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Stock market liquidity: Implication of local and global investor sentiment

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Abstract

This paper examines the impact of local and global investor sentiment on stock market liquidity using data from an order-driven emerging market. Along with four different liquidity proxies, the empirical analysis uses one domestic investor sentiment index and four global sentiment proxies that represent investor sentiment of US, Europe, and aggregate emerging market sentiment. Granger-causality test results suggest that investor sentiment significantly Granger-causes stock market liquidity. We also find that investor sentiment is an essential determinant of stock market liquidity and the impact of global investor sentiment persists even after controlling local sentiment. The empirical findings are robust across different sample periods and liquidity measures.

Keywords: Emerging stock market, Investor sentiment, Stock market liquidity

JEL: G04, G15

1. Introduction

Liquidity is considered as a critical component of financial market development as it influences transaction cost, investment decision, market efficiency, expected return, cost of capital, and allocation of capital across competing investments (Acharya and Pedersen, 2005; Bekaert et al., 2007; Chordia et al., 2008; Lee, 2011; Pástor and Stambaugh, 2003;Wurgler, 2000;Zhu, et al., 2004). The global financial crisis of 2007-08 heightened the fact that lack of liquidity in financial markets, particularly during episodes of price bubbles and uncertain market conditions, can have considerable implications for market participants, and the economy as a whole. Given the economic significance of the effect of stock market liquidity, identification of its determinants is becoming one of the major concerns for investment practitioners and market regulators. Academic research supports the fact that there is significant commonality in liquidity (Chordia et al., 2000; Karolyi et al., 2012;Moshirian et al., 2017), which implies that there may be some underlying macroeconomic forces or behavioral factors responsible for the variation of liquidity. Related literature suggests that the fundamental sources that drive the time-variation of liquidity commonality can be attributed to market volatility (Vayanos, 2004),funding constraints (Hameed et al., 2010),monetary policy (Goyenko and Ukhov, 2009), business cycle (Naes et al., 2011), financial market development (Moshirian, 2017), institutional ownership (Kamara et al., 2008), noise trading (Huberman and Halka, 2001), behavioural factors(Moshirian et al., 2017) and investor sentiment (Baker and Stein, 2004; Liu, 2015, Debata et al., 2017).

In this backdrop, this paper examines the sentiment and liquidity relationship using data from an order-driven emerging stock market. In an order-driven framework there is no obligation on the part of any market participant to submit limit orders and, consequently, no market maker or liquidity supplier of last resort (Brockman and Chung, 2002). How such a liquidity-provision mechanism responds to local and global investor sentiment is an open empirical issue and the focus of our study. Specifically, we answer whether the local (domestic) and global (foreign investors i.e., the U.S., Europe and aggregate emerging market) investor sentiment matter for Indian stock market liquidity. In this regard, our paper aims to answer several important research questions: does investor sentiment represent a source of liquidity commonality in emerging market? whether liquidity in an order driven market susceptible to investor sentiment? Is there a global sentiment component (US and Europe) to the variation in Indian stock market liquidity or is it merely due to local investor sentiment? whether the impact of global investor sentiment on liquidity is persistent even after controlling the effects of local sentiment?

Existing literature advocates that investor sentiment can influence stock market liquidity, either in a direct way by causing more noise trading (Baker and Stein, 2004; DeLong et al., 1990; Huberman and Halka, 2001) or in an indirect manner by indicating the higher overconfidence level in the market (Gervais and Odean, 2001; Griffin et al., 2007; Statman et al., 2006). Consistent with the theoretical arguments, a recent study by Liu (2015) using data from the US stock market find that there is a positive impact of investor sentiment on stock market liquidity. Considering the intuitively appealing sentiment and liquidity relationship, a relatively little attention has been given to its empirical assessment using data from emerging stock market. Both the existing theoretical model of Baker and Stein (2004) and successive empirical findings of Liu (2015) focuses on one of the most liquid markets in the world with a quote driven market structure. In recent years, stock exchanges of emerging markets have drawn considerable interest for portfolio diversification opportunities. Given the fact that, liquidity premium is an important feature of emerging market portfolio performance (Bekaert et al., 2007; Jun et al., 2003) and investor behaviour in such market is noticeably very different from developed markets (Kim and Nofsinger, 2008), an out-of-sample study (Lo and Mackinlay, 1990) using data from emerging market can be helpful to shed more insights on this important issue. Moreover, negligible attention has been paid towards the impact of global investor sentiment on emerging market liquidity. A recent study by Debata et al. (2017) provides empirical evidence to suggest that investor sentiment is one of the important factor that drives emerging stock market liquidity. Although our study derives its motivation from Debata et al. (2017), our empirical approach is distinctively different from them in three aspects. First, our study uses sentiment index constructed from several implicit market related proxies. The country specific sentiment proxy employed by Debata et al. (2017) is the consumer confidence index (CCI). In a multi country sample CCI may be a reasonable approximation of sentiment proxy. However, CCI being a consumer sentiment proxy does not give a close substitute proxy for investor sentiment. Second, the sample period of Indian sentiment data in Debata et al. (2017) is only for three years (2011-2015, 48 monthly observations). Our empirical analysis encompasses larger sample period January 2003 till March 2015. Unlike index based (NSE Nifty 50) liquidity measured used by Debata et al. (2017), our study uses the monthly average of daily liquidity measures constituted from all listed firm listed in National Stock Exchange of India. Third, unlike multi country focus of Debata et al. (2017) our focus on a single country allows us to pay attention to market-specific features and issues, compared to multi-country studies. Our study also employs an array of time-series estimation techniques (Liu, 2015) as compared to cross-country panel estimation evidence of Debata et al. (2017).

