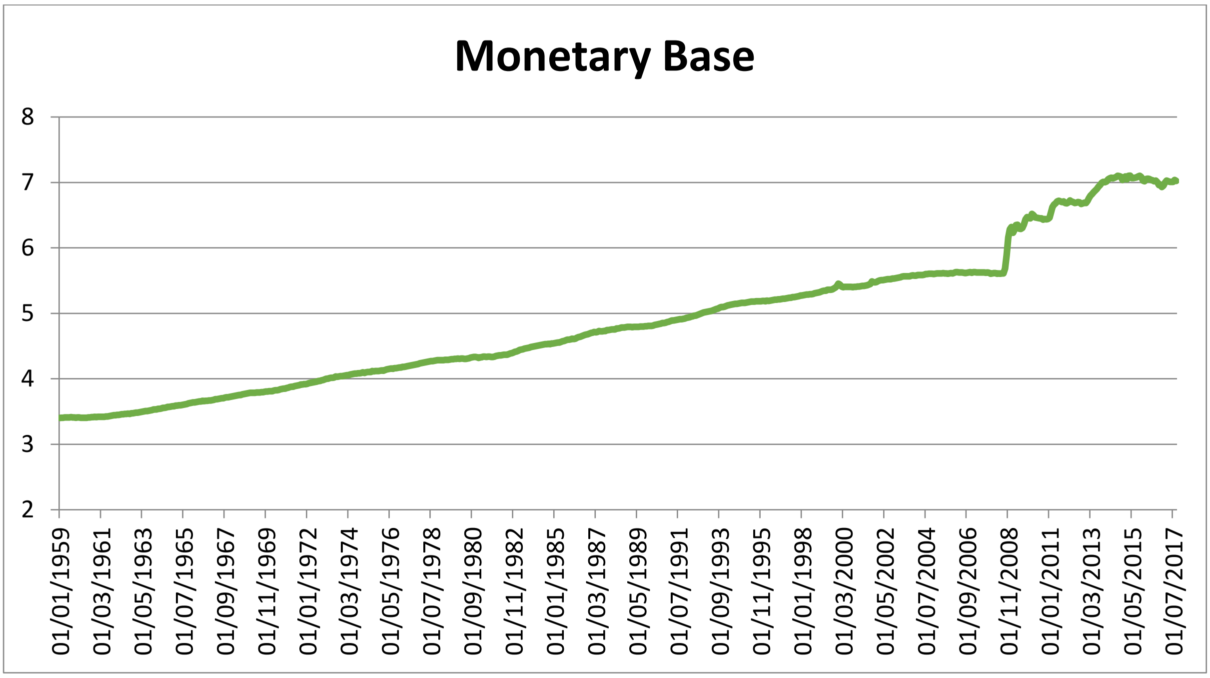
FIGURE 2. 3 LOG OF THE U.S MONEY MULTIPLIER ADJUSTED FOR SEASONALITY AND INFLATION



On the contrary to the M1 and M2 graphs, the money multiplier in Figure 2.3 exhibits a downward trend throughout the observed time frame. The graph suggests that the banks created less money on the economy per unit of reserved deposits in the Federal Reserve year by year since 1959.

12 https://fred.stlouisfed.org/series/AMBSL

FIGURE 2. 4 LOG OF THE U.S MONEY BASE ADJUSTED FOR SEASONALITY AND INFLATION



Considering the fact that M1 (Figure 2.1) exhibits an upward trend throughout the period, the downward pattern in the U.S money multiplier might be explained by an explosively increasing monetary base. Figure 2.4 confirms this supposition, as the increasing trend in the money base amount starting 2000s years, is followed by an explosive growth since last financial crisis. On the other hand, the considerable increase in the monetary base might be linked to the increased regulatory pressure on the banks since financial crises including "Dodd-Frank", the implementation the new Basel rules and so on.

Table 2.1 presents the summary statistics of the underlying U.S monetary aggregates across the presidential cycles. In our estimation period, Republicans have more presidents with seven compared to the Democrats with five presidents. In general, Republicans have been in the office for 369 months compared to 348 months of Democrats. The new elected president usually starts governing the White House after the inauguration day which takes place about 2-3 months after the election day. The U.S presidential elections usually take place in

November followed by the inauguration day in January. However, the certain historical events contributed to the breaking of this chain such as John F. Kennedy's assassination of in November 1963 and Richard Nixon's resignation in August 1974.

Although, the political science literature (e.g Bartels, 2008; Comiskey and Marsh, 2012) frequently prefers to adopt one year lag or more to estimate the effect of changing political parties, we apply the most recent approach (Pastor and Veronesi, 2017) from the political economy literature which attributes the inauguration day as the beginning of each presidential term. The rationale behind this approach is to take the fact into account that the partisan political gap of the economic and financial indicators is found to be more robust in the first year of each presidency (Pastor and Veronesi, 2017). Nevertheless, we carry out the robustness checks to examine several other lagged responses.

Continuing with Table 2.1, the monetary aggregates, in growth terms, are observed with a higher magnitude under the Republican presidencies (3.95% and 5.16% p.a for M1 and M2, respectively) than the Democrat presidencies (3.35% and 4.93% p.a for M1 and M2, respectively) which are associated with lower growth rate of the monetary aggregates, albeit almost the same standard deviations. Mr. Obama's presidential terms are observed with relatively higher growth rates of the monetary aggregates. Mr. Obama's presidential terms started in the peak of finacial crisis in January 2009, although he was elected in November 2008 and heightened public expectations[13] that his government was likely going to adopt an expansionary fiscal policy.

Although, the Federal Reserve System started to decrease the fund rate from the end of 2007, the transmission was either delayed or less noticeable. Fed subsequently accompanied the

[13] It is specifically about Obama's government but in general, left-wing government. Nevertheless, liberal economists (e.g see Krugman (2009)) had higher expectations from Obama's government.

expansionary monetary policy in 2008 by decreasing the fund rate six times and reached to *de-facto* zero rates[14]. From an econometric perspective, the lagged responses of the monetary aggregates to the monetary shocks absolutely make sense. Since most of the monetary shocks materialized under Obama's presidency, the monetary aggregates expose high volatility. A complementary note that in November 2008, the Federal Reserve Open Market Committee launched the first quantitative easing package and announced it would purchase up $600 billion agency mortgage-backed securities and agency debt. The decision was made two months before the Obama's inauguration day. Consequently, the combined effect of the monetary policy shocks and the quantitative easing package contributed to the high volatility of the monetary aggregates during the Obama's presidential terms in the White House.

[14] https://www.federalreserve.gov/monetarypolicy/historical-approaches-to-monetary-policy.htm

TABLE 2. 1 THE GROWTH RATES OF THE MONETARY AGGREGATES ACROSS THE U.S PRESIDENTIAL CYCLES

Notes: *The figures are adjusted for seasonality and consumer price index. Column 2 shows the official presidential terms. Following (Pastor and Veronesi, 2017), we adopt the inauguration day as the beginning of each presidential term. Although, Eisenhower's office period started in 1953, we do not count his presidential term until 01/1959 when the data set starts to cover. The disruptions of the presidential terms are linked to the certain political events such Kennedy's assassination in 11/1963 and Nixon's resignation in 08/1974.*

President (Party)	Period in office	M1		M2		Money Multiplier	
		Mean	Standard Dev.	Mean	Standard Dev.	Mean	Standard Dev.
Panel A. By President							
Dwight Eisenhower (R)	01/1959-01/1961	1.47	4.11	5.27	2.75	-0.017	0.0091
John F. Kennedy (D)	02/1961-11/1963	2.75	2.45	6.54	1.35	-0.044	0.0078
Lyndon B. Johnson (D)	12/1963-01/1969	4.28	4.21	4.55	2.51	-0.033	0.0079
Richard M. Nixon (R)	02/1969-07/1974	3.81	4.33	6.24	5.28	-0.066	0.0092
Gerald R. Ford (R)	08/1974-01/1977	1.98	4.23	8.76	4.63	-0.063	0.0096
James E. Carter (D)	02/1977-01/1981	3.10	6.48	3.92	3.37	-0.082	0.0081
Ronald W. Reagan (R)	02/1981-01/1989	6.04	7.56	5.71	5.06	-0.027	0.0074
George H.W. Bush (R)	02/1989-01/1993	4.47	6.61	0.93	3.08	-0.046	0.0059
William J. Clinton (D)	02/1993-01/2001	-0.79	6.15	2.09	3.62	-0.063	0.0046
George W. Bush (R)	02/2001-01/2009	3.15	14.19	4.84	6.39	-0.041	0.0125
Barack H. Obama (D)	02/2009-01/2017	8.42	11.15	7.72	4.61	-0.007	0.0076
Donald J. Trump (R)	02/2017-09/2017	5.96	14.91	3.76	3.65	-0.009	0.0045
Panel B. By Party							
Political party	**Total months in office**	**M1**		**M2**		**Money Multiplier**	
		Mean	Standard Dev.	Mean	Standard Dev.	Mean	Standard Dev.
Republicans	370	3.95	7.99	5.16	4.41	-0.038	0.0083
Democrats	335	3.35	6.09	4.93	3.09	-0.046	0.0051

Table 2.2 presents the results of unit root tests for the log of the U.S monetary aggregates across the sample period. We employ three different, widely applied unit root tests. Augmented Dickey Fuller (ADF) and Philips Perron (PP) tests are performed under the null hypothesis that the series contains a unit root against the alternative that the series are stationary. The PP test is the modified version of the ADF test as it accounts for the serial correlation in the innovations. Conversely, KPSS test assumes that the observed time series are stationary around the deterministic trend (i.e trend stationary) against the alternative of a unit root.

The results from the three tests demonstrate that the U.S monetary aggregates contain a unit root throughout the sample period. Apparently, we fail to reject the ADF and PP tests under the null hypothesis that the series follow a unit root process. Meanwhile, the null hypothesis that the series are stationary around the deterministic trend is significantly rejected with KPSS test. It is also revealed the first differences (i.e growth rates) of the underlying monetary aggregates are stationary. Concluding from the respective p values, the null hypothesis that the first differences are unit root processes are significantly rejected under the ADF and PP tests whereas fails to reject the null hypothesis of the stationarity for the KPSS test.

TABLE 2. 2 UNIT ROOT TEST FOR THE U.S. MONETARY AGGREGATES

Notes: *The series are converted into the natural logarithm values before carrying out the unit root tests. By definition, the null hypothesis of ADF and Philips Perron test are imposed as the series contain unit root whereas KPSS test assumes series are stationary under the null hypothesis.*

	ADF test; H_0: Series contain unit root		
	M1	**M2**	**Money Multiplier**
	P value		
Level	0.97	0.99	0.64
First difference	0.00	0.00	0.00
	KPSS test; H_0: Series are stationary		
	M1	**M2**	**Money Multiplier**
	P value		
Level	0.01	0.00	0.00
First difference	0.65	0.64	0.73
	Philips-Perron test; H_0: Series contain unit root		
	M1	**M2**	**Money Multiplier**
	P value		
Level	0.99	0.99	0.73
First difference	0.00	0.00	0.00

2.3.2 Methodology

We start our empirical estimations with linear models which were previously employed in exploring other areas of the partisan gap in economics and finance. To build the baseline models, we define our political variable as π_t following Santa-Clara and Valkanov (2003) and run the following regression:

$$\Delta lny_t = \alpha + \beta\pi_t + u_t \tag{2.1}$$

Where the left-hand side variable is log growth rate of the underlying monetary aggregate and π_t is the political variable included as an additive dummy indicate the Republican presidencies as 1, alternatively 0 for the Democratic presidents. Alternatively defining:

$RD_t = 1$ if a Republican is in office at time t; $RD_t = 0$ otherwise

and

$DD_t = 1$ if a Democrat is in office at time t; $DD_t = 0$ otherwise

Then regression (2.1) can also be estimated as with two dummies (and without intercept) as in Santa-Clara and Valkanov (2003):

$$\Delta lny_t = \alpha_1 RD_t + \alpha_2 DD_t + u_t \tag{2.2}$$

The lagged coefficients are shown to be the main explanatory variables for monetary aggregates growth rates (Nelson, 2003). Therefore, in the second step, we allow the autoregressive components in the equation (2.1) to examine the ability to eliminate the significance of the partisan gap:

$$\Delta lny_t = \mu_t + \sum_{i=1}^{p} \rho_i \Delta lny_{t-i} + \beta\pi_t + u_t \tag{2.3}$$

Following Blinder and Watson (2016), we choose the optimal number of lags for the autoregressive component based on SBIC information criteria due to the fact AIC inherently choose a higher order model that is not necessary in this study.

In previous equations, we assess the relation between growth rates of the underlying monetary aggregates and two political regimes. Following Sy and Zaman (2011), we next allow the coefficients of the autoregressive components change across the presidential cycles, so called multiplicative dummies given as follows:

$$\Delta lny_t = \mu_t + \sum_{i=1}^{p}(\rho_i + \pi_t)\Delta lny_{t-i} + \beta\pi_t + u_t \tag{2.4}$$

Where $(\rho_i + \pi_t)$ implies that, the coefficients of lagged growth rates of monetary aggregates can be different under different political regimes.

Monetary policy decisions are considered an important determination of monetary aggregates. Hence, we control for the federal funds rate by augmenting the equation (2.3). Specifically, following Blinder and Watson (2016), we estimate the model based on the Autoregressive Distributed Lag Specification given by:

$$\Delta lny_t = \mu_t + \sum_{i=1}^{p}\rho_i\Delta lny_{t-i} + \sum_{j=0}^{q}\varphi_j\Delta lni_{t-j} + \beta\pi_t + u_t \tag{2.5}$$

where i is the federal funds rate defined[15] as the interest rate at which depository institutions trade federal funds with each other overnight.

For the first time in the literature, we employ non-linear Markov Switching models to provide further evidence. Since the White House has been governed by only the Republicans and the Democrats parties, switching models can be applied to model US monetary liquidity in two political regimes. Non-linear time series models allow underlying variable(s) change under the

[15] https://fred.stlouisfed.org/series/FEDFUNDS

existence of different regimes, so called state-dependent models (Gonzalez-Rivera and Hwy Lee, 2008). In spite of the large number of non-linear models in econometric literature, Hamilton (1989, 1990) and Tong (1983, 1990) are considered as two widely applied models in financial time series (Brooks, 2014).

Markov switching model

The first class of non-linear model we employ is the Markov switching model with two separate regimes. We denote the republican presidencies in White House as *"republican regime" (regime 1)* and the democrat presidencies in office as *"democrat regime"* (*regime 2*) Under Markov switching models, underlying monetary liquidity variables y_t switches regime according to some unobserved state variables s_t , takes two values. In other words, when s_t is equal 1, we will observe pattern of the US monetary liquidity in *regime 1, "republican regimes",* otherwise $\mathrm{s_t}$ takes value 2, the dependent variables will be observed in *regime 2, "democrat regime"*. The model assumes the movements of the state variable between regimes are governed by a Markov process which can be expressed as

$$P[a < y_t \leq b | y_1, y_2, \dots, y_{t-1}] = P[a < y_t \leq b | y_{t-1}] \tag{2.6}$$

The equation states that the probability distribution of the state at any time t depends only on the state at time $t-1$ not on the states that were passed through at times $t-2, t-3, ..$ Therefore, Markov process are not path dependent (Brooks, 2014).

In a two-regime model, Hamilton (1989) defines an unobserved, latent state variable denoted as z_t evaluated in the first order Markov process

$$prob[z_t = 1 | z_{t-1} = 1] = p_{11} \tag{2.7}$$

$$prob[z_t = 2 | z_{t-1} = 1] = 1 - p_{11} \tag{2.8}$$

$$prob[z_t = 2|z_{t-1} = 2] = p_{22} \quad (2.9)$$

$$prob[z_t = 1|z_{t-1} = 2] = 1 - p_{22} \quad (2.10)$$

Where p_{11} and p_{22} denote the probability in regime one, given that the system was in regime one during the previous period and the probability of being in regime two, given that the system was in regime two during the previous period, respectively. Accordingly, $1 - p_{11}$ defines the probability that y_t will change from state one in the period $t - 1$, to state two in the period t and $1 - p_{22}$ defines the probability of a shift from state two to state 1 between times $t - 1$ and t. Based on this specification, z_t evolves as an AR (1) process

$$z_t = (1 - p_{11}) + \rho z_{t-1} + \vartheta_t \quad (2.11)$$

Where $\rho = p_{11} + p_{22} - 1$. In our case, assuming the US monetary aggregates follow a Markov process, to forecast the probability in a given regime during the next period, we have to find out the current period probability and a set of transition probabilities given for the case of "republican regime" and "democrat regime".

To get a univariate Markov switching model, we use an autoregressive p order process for the underlying monetary aggregates y_t which can be specified as follows:

$$y_t = \mu_{s_t} + \sum_{i=1}^{p} \rho_{i,s_{t-i}} y_{t-i} + \sigma_{s_t} \varepsilon_t \quad (2.12)$$

Where the parameters in the regression (2.2) can be defined as:

$$\mu_{S_t} = \mu_1(1 - S_t) + \mu_2 S_t = \mu_1 + (\mu_2 - \mu_1) \quad (2.13)$$

$$\rho_{i,S_{t-i}} = \rho_{i,0}(1 - S_{t-i}) + \rho_{i,1} S_{t-i} = \rho_{i,0} + \left(\rho_{i,1} - \rho_{i,0}\right) S_{t-i} \quad (2.14)$$

$$\sigma_{S_t} = \sigma_0(1 - S_t) + \sigma_1 S_t = \sigma_0 \left(1 + \frac{(\sigma_1 - \sigma_0)}{\sigma_0} S_t\right) = \sigma_0(1 + hS_t) \quad (2.15)$$

Where $\mu_{S_t}$is the regression constant that defines μ_1 and μ_2 as the regression means for the *"republican regime"* and *"democrat regime"*, respectively; $\rho_{i,S_{t-i}}$ is the slope coefficient for the i^{th} order regression term; σ_{S_t} is the standard deviation; ε_t is a zero mean and unit variance shock; S_t is the Markov switching variable takes value 0 at the *"republican regime"* and value 1 for the *"democrat regime"*. The transition probabilities are assumed to be time-invariant and constant over time.

TABLE 2. 3 THE U.S. MONETARY AGGREGATES ACROSS THE PRESIDENTIAL CYCLES

***Notes**: The table reports the empirical results based on the following regressions:*

$$\Delta lny_t = \alpha + \beta\pi_t + u_t$$

$$\Delta lny_t = \alpha_1 RD_t + \alpha_2 DD_t + u_t$$

*All the data covers the period from 1959:01 to 2017:09. The growth rates of the monetary aggregates are annualized by multiplying the monthly growth rates by 12. The numbers in the parentheses below the coefficients of "RD" and "DD" dummies represent p values under the null hypothesis that the estimated growth rates are not significantly different from zero. The p values of the tests are calculated using Newey-West (1987) heteroskedasticity and serial-correlation robust t-statistics following Santa-Clara and Valkanov (2003). The p values under the coefficients in the "Diff" column is also obtained from Newey-West test indicating the null hypothesis that the monetary aggregates growth rates across the democrat and the republican presidencies are not significantly different from each other. The row "T/Republicans" indicates the number of observations and the number of the months that republican presidents are in the office throughout the sample period. The $\bar{R}^2$ row displays the average adjusted R^2 during full sample and the first four years. The symbols *, **, *** are used indicate the statistical significance at 10%, 5% and 1% significance levels, respectively.*

Monetary Aggregates	**Full Sample**			**First Terms**		
	RD	*DD*	*Diff*	*RD*	*DD*	*Diff*
M1	13.19*** (0.00)	18.34*** (0.00)	-5.15*** (0.00)	13.56*** (0.00)	13.37*** (0.00)	0.19* (0.07)
M2	59.28*** (0.00)	68.4*** (0.00)	-9.12*** (0.00)	53.18*** (0.00)	40.32*** (0.00)	12.85** (0.03)
MM	-0.036*** (0.00)	-0.042*** (0.00)	-0.01* (0.10)	-0.036*** (0.00)	-0.056*** (0.00)	0.0198** (0.03)
T/Republicans	705/370			435/255		
$\bar{R}^2$	0.03			0.01		

2.4 Empirical Results

We start with the significance of the correlation test between U.S monetary aggregates and political cycles by using an additive dummy variable which represents political parties in the USA. After estimating regression (2.2), we re-estimate the monetary aggregates across the political parties based on the equation (2.1) for the full sample period. Subsequently, we eliminate the second presidential terms from the data to examine the previous empirical findings that the partisan gap in the economic variables might be much stronger while considering only the first four years[16] in the office rather than full presidential period (Blinder and Watson, 2016).

Table 2.3 reports the significance of the correlation between growth rates of the underlying U.S monetary aggregates and the additive dummy variable indicating two political parties in the repeated manner. We conduct regression (2.1) and regression (2.2) across the full sample and only first four years of the presidential periods, accordingly. During the full sample period, from 1959:01 to 2017:09, real growth rate of the U.S narrow money aggregate (i.e M1) is on average 18.34 percent per year under the Democratic presidencies versus 13.19 percent under the Republican presidential terms in the office. The Democratic partisan gap amounting 5.15 percent is found to be statistically and economically significant. Likewise, real growth rate of the broader money aggregate considered as M2 is found on average 68.4 percent per year under the Democratic presidencies whereas 59.28 percent during the Republicans' office periods. The suggested 9.12 percent Democratic partisan gap is found even more economically meaningful than M1 aggregate. We can observe similar findings for the money multiplier, albeit the growth difference across the political cycles appears less significant.

[16] Even more robust in the first years

Surprisingly, the partisan gap in the monetary aggregates during the first presidential terms is found exactly opposite to the results of the full sample period. The growth rates of the underlying monetary aggregates are found to be more favourable under the Republican president in the office than the Democratic presidencies. The growth differences of the money aggregates are found to be statistically significant, albeit less economically notable. This finding is contrary to what Blinder and Watson (2016) found for the partisan gap in economic output.

TABLE 2. 4 MONETARY AGGREGATES CONTROLLED BY AUTOREGRESSIVE COMPONENTS

***Notes**: The table represents the statistical results based on the following regression:*

$$\Delta lny_t = \mu_t + \sum_{i=1}^{p} \rho_i \Delta lny_{t-i} + \beta\pi_t + u_t$$

*All the data covers the period from 1959:01 to 2017:09. The optimal lag length is chosen with SIC information criteria which determines two lags for the M1 and M2 equations, while only AR(1) component for the MM equation. In the table, ρ_1 and ρ_2 indicate the coefficients of AR (1) and AR (2) components, respectively. The political variable is measured by π_t which indicates 1 if a Republican president is in the office, otherwise 0 if a Democrat president is in the office. Under the null hypothesis, the political variable should not be significantly different from zero. The numbers in the parentheses shows the p values to present the statistical significance of the coefficients. The p values of the tests are calculated using Newey-West (1987) heteroskedasticity and serial-correlation robust t-statistics. The regression performance is given by $\overline{R^2}$ in last column. The symbols *, **, *** are used indicate the statistical significance at 10%, 5% and 1% significance levels, respectively.*

	μ_t	ρ_1	ρ_2	π	$\overline{R^2}$
M1	0.96***	0.11***	0.27***	-0.29***	0.21
	(0.00)	(0.00)	(0.00)	(0.00)	
M2	2.21***	0.47***	0.14***	-0.35***	0.41
	(0.00)	(0.00)	(0.00)	(0.00)	
MM	-0.003***	0.27***	-	-0.001*	0.15
	(0.00)	(0.00)		(0.09)	

Table 2.4 presents the statistical results of the estimating equation (2.3) which allows autoregressive components in assessing the presidential gap in the growth rates of monetary aggregates. The number of AR lags is determined with SIC criteria which allow two lags for

the M1 and M2 equations, while only one lag for the MM equation. The maximum number of lags is chosen based on the frequency of the data (i.e if it is monthly, then 12) following the rule of thumb.