Using the theoretical rationale outlined in the related literature, the purpose of this paper is twofold. First, we examine the impact of local (domestic) investor sentiment on Indian stock market liquidity. Second, we extend our analysis to consider the impact of global investor sentiment (represented by US sentiment, European market sentiment, and aggregate emerging market sentiment) on stock market liquidity of India. We carry out our analysis in two steps. In the first step, to study the relationship between investor sentiment and stock market liquidity, we conduct Granger-causality test and impulse response functions analysis. In the second step, we investigate the effect of investor sentiment on stock market liquidity using time-series regression analysis. Considering the multidimensional features of liquidity, we have used four different liquidity proxies to measure trading activity, price impact and transaction cost aspects of liquidity. This approach helps to identify which aspects of liquidity may have more prominence for sentiment effect. We use aggregate sentiment index constructed from implicit sentiment proxies to measure the Indian investor sentiment. We incorporate Baker and Wurgler (2006) sentiment index and American Association of Individual Investors survey to gauge US investor sentiment. Eurozone Sentix investor confidence index has been used as proxies for European investor sentiment. Aggregate emerging market sentiment index has been constructed using irrational component of consumer confidence survey data of 15 emerging markets(Brazil, Chile, China, Czech Republic, Hungary, Indonesia, India, Malaysia, Mexico, Philippines, Poland, Russia, South Africa, Thailand and Turkey). We have also employed an array of macroeconomic control variables. For robustness test, we address the issue of the structural break and carryout empirical analysis using two sub-samples. The results from Granger-causality tests document a significant flow of causality from investor sentiment to stock market liquidity. Further, the impulse response functions analysis indicates that higher investor sentiment is associated with high liquidity.This empirical evidence establishes a strong relationship between global investor sentiment and emerging market liquidity. The positive (negative) relationship between investor sentiment and market liquidity (illiquidity) persists even after controlling the impact of other fundamental factors. This finding is consistent with the argument that noise trading and sentiment induced trading behavior of investors is a pertinent source of liquidity commonality (Huberman and Halka, 2001; Karolyi et al., 2012; Liu, 2015).

Our study extends the related literature in two aspects. First, our paper extends the discussion related to the impact of local and global investor sentiment on stock market liquidity of order-driven emerging market. Our findings help to corroborate the importance of investor sentiment as a determinant of liquidity commonality. Our paper also provides an out of sample empirical evidence to extend the argument of Liu (2015) towards the behavioural explanation of stock market liquidity. Second, our paper extends the growing body of literature which argues the contagious effect of investor sentiment (see for e.g., Aissia, 2016; Baker et al., 2012; Bathia et al., 2016; Hudson and Green, 2015; Verma and Soydemir, 2006). Our study contributes the related strand of literature by analysing the contagious effect of foreign investor sentiment on domestic stock market liquidity.

The remainder of this paper is organized as follows. Section 2 presents literature review and motivation of the study. Section 3 describes data. Section 4 deals with variables description and preliminary analysis. Section 5 presents empirical approach. Section 6 discusses empirical results. Section 7 concludes the paper.