As one might expect the AR lags are found to be positive and highly significant at the 1 percent level. However, it does not eliminate the significance of the political variable. The additive dummy indicating the presidential parties is still significant for all three equations albeit less economically noticeable for the MM equation. The positive Democratic gap (or negative Republican) in the growth of the monetary aggregates remains significant after controlling for the lagged growth rates as explanatory variables.

In the previous estimations, we measured the presidential gap in the monetary aggregates growth rates by only additive dummy. Table 2.5 reports the empirical results based on the equation (2.4) which allows the coefficients of AR lags change across the presidential parties by simultaneously enabling the previously estimated additive dummy. The table exhibits interesting findings. The coefficients of the multiplicative dummies, as expected, are negative indicating the positive democratic gap (or negative republican gap) in the coefficients of AR lags and statistically significant in the all three equations. Moreover, after controlling for the multiplicative dummies, the additive dummies become less significant, albeit still economically meaningful.

One the one hand, this finding might be explained by the relative explanatory power of multiplicative political variable over the additive political dummy. On the other hand, however, it can be due to the merely econometrical reasons. We controlled both political variables in the same equation which may potentially increase the chance of the existence of the multicollinearity problem in the regression, even if R^2 value deliberately increases.

Nevertheless, the additive political variables for the M1 and M2 equations are still significant at 10 percent and 5 percent levels, respectively whereas insignificant in the MM equation.

TABLE 2. 5 MONETARY AGGREGATES WITH CONTROLLED BY AUTOREGRESSIVE COMPONENTS AND MULTIPLICATIVE POLITICAL DUMMIES

***Notes**: The table represents the statistical results based on the following regression:*

$$\Delta lny_t = \mu_t + \sum_{i=1}^{p}(\rho_i + \pi_t)\Delta lny_{t-i} + \beta\pi_t + u_t$$

*All the data covers the period from 1959:01 to 2017:09. The optimal lag length is chosen with SIC information criteria which determines two lags for the M1 and M2 equations, while only AR(1) component for the MM equation. In the equation, ρ_1 and ρ_2 indicate the coefficients of AR (1) and AR (2) components, respectively. The political variable is measured by π_t, an additive dummy variable which indicates 1 if a Republican president is in the office, otherwise 0 if a Democrat president is in the office. In the meantime, multiplicative dummies are added to the AR coefficients to measure the changes in the coefficients across the political cycles. Under null hypothesis the political variable should not be significantly different from zero. The numbers in the parentheses shows the p values present the statistical significance of the coefficients. The p values of the tests are calculated using Newey-West (1987) heteroskedasticity and serial-correlation robust t-statistics. The regression performance is given by $\overline{R^2}$ in last column. The symbols *, **, *** are used indicate the statistical significance at 10%, 5% and 1% significance levels, respectively.*

	μ_t	ρ_1	ρ_1*π	ρ_2	ρ_2*π	π	$\overline{R^2}$
M1	0.91***	0.16***	-0.11**	0.25***	-0.03 **	-0.197*	0.29
	(0.00)	(0.00)	(0.03)	(0.00)	(0.05)	(0.07)	
M2	2.12***	0.43***	-0.09**	0.21***	-0.13***	-0.17**	0.48
	(0.00)	(0.00)	(0.03)	(0.00)	(0.01)	(0.05)	
MM	-0.001**	0.18***	-0.15**	-	-	0.00	0.20
	(0.04)	(0.00)	(0.05)			(0.14)	

The money supply is thought to be linked to monetary policy. One might suspect that the presidential gap in the monetary aggregates growth rates could be merely explained by the monetary policy decisions. Hence, we control the federal funds rate in the estimations based on the equation (2.5). Following Blinder and Watson (2016) on studying the partisan gap in the economic output, we model the growth rates of the monetary aggregates in the Autoregressive Distributed Lag framework which allows the current and lagged values of the federal funds rates as well as the lagged values of the growth rates of monetary aggregates as the explanatory variables. Consistent with the previous estimation, the optimal lag length is determined with SIC criteria. Meanwhile, the political variable is modelled with an additive dummy variable

Table 2.6 reports the findings. Apparently, the SIC criteria choose a lag of federal funds for the M1 equation while leaves only contemporaneous values for the M2 and MM equations. As expected, the federal funds rates are highly significant and negatively linked to the monetary aggregates growth rates. However, an interesting finding is that the partisan gap becomes even stronger after controlling for the funds rate. The coefficients of the dummy variable are found to be highly significant; the absolute values of the coefficients are even higher than the previous estimations.

Table 2.7 and 2.8 report the findings of Markov Switching Autoregressive model and its transition probabilities. In the estimations, we allowed the intercept and the volatilities to change across the regimes, while remaining the AR coefficients constant (i.e non-switching regressors). The switching intercepts and volatilities are found significant and economically meaningful. The democratic presidential periods in the office are observed with higher growth rates whereas low growth rates are associated with the republican office periods. As expected, the AR coefficients are mostly positive and highly significant, except AR (2) in the M2 equation. It is clear from Table 2.8 that the regimes are highly stable with less than 10% probability that the monetary aggregates may shift from a low growth rate state (the republican state) to a high growth state (the democratic state) or vice versa. The monetary aggregates growth rates tend to exhibit path dependence as dictated by the theory of Markov process.

TABLE 2. 6 MODELLING MONETARY AGGREGATES WITH AUTOREGRESSIVE COMPONENTS CONTROLLED BY POLITICAL DUMMY AND FED FUND RATES

Notes: *The table represents the statistical results based on the following ARDL regression:*

$$\Delta lny_t = \mu_t + \sum_{i=1}^{p} \rho_i \Delta lny_{t-i} + \sum_{j=0}^{q} \varphi_j \Delta lni_{t-j} + \beta \pi_t + u_t$$

*All the data covers the period from 1959:01 to 2017:09. The optimal distributed lag length is chosen with SIC information criteria which determines two lags for the growth rate of M1 and the growth rate of the federal funds rate in the first row. M2 equation, however, is specified only AR (1) component and the contemporaneous funds rate followed by the fixed repressor political variable. The Money Multiplier equation is determined by only AR (1) and the contemporaneous value of the funds rate. In the equation, ρ_1 and ρ_2 indicate the coefficients of AR (1) and AR (2) components while φ_0 and φ_1 represent the current and lagged value of the federal funds rate. The political variable is measured by π_t, an additive dummy variable which indicates 1 if a Republican president is in the office, otherwise 0 if a Democrat president is in the office. Under null hypothesis the political variable should not be significantly different from zero. The numbers in the parentheses shows the p values present the statistical significance of the coefficients. The p values of the tests are calculated using Newey-West (1987) heteroskedasticity and serial-correlation robust t-statistics. The regression performance is given by $\overline{R^2}$ in last column. The last column presents the F statistics results under the null hypothesis that all the coefficients of the repressors are simultaneously equal to zero. The symbols *, **, *** are used indicate the statistical significance at 10%, 5% and 1% significance levels, respectively.*

	μ_t	ρ_1	ρ_2	φ_0	φ_1	π	$\overline{R^2}$	Pr(Fstat)
M1	1.08***	0.09***	0.26***	-2.25*	-3.89***	-0.48***	0.34	0.00
	(0.00)	(0.01)	(0.00)	(0.10)	(0.01)	(0.00)		
M2	2.41***	0.46***	0.14	-8.73***	-	-0.58***	0.54	0.00
	(0.00)	(0.00)	(0.21)	(0.00)		(0.00)		
MM	-0.29***	0.22***	-	0.02***	-	0.04**	0.25	0.00
	(0.00)	(0.00)		(0.00		(0.05)		

TABLE 2. 7 MODELLING THE U.S. MONETARY AGGREGATES WITH MARKOV SWITCHING MODEL

Notes: *The table represents the statistical results based on the following Markov Switching Autoregressive model*

$$y_t = \mu_{s_t} + \sum_{i=1}^{p} \rho_{i,s_{t-i}} y_{t-i} + \sigma_{s_t} \varepsilon_t$$

All the data covers the period from 1959:01 to 2017:09. The optimal AR lags is chosen based on the findings from the previous estimations. We allow intercept and volatility to change across the regimes while remaining the autoregressive coefficients constant. N_1 *and* N_2 *denote the number of observations through the republican and the democrat regimes. Last two columns show the average expected duration of two regimes across the equations. The numbers in the parentheses indicate the p values.*

Statistic	μ_1	μ_2	σ_1^2	σ_2^2	*AR(1)*	*AR(2)*	N_1	N_2	d_1	d_2
M1	-0.33	0.60	0.83	3.36	0.43	0.22	370	332	27.84	12.85
	(0.00)	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)				
M2	3.04	10.11	0.70	2.03	0.68	0.04	370	332	44.19	94.58
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.39)				
MM	-0.07	-0.02	-4.13	5.19	0.25	-	370	332	10.69	39.81
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					

TABLE 2. 8 THE TRANSITION PROBABILITIES OF THE MARKOV SWITCHING AUTOREGRESSIVE MODEL

Notes: *The table represents the transition probabilities under the Markov Switching model*

$$prob[z_t = 1|z_{t-1} = 1] = p_{11}$$

$$prob[z_t = 2|z_{t-1} = 1] = 1 - p_{11}$$

$$prob[z_t = 2|z_{t-1} = 2] = p_{22}$$

$$prob[z_t = 1|z_{t-1} = 2] = 1 - p_{22}$$

In the equations, p_{11} and p_{22} denote the probability in regime one, given that the system was in regime one during the previous period and the probability of being in regime two, given that the system was in regime two during the previous period, respectively. Accordingly, $1 - p_{11}$ defines the probability that y_t will change from state one in the period $t - 1$, to state two in the period t and $1 - p_{22}$ defines the probability of a shift from state two to state 1 between times $t - 1$ and t.

Statistic	p_{11}	p_{12}	p_{22}	p_{21}
M1	0.96	0.04	0.92	0.08
M2	0.98	0.02	0.99	0.01
MM	0.91	0.09	0.97	0.03

Fed chairs have political views either having party membership or an ideological outlook. More importantly, the Fed governing cycles are independent[17] from presidential cycles, as there has been a long tradition that the presidents allow for the continuation of the current chair even if he/she is a member of the rival party. The only exception can be considered the most recent case that president Trump removed Janet Yellen at the end of her first term.

In Table 2.9, we present descriptive statistics of the growth rates of the U.S Monetary Aggregates under partisan Fed chair cycles. Although Democrats are represented with four, Republicans with three governors, Republican Fed governors are reported to be 413 months in the office compared to 291 months of Democrats. In annualized percentage growth term, M1 and MM are observed to be higher under Democrat Fed governors (4.9% and -0.42%, respectively) than the Republicans (4.2% and -6.51%, respectively) whereas the opposite for M2 being 5.16% and 5.04% for Republicans and Democrats, respectively.

The U.S monetary policy history of last 50-60 years may suggest us to hypothesize that whether partisan FED chairs are able to explain the presidential gap in the monetary aggregates. For instance, we already know that Paul Volcker (Democrat) was quite successful in curbing high inflation inherited from the Arthur Burns's (Republican) governing years (Silber, 2012). Alan Greenspan (Republican) is known his ultra-liberal views on the financial regulation which is partially blamed[18] for dotcom bubble as well as 2008-2009 crisis. We test the significance of partisan FED chair gap in explaining the presidential gap in the monetary aggregates. Firstly, we carry out the significance of the correlation analysis as done for the presidential gap in Table 2.10.

[17] https://www.federalreserve.gov/aboutthefed/bios/board/boardmembership.htm
[18] https://www.nytimes.com/2008/10/24/business/economy/24panel.html

TABLE 2. 9 THE REAL GROWTH RATES OF THE MONETARY AGGREGATES ACROSS THE U.S PRESIDENTIAL CYCLES

FED Chair (Party)	Period in Office	M1		M2		MM	
		Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
Panel A. By FED Cahir							
William Martin (D)	01/1959-01/1970	2.99	3.96	5.97	2.78	-1.31	3.85
Arthur F. Burns (R)	02/1970-01/1978	3.99	4.21	7.65	4.83	-3.46	5.08
G. William Miller (D)	03/1978-08/1979	3.91	4.28	3.64	1.92	-4.09	4.19
Paul A. Volcker (D)	09/1979-08/1987	5.87	8.33	5.6	5.28	-2.19	6.86
Alan Greenspan (R)	09/1987-01/2006	1.56	8.06	2.97	4.15	-5.07	7.39
Ben Bernanke (R)	02/2006-01/2014	7.06	14.82	4.86	6.42	-10.99	44.09
Janet Yellen (D)	02/2014-09/2017	6.69	10.94	4.95	3.12	5.94	31.34
Panel B. By Party							
Political Party	Total months in office	M1					
		Mean	Std Deviation	Mean	Std Deviation	Mean	Std Deviation
Republicans	413	4.2	9.03	5.16	5.13	-6.51	18.85
Democrats	291	4.9	6.9	5.04	3.28	-0.42	11.56

TABLE 2. 10 THE U.S MONETARY AGGREGATES GROWTH RATES ON THE PARTISAN FED CHAIRS CYCLES

Notes*: The table reports the empirical results based on the following regressions:*

$$\Delta lny_t = \alpha + \beta\pi_t + u_t$$

$$\Delta lny_t = \alpha_1 RD_t + \alpha_2 DD_t + u_t$$

*All the data covers the period from 1959:01 to 2017:09. The growth rates of the monetary aggregates are annualized by multiplying the monthly growth rates by 12. The numbers in the parentheses below the coefficients of "RD" and "DD" dummies represent p values under the null hypothesis that the estimated growth rates are not significantly different from zero. The p values of the tests are calculated using Newey-West (1987) heteroskedasticity and serial-correlation robust t-statistics following Santa-Clara and Valkanov (2003). The p values under the coefficients in the "Diff" column is also obtained from Newey-West test indicating the null hypothesis that the monetary aggregates growth rates across the democrat and the republican FED cycles are not significantly different from each other. The row "T/Republicans" indicates the number of observations and the number of the months that republican FED chairs are in the office throughout the sample period. The symbols *, **, *** are used indicate the statistical significance at 10%, 5% and 1% significance levels, respectively.*

	RD	***DD***	***Diff***
M1	12.36***	27.24***	-14.88***
	(0.00)	(0.00)	(0.00)
M2	56.76***	87.96***	-31.2***
	(0.00)	(0.00)	(0.00)
MM	-0.05***	-0.03***	-0.02***
	(0.00)	(0.00)	(0.00)
T/Republicans		705/547	

Table 2.10 shows that there is an economically and statistically significant Democratic (or negative Republican) Fed chair gap in the growth rates of narrow and broad money indicators. Although, money multiplier is also found to be significant, it is economically less notable. Remarkable Democratic gap is found as much as 14.88 and 31.2 percent for the M1 and M2 growth rates, respectively which apparently outperform respective presidential gaps.

Afterwards, for the first time in the literature, we check the statistical significance of partisan Fed chair gap in explaining the presidential gap. As emphasized above, we can simultaneously model partisan the Fed chair gap with the presidential gap in the same equation, as there is no direct relationship between them based on the structure of the U.S political system. In other words, the equation will not suffer from multicollinearity problem. Therefore, we include the Fed chair variable in the equation (2.1) to check the possible explanatory power of partisan Fed chair in explaining the presidential gap. Under the null hypothesis, the coefficient of partisan Fed chair should not be significantly different from zero.

TABLE 2. 11 THE U.S MONETARY AGGREGATES IN THE PARTISAN FED CHAIR AND PRESIDENTIAL CYCLES

Notes*: The table reports the empirical results based on the following regressions:*

$$\Delta lny_t = \mu + \beta_1\pi_{FED} + \beta_2\pi_{Pres} + u_t$$

*All the data covers the period from 1959:01 to 2017:09. The growth rates of the monetary aggregates are annualized by multiplying the monthly growth rates by 12. The numbers in the parentheses below the coefficients of π_{FED} and π_{Pres} dummies represent p values under the null hypothesis that the estimated growth rates are not significantly different from zero. The p values of the tests are calculated using Newey-West (1987) heteroskedasticity and serial-correlation robust t-statistics following Santa-Clara and Valkanov (2003). The row "T/Republicans" indicates the number of observations and the number of the months that republican FED chairs are in the office throughout the sample period. The symbols *, **, *** are used indicate the statistical significance at 10%, 5% and 1% significance levels, respectively.*

	μ	π_{FED}	π_{Pres}
M1	2.52***	-1.26***	-0.45
	(0.00)	(0.00)	(0.12)
M2	7.78***	-2.63***	-0.81
	(0.00)	(0.00)	(0.11)
MM	-0.01***	-0.002***	-0.01
	(0.00)	(0.00)	(0.27)

Finally, to test the robustness of the explanatory power of the partisan Fed chair gap, we control autoregressive components of the monetary aggregates in the same equation. As previously carried out, the optimal lag length is chosen with SBIC information criteria.

TABLE 2. 12 THE U.S MONETARY AGGREGATES CONTROLLED BY AUTOREGRESSIVE COMPONENTS IN THE PARTISAN FED CHAIR AND PRESIDENTIAL CYCLES

Notes*: The table represents the statistical results based on the following regression:*

$$\Delta lny_t = \mu_t + \sum_{i=1}^{p} \rho_i \Delta lny_{t-i} + \beta_1 \pi_{FED} + \beta_2 \pi_{Pres} + u_t$$

*All the data covers the period from 1959:01 to 2017:09. The optimal lag length is chosen with SIC information criteria which determines two lags for the M1 and M2 equations, while only AR(1) component for the MM equation. The political variable is measured by π_t which indicates 1 if a Republican is in the office, otherwise 0 if a Democrat is in the office. Under the null hypothesis, the political variable should not be significantly different from zero. The numbers in the parentheses shows the p values to present the statistical significance of the coefficients. The p values of the tests are calculated using Newey-West (1987) heteroskedasticity and serial-correlation robust t-statistics. The symbols *, **, *** are used indicate the statistical significance at 10%, 5% and 1% significance levels, respectively.*

	μ_t	AR (1)	AR (2)	π_{FED}	π_{Pres}
M1	2.45***	0.11***	0.26***	-1.18***	-0.45
	(0.00)	(0.00)	(0.00)	(0.00)	(0.31)
M2	2.36***	0.47***	0.14***	-0.89**	-0.38
	(0.00)	(0.00)	(0.00)	(0.03)	(0.44)
MM	-0.002**	0.27***	-	-0.03*	-0.01
	(0.05)	(0.00)		(0.07)	(0.93)

Table 2.11 apparently shows that the Fed chair gap remains its power in explaining the presidential gap even after controlling for the autoregressive components.

2.5 Discussion and Conclusion

We explore the presidential gap in U.S monetary aggregates. The consistent findings regarding the partisan gap in the U.S economic output (Blinder and Watson, 2016) and stock market performance (Santa-Clara and Valkanov, 2003) motivated us to investigate the similar gap in the monetary aggregates. Based on strong theoretical and empirical links between monetary aggregates and economic activity as well as stock market return, we impose a hypothesis that the presidential gap might be present in the monetary aggregates. Additionally, this study potentially aims to shed light on the unexplored reasons of excessive growth rates of monetary aggregates over economic activity and monetary policy decisions. The major findings can be summarized as the followings.

A positive and significant democratic gap is existent in the U.S monetary aggregates. While the gaps are found as much as 5 percent and 9 percent per annum in the M1 and M2 growth rates, respectively, the MM gap is less economically noticeable. The partisan gap remains significant after controlling for the autoregressive components and the federal funds rates. The presidential gap is not only persistent as an additive component to the growth rates, but also highly significant in the coefficients. Hence, the magnitudes of the lagged growth rates are sensitive to the presidential cycles.

The monetary aggregates are also found significantly different under the Democratic FED chairs than the Republican governors. The gaps are remarkably high, as much as 14 percent and 31 percent in the M1 and M2 growth rates which considerably outperform the similar presidential gaps. Moreover, controlling the Fed chair gap sweeps away the statistical significance of the presidential gaps. Consequently, the Democratic FED chair gap is found more robust partisan gap than the Democratic presidential gap.

In general, this study might be suggestive to the new way of thinking in the U.S presidential puzzle literature. The local partisan gaps might be a more promising way of exploring the binary nature of the appropriate growth rather than the whole, country wide political picture.

Chapter 3. Commodity Prices and FX Liquidity: A GVAR Approach

3.1 Introduction

The foreign exchange (FX) market is one of the biggest and most liquid in the financial markets. As of 2016 data, the average daily market turnover was $5.1 trillion per day (BIS, 2016).

In recent years, a considerable number of studies has been dedicated to explore the determinants, commonality and the investment implications of FX liquidity (Banti et al., 2012; Banti and Phylaktis, 2015; Karnaukh, Ronaldo and Soderlind, 2015; Mancini et al., 2013; Menkhoff et al., 2012). Common findings can be summarized as: (i) liquidity risk is priced in the cross section of currency returns, especially, the currencies of the emerging economies (ii) the TED spread (i.e the difference between the interest rates on interbank loans and short term U.S government debt) and market volatility are significant commonality factors of FX liquidity (iii) local money market rates and capital flows with the country of quoted currency are significant determinants of the cross section of the liquidity of floating exchange rates. However, none of these papers studies the potential transmission of commodity price movements to FX liquidity.

The linkages between commodity prices and international finance have received some attention in the exchange rate literature. The introduction of the concept of "commodity currencies" (Chen and Rogoff, 2003) led to the findings that commodity price is an important driver of the exchange rate movements under the sticky-price model of an open economy with non-traded goods, a portfolio balance model and the terms-of trade hypothesis (Chen, 2004).

In the meantime, similar findings are also documented from the other perspective. Exchange rates also influence or Granger-cause commodity prices as they are determined by the net present value of fundamental asset prices (Zhang et al., 2016; Obstfeld and Rogoff, 1996; Engel and West, 2005; Chen at al., 2010; Alquist et al., 2012). Finally, multiple studies (notably, Ferraro et al., 2015; Chen et al., 2010; Zhang, et al., 2016) document that commodity prices have the power to forecast exchange rates or vice versa, particularly in the case of "commodity currencies".

Given the numerous findings on the linkage between commodity prices and exchange rates, it is a surprising fact that the FX liquidity literature never, as far as we know, emphasises commodity prices as potential determinant or commonality factor. Commodity prices may influence FX liquidity from different channels. From the demand side perspective, commodities are vital part of international trade flows and this generates a demand for FX liquidity, hence can be determinant of FX liquidity. Since commodity prices are one of the factors that the exchange rates and economies are linked to each other, it would be a potential driver of FX liquidity from the commonality perspective. Finally, as commodity prices may significantly influence the local funding conditions especially in economies that are significantly exposed to exporting commodities, then they affect FX liquidity from the supply side perspective. Considering the channels above that commodity prices may transmit to FX liquidity, it is clearly worthwhile exploring whether commodity prices are a determinant of FX liquidity.

Exploring FX liquidity is also of interest to investors. Factor investing is a growing field of investment management. It is based on dedicating a specific fund to each factor or building a multifactor investment structure (Bender et al., 2013). Liquidity based investment involves exploiting a liquidity premium from holding illiquid assets rather than liquid assets. This study can be useful to investors who aim to exploit profit opportunities from the liquidity factor in the FX market by introducing commodity prices as an additional tool to model the direction of the liquidity of major exchange rates.

This chapter contributes to the literature in three ways. First, we assemble a new dataset for CTOT. Specifically, we improve the existing resources in three aspects: 1) We construct CTOT at a new monthly frequency which can be useful for other researchers 2) We apply yearly updated trading weights of countries' trade composition to commodity prices in contrast to the currently available dataset which has been constructed with fixed weights and 3) We also extend the latest available data of 2010 to the end of 2016. We cover 41 countries (of which 19 are eurozone countries) to cover floating exchange rates over the period 01/1994 to 12/2016.

The second contribution is exploring the transmission of commodity prices to the cross-sectional illiquidity of the currencies. We estimate the impulse responses of illiquidity to one-unit local CTOT shock. Analogous estimations are carried out on the supply and demand side models of liquidity, separately. We also explicitly explore commodity price as a commonality factor by taking advantages of a GVAR model.

The third contribution is applying a GVAR model to the international finance literature. Similar works have already been carried out in other areas of finance (see Pesaran et al., 2006; Pesaran et al., 2007a; Favero, 2013; Gray et al., 2013). The GVAR model allows us to build a local currency specific endogenous FX liquidity model to enable us to estimate the interlinkages of FX liquidity among currencies by applying common variables. In this manner, we are able to explore CTOT as a domestic and weighted foreign determinant of cross-sectional currency illiquidity, while allowing previously known commonality factors (e.g TED spread, VIX, FX volatility) to be global variables. In the second stage, we jointly model cross-sectional demand and supply side factors together, while defining commodity price as a global variable, therefore modelling the commodity price as a commonality factor in FX liquidity.

Some clear results emerge from our estimations. First, we find commodity prices do matter for FX illiquidity; in particular, the illiquidity of the currencies of developing economies experience a persistent fall, following a positive local CTOT shock in the supply side model. We do not a find a similar effect for the highly liquid currencies from developed economies which might be explained by the high explanatory power of local money market rates and global funding conditions, as well as, the influence of short-term trading strategies. In the meantime, local CTOT shocks leave a significant but temporary effect on the illiquidity of the currencies of developed economies that are relatively more exposed to commodity exporting such as AUD, CAD, NZD, ZAR and NOK.

Second, we find strong evidence for the effect of local CTOT shocks on cross-sectional FX illiquidity in the demand side framework. A one-unit standard deviation shock on local CTOT is followed by a negative and persistent effect on illiquidity for most currencies excluding the highly liquid and some Asian currencies. CTOT shocks stimulate the market demand for the local currency and push liquidity up for most currencies. On the other hand, jointly modelling capital flows while controlling for market sentiment (VIX) and general market condition enhances the effects of CTOT shocks. We can explain the insignificant effect for highly liquid currencies (GBP, CHF, EUR, JPY) with the similar reasons in the supply side model.

Third, we find that the illiquidity of currencies that are considerably exposed to commodity exporting, also known as "commodity currencies" (AUD, CAD, BRL, ZAR, NOK, NZD, MXN) are significantly influenced by the common commodity price shocks. The currencies of small economies (CLP, SEK, PLN, HUF, CZP and DKK) are also significantly influenced by commodity price shocks. Consistent with the findings above, highly liquid currencies are not significantly affected by common commodity price shocks that might be explained by the similar reasons- the impact of local money market rates and global funding conditions, as well as, trading strategies.

The rest of this chapter is organized as follows. The second section reviews the literature on different aspects of FX liquidity, the featured works on the linkages between commodity prices and exchange rates and the theory and practice of GVAR modelling. In the third section, we present the data sources, the description of monthly CTOT and the key features of GVAR model. The fourth section discusses the empirical findings and the theoretical implications. We discuss the major findings with concluding remarks in last section.

3.2 Related Literature and theoretical underpinnings

3.2.1 Commonality in FX Liquidity

The extant literature explores cross-sectional commonality of liquidity in the stock market and several papers find a significant co-movement (Datar et al.,1998; Chordia et al., 2000, 2001; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Lesmond, 2005). For some reason, FX market liquidity has not received similar attention until relatively recently perhaps due to the to the segmented structure of the FX market and the heterogeneity of economic players (Mancini et al., 2013). Commonality in the FX market has been empirically investigated for the recent global financial crisis (Melvin and Taylor, 2009; Mancini et al., 2013) suggesting that the FX market has expose commonality during the crisis years However, since the time span is limited, drawing general conclusion regarding strong commonality is overly ambitious.

Covering both the crisis and non-crisis years from 1994 to 2008, Banti et al., (2012) find a similar co-movement pattern in 20 exchange rates. They additionally document that a liquidity risk premium is more prominent in the returns of the emerging market currencies. Extending the works carried out using bond and equity markets, Mancini et al. (2013) develop a PCA factor model by using intraday data from 2007 to 2009 for testing commonality in the FX market and find that commonality in the FX market is more pronounced than in equity markets.

Given the relatively short estimation period of previous papers, Karnaukh, Ronaldo and Söderlind (2015) empirically test the FX market commonality with a monthly data set covering thirty exchange rates from 1991 to 2012. They find a stronger co-movement of FX liquidity in distressed markets, especially when combined with the underlying negative determinants of FX liquidity such as high volatility, funding constraints and losses of FX speculators.

3.2.2 Determinants of FX liquidity

Previous studies explore the determinants of FX liquidity in three groups. From demand side factors, Banti and Phylaktis (2015) document capital flows as the main driver of the time variation of FX liquidity. As large capital flows improve the efficiency of the FX market, they are documented to positively influence FX liquidity. In the meantime, volatility is reported as the main important determinant of FX market by multiple studies including Menkhoff et al. (2012), Lustig, Rousssanov and Verdelhan (2011) and Banti and Phylaktis (2015). Since volatility, typically proxied by VIX, is a measure of financial uncertainty, it negatively influences FX liquidity.

Additionally, Karnaukh, Ronaldo and Söderlind (2015) provide empirical evidence that FX liquidity is not just negatively influenced by volatility in the FX market, but also general market conditions including bond and stock market liquidity. In recent work, Karnaukh, Ronaldo and Söderlind (2015) extend the empirical investigation of the demand side factors to current accounts, portfolio balances, and sentiment by using additional proxies. They find that FX liquidity declines with the deterioration of investor sentiment, the demand for U.S safe assets and depreciation of local currencies.

The supply side drivers demonstrate to what extent financial intermediaries are inclined to provide liquidity during either tight or loose funding (Karnaukh, Ronaldo and Söderlind, 2015). In particular, the basic idea is in line with the earlier work of Brunnermier and Pederson (2009) suggesting a feedback loop effect between market liquidity and funding liquidity. Brunnermier and Pederson (2009) document that market liquidity can dry up quickly during lower prices and higher volatility of securities. Meanwhile, a deterioration of market liquidity is quickly followed by further losses and margin calls, ultimately creating "liquidity spirals". Drawing on the underlying theoretical model, studies (i.e Mancini et al., 2013; Banti and Phylaktis, 2015; Karnaukh, Ronaldo and Söderlind, 2015) show evidence that FX liquidity decreases with higher money market rates, TED spread and monetary aggregates.

Finally, Karnaukh, Ronaldo and Söderlind (2015) explore the cross-sectional determinants of FX liquidity. Consistent with the time-series explorations, the cross-sectional determinants are estimated with demand and supply side characteristics while substituting market conditions with economic performance as control variables. They find that higher central bank transparency, sovereign credit rating and higher GDP per capita are associated with higher commonality in cross-sectional FX liquidity. In other words, institutional factors stimulate more international trading. Conversely, the findings imply that local money market rates tend to decrease commonality as it induces higher funding costs from the supply side.

3.2.3 Measurement of FX liquidity

Liquidity is an unobservable phenomenon as real market data do not explicitly reveal liquidity of an asset. In practice, the liquidity component is extracted from data based on measurement concepts theories such as "tightness", "depth", and "resiliency".

Bid-ask spread as a transaction cost measure of liquidity is widely applied by academic literature and practitioners (Bessembinder, 1994; Bollerslev and Melvin, 1994; Lee, 1994; Hsieh and Kleidon, 1996). The bid-ask spread as a measurement, is known to have obvious limitations. For example, Grossman and Miller (1988) emphasize the need to be cautious when using bid-ask spread as it is an indication of immediate cost of market makers in the contemporaneous buy and sell transactions. In practice, immediate cost of market makers might not be clearly observed since larger transactions might take a longer time to realize.

Price-impact measures (such as Pastor and Stambaugh, 2003; Amihud, 2002) are considered as alternatives to transaction cost measurements, particularly in the case of estimation with lower frequency of data (Goyenko, Holden and Trzcinka, 2009). Vayanes and Wang (2013) show that the Pastor and Stambaugh (2003) measure does not suffer from the shortcomings of bid-ask spread. In the spirit of Pastor and Stambaugh (2003), Banti et al. (2012) develop an analogous price-impact measure of liquidity in the FX market.

3.2.4 Commodity Currency

As opposed to standard exchange models which cannot explain the high volatility and persistence of the real exchange rate, Chen and Rogoff (2003) introduce the phenomenon of commodity currencies by focusing on three OECD economies (Australia, Canada and New Zealand) where commodities comprise a significant share of total exports. They show that the US dollar price of commodity exports of the underlying countries has a persistent effect on their floating exchange rates.

But why might commodity prices affect currencies? Based on the theoretical relationship between the macroeconomy and trade, an increase in the price of commodity fires the demand for national currencies of the countries whose exports heavily depend on this particular commodity. Thus, exchange rate movements can be predicted via economic indicators such as commodity prices.

The idea that commodity prices can be an important driver of exchange rate movements is supported with a sticky-price model of an open economy with non-traded goods, a portfolio-balance model, and the terms-of-trade hypothesis (Chen and Rogoff, 2003; Chen, 2004).

However, studies focusing on the effect of the export side of commodity trading, neglect countries that are heavily dependent on the imports of commodities. Moreover, the existing commodity currency studies generally emphasize only a few commodities such as crude oil, gold and copper.

A second group of literature explores the opposing relationship arguing that exchange rates should influence or Granger-cause commodity prices as they are determined by the net present value of fundamental asset prices including commodities (see Zhang et al., 2016; Obstfeld and Rogoff, 1996; Engel and West, 2005; Chen at al., 2010; Alquist et al., 2012).

Apart from the theoretical works, several studies use an empirical approach to explore whether exchange rates have the power to forecast commodity prices (or the other way around) in an out-of-sample framework. A common finding is that the theoretical link between exchange rates and commodity prices, irrespective of the direction of effect, is statistically more justified with relatively high frequency estimation (i.e daily) rather than lower frequency (i.e monthly and quarterly) (see Ferraro et al., 2015; Chen et al., 2010; Zhang, et al., 2016).

However, studies find conflicting results as to whether exchange rates are statistically more powerful in forecasting commodity prices or vice versa. Notably, Chen et al. (2010) finds that exchange rates of "commodity currencies" have robust statistical power to predict global commodity prices while the reverse relationship remains less robust. The theoretical explanation is a suggest that exchange rates are strongly forward looking, while commodity prices remain fragile with short-term fluctuations.

Conversely, Ferraro et al. (2015) find both contemporaneous and lagged commodity prices (focusing on oil prices) have robust statistical power to forecast exchange rates in daily out-of-sample forecasting work. Zhang et al. (2016) emphasizes findings from causality analysis at multiple horizons. They show evidence that there is strong Granger-causality between commodity prices and exchange rates at multiple horizons in both directions, although the direction is statistically stronger from commodity price to exchange rates. It should be noted that these findings are robust after controlling for the U.S dollar denomination effect

3.2.5 Theory and practice of GVAR modelling

The GVAR model, originally developed for credit risk analysis in Pesaran et al. (2004) is a systematic tool to assess regional and global macroeconomic interdependences across various countries. The model has also a wide range of policy applications (Galesi and Lombardi, 2009; Anderton *et al*., 2010).

Conceptually, the GVAR encompasses a two-step modelling procedure. In the first step, country specific macro-econometric models are estimated using Vector Autoregressive (VAR) models with exogenous variables denoted as VARX*. Country specific models include domestic variables and the weighted cross-sectional averages of foreign variables which are assumed to be weakly exogenous. In the second step, the country specific models are solved as a system in a global VAR model. This approach permits measurement of interdependence among cross sections-not only countries but also regions, industries and banks- while allowing simultaneously control country specific determinants.

A number of GVAR applications for finance have been developed in recent years. Credit risk modelling on a global perspective (Pesaran et al., 2006), the determinants of portfolio diversification across industry sectors and different countries (Pesaran et al., 2007a) are both employed as original GVAR applications. Several policy related papers focus on modelling different kinds of risk including the determinants of sovereign bond spreads across euro zone countries (Favero, 2013), interactions of banking sector risk, sovereign risk, corporate sector risk, real economic activity and credit growth of 15 European countries and the U.S (Gray et al., 2013).

Another major area of GVAR practice is evaluating systemic risk and modelling macro-financial linkages across regional groups of countries. For instance, Alessandri et al. (2009) develop a quantitative model to evaluate the transmission mechanisms of systemic risk to banks' balance sheets via feedback effects of macro-credit risk, interest income risk and market risk. The model is widely applied in the macro stress test modelling framework of the European Central Bank (ECB) (Foglia, 2009). Chen et al. (2010) also show international evidence for macro-financial linkages within domestic and global economies which lead to the transmission of bank and corporate default risk at the global level.

More recent GVAR evidence shows that liquidity shocks are strongly linked to price bubbles in global asset markets (Dreger and Wolters, 2011) and the evidence is more pronounced for advanced economies (Chudik and Fratzscher, 2011). Cesa-Bianechi et al. (2014) explore the linkages between financial market volatility and macroeconomic conditions. They show that the transmission of news is more pronounced in financial markets than the real economy. The evidence from a GVAR framework suggests that volatility can be considered as an ex-post symptom of economic "disease" rather a cause of instability.

Another interesting application of GVAR framework is investigating the hypothesis that global financial cycles determine domestic financial conditions regardless of the exchange regime. Georgiadis and Mehl (2014) find evidence from the interrelationships of 59 economies that the classical Mundell-Flemming trilemma still remains valid, in spite of globalization and the increased country interlinkages in global economy.

Most notably for our study, a few studies attempt to model global commodity prices, supply and demand by applying the GVAR model. Gutierrez and Piras (2013) model a global wheat market in the GVAR framework by considering feedback effects between real and financial sectors as well food and energy prices. They find that inflationary effects on wheat export prices can be explained by a negative shock to wheat consumption, an increase in oil prices and exchange rate devaluations, despite the heterogeneity across wheat export countries. Identification of oil shocks is also attempted in the GVAR context. For example, Cashin et al., (2014c) shows that economic consequences of supply and demand shocks are inherently different. A positive oil demand shock is found to be linked with inflationary pressures, an increase in real output, a rise in interest rates and a fall in equity prices while the negative impact of adverse oil supply shocks is observed in the economic growth of energy importers.

3.3 Data and Methodology

3.3.1 Commodity terms of trade

The commodity terms-of-trade (CTOT) index, as a comprehensive measurement, was initially constructed by Spatafora and Tytell (2009) based on 32 main commodities[19] over the period 1970-2007 and using an annual frequency. Makhlouf, Kellard and Vinogradov (2017) extend this dataset to 2010.

We improve the existing dataset in three aspects: 1) We construct CTOT at a monthly frequency which we expect will be useful for other researchers, especially when integrating the higher frequency data of financial markets with the lower frequency data of macro-econometric variables 2) Previous studies apply time-averaged weights of countries' trade composition to commodity prices. As a result, any fluctuations in CTOT are merely related to the changes in global commodity prices (Makhlouf, Kellard and Vinogradov, 2018). We improve this approach and update trading weights every year 3) We also extend the latest available data of 2010 to the end of 2016. We cover 41 countries (of which 19 are eurozone countries) over the

[19] Shrimp, Beef, Lamb, Wheat, Rice, Maize, Bananas, Sugar, Coffee, Cocoa, Tea, Soybean meal, Fish meal, Hides, Soybeans, Natural Rubber, Log, Cotton, Wool, Iron Ore, Copper, Nickel, Aluminium, Lead, Zinc, Tin, Soy oil, Sunflower oil, Palm oil, Coconut oil, Gold, Crude oil

period 01/1994 to 12/2016. The reason for choosing these countries to cover floating exchange rates over this period.

The general description of the equation is given as follows:

$$CTOT_{it} = \frac{\Pi_j\left(\frac{P_{jt}}{MUV_T}\right)^{X_{ijT}}}{\Pi_j\left(\frac{P_{jt}}{MUV_T}\right)^{M_{ijT}}} \tag{3.1}$$

Where P_{jt} is the price of commodity j at month t, MUV_t is a manufacturing unit value index of year T used as a deflator, $X_{ijT}(M_{ijT})$ is the share of export (import) of commodity j in country $i's$ GDP, updated every year.

Taking the logarithm, equation (3.1) can be rewritten as follows:

$$lnCTOT_{it} = \sum_j \left(X_{ijT} - M_{ijT}\right) \ln\left(\frac{P_{jt}}{MUV_t}\right) \tag{3.2}$$

Equation (3.2) demonstrates that country-specific net exports $\left(X_{ijT} - M_{ijT}\right)$ determine how a country's index respond to the global commodity price movements $\ln(\frac{P_{jt}}{MUV_t})$. In our dataset, therefore $CTOT_{it}$ is not only influenced by the changes in the underlying commodity prices, but also a country's trade composition.

As this paper aims to explore the transmission of commodity prices to the liquidity of exchange rates, $CTOT_{it}$ is again computed for euro by weighting eurozone countries with the share of a member country's GDP in the eurozone's total GDP. Table 3.1 demonstrates summary statistics of monthly CTOT.

The prices of the 32 commodities are collected from the IMF *Commodity Price System* database. The MUV deflator are taken from the IMF's *World Economic Outlook* database or the World Bank's database. Exports and imports of individual commodities are obtained from the United Nations' COMTRADE database. Total GDPs of the countries are collected from the World Bank's World Development Indicators and the IMF's *World Economic Outlook* database.

TABLE 3. 1 MONTHLY CTOT OF 23 COUNTRIES/REGIONS FROM 01/1994 TO 12/2016

CTOT	Mean	Median	Max	Minimum	Std Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Australia	99.61	99.84	100.37	98.33	0.60	-0.45	-1.34	29.75	0.00
Canada	99.83	99.68	101.08	98.55	0.65	0.19	-1.31	21.37	0.00
New Zealand	99.76	99.75	101.53	98.41	0.88	0.18	-1.27	20.03	0.00
South Africa	99.98	100.01	100.21	99.62	0.13	-0.78	-0.47	58.14	0.00
Norway	99.98	99.98	100.10	99.87	0.05	0.35	0.09	5.64	0.00
Brazil	99.90	99.94	100.10	99.39	0.16	-0.99	0.01	44.79	0.00
Mexico	99.69	99.86	100.47	98.43	0.54	-0.64	-0.76	25.09	0.00
Malaysia	99.71	99.62	101.32	98.34	0.77	0.01	-0.86	8.49	0.00
Thailand	96.85	98.30	107.64	84.71	6.25	-0.31	-1.23	21.53	0.00
Eurozone	99.16	99.88	100.46	95.62	1.62	-1.32	-0.13	79.29	0.00
Czech	99.99	100.00	100.03	99.95	0.02	-0.46	-0.99	19.38	0.00
Switzerland	100.03	100.05	100.22	99.79	0.11	-0.23	-1.18	16.30	0.00
Denmark	99.97	99.90	101.36	99.20	0.52	0.42	-0.84	16.25	0.00
Turkey	99.99	99.99	100.02	99.94	0.02	-0.42	-0.63	13.06	0.00
UK	100.01	100.01	100.06	99.97	0.02	0.34	-0.01	5.23	0.00
Japan	100.26	100.22	101.25	99.22	0.61	0.01	-1.48	24.79	0.00
Singapore	99.99	99.99	100.75	99.21	0.35	-0.20	-0.67	7.10	0.00
Chile	99.98	99.99	100.17	99.74	0.10	-0.51	-0.39	13.53	0.00
Sweden	100.05	100.07	100.44	99.63	0.20	-0.16	-1.16	16.69	0.00
Poland	100.01	100.01	100.15	99.93	0.05	0.45	-0.16	9.67	0.00
Korea	99.98	100.07	100.5	99.39	0.27	-0.44	-0.94	19.25	0.00
Hungary	99.99	100.00	100.02	99.97	0.01	-0.51	-0.71	17.81	0.00
USA	100.08	100.12	100.53	99.51	0.28	-0.23	-1.31	21.92	0.00

TABLE 3. 2 MONTHLY QUOTED BID-ASK SPREAD

Notes: The table shows summary statistics for the quoted bid-ask spread of twenty-two currency pairs with USD dollar over the period 01/1994 and 12/2016. For comparability purposes, the spread is calculated as the difference between ask and bid prices divided by mid prices.

Statistics	AUD	CAD	NZD	ZAR	NOK	BRL	MXN	MYR	THB	EUR	CZK	CHF	DKK	TRY	GBP	JPY	SGP	CLP	SEK	PLN	KRW	HUF
Mean	1.83	1.12	2.84	8.61	1.88	2.24	3.48	2.08	4.85	0.85	4.04	1.35	1.15	8.60	0.89	1.17	1.63	2.60	2.41	4.44	4.17	5.51
Median	1.69	0.98	2.60	4.48	1.69	1.82	2.32	1.59	2.92	0.74	3.04	1.29	1.16	4.47	0.77	1.11	1.49	2.00	2.43	3.49	2.39	4.58
Std. dev.	1.29	0.44	1.49	8.19	1.04	2.94	5.55	2.33	6.52	0.50	3.10	0.63	0.61	14.94	0.45	0.55	0.97	1.83	1.18	3.68	4.92	4.69
Skewness	7.03	0.71	3.23	1.14	1.04	5.87	8.90	4.04	3.41	0.95	2.55	0.73	0.48	5.24	1.29	0.86	3.33	2.88	0.98	2.98	2.42	1.99
Kurtosis	79.98	1.17	19.63	0.59	1.71	44.80	108.32	25.31	13.74	1.47	9.22	0.41	0.08	33.96	0.63	1.07	17.7	13.6	2.21	13.27	5.77	5.60

3.3.2 Liquidity measure

We apply the quoted bid-ask spread calculated as the difference between ask and bid prices divided by mid-price as the liquidity measure while bearing in mind its limitations (Grossman and Miller, 1988). In Table 3.2, we report summary statistics for the monthly bid-ask spreads of twenty-two currency pairs with the U.S (USD) dollar over the period 01/1994 to 12/2016. The table shows that the most liquid currency pairs with USD, as expected, are EUR, GBP and CAD while the least liquid currencies are found to be TRY, ZAR and HUF. In the meantime, more liquid currencies tend to exhibit smaller volatility, lower skewness and kurtosis of the spread and vice versa for relatively less liquid currencies.