2. Related Literature and Motivation of the Study

Related literature provides several compelling arguments towards the direct and indirect relationship between investor sentiment and liquidity. Early research by Kyle (1985), Black (1986) and Trueman (1988) suggests that noise trading plays a significant role in providing liquidity. As Black (1986) cogently put it, “people who trade on noise are willing to trade even though from an objective point of view they would be better off not trading”. Noise trader perceives noise as if it were information (DeLong et al., 1990) and hence, the more noise trading there is, systematic component of the temporal variation of liquidity will be high (Huberman and Halka, 2001) due to higher sentiment. In other words, noise traders can significantly affect the level of asset prices, if, there are short-sales constraints and arbitrage is costly. Consequently, the price impact created by noise traders could manifest itself as a source of variation in liquidity. Baker and Stein’s (2004) theoretical model also ascertains that irrational investors or noise traders underreact to the information contained in order flow and thereby, boost liquidity. Following the direct relationship between noise trading and sentiment, it is likely that causality runs from sentiment to market liquidity. On the other hand, if we ask how sentiment might be generated, it is reasonable to hypothesize that past market behaviour should influence sentiment, which subsequently may indirectly affect liquidity. Existing literature provides two eloquent insights through which market behavior can influence investor sentiment, i.e., overconfidence and disposition effect. Following Odean (1998), Daniel et al. (1998), Gervais and Odean (2001) there is a growing body of literature such as that accentuates the relationship between market participants trading behavior and overconfidence. Due to self-attribution bias, the positive portfolio returns induce investors to overestimate their skill and the precision of information. Investors might trade more (less) following positive (negative) returns as overconfidence grows with past success in the markets (Griffin et al., 2007;Statman et al., 2006). In simple terms, people are overconfident, and overconfidence leads to too much trading (Barber and Odean, 2000). Therefore, high turnover follows higher return in the market. The disposition effect (Shefrin and Statman, 1985)also supports the argument that trading volume should increase following positive return because investors prefer to hold losers too long and sell winners too early. The positive (negative) correlation between volume and past high (low) return may indicate that investors are willing (reluctant) to trade (hold) stocks after increase (decrease) in share prices. To briefly sum up, sentiment increases stock market liquidity, either in a direct way by causing more noise trading or in an indirect manner by indicating the higher overconfidence level in the market (Liu, 2015).

Taking into account the intuitively appealing sentiment and liquidity relationship, relatively little attention has given to its empirical estimation. The present paper aims to shed more insight on this issue by examining the impact of local and global investor sentiment on Indian stock market liquidity. Several compelling arguments motivate us to carry out this research. First, there is no inclusive empirical evidence on the sentiment and liquidity relationship in the context of order driven emerging market. The only available study in this regard by Liu(2015) uses data from quote driven US stock market. The existing theoretical model (Baker and Stein, 2004) that supports sentiment and liquidity relationship due to noise trading also inherently consider a quote driven market structure in which market maker is seen as an important economic agent to supply liquidity. However, the order driven markets are fundamentally very different from the quote-driven market. Order-driven markets generate liquidity demand and supply schedules that are consistent with equilibrium under perfect competition (Brockman and Chung, 2002). Moreover, the related literature suggests that in an order-driven market there is no market maker or liquidity supplier of last resort, and thus, order-driven systems are more susceptible to liquidity commonality (Brockman and Chung, 2002).On similar lines Comerton-Forde et al., (2005) also suggest that the introduction of anonymous limit orders improves market liquidity. This uniqueness of order-driven market structure invites more research using data from such markets to understand the sentiment and liquidity relationship better.

Second, it is improbable that the findings of Liu (2015) can be generalised in the context of emerging markets. Although the results of Liu (2015) provide first-ever comprehensive empirical evidence on sentiment and liquidity relationship, the market focus in his study is arguably the most liquid market in the world. Nevertheless, US stock market and its economic policies probably one of the most vital factor to influence the market behaviour around the world(Brockman and Chung, 2002; Dees and Guilhem, 2011) hence, it is implausible to expect that sentiment of other markets will influence US stock market liquidity. Conversely, the liquidity of emerging market may be dependent on the sentiment of other developed markets, and thus, the impact of global sentiment on emerging market liquidity is an important issue. A growing body of recent literature supports the fact that investor sentiment is having a contagious effect on stock return behavior of other markets (Aissia, 2016; Baker et al., 2012; Bathia et al., 2016;Hudson and Green, 2015; Verma and Soydemir, 2006). For instance, Verma and Soydemir(2006), Hudson and Green(2015), and Bathia et al.(2016) find that US investor sentiment can help to predict UK, Mexico, Brazil and G7 aggregate markets equity returns. If, exchangelevel liquidity is significantly influenced by co-movements in the global liquidity of other exchanges (Brockman et al., 2009) and sentiment is showing a contagious effect on other stock market behaviour (Baker et al., 2012;Karolyi et al., 2012) then, it is arguably imperative to test whether global investor sentiment can explain exchange level liquidity of emerging market.