3.3.3 The Global VAR (GVAR) methodology

We employ a GVAR system to build the local currency specific endogenous FX liquidity model, as well as, to estimate the interlinkages of FX liquidity among the currencies by applying common variables which are supposed to be weakly exogenous. We follow the similar application of the model to the global and regional economies in Pesaran, Schuermann and Weiner (2004), Cashin et al. (2014), Dees et al. (2007a, b) and Chudik and Pesaran (2016).

We consider $N + 1$ currencies indexed by $i = 0, 1, \dots., N$. We label USD dollar as 0 and indicate it as the reference currency while the other N currencies are modelled as endogenous liquidity models during the time -periods $t = 1, 2, \dots T$. Denoting x_{it} as a $k_i \times 1$ vector of local determinants of FX liquidity treated as endogenous and $x_t = (x'_{1t}, x'_{2t}, \dots \dots, x'_{Nt})$ denote a $k * 1$ vector of all the variables in the panel where $k = \sum_{i=1}^{N} k_i$. The VARX* model is used to build the individual liquidity models. The individual models are designed to estimate domestic variables of the liquidity of a given currency, x_{it}, conditional on currency-specific averages of foreign variables, collected in the $k^* \times 1$ vector

$$x_{it}^* = W_i' x_t \tag{3.3}$$

for $i = 0, 1, \dots, N$, where W_i' is $k \times k^*$ matrix of country-specific weights, constructed using data of bilateral capital flows. The model performs best by treating k_i and k^* relatively small, up to 4 and 6. x_{it} is modelled as a VARX* model representing a VAR model augmented by the vector of the "star" variables x_{it}^*, and their lagged values,

$$x_{it} = \sum_{l=1}^{p_i} \Phi_{il} x_{i,t-l} + \Lambda_{i0} x_{it}^* + \sum_{l=1}^{q_i} \Lambda_{il} x_{i,t-l}^* + \varepsilon_{it} \tag{3.4}$$

for $i = 1,2, \dots N$, where $\boldsymbol{\Phi_{il}}$, for $l = 1, 2, \dots, p_i$, $\boldsymbol{\Lambda_{il}}$, for $l = 0, 1, 2, \dots q_i$ are $k_i \times k_i$ and $k_i \times k^*$ matrices of unknown parameters, respectively, and ε_{it} are $k_i \times 1$ error vectors. Star variables x_{it}^* in liquidity-specific models are treated as weakly exogenous to estimate unknown coefficients of the conditional exchange rate specific liquidity models. The assumption of weak exogeneity can be tested by Harbo et al. (1998) and Pesaran et al. (2000). It is not a particularly strong assumption due to the fact that the impact of individual exchange rates is small relative to the rest of the world and the weights used in the construction of the star variables are granular.

Next, we denote $z_{it} = (x_{it}', x_{it}^{*\prime})$ as a $k_i + k^*$ dimensional vector of domestic and exchange rate-specific foreign variables included in the submodel of exchange rate i and therefore (3.4) can be rewritten as:

$$A_{i0} z_{it} = \sum_{l=1}^{p} A_{il} z_{it-l} + \varepsilon_{it} \tag{3.5}$$

where $A_{i0} = (I_{k_i} - \Lambda_{i0})$, $A_{il} = (\Phi_{il}, \Lambda_{il})$ for $l = 1, 2, \dots . p$

and $p = \max_i(p_i, q_i)$. We define $\Phi_{il} = 0$ for $l > p_i$ and similarly $\Lambda_{il} = 0$ for $l > q_i$.Individual exchange rate models in (3.5) can also be written in the form of an error-correction representation as follows:

$$\Delta x_{it} = \Lambda_{i0}\Delta x_{it}^{*} - \prod z_{i.t-1} + \sum_{l=1}^{p} H_{il}\Delta z_{i,t-1} + \varepsilon_{it} \tag{3.6}$$

where $\Delta = 1 - L$ is the usual first difference operator and

$$\prod = A_{i0} - \sum_{l=1}^{p} A_{il} \text{ and } H_{il} = -(A_{i,l+1} + A_{i,l+2} + \cdots. + A_{i,l+p})$$

The second step of the GVAR approach consists of stacking estimated exchange rate models to form one large global VAR model. Using the $(k_i + k^*) \times k$ dimensional "link" matrices $W_i = (E'_i, \widetilde{W_\iota})$, where E_i is a $k \times k_i$ dimensional selection matrix that select x_{it}, and $x_{it} = E_i' x_t$ and $\widehat{W'}_\iota$ is the weight matrix introduced in (3.3) to define exchange rate specific foreign star variables, then we have:

$$z_{it} = (x_{it}', x_{it}^{*})' = W_i x_i \tag{3.7}$$

Using (3.7) in (3.5), we get

$$A_{i0} W_i x_t = \sum_{l=1}^{p} A_{il} W_i x_{t-l} + \varepsilon_{it}$$

And stacking these models for $i = 1, 2, \ldots \ldots N$, we obtain

$$G_0 x_t = \sum_{l=1}^{p} G_l x_{t-l} + \varepsilon_t \tag{3.8}$$

Where $\varepsilon_t = (\varepsilon'_{1t}, \varepsilon'_{2t}, \ldots \ldots \varepsilon_{Nt}')'$ and

$$G_l = \begin{pmatrix} A_{1,l} & W_1 \\ A_{2,l} & W_2 \\ A_{N,l} & W_N \end{pmatrix} \tag{3.9}$$

If the matrix G_0 is invertible, then by multiplying (3.9) by G_0^{-1} from the left we obtain the solution to the GVAR model

$$x_t = \sum_{l=1}^{p} F_l x_{t-l} + G_0^{-1}\varepsilon_t \tag{3.10}$$

Where $F_l = G_0^{-1} G_l$ for $l = 1, 2, \ldots . . p$.

Afterwards, we introduce a dominant exchange rate model by following a similar approach of dominant country model in Chudik and Pesaran (2013b). The conditional exchange rate models need to be augmented by ω_t and its lagged values, in addition to the exchange rate specific vector of cross-section averages of the foreign variables, namely

$$x_{it} = \sum_{l=1}^{p_i} \Phi_{il} x_{i,t-l} + \Lambda_{i0} x_{it}^* + \sum_{l=1}^{q_i} \Lambda_{il} x_{i,t-l}^* + D_{i0}\omega_t + \sum_{l=1}^{s_i} D_{il}\omega_{t-l} + \varepsilon_{it} \tag{3.11}$$

for $i = 1, 2, \ldots . N$. Both common variables and cross-section averages are treated as weakly exogenous to estimate the model.

Finally, we conduct an impulse-response analysis which is similar to the one in small-scale VARs but complicated due to the dimensionality of the GVAR model. We suppose k distinct structural (orthogonal) shocks. Identification of structural shocks, defined by $v_t = P^{-1}\varepsilon_t$ requires finding the $k \times k$ matrix of contemporaneous dependence, P, such that

$$\sum = E(\varepsilon_t {\varepsilon'}_t) = PP' \tag{3.12}$$

Therefore, by construction we have $E(v_t v_t') = I_k$ and the $k \times 1$ vector of structural impulse response function is given by

$$g_{vj}(h) = E\left(x_{t+h} \middle| v_{jt} = 1, \mathcal{J}_{t-1}\right) - E(x_{t+h} | \mathcal{J}_{t-1}) = \frac{R_h G_0^{-1} P e_j}{\sqrt{e_j' \Sigma e_j}} \tag{3.13}$$

For $j = 1, 2, \ldots . k,$ where $\mathcal{J}_t = \{x_t, x_{t-1}, \ldots .\}$ is the information set consisting of all available information at time t, and e_j is a $k \times 1$ selection vector that selects the variable j and the $k \times k$ matrices, The R_h are obtained recursively as:

$R_h = \sum_{l=1}^{p} F_l R_{h-l}$ with $R_0 = I_k$ and $R_l = 0$ for $l < 0$

Previous GVAR studies (Pesaran et al., 2004; Pesaran and Smith, 2006; Dees et al., 2007a) tend to adopt the generalized impulse response function (GIRF) approach as it does not aim at identification of shocks according to some canonical system or a priori economic theory but considers a counterfactual exercise where the historical correlations of shocks are assumed as given. In the context of GVAR model (3.10) the $k \times 1$ vector of GIRFs is given by

$$g_{\varepsilon j}(h) = E\left(x_{t+h} \middle| \varepsilon_{jt} = \sqrt{\sigma_{jj}}, \mathcal{J}_{t-1}\right) - E(x_{t+h} | \mathcal{J}_{t-1}) = \frac{R_h G_0^{-1} \Sigma e_j}{\sqrt{e_j{}' \Sigma e_j}} \tag{3.14}$$

For $j = 1, 2, \ldots ., k$, $h = 0, 1, 2, \ldots ..$, where $\sqrt{\sigma_{jj}} = \sqrt{E(\varepsilon_{jt}^2)}$ is the size of shock which is set to one standard deviation (s.d) of ε_{jt}.

3.3.4 Supply side modelling

Following the FX liquidity literature, we attempt to investigate the transmission of commodity prices to FX liquidity from the cross-sectional demand and supply-side sources, as well as, a commonality factor.

The supply-side represents to what extent financial intermediaries are inclined to provide liquidity in favourable (or adverse) times of funding. Based on the structure of GVAR model, we use two common variables: 1) the TED spread (i.e the difference between the interest rates on interbank loans and short term U.S government debt) to capture general funding conditions and 2) FX volatility (i.e changes in the JP Morgan Global FX volatility index which tracks the implied volatility of three-month at-the-money forward options on major and developed currencies) to control the general market condition.

From the domestic side, we endogenously model the cross section of liquidity of 23 exchange rates by using individual bid-ask spreads, local money market interest rates, and country specific CTOT. In Table 3.3, we present a detailed description of all the relevant data sources.

3.3.5 Demand side modelling

The demand side represents the determinants that increase the market demand for a specific currency. Following Karnaukh, Ronaldo and Soderlind (2015), we adopt trade and capital flows as the main determinants of the demand side of FX liquidity. To test the effect of CTOT, we jointly model the cross section of bid-ask spreads and capital flows (i.e measured as total export to the U.S scaled by the GDP of the quoted currency) in the endogenous system. Since more financially developed countries can benefit from better funding conditions and higher leverage (see Maggiori, 2012) and currencies of larger economies can better hedge against global shocks (see Hassan, 2013), we use two common variables in the demand side model: 1) VIX as a global volatility index 2) FX volatility as a proxy for the market condition. Again, in Table 3.3, we present a detailed description of all the relevant data sources.

3.3.6 Commodity price as a commonality

In the demand and supply sides equations, we estimate the impulse responses of the spreads to the exchange rate specific CTOT shocks.

Additionally, by taking the advantage of the GVAR model, we also explore commodity prices as a commonality factor of FX liquidity. The model allows us to explicitly define a common variable in the model setup rather than finding covariances between an exchange rate and the average market which is commonly used in the FX liquidity literature. In this manner, we can estimate the impulse responses of individual bid-ask spreads to the shocks to global commodity price index.

In this setup, we jointly model the cross-sectional bid-ask spreads together with supply and demand determinants (i.e local money market rates and capital flows) in the endogenous system, while using commodity prices index of IMF and FX market volatility indicators as common variables. In Table 3.3, we show the detailed description of the data sources.

TABLE 3. 3 DESCRIPTION OF THE DATA SOURCES

Variable	Description	Source
TED spread	The difference between the interest rates in interbank loans and on short term U.S government debt	Bloomberg
FX volatility	JP Morgan Global FX volatility index which tracks implied volatility of three-month at-the-money forward options on major and developed currencies	Bloomberg
Local money market rates	Short-term money market interest rates	DataStream
VIX	Chicago Board Options Exchange Market Volatility (VIX) Index which measures implied volatility of S&P 500 index options	Bloomberg
Export of BC to QC	Export from the BC country to the QC country, scaled by the BC GDP	DataStream
Commodity price index	IMF commodity price index calculated based on the prices of all commodities	IFS
Bid-ask spread	The difference bid-ask prices divided by mid prices	DataStream

3.4 Empirical Results

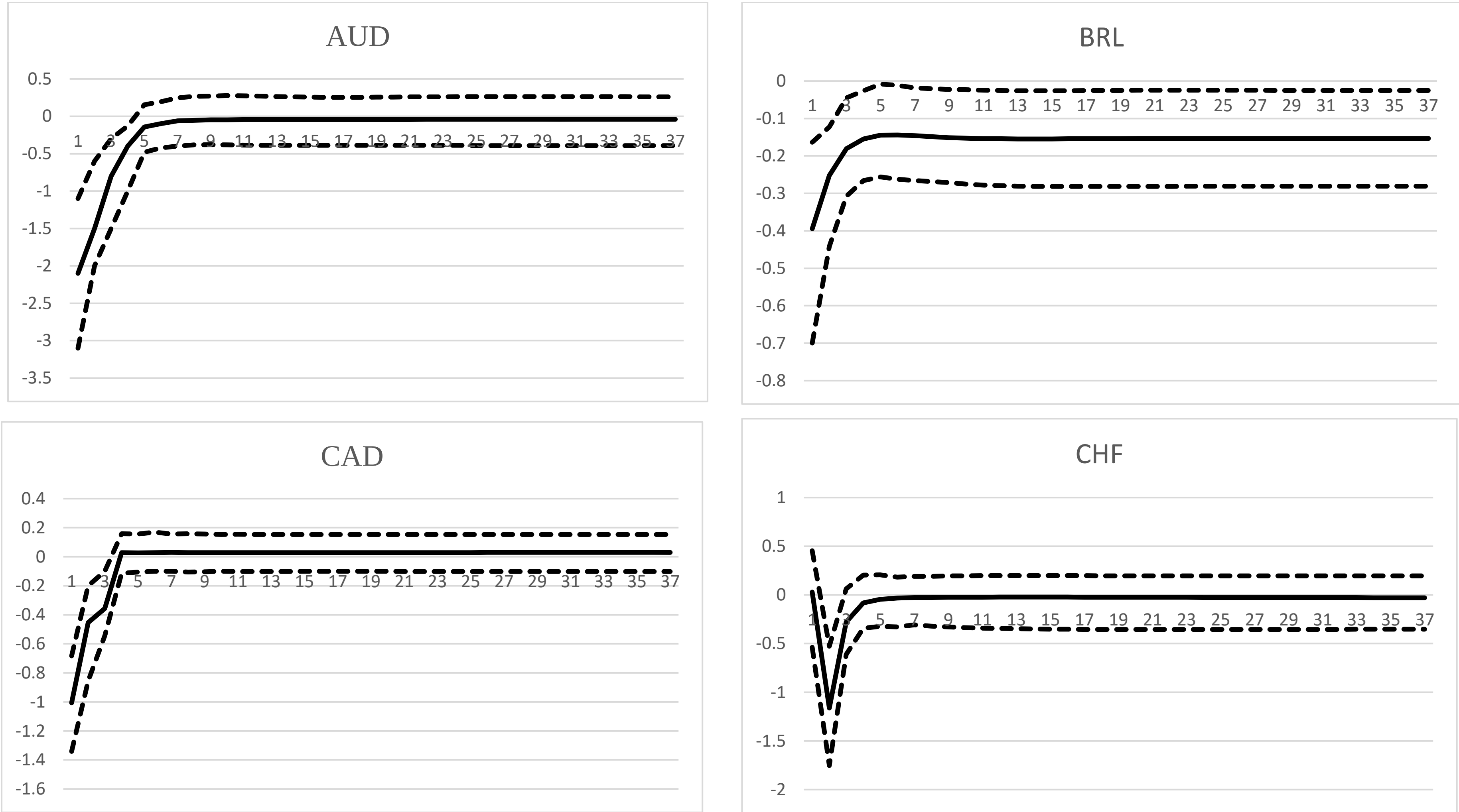
As explained in the previous section, we estimate the impulse responses of the cross-section currency illiquidity to exchange-rate specific CTOT shocks, as well as, including a commodity price index shock as a commonality factor. Specifically, we obtain the generalized impulse response functions as given in equation (3.14). We separately estimate the CTOT shocks in the cross-sectional supply and demand side of FX liquidity by following previous studies (Karnaukh, Ronaldo and Soderlind, 2015; Banti and Phylaktis, 2015). Afterwards, we estimate the transmission of commodity price shocks as a commonality factor to the cross-sectional illiquidity while simultaneously controlling the main cross-sectional demand and supply determinants as domestic and foreign variables.

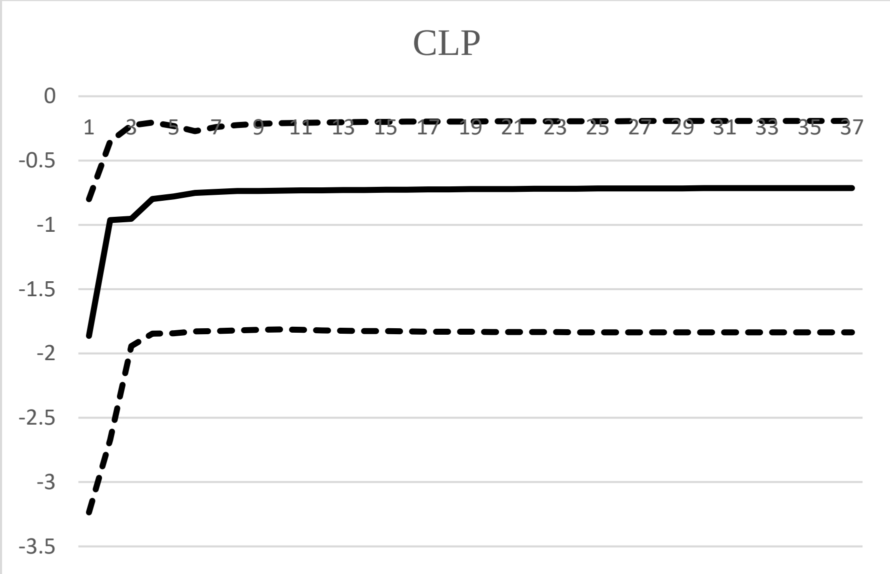
First then, we estimate the impulse responses of the cross-sectional illiquidity to the exchange specific CTOT shocks in supply side context. Although, the commodity price as a factor seems more appropriate to the demand side model, the exchange rates, especially those which have a small and commodity-export based economy can be expected to be affected by CTOT shocks via the local and global funding rates channels. CTOT shocks can influence the investment decisions and sentiments of local financial intermediaries, can be ultimately reflected in the illiquidity of local currency.

Figure 3.1 reports the median (solid line) impulse responses of illiquidity of the currencies to one-unit standard deviation shock for country specific CTOT in the supply side framework over 3 years (36 months). The estimation period covers from 01/1994 to 12/2016. The dotted lines are bootstrap 95% confidence bands obtained with 1000 bootstrap replication.

The graphs show that illiquidity of the currencies belonging to relatively developed economies (such as GBP, JPY, CHF, SGD, KRW), excluding SEK is not significantly influenced by local CTOT shocks.

Figure 3. 1 GIRFs of the cross-Sectional illiquidity to one standard deviation shock to country specific CTOT shocks within the supply side framework. The estimation period covers 01/1994 to 12/2016. The solid line indicates the median impulse response while the dotted lines are bootstrap 95% confidence bands obtained with 1000 bootstrap replications. The magnitudes of the responses are scaled up by the same amount.

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-3
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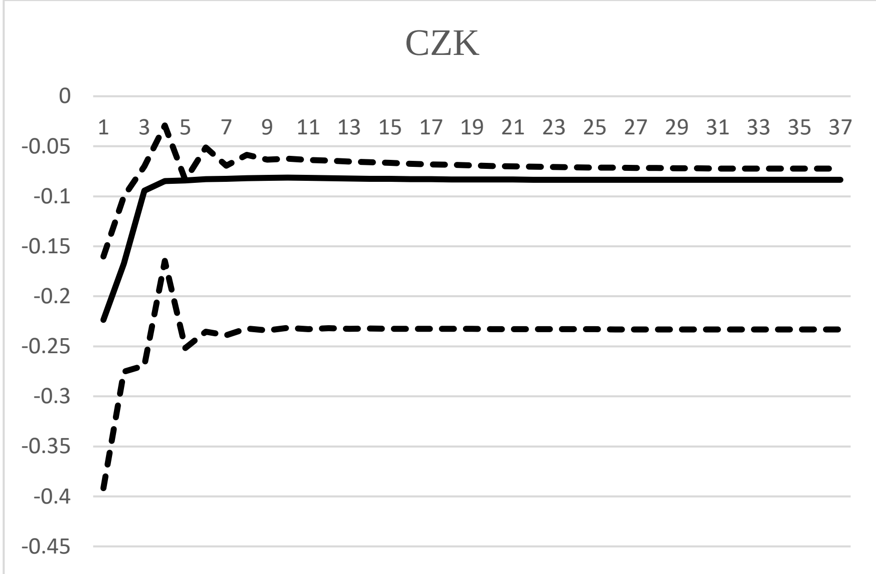
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-0.4
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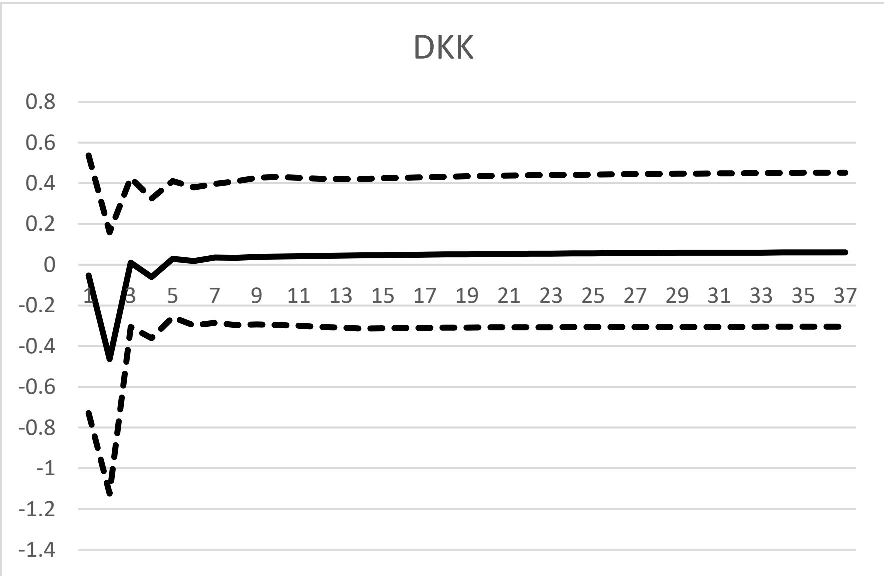
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0
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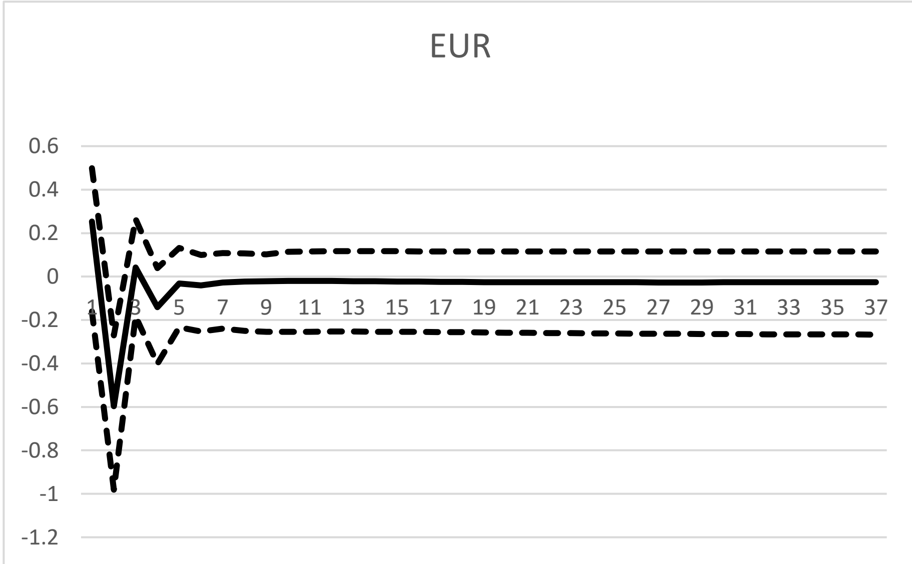
-1.2
-1.4
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37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-1
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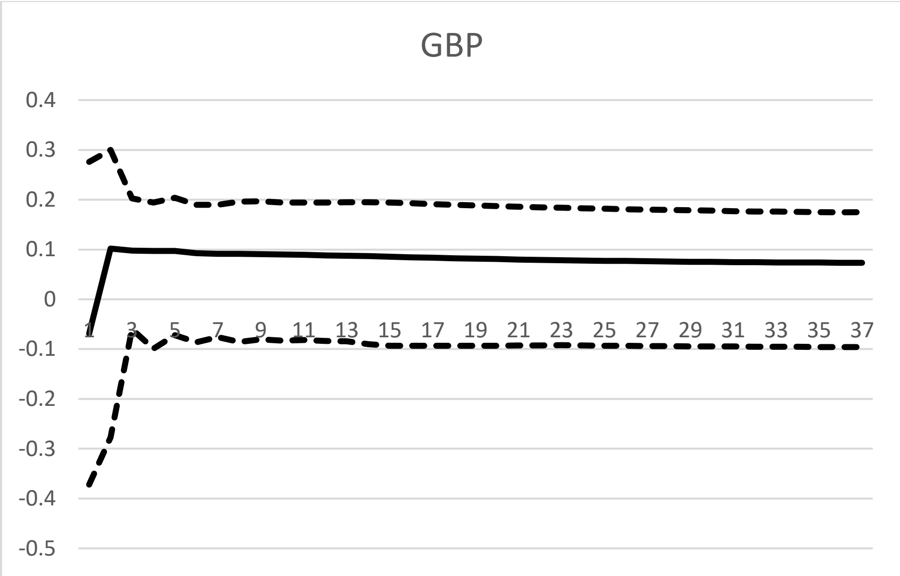
GBP
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0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