Third, emerging market investors' behavior and liquidity characteristics are noticeably different from the developed markets (Bekaert et al., 2007; Kim and Nofsinger, 2008). It has also been argued that the magnitude of sentiment effect also varies from country to country depending upon the market structure and cultural factors (Schmeling, 2009;Moshirian et al., 2017). Given the argument that liquidity premium is an important feature of emerging market data (Bekaert et al., 2007; Jun et al., 2003) and investor sentiment of such markets evidently different from developed market (Kim and Nofsinger, 2008), it is therefore, important to carry out a fresh study to have better understanding of this important issue.

Fourth, exchange level liquidity is an important parameter for global investment practitioners to implement a better portfolio diversification strategy. Over the past decade, there has been a considerable attention towards the interaction of international stock markets. Recent studies on market integration suggest that capital markets have become increasingly globalized because of lower information technology costs, financial liberalisation, abolition of foreign exchange controls, trade integration, and international capital flows (see for e.g., Beckmann et al., 2011; Brockman et al., 2009;Mun and Brooks,2012;Phylaktis and Ravazzolo, 2005among others).Concomitant with globalized capital markets due to capital movements are globalized liquidity movements (Brockman et al., 2009). The determinants of this increasing interdependence of international markets gained considerable attention in the related literature; however, an important but hitherto question related to investor sentiment remains unanswered. For example, Baker et al., (2012) and Hudson and Green (2015) suggest that there can be three channels through which foreign country investor sentiment can impact market behaviour of another country, i.e., optimism about investment prospects in another country, shift towards the risky assets (international equity) of other country due to better expected return, optimism of foreign investors about their own country can influence the optimism of foreign country investors due to herd behaviour. Consistent with such arguments, a recent study by Karolyi et al. (2012) using Baker and Wurgler (2006) sentiment index suggests that the global investor sentiment as a source for liquidity commonality in other markets cannot be ruled out completely. Since, investor sentiment is considered to have a contagious effect on other stock markets return behaviour (Baker et al., 2012;Hudson and Green, 2015; Karolyi et al., 2012; Verma and Soydemir, 2006), the relative strength of global and local investor sentiment for determining emerging market liquidity is an important empirical question.

Fifth, from policy perspective understanding the implication of investor sentiment for aggregate market liquidity demands significant attention. In view of the fact that, the overall impact of noise trading on economic welfare and market stability is negative (De long et al., 1989; Shleifer and Summers, 1990), and systematic mispricing in the market due to higher investor sentiment can cause substantial resource misallocation (Daniel et al., 2002), the understanding of the noise trading induced sentiment effect on market liquidity (Black, 1986; Baker and Stein, 2004; Huberman and Halka, 2001) is a germane policy concern. The related literature emphasizes that understanding the causes underlying liquidity commonality is important not only because liquidity is related to equity returns but because it might provide a clue to solving the puzzle of market crashes (Brockman and Chung, 2002;Brockman et al., 2009; Karolyi et al., 2012).During episodes of unprecedented market movements, a better understanding of the causes of liquidity commonality might contribute to market stabilization policies.

Motivated by the arguments from preceding paragraphs we use data from an over-driven emerging Indian stock market to make a comprehensive analysis of the sentiment and liquidity relationship. Apart from being an emerging market, Indian capital market provides several merits to become an ideal candidate for this study. Financial sector reforms initiated in the early 1990s provided a strong impetus to the development of Indian capital market, and over the past two decades it has made remarkable progress concerning the market size and liquidity. For example,in 2015, the National Stock Exchange (NSE) of India became the fourth largest in the world by equity trading volume. In the year 2016, Indian stock market ranked as 6th and 7th largest stock market in the Asia Pacific region concerning market capitalization and value of share trading respectively (World Federation of Exchanges, 2016).The importance of global sentiment for determining exchange level liquidity of Indian stock market retains its own merit because the participation of foreign institutional investors (FIIs)in the Indian stock market has increased voluminously in last two decades. It is not uncommon to observe increasing dominance of FIIs in the Indian stock market through popular financial press reports. For instance, during December 2015 popular financial press reveals that "FIIs, the lifeline of the Indian equity market, have turned net sellers in the past four months. But, it's important not to have a myopic view of India and the Indian markets. India is not an isolated market and isn't decoupled from other countries" (Nayak, 2015). Moreover, "analysts attribute FIIs' preference for India for more than a decade to superior demographics, stronger economic growth among peers, robust corporate earnings, better government policies, availability of a variety of industries, opening of capital markets and quantitative easing by developed economies after the 2008 financial crisis" (Kansara, 2017). The observations from financial press help to reemphasize our arguments regarding the growing demand for the Indian equity as a preferred asset class among foreign fund managers, and thus, the influence of foreign country sentiment on the domestic market liquidity cannot be ruled out completely. Figure 1 presents the time series pattern of Indian stock market liquidity (measured by trading volume i.e., TV) and the net FII fund flow.

{Insert of Figure 1 here}

Some interesting observation emanate from Figure 1.We observe a steep increasing trend of stock market liquidity, which is consistent with the recent findings from literature that the post liberalisation period has been instrumental to enhance liquidity of emerging economies. Consistent with the increasing pattern of liquidity we document an increasing trend of foreign institutional investor inflows into Indian stock market over the sample period. During the global financial crisis period, i.e., 2007-08 both liquidity and FII has fallen to a great extent. It should be noted that the net FII inflows into Indian stock market was amounted to be $20 billion in the beginning of the year 2007-08. However, FII had pulled out approximately $11.1 billion in the first nine months of the calendar year 2008, which impacted a remarkable increase in the market volatility (IMF Country Report, 2014).From these inferences, we believe that FII and stock market liquidity might be related. All these observations compel us to believe that foreign investor and their sentiment might be crucial to study the liquidity dynamics of domestic stock market. In this regard, our focus on order-driven Indian stock market helps us to carry out an out-of-sample test (Lo and Mackinlay, 1990) for examining whether the local or global component of investor sentiment plays a significant role in determining the emerging market liquidity.

2. Data

Our study considers stocks listed on the National Stock Exchange (NSE) of India for the sample period January 2003 till March 2015. The choice of the sample period is based on the availability of continuous data for all market implicit investor sentiment proxies and liquidity variables. Our sample period also helps us to avoid any impact of the transition from the Badla system to the rolling settlement cycle (T+3) in the Indian stock market. Our stock selection criteria are consistent with the approach of Chordia et al. (2005).Considering the stock selection criteria of Chordia et al. (2005), we find 510 firms to constitute our study sample. We have collected the daily high price, low price, open price and closing price for all selected stocks from Bloomberg database to determine daily return, daily volatility, and liquidity proxies. Then, the daily measures are averaged out to construct a monthly proxy as most of the macroeconomic variables are available at a monthly frequency. The total number of observations for time series analysis is 147 monthly observations. The macroeconomic variables data are obtained from the Handbook of statistics published by Reserve Bank of India (RBI).All market related implicit sentiment proxy data in monthly frequency are collected from various sources like Security Exchange Board of India (SEBI), Association of Mutual Funds of India (AMFI), and NSE websites. We gather data for Baker and Wurgler (2006) sentiment index data from Prof. Jeffrey Wurgler website of New York University, Stern School of Business. Survey data for US retail investor sentiment has been collected from American Association of Individual Investors website. Eurozone Sentix investor confidence index data has been collected from Investing.com managed by Fusion Media Ltd. Consumer confidence and country-specific macro-economic data for aggregate emerging market sentiment index construction have been collected from Organisation for Economic Co-operation and Development (OECD) website, Bloomberg database, International Monetary Fund (IMF) database. We also rely on central bank websites of selected countries to collect data for individual country specific macro-economic indicators.

4. Variables and Descriptive Statistics

This section has been divided into four parts. The first part discusses liquidity variables and their measurement. The second part elaborates sentiment proxies and their construction. The third part presents control variables. The descriptive statistics and some preliminary analysis have been presented in the fourth part.

4.1Liquidity Variables

Liquidity, by its very nature, is difficult to measure because it encompasses a number of transactional properties of the underlying asset (Kyle,1985; Lesmond,2005).Stock market liquidity has multiple dimensions, such as tightness, depth, immediacy and resiliency (Kyle, 1985; Sarr andLybek, 2002). Considering the multidimensional nature of liquidity, we employ four different liquidity proxies to capture various attributes like trading activity, impact cost and transaction costs.

The selection of liquidity proxies with respect to trading activity is motivated by the findings of Amihud and Mendelson (1986), which assert the liquidity of a stock is an increasing function of trading frequency in equilibrium. Hence, investors prefer to hold securities with higher trading frequency to avoid illiquidity risk (Datar et al., 1998).Following Fernández-Amador et al. (2013), we use turnover ratio (TR) and traded value (TV) as the proxies to measure the trading activity of stocks.TR is measured as the ratio of the number of shares traded to the number of shares outstanding. TV is measured as the product of the number of shares traded with respective stock prices. Higher values of TR and TV exhibit greater liquidity (Brennan et al., 1998;Datar et al., 1998).