HUF
0
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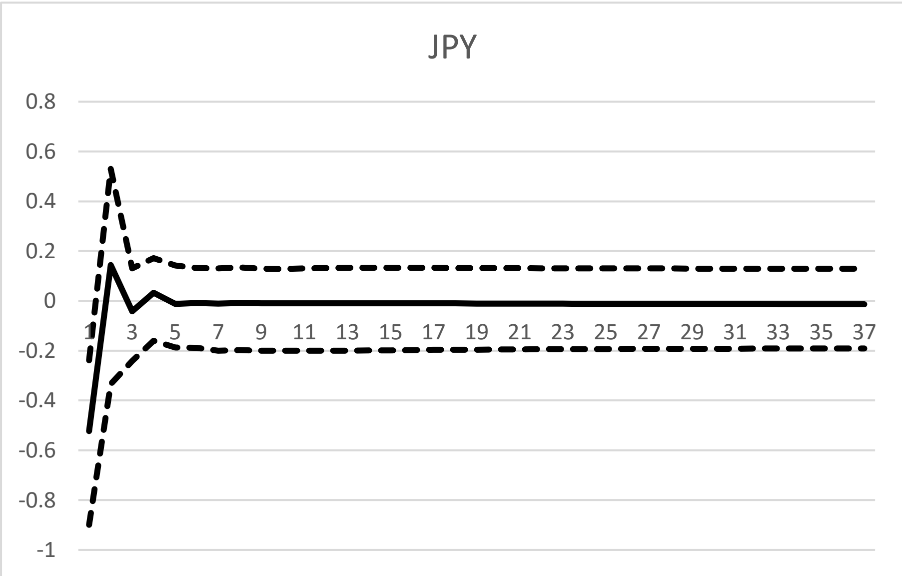
-0.4
-0.6
-0.8
-1
-1.2
-1.4
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41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-0.6
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-1
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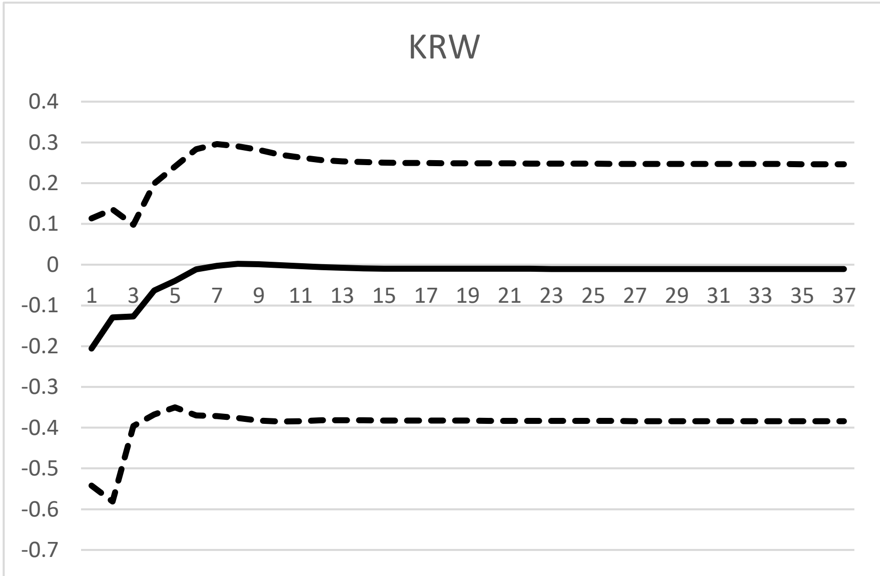
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-0.7
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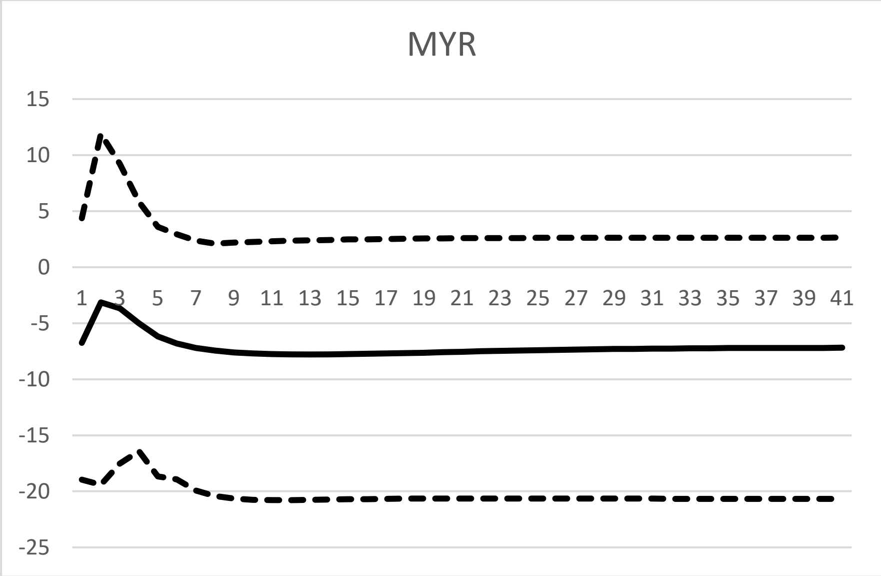
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5
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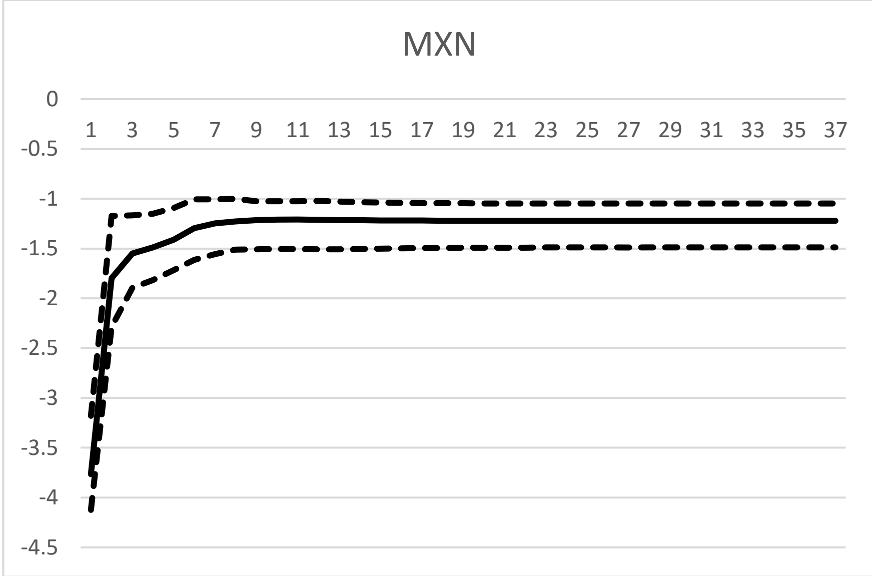
-20
-25
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41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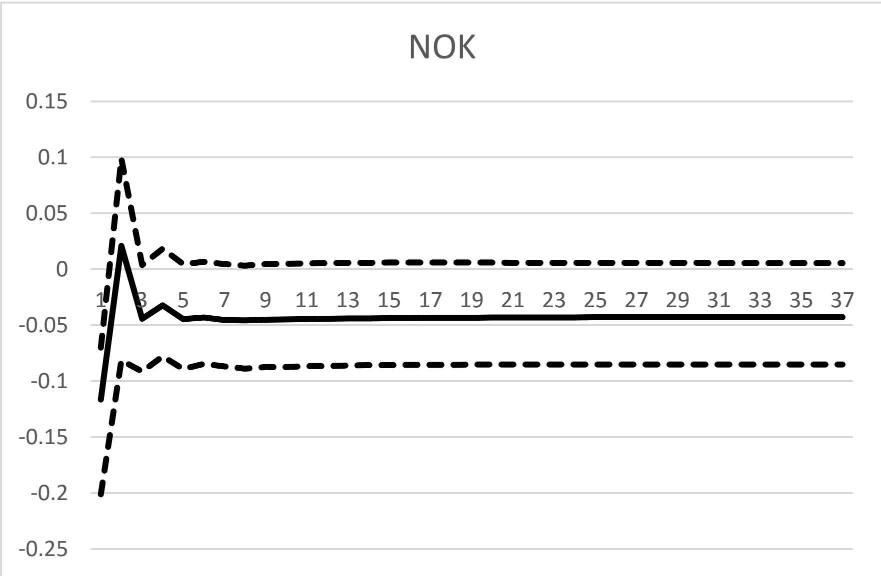
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0.05
0
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-0.1
-0.15
-0.2
-0.25
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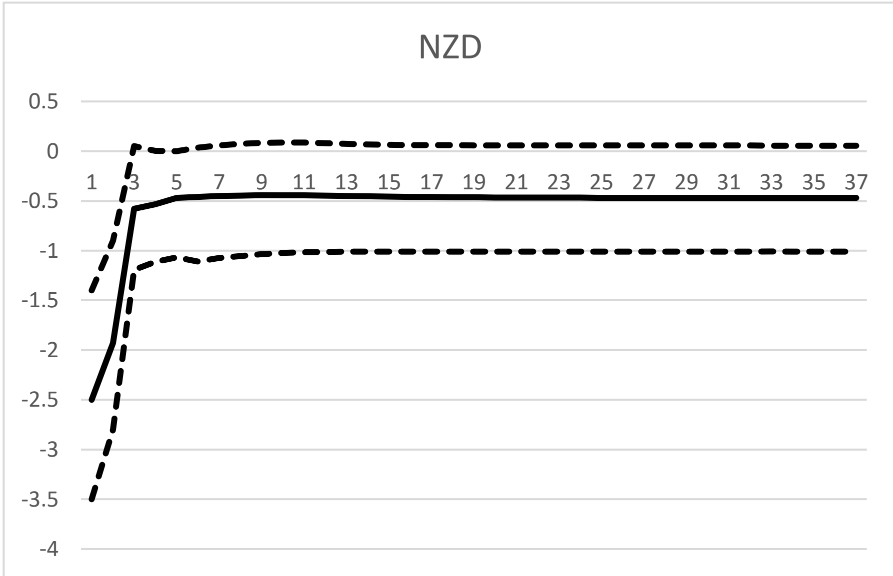
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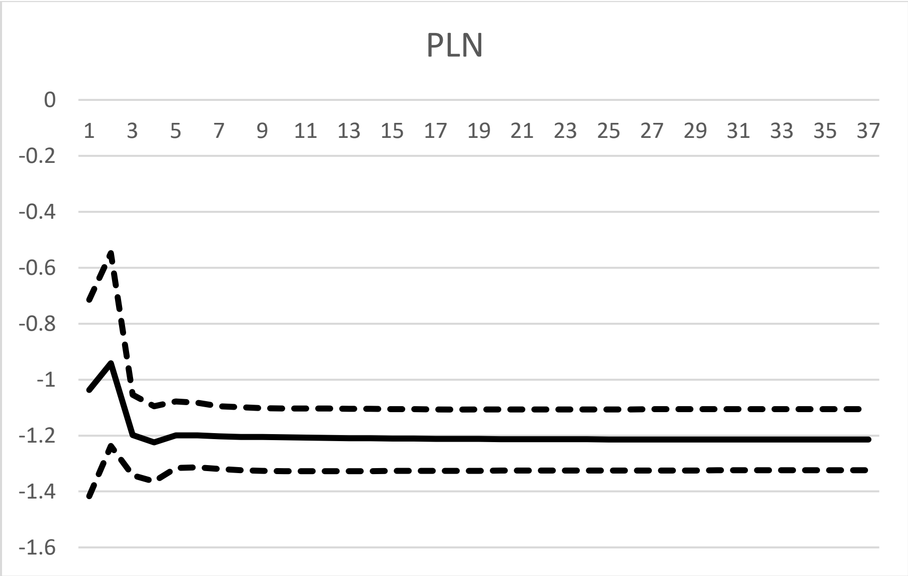
-2
-2.5
-3
-3.5
-4
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


PLN
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-0.6
-0.8
-1
-1.2
-1.4
-1.6
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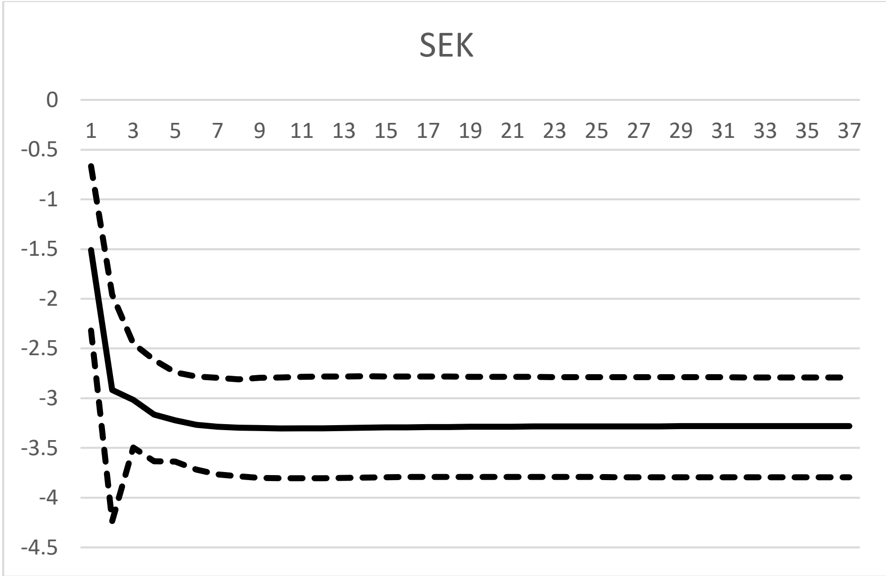
SEK
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-1
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-3
-3.5
-4
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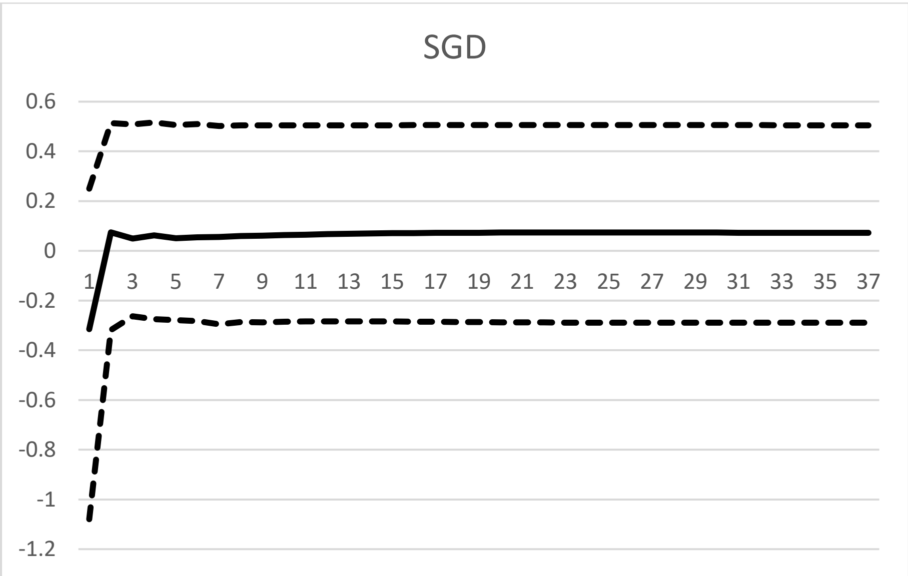
SGD
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0.4
0.2
0
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-0.4
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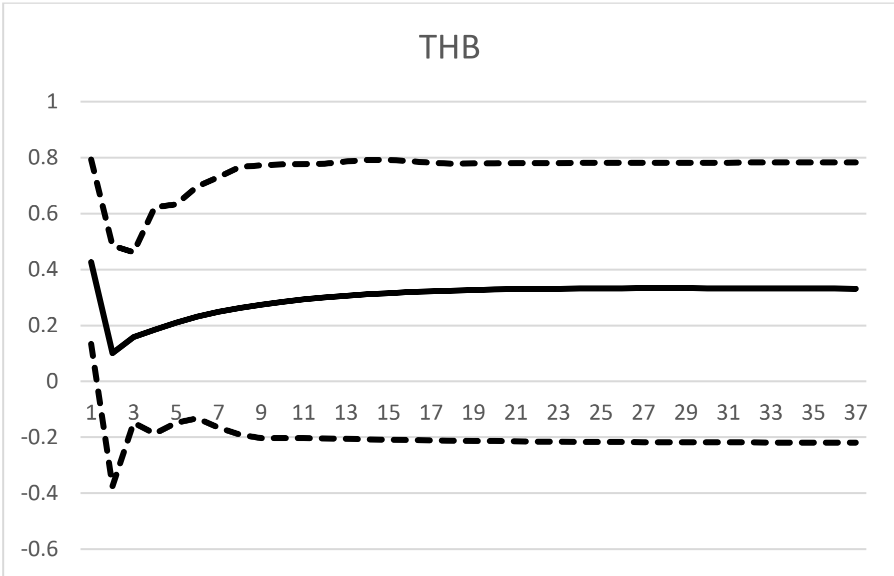
-0.8
-1
-1.2
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


THB
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


TRY
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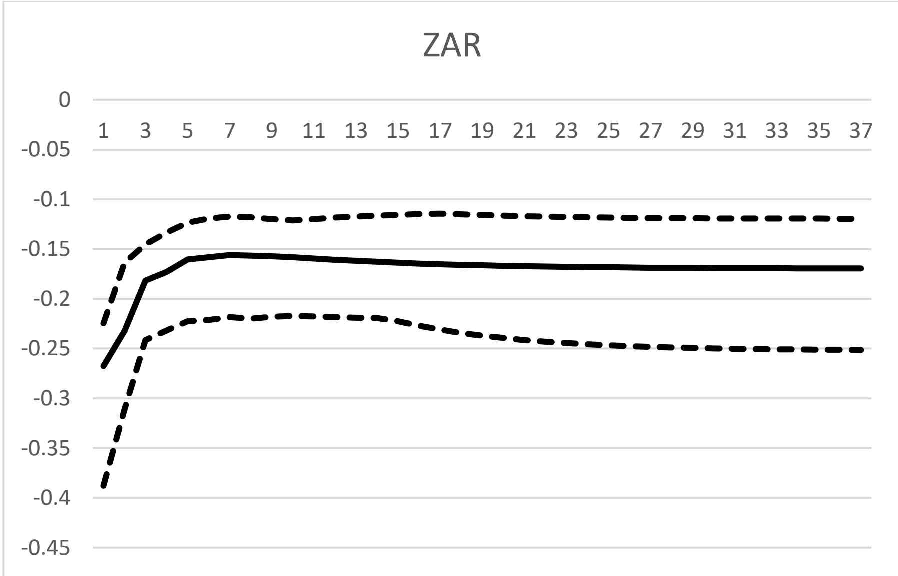
1
0.5
0
-0.5
-1
-1.5
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37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-0.1
-0.15
-0.2
-0.25
-0.3
-0.35
-0.4
-0.45
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37

It is not hard to explain this finding as the variation in illiquidity of the currencies of developed economies can be significantly explained by local money market rates within the supply side model.

Additionally, combining global FX volatility and TED spread which are known as highly significant commonality factors for the most popular currencies in the supply model, leave a very small room for CTOT shocks to explain the variation in the cross-sectional illiquidity. Of course, it should be noted that currency illiquidity of developed economies but are more exposed to commodity exporting (such as AUD, NOK, NZD, CAD) does respond the local CTOT shocks significantly during first few lags but dies away afterwards. In these cases, the local CTOT shocks may stimulate the sentiments of market participants in these countries due to their dependence on commodity exporting. However, portfolio rebalancing, international investments can reasonably stabilize the short-term plunges in illiquidity.

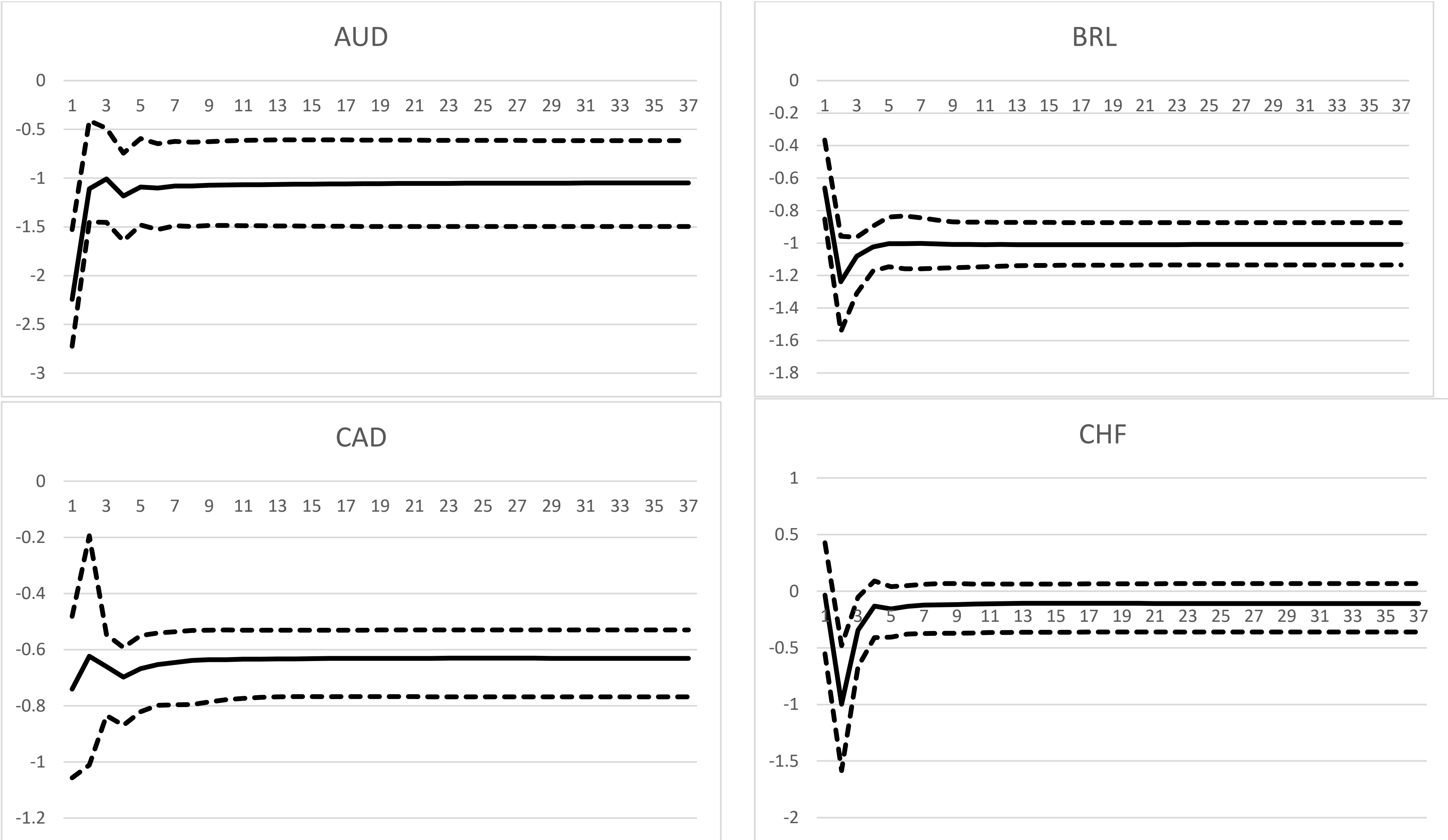
Conversely, the currency illiquidity of less developed countries (commodity currencies or others) significantly respond to the local CTOT shocks over a prolonged period. Following the CTOT shocks, the illiquidity of the currencies such as BRL, CLP, CZK, HUF and PLN tend to experience a persistent, long-lived fall. Three currencies, MYR, THB, TRY, can be considered exceptions because they are less developed currencies, but illiquidity is not influenced by the CTOT shocks.

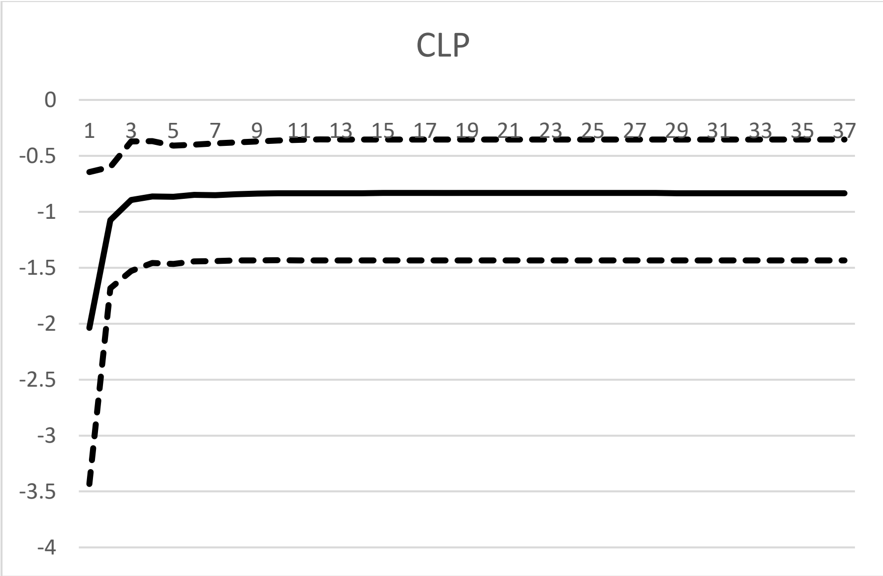
Subsequently, we estimate the impulse responses of cross-sectional illiquidity to the exchange specific CTOT shocks in the cross- sectional demand side framework. We replace local money market rates with capital flows (i.e export to U.S) as a domestic variable. Thus, we jointly model bid-ask spreads, capital flows with U.S and CTOT in the endogenous system. Similarly, we add the VIX index, known as a common determinant in FX liquidity, as a proxy for market sentiment, instead of the TED spread as a global variable. We also keep FX volatility as a global variable for proxying general market conditions.

Figure 3.2 reports the median (solid line) impulse responses of illiquidity of the currencies to one-unit standard deviation for the country specific CTOT shocks in the demand side framework over 3 years (36 months). The estimation period covers 01/1994 to 12/2016. The dotted lines are bootstrap 95% confidence bands obtained with 1000 bootstrap replication.

As expected, illiquidity of most of the currencies significantly responds to local CTOT shocks. A one-unit standard deviation shock is followed by a persistent effect on illiquidity in most of currencies, excluding highly liquid currencies such as CHF, JPY and GBP and Asian currencies such as THB, KRW, MYR and SGD.

FIGURE 3. 2 GIRFS OF THE CROSS SECTION OF ILLIQUIDITY TO THE COUNTRY SPECIFIC CTOT SHOCKS WITHIN THE DEMAND SIDE FRAMEWORK. THE ESTIMATION PERIOD COVERS 01/1994 TO 12/2016. THE SOLID LINE INDICATES THE MEDIAN IMPULSE RESPONSE WHILE THE DOTTED LINES ARE BOOTSTRAP 95% CONFIDENCE BANDS OBTAINED WITH 1000 BOOTSTRAP REPLICATIONS. THE MAGNITUDES OF THE RESPONSES ARE SCALED UP BY THE SAME AMOUNT.

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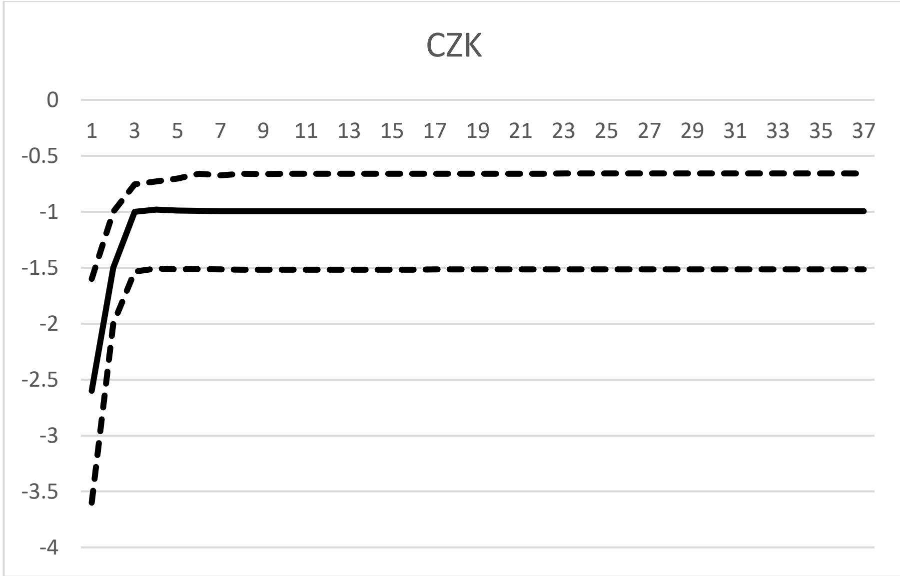
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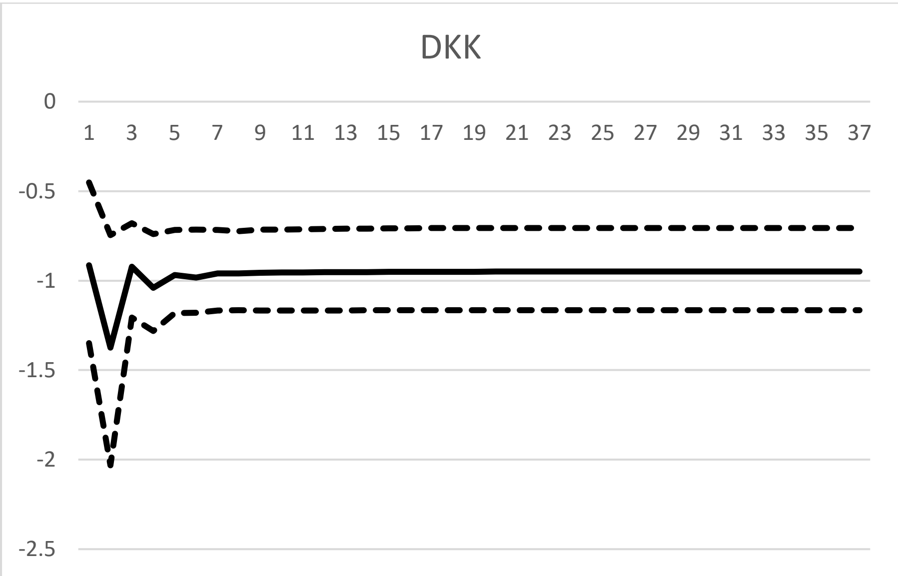
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-1
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1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37

EUR
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


GBP
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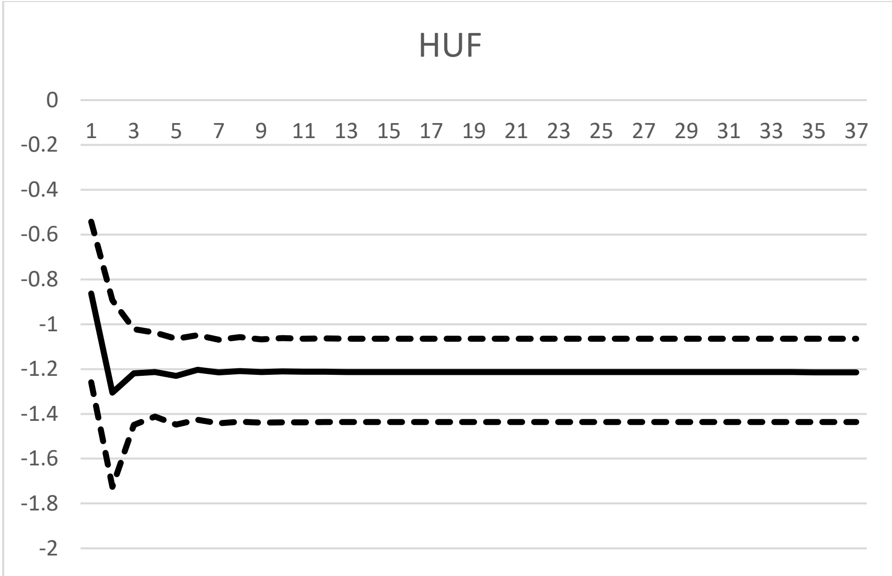
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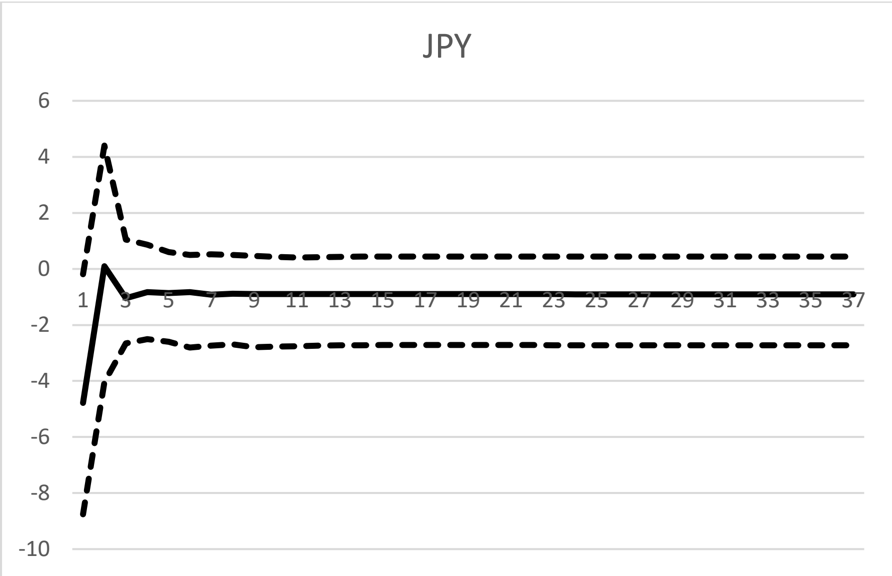
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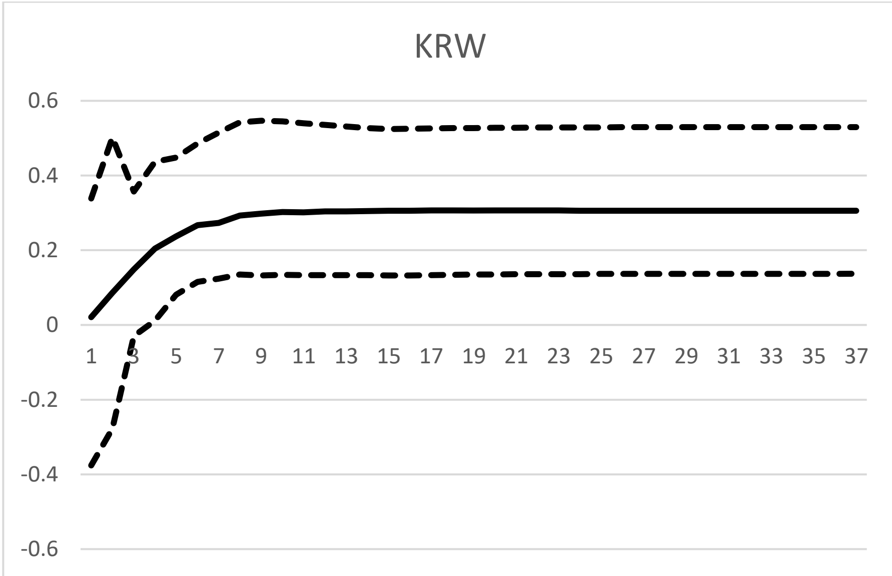
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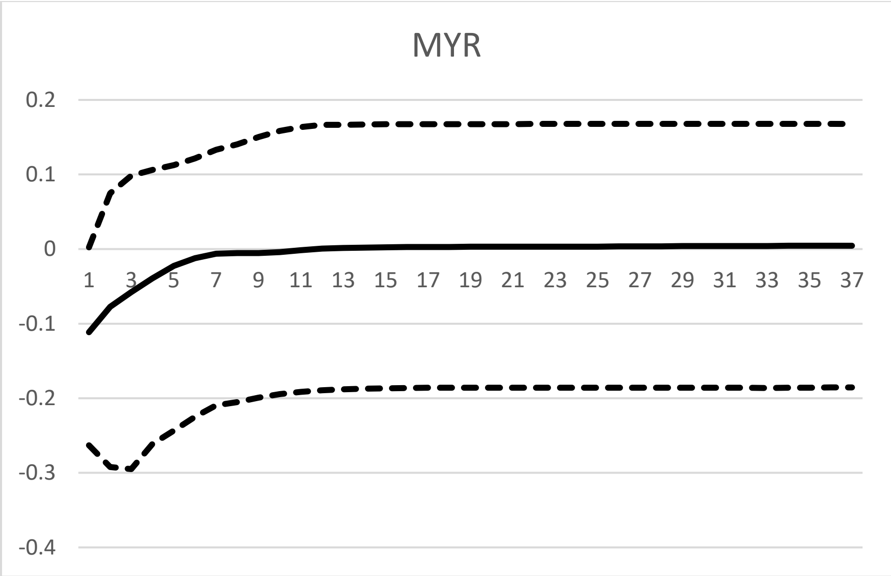
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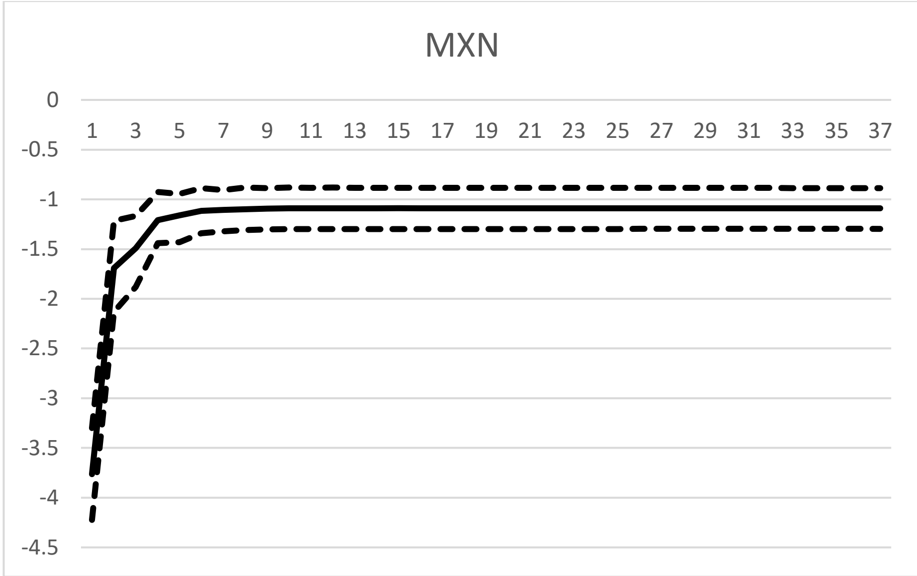
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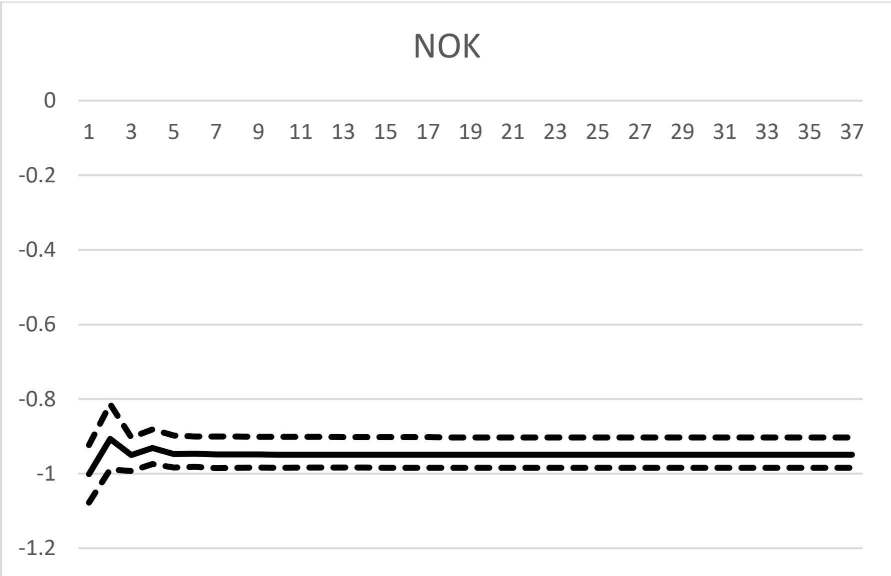
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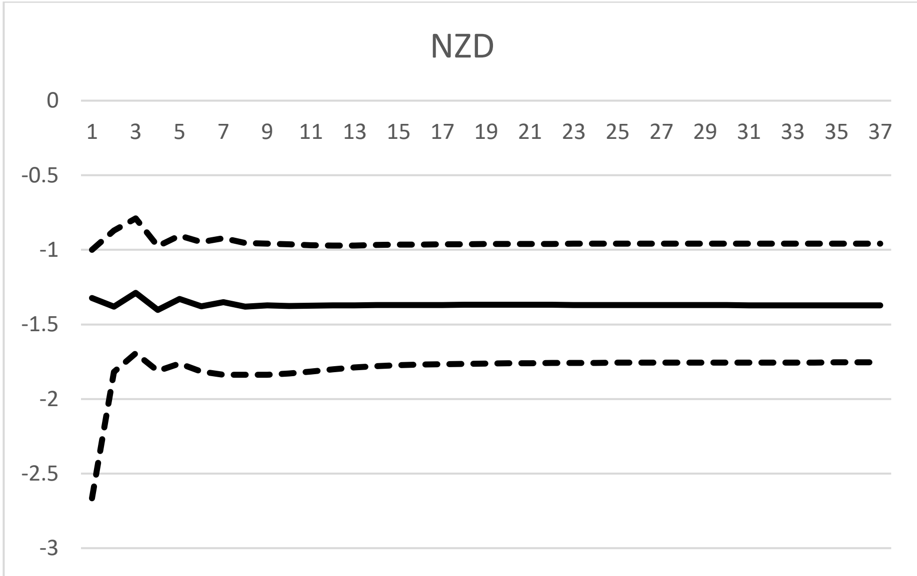
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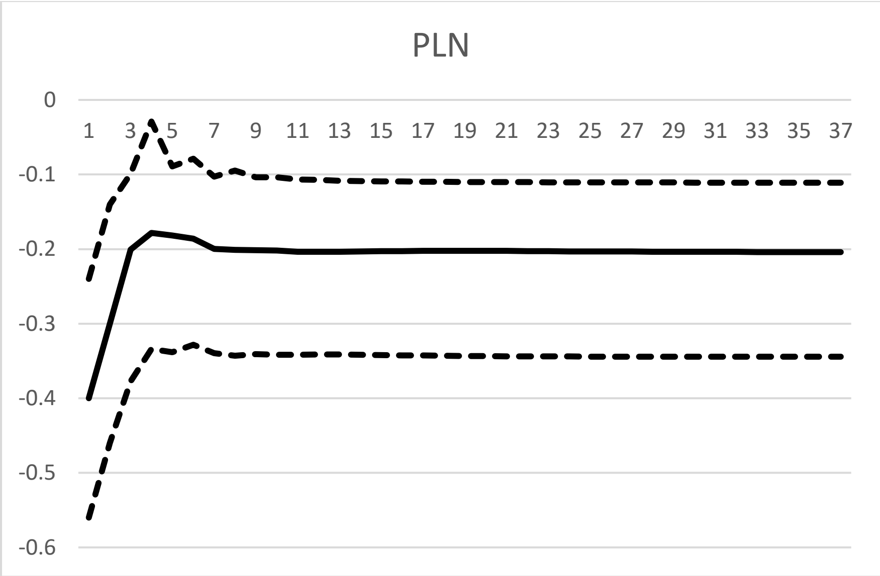
PLN
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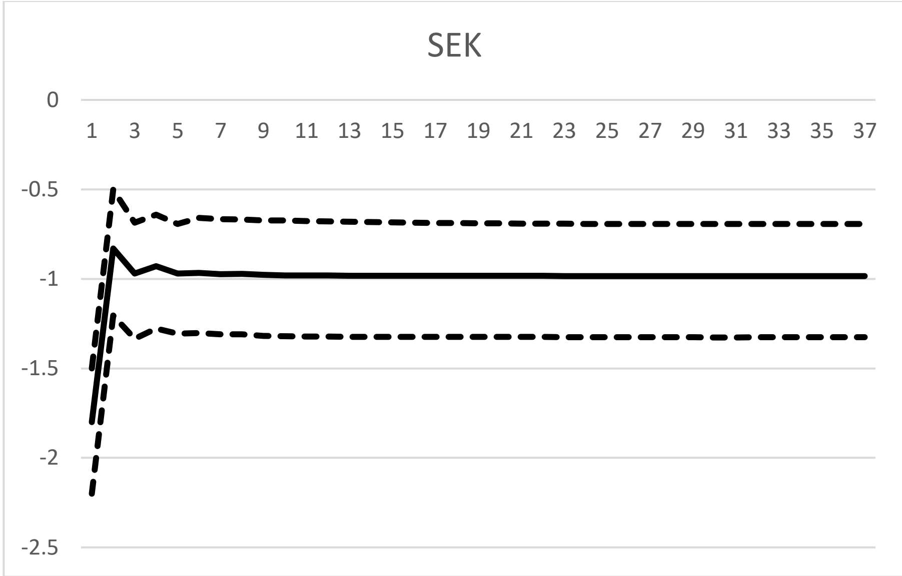
-0.2
-0.3
-0.4
-0.5
-0.6
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37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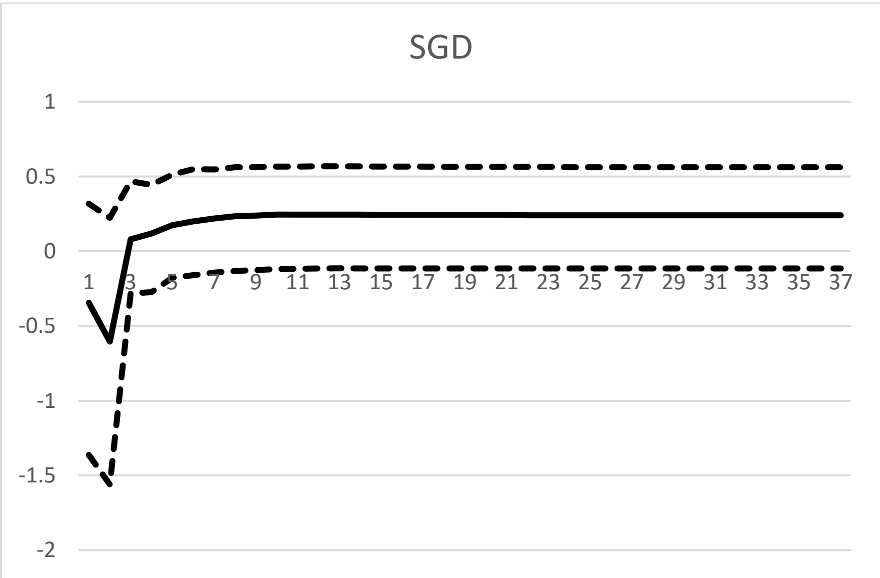
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-2
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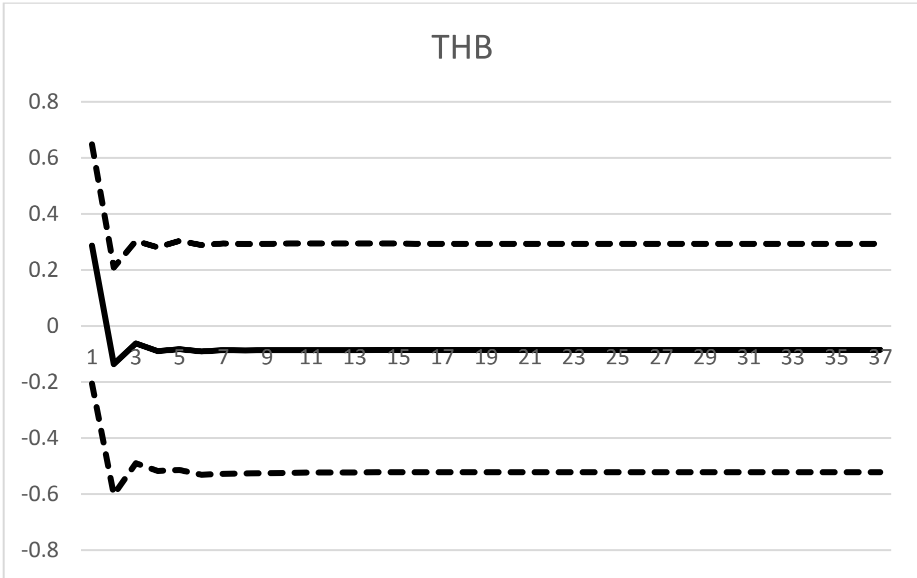
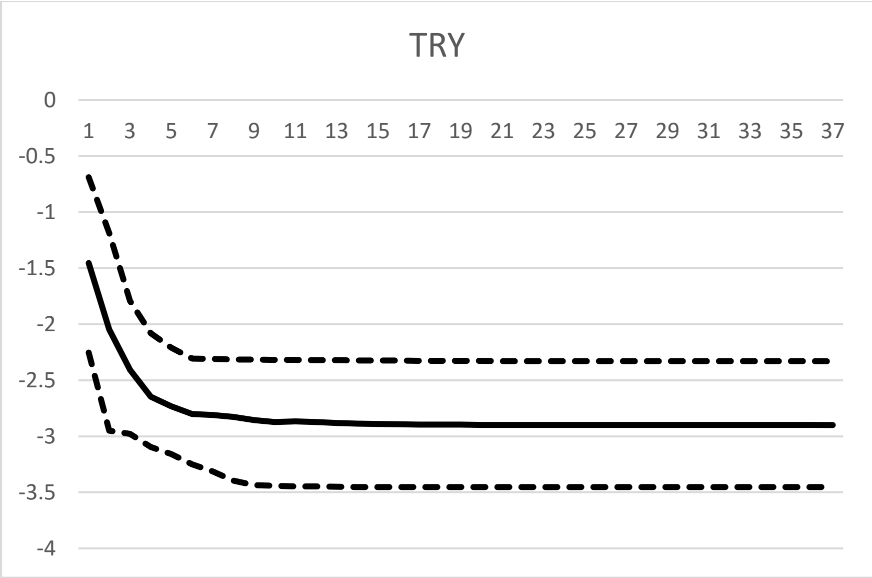
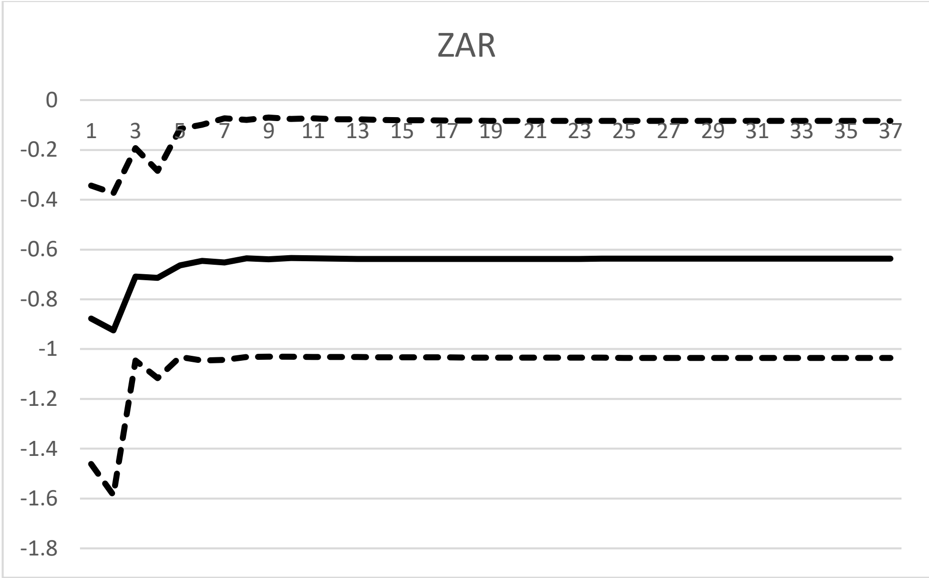