The price impact dimension of liquidity can be defined as the change in the price of an asset for a unit change in the volume of a transaction (i.e., the response of asset's price to the flow of orders). We have employed Amihud (2002) illiquidity measure (ILLIQ) to capture the price impact characteristics of stock liquidity and shows the response of return from a stock for every rupee change in trading volume (Amihud, 2002). It serves as a good empirical proxy for determining liquidity and serves the purpose a reasonable measure of price impact among most of the low-frequency liquidity proxies (Goyenko and Ukhov, 2009; Korajczyk and Sadka, 2008; Lesmond, 2005). This ratio can be computed as the absolute return from any security'i' (for the month t) ($|\mathrm{R}_{\mathrm{i,d}}|$)on the traded volume ($TV_{i,d}$), averaged over the number of trading days in that month (D_i).

$$ILLIQ = 1/D_i \sum_{d=1}^{Di} \frac{|R_{i,d}|}{TV_{i,d}}$$

To capture the transaction cost aspect of liquidity, we have employed high-low spread ratio (HLS) of Corwin and Schultz (2012) as a measure of illiquidity. The computation of this ratio requires daily high (reflects trades initiated by buyers), and low (reflects trades initiated by sellers)prices of stocks. We calculate HLS ratio as follows:

$$HLS = \frac{2 * \ (e^{\alpha} - 1)}{1 + e^{\alpha}}$$

whereα can be determined as $\alpha = \frac{\sqrt{(2*\beta)}-\sqrt{\beta}}{3-2*\sqrt{2}} - \sqrt{\frac{\gamma}{3-2*\sqrt{2}}}$, $\beta = \sum_{i=0}^{1} \ln\left(\frac{H_{t+i}^{O}}{L_{t+i}^{O}}\right)$, $\gamma = \sum_{i=0}^{1} \ln\left(\frac{H_{t,t+d}^{O}}{L_{t,t+d}^{O}}\right)$, H^O= observed high price of a stock on day d, L^O = observed low price of a stock on day d.

4.2 Sentiment Variables

Existing behavioral finance literature suggests that there are two different approaches to measure the unobservable sentiment variable, i.e., survey method and sentiment proxies derived from the selected market statistics. However, there is no uncontroversial and universal proxy for measuring investor sentiment(Baker and Wurgler, 2006). For measuring local investor sentiment (SENT), following the top-down approach of Baker and Wurgler (2006) we construct a sentiment index using seven implicit sentiment proxies. Consistent with related literature (see for e.g. Baker and Wurgler, 2006; Brown and Cliff, 2004;Baker et al., 2012 among others), the selected sentiment proxies are advance decline ratio (ADR), put-call ratio (PCR), number of IPOs (NIPO),equity issue in total issue (EITI),dividend premium (DP), fund flow (FF),cash to total assets (CTA), and market turnover (TOV). Considering the theoretical sign of respective sentiment proxies the SENT index can be represented as:

$$SENT_t = ADR_t - PCR_t + NIPO_t + NIPO_t - DP_t + FF_t - CTA_t + TOV_t \dots\dots\dots\dots\dots\dots (1)$$

However, it is likely that each of the sentiment proxy may include a non-fundamental (i.e., irrational) and a fundamental (i.e., rational) component (Brown and Cliff, 2004). We follow the approach of Baker and Wurgler(2006) to orthogonalise each of the sentiment variables using fundamental factors. Specifically we use reserve money growth rate, term spread, inflation growth rate, industrial production growth rate, short term interest rate and FII inflow as macro-economic control variables to orthogonalise our raw sentiment proxies. The error term of the orthogonal equation has been considered as irrational component of the sentiment proxy. After making the sentiment proxies orthogonal to fundamental factors we use principal components analysis for measuring the common variation. The principal component analysis filters out idiosyncratic noise in the orthogonal sentiment measures and captures their common component.We also use the approach of Baker and Wurgler (2006) to capture the relative timing of each orthogonal sentiment proxies for the construction of SENT index.The second principal component having 47 per cent of the sample variance, gives the following measure of our sentiment index:

$$SENT_t = (0.398)ADR_{t-1} - (0.025)PCR_{t-1} + (0.557)NIPO_t - (0.256)DP_t + (0.643)FF_{t-1} - (0.138)CTA_{t-1} + (0.176)TOV_{t-1} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots ... (2)$$