THB
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


TRY
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
-4
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37

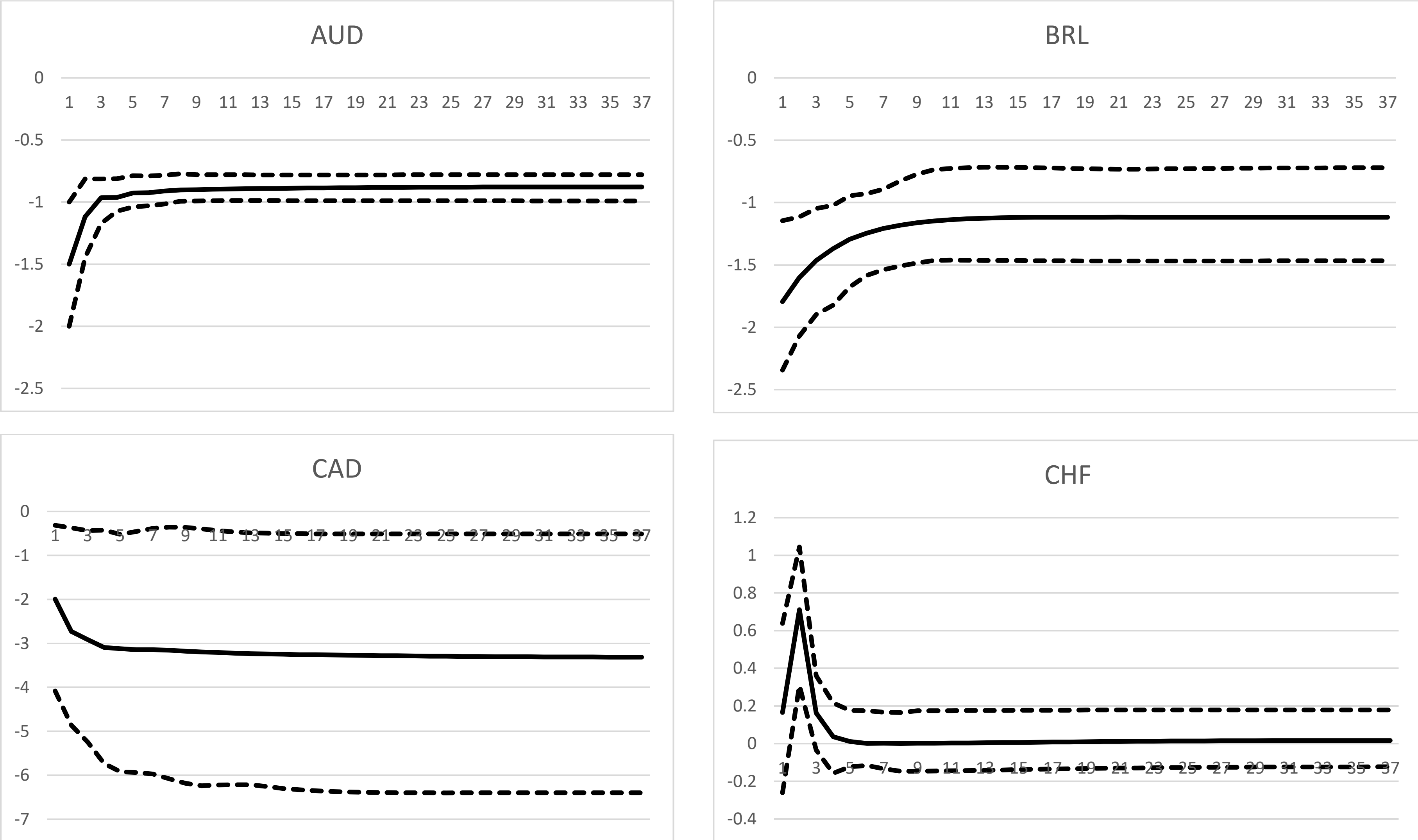

ZAR
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
-1.6
-1.8
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37

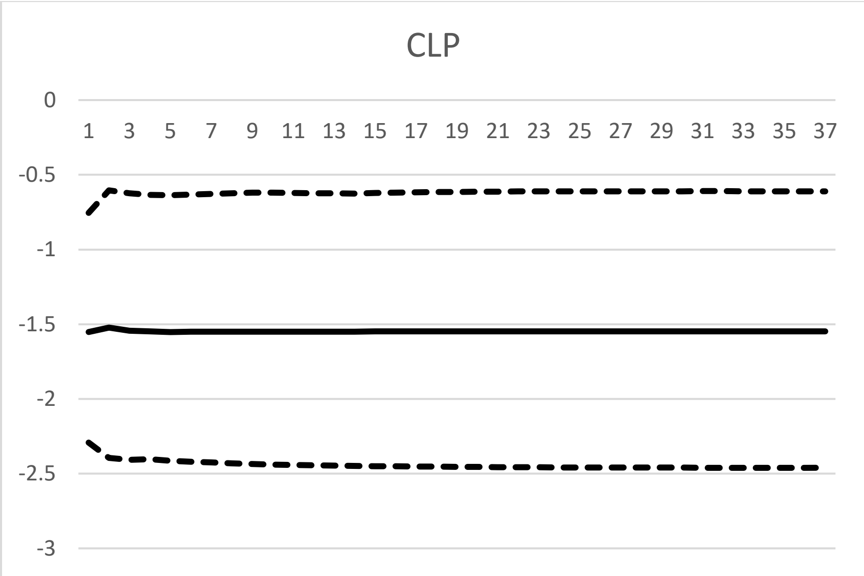
Our demand side approach explores the determinants that increase the market demand for a specific currency. CTOT shocks stimulate the market demand for the local currency and pushes up liquidity for most of our currencies. Not surprisingly, jointly modelling capital flows while controlling for market sentiment (VIX) and general market condition increases the effects of CTOT shocks. The reason for not observing a significant effect on highly liquid currencies might be that illiquidity of these currencies is influenced by a lot of other factors. Therefore, the effect of CTOT shocks on monthly basis might not be observable.

Finally, we explicitly explore commodity price as a commonality factor in the cross-sectional variation of illiquidity of the currencies. The GVAR model allows us to explicitly define commonality factor in the global variables section. The common factor pass-through to the cross-sectional variable of interest via trade flow and interlinkages of cross sections. Since CTOT is a country specific data, we use the commodity price index from the IMF as a global variable. In the endogenous system, we simultaneously model cross-sectional demand (capital flows), supply (local money market rates) side factors and bid-ask spread.

Figure 3.3 reports the median (solid line) impulse responses of illiquidity of the currencies to a one-unit standard deviation shock for commodity price index over 3 years 6 months). The estimation period covers from 01/1994 to 12/2016. The dotted lines are bootstrap 95% confidence bands obtained with 1000 bootstrap replications.

FIGURE 3. 3 GIRFS OF THE CROSS SECTION OF ILLIQUIDITY TO THE COMMON COMMODITY PRICE SHOCKS. THE ESTIMATION PERIOD COVERS 01/1994 TO 12/2016. THE SOLID LINE INDICATES THE MEDIAN IMPULSE RESPONSE WHILE THE DOTTED LINES ARE BOOTSTRAP 95% CONFIDENCE BANDS OBTAINED WITH 1000 BOOTSTRAP REPLICATIONS. THE MAGNITUDES OF THE RESPONSES ARE SCALED UP BY THE SAME AMOUNT.




CLP
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-0.5
-1
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-2
-2.5
-3
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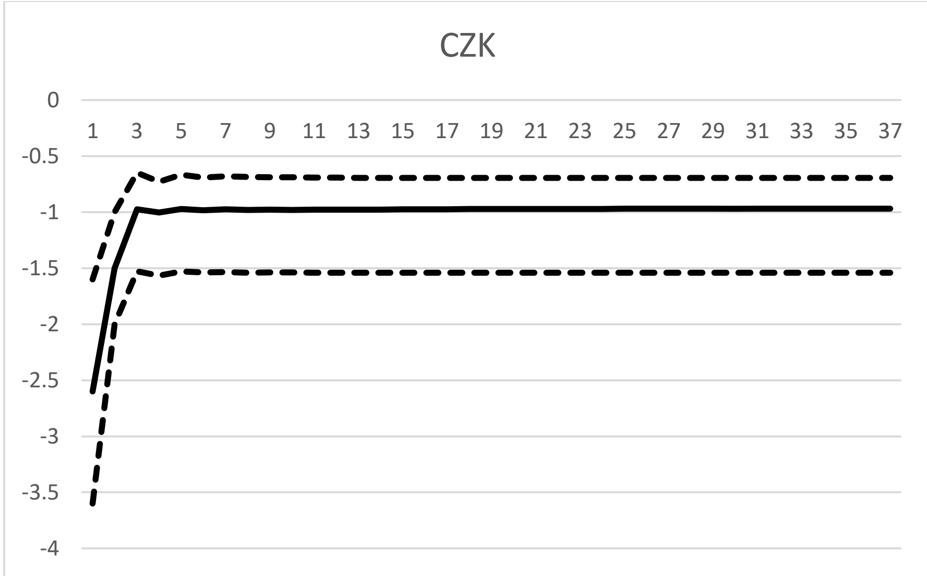
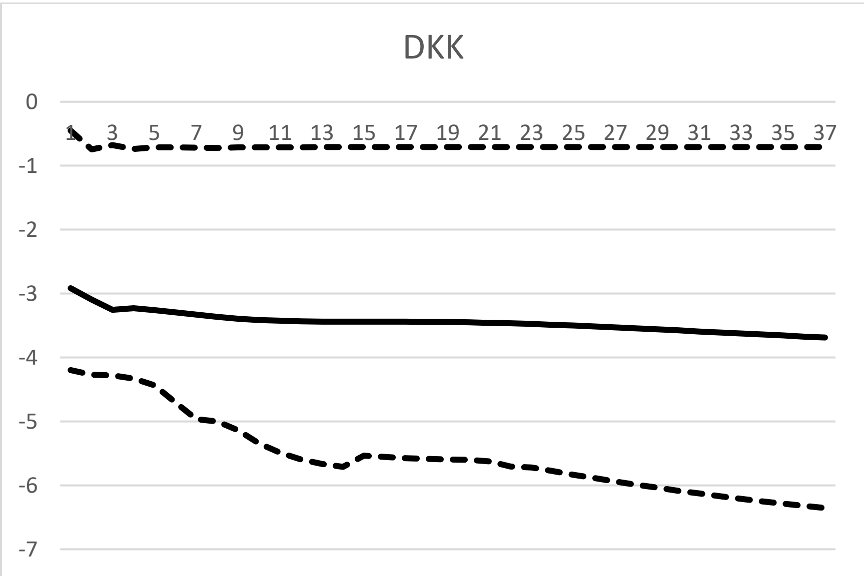

CZK
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
-4
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