We use four proxies to capture the global investor sentiment. Baker and Wurgler (2006) sentiment index (BWSI) and American Association of Individual Investors survey (AAIISI) have been used to capture US investor sentiment. In behavioural asset pricing literature BWSI and AAIISI has been widely used to represent aggregate market sentiment of US stock market (Aissia, 2016; Bathia et al., 2016; Hudson and Green, 2015; Verma and Soydemir, 2006; Verma and Verma, 2009). In order to capture the European investor sentiment we use Eurozone Sentix investor confidence index (EUROSI). EUROSI, a closely watched gauge of confidence among investors and analysts in the European common currency area and rates the relative six-month economic outlook for the euro zone. The data is compiled from a survey of about 2,800 investors and analysts. A higher (lower) than expected reading taken as positive/bullish (negative/bearish) sentiment. Our choice of EUROSI as a single European sentiment indicator is due to unavailability of any other Eurozone sentiment indicator.

Ourfourth global sentiment indicator is an aggregate emerging market sentiment index (EMSI) constructed by using irrational component of consumer confidence survey data of 15 emerging markets (Brazil, Chile, China, Czech Republic, Hungary, Indonesia, India, Malaysia, Mexico, Philippines, Poland, Russia, South Africa, Thailand and Turkey). Our focus on the selected emerging markets is due to their persistence presence the MSCI, Dow Jones and Standard & Poor's emerging markets indices. The three major emerging market equity indices represent free float-adjusted market capitalisation index that is designed to measure equity market performance of emerging markets. Since, consistent and uniform market related implicit sentiment proxy across the selected emerging markets is a serious data availability constraint, we focus on consumer confidence survey data as a proxy for investor sentiment. Related strand of literature provide compelling empirical evidence towards the application of consumer confidence index (CCI) data as a suitable proxy for investor sentiment. For instance, Fisher and Statman (2002), Lemmon and Portniaguina (2006), Chung et al. (2012) for US stock market, Schmeling (2009) for 18 European countries, Kadilli (2015) for 20 developed countries show that CCI can be considered as a potential measure of investor optimism. Nevertheless, Schmeling (2009) suggest that it seems natural to use CCI metric as a sentiment proxy for an international analysis, because consistent data availability across different countries for reasonable periods of time and perhaps the only consistent way to obtain a sentiment proxy that is largely comparable across countries. For our EMSI construction we follow two steps. In the first step, similar to the approach of Lemmon and Portniaguina (2006) and Kadilli (2015) we regress each country CCI data with one month lag value of macroeconomic variables of the respective country. Specifically, we consider inflation, industrial production growth rate, term spread, and change in money supply. It is worthwhile to mention that, one general criticism that applies to our approach is that we may have missed some of the important country specific macroeconomic variables that might account a substantial portion of fundamental information. However, the selection of set of macroeconomic variables is constrained upon the consistent availability of data across different countries. The residual from this regression is considered as our measure of irrational component of CCI unwarranted by fundamentals. In the second step, we carry out a principal component analysis of irrational CCI data to captures common component. The first principal component having 41 per cent of the sample variance, gives the following measure of our sentiment index (EMSI).

$$\begin{aligned} EMSI_t = {} & (0.358)Brazil_t + (0.052)Chile_t + (0.165)China_t + (0.366)Czech\,Republic_t \\ & + (0.341)Hungary_t + (0.221)Indonesia_t + (0.209)India_t + (0.129)Malaysia_t \\ & + (0.231)Mexico_t + (0.071)Philippines_t + (0.335)Poland_t + (0.291)Russia_t \\ & + (0.155)South\,Africa_t + (0.089)Thailand_t + (0.310)Turkey_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3) \end{aligned}$$

For the purpose of brevity we do not present separate descriptive statistics for all the sentiment proxies.

4.3 Control Variables

Following the existing studies (Chordia et al., 2001;Eisfeldt, 2004; Fernández-Amador et al., 2013; Fujimoto, 2003; Goyenko and Ukhov, 2009; Soderberg, 2008; Taddei, 2007) we have used the rolling twelve-month reserve money growth rate (RM), term spread (TS, which is measured as the difference between the yield of 10-years Government bond and 91-days Treasury bill), twelve-month growth rate of inflation (IR), industrial production growth rate (IP), and funds flow from foreign institutional investors (FII) in our study. Considering the effect of market conditions on stock market liquidity (Brunnermeier and Pedersen, 2009; Copeland and Galai, 1983; Hameed et al., 2010), we have included stock market returns (RET) and stock market volatility (STDV) as market related control variables in our model.