DKK
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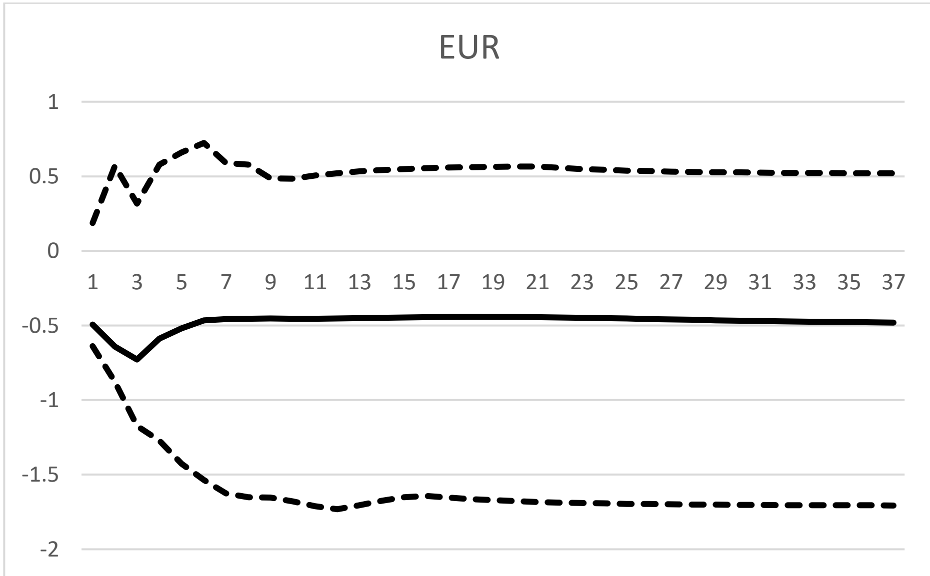
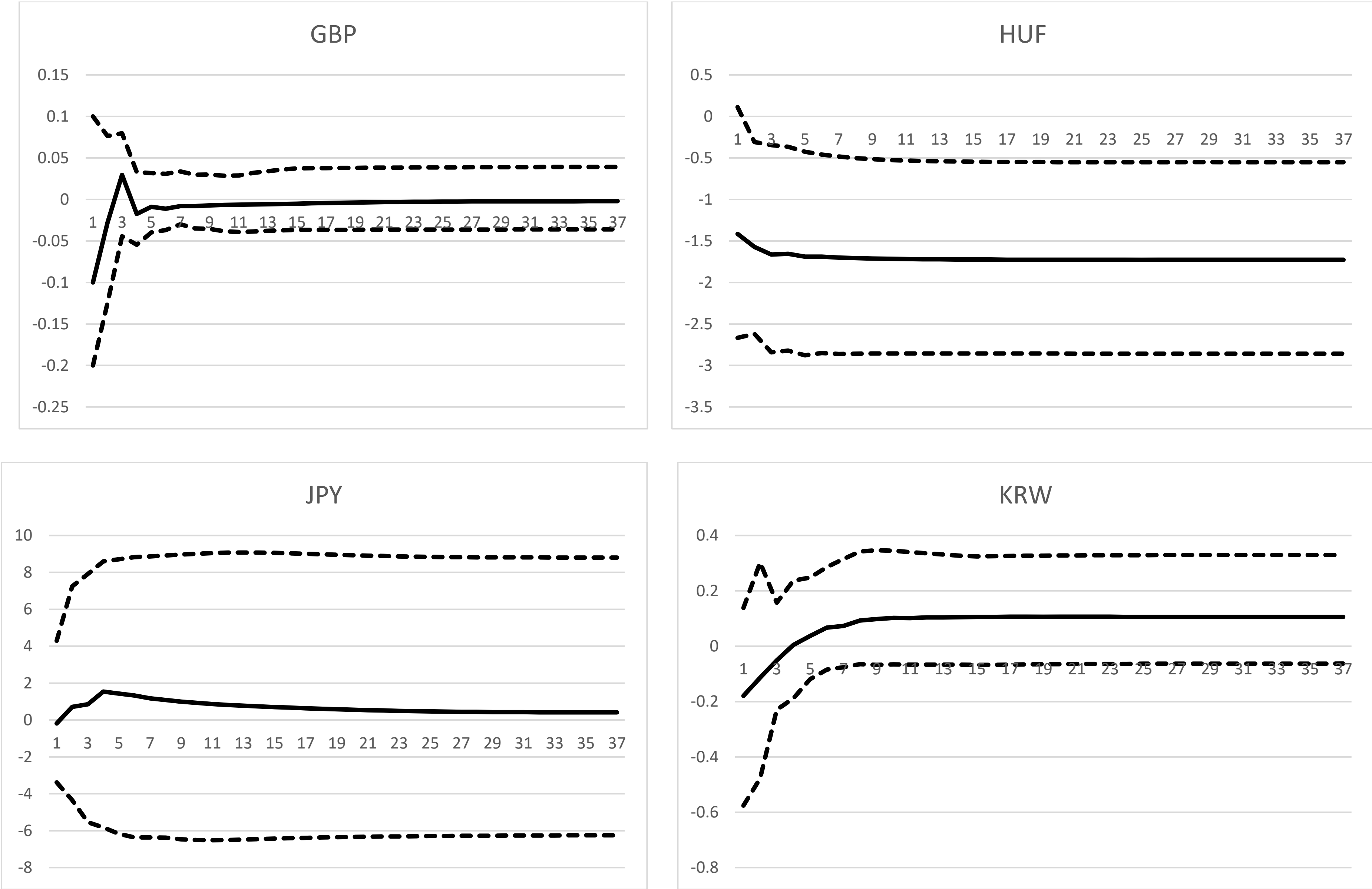
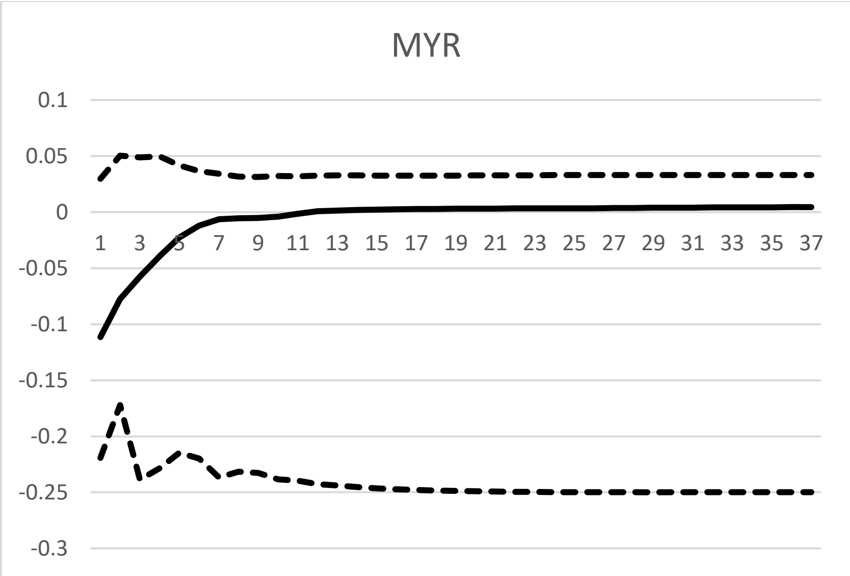
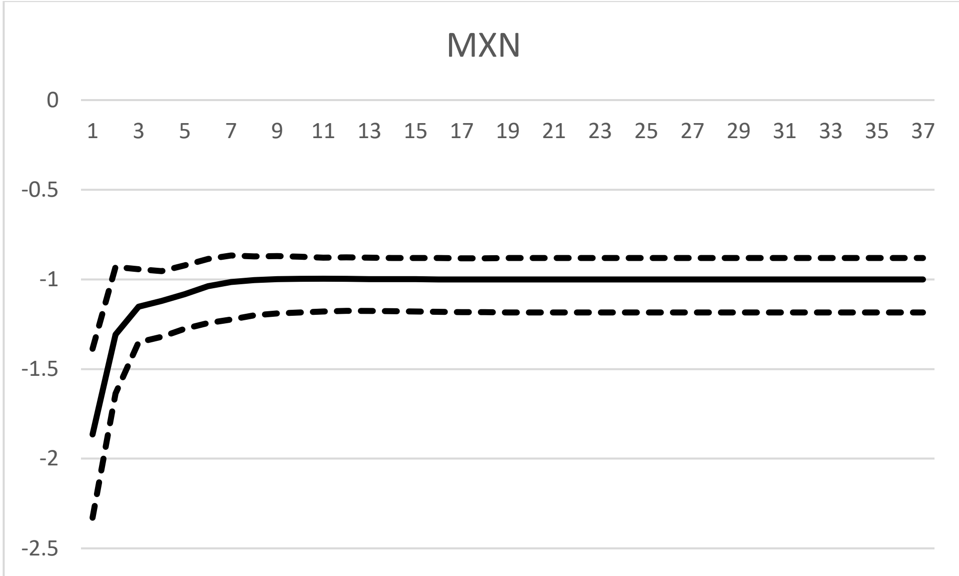
-1
-2
-3
-4
-5
-6
-7
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37

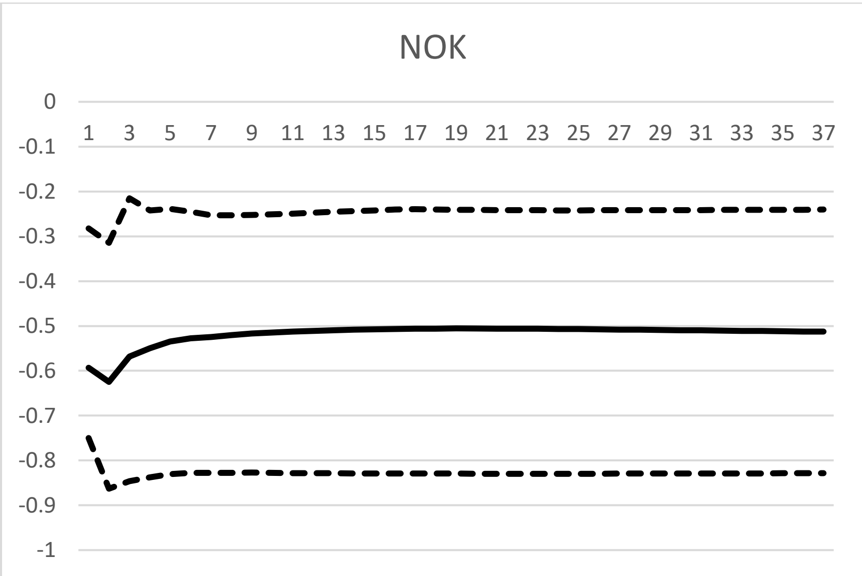

EUR
1
0.5
0
-0.5
-1
-1.5
-2
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37

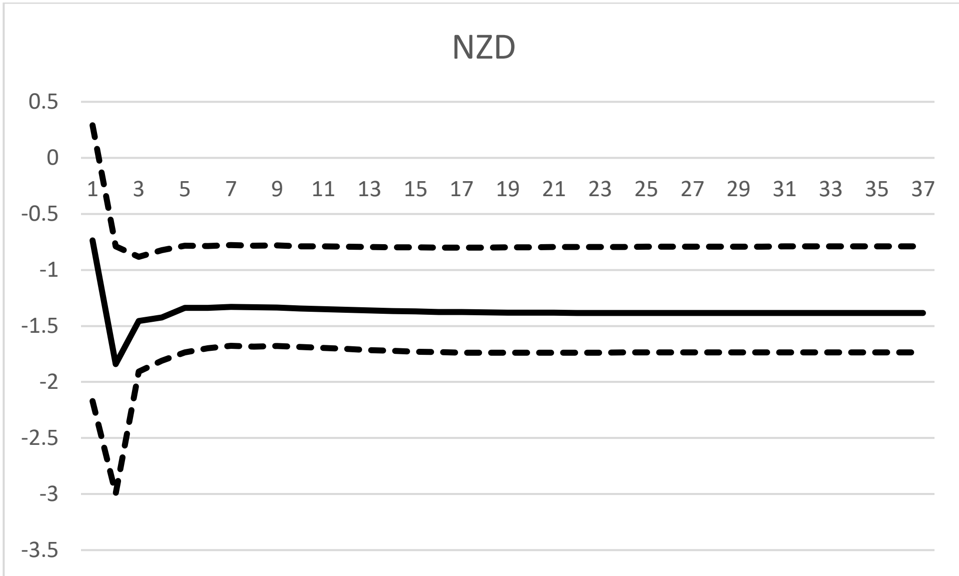


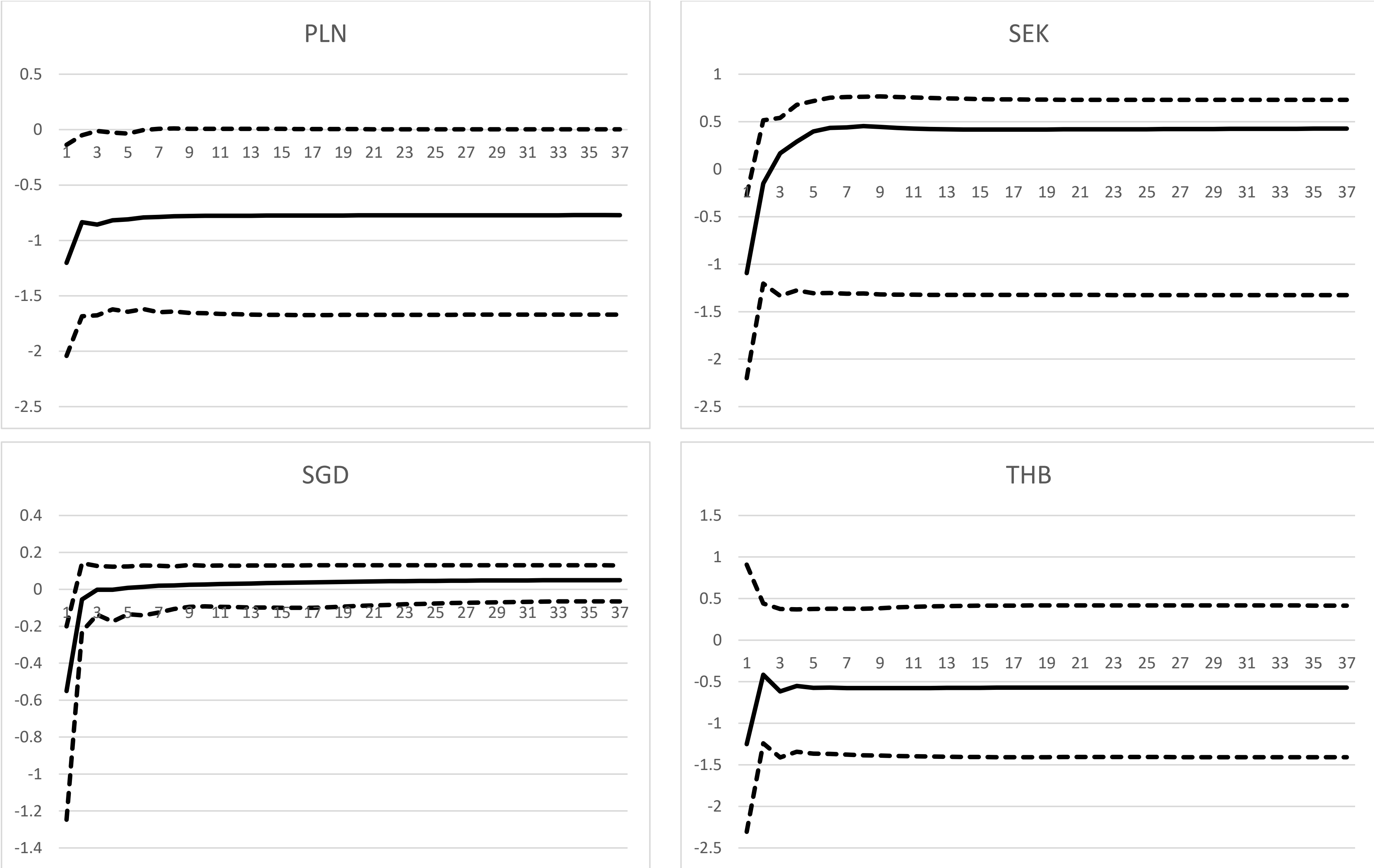
GBP
HUF
JPY
KRW

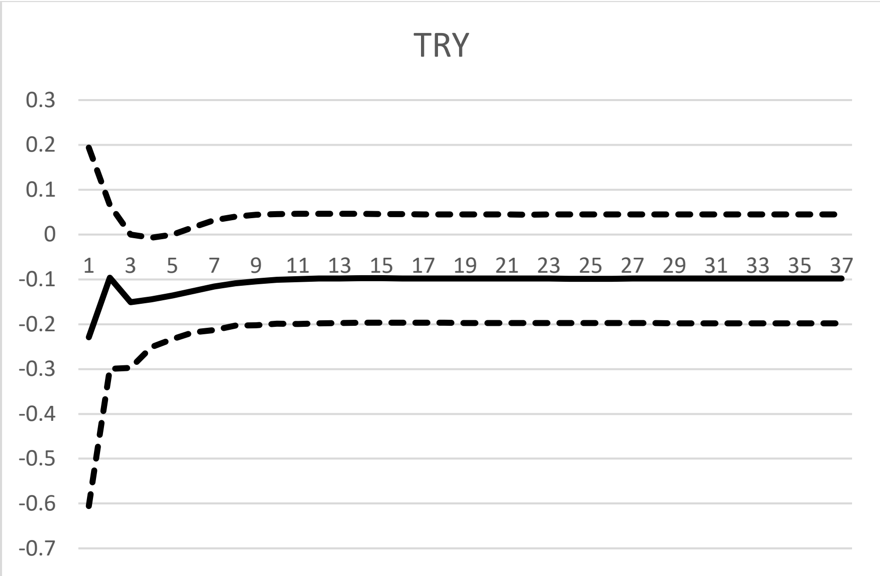

MYR
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37

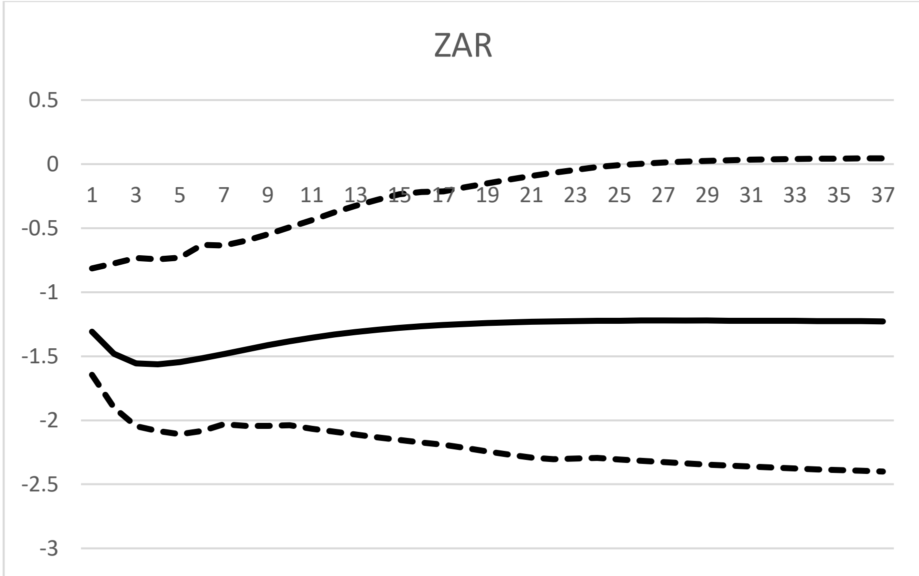

MXN
0
-0.5
-1
-1.5
-2
-2.5
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


NOK
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-0.7
-0.8
-0.9
-1
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


NZD
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


PLN
0.5
0
-0.5
-1
-1.5
-2
-2.5
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37
SEK
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37
SGD
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37
THB
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


TRY
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-0.7
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37


ZAR
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37

The graphs show that illiquidity of the currencies considerably exposed to commodity exporting, also known as "commodity currencies" (AUD, CAD, BRL, ZAR, NOK, NZD, MXN) are significantly influenced by the common commodity price shocks. The currencies of small economies (CLP, SEK, PLN, HUF, CZP, DKK) are also significantly influenced by commodity price shock. As in the demand side model, highly liquid currencies are not significantly affected by common commodity price shock which might be explained by similar reasons.

3.5 Conclusion

This chapter explores the transmission of commodity prices to the illiquidity of 22 currency pairs with the USD. The empirical findings in the extant literature on the linkages between commodity prices and exchange rates, the role of liquidity in factor investing and the shortcomings of methodologies used in the FX literature motivated us to investigate commodity price pass-through to FX liquidity. In particular, we construct a new monthly dataset of country specific CTOT with updated trade weights and apply this in a GVAR framework.

This study can be useful for other researchers in the international finance area who wish to use higher frequency country-specific commodity terms-of-trade data. Our novelty lies in the dataset, considering commodity price as an additional determinant of FX liquidity, and the use of the GVAR approach. Moreover, we contribute to the FX liquidity literature with the following findings.

Illiquidity of the currencies of less developed economies experience a persistent fall, following local CTOT shock in the supply side framework. In the meantime, local CTOT shocks leave a significant but temporary effect on illiquidity of the currencies of developed economies but relatively more exposed to commodity exporting. Illiquidity of most currencies significantly responds to local CTOT shocks in the demand side framework. A one-unit standard deviation shock is followed by a persistent effect on illiquidity in most of currencies, excluding highly liquid currencies. Illiquidity of the currencies that are considerably exposed to commodity exporting is significantly influenced by common commodity price shocks. The currencies of small economies are also significantly influenced by commodity price shocks. We do not a find a similar effect for highly liquid currencies which might be explained by a high explanatory power of local money market rates and global funding conditions, as well as, the influence of short-term trading strategies.

This study suggests to the international finance literature that it is important not to limit with commodity currencies to explore the links between commodity price and exchange rates. Given the significant variation in the sensitivity of the exchange rates to the commodity price changes, the selection of an appropriate commodity price indicator might be a decisive factor to have comprehensive empirical findings. Apart from the international finance literature, this study can be useful to investors who wish to exploit the illiquidity premium in factor investing. The findings suggest investors that commodity prices can be an additional tool to model the direction of the liquidity of floating exchange rates.

Concluding Remarks

Liquidity is characterized by transaction cost, time and price impact dimensions to execute market operations. Due to its importance in financial markets, market liquidity has received considerable attention by researchers in recent years. At the stock market level, although the time series and cross-sectional determinants are extensively investigated, forecasting stock market liquidity has not been attempted so far. Monetary aggregates are known to have been influenced by monetary policy and economic activity, but never explored in different political regimes. While FX liquidity can be considered as a relatively new area in market liquidity, a number of studies have explored its cross-sectional and time series determinants after recent financial crisis. Although a strong link between commodity prices and exchange rates has been documented in the literature, none of the studies attempts to study commodity prices as a potential cross-sectional determinant and commonality factor of FX liquidity.

This thesis studies three aspects of market liquidity, namely, forecasting stock market liquidity, exploring the US monetary aggregates under different political regimes and the transmission of commodity price to FX liquidity.

The first chapter explores the power of investor sentiment to forecast stock market liquidity. Motivated by the theoretical links between market liquidity and investor sentiment, the chapter aims to investigate whether investor sentiment has the ability to forecast stock market liquidity. By carrying out 1-4 steps at the weekly and 1-2 steps at the monthly out-of-sample forecasting works, the study finds that investor sentiment is a statistically significant indicator to forecast NYSE liquidity at the weekly and monthly frequences. The forecasting performance is found to be better at the weekly than monthly estimations. Moreover, investor sentiment spread is shown to exhibit a better performance than the Baker and Wurgler (2006) sentiment index. The study contributes to the scarce liquidity forecasting literature, and also provides empirical insight to the microstructure of the stock market literature.

The second chapter explores the partisan gap in U.S. monetary aggregates. Based on strong theoretical and empirical links between monetary aggregates and economic activity, as well as stock market returns, the chapter aims to investigate whether the presidential gap might be present in the monetary aggregates. The study documents that there is a positive Democratic gap in U.S. monetary aggregates. The gap found is as much as 5 percent and 9 percent per annum in the M1 and M2 growth rates, respectively. The study finds a partisan Fed chair is a statistically significant indicator to explain the presidential gap. In other words, the Democratic Fed chair gap is found to be statistically more robust than the Democratic presidential gap in the growth rates of the monetary aggregates. The chapter contributes to the money supply literature by exploring it under political regimes to enrich the U.S. presidential puzzle literature.

The third chapter explores the transmission of commodity prices to the illiquidity of 22 currency pairs relative to the U.S. dollar. The chapter investigates commodity price pass-through to FX liquidity by exploiting a new monthly dataset of country specific CTOT with updated trade weights in a GVAR framework. The chapter finds that illiquidity of the currencies of less developed economies and commodity currencies experience a persistent fall, following a local CTOT shock in the supply side framework. The chapter also documents that illiquidity of most currencies, excluding highly liquid ones significantly responds to local CTOT shocks in the demand side framework. Finally, illiquidity of the commodity currencies and the currencies of small economies are significantly influenced by commodity price shocks. The chapter suggests to the international finance literature that commodity price shocks significantly influence the illiquidity of the FX market not only for the commodity currencies but for most floating exchange rates. Given the significant variation in the sensitivity of the exchange rates to the commodity price changes, the selection of an appropriate commodity price indicator might be an important factor in improving estimation.

As in all research, these thesis chapters have several limitations. In the first chapter, the original liquidity metrics have to be filtered to match the data series with the econometric requirements of the forecasting model. One might consider it forecasting a filtered series rather than liquidity metrics. In the second chapter, I empirically demonstrate that the democratic FED chair gap can statistically explain the democratic presidential gap. However, the political aspects of whether Fed chair cycles are truly independent from presidential cycles have not been explored, as it is beyond the scope of the chapter. In the third chapter, I document that commodity prices shocks matter for the illiquidity of most floating exchange rates. However, only the transaction cost aspect of market liquidity is employed due to the data limitations. Perhaps, using a price-impact measure may produce different results, as bid-ask spread is not always a reliable measure.

The findings of this thesis can be further studied in several ways. First, forecasting stock market liquidity with or without investor sentiment can be carried out in a more sophisticated modelling framework. Second, the political and institutional aspects of the relationship between U.S president and Fed chair and the implications for the monetary aggregates can be further explored. Empirically, bootstrap tests can be applied to overcome small sample problem. Finally, the third chapter can be further extended to explore the reasons why commodity price shocks matter for the illiquidity of some currencies but not others. Moreover, it might be a good idea to revisit the “commodity currency” concept, as we find that commodity terms of trade shocks leave more persistent effects on the illiquidity of the currencies of less developed economies rather than on commodity currencies.

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