4.4Descriptive Statistics and Preliminary Analysis

The summary statistics and correlation matrix of stock market liquidity (TV, TR, ILLIQ, HLS), investor sentiment (SENT, BWSI, EUROSI, AAIISI) and other control variables (RM, TS, IP, IR, FII, STDV, RET) are presented in Table1.Panel (A) and Panel (B) of Table1 present the descriptive statistics and correlation matrix of all the variables. Some interesting observations emerge from the correlation matrix. First, the liquidity measures like TV and TR are positively associated with SENT, and measures of illiquidity such as ILLIQ and HLS are negatively correlated with investor sentiment. This indicates that when the investor sentiment is high the market is more liquid.

Apart from domestic investor sentiment, we have also found a positive correlation between global investor sentiment and stock market liquidity. Second, we observe a significant and positive correlation between SENT and measures of global investor sentiment, i.e., BWSI, EUROSI and EMSI. From these relationships, one may postulate a strong influence of global investor sentiment upon domestic investor sentiment or vice-versa. Further, we observe a high correlation between FII and BWSI, FII and EUROSI, FII and EMSI, and FII and stock market liquidity. This helps to infer that the sentiment of foreign players might be crucial to determine domestic stock market liquidity. Third, the correlation between stock returns and liquidity depicts that returns of a stock in an increasing function of liquidity and the stock volatility is an indicator of illiquidity. Among the macroeconomic variables, we have seen a high positive correlation between monetary policy (RM) and market liquidity (TV, TR). This indicates that an expansionary monetary policy may lead to enhance stock market liquidity. Our correlation analysis reflects a small degree of association among liquidity measures. This may be due to the fact that liquidity is multidimensional in nature and the employed liquidity proxies measure the different aspects of liquidity and do not represent the same sets of information.

{Insert of Table 1 here}

Table 2 presents the comparison of the average liquidity levels various proxies across high and low sentiment sub periods. Consistent with the Liu (2015) approach in order to compute average values of liquidity proxies in high and low sentiment periods, we first rank all the available months by the sentiment values and classify the whole sample period into two equal length sub-periods: high sentiment sub-period (sentiment values higher than the median sentiment value over the whole sample period) and low sentiment sub-period (sentiment values lower than the median sentiment value over the whole sample period). We classify the high and low sentiment sub-periods for each investor sentiment measure separately. As shown in Table 2, the mean difference value between high and low sentiment sub-periods is statistically significant for TV, TR and HLS liquidity proxies. In consistent with Liu (2015) for US stock market we do not observe any significant mean difference for Amihud's (2002) illiquidity measure. The reported results in Table 2 indicate that high (optimism) and low (pessimism) sentiment periods accounts for significant difference in liquidity variation. The average values of TV and TR in different sub-samples show that market is apparently more liquid in high sentiment periods than it is in low sentiment periods. The sentiment and liquidity relationship is consistent across different local and global sentiment proxies.

{Insert of Table 2 here}

5. Empirical Approach

This section describes the models used to elucidate the impact of investor sentiment on stock market liquidity. This section is divided into two parts. The first part deals with the causal relationship between market liquidity and investor sentiment using Granger causality tests (1969, 1988). The remaining part deals with the effect of investor sentiment on stock market liquidity using time series regression analysis.

5.1 Granger Causality Test

This section of the empirical approach investigates the causality between investor sentiment and liquidity. The concept of Granger's causality test (1969, 1988) examines the dynamic linkage between the two time series. For instance, a time series x_t Granger-causes another time series y_t, if the series y_t can be predicted with better accuracy by using past values of x_t. In our empirical analysis the causality investor sentiment (SENT) and stock market liquidity (LIQ; LIQ represents all the four measures of liquidity, i.e., TV, TR,ILLIQ and HLS) is tested using a bivariate Vector Autoregression (VAR) model of the following kind:

$$LIQ_t = \alpha + \sum_{i=1}^{m} \delta_i * LIQ_{t-i} + \sum_{i=1}^{m} \gamma_i * SENT_{t-i} + u_t \text{----------------------------------} (4)$$

$$SENT_t = \alpha + \sum_{i=1}^{m} \gamma_i * SENT_{t-i} + \sum_{i=1}^{m} \delta_i * LIQ_{t-i} + v_t \text{--------------------------------} (5)$$

where, LIQ vector represents the monthly stock market liquidity measures at time 't-i' and SENT stands for the monthly measures of investor sentiment at time 't-i'. Where 'i' represents the minimum lag length. In order to choose the optimal lag length m, we have employed Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). Although the two criteria show different lag lengths, we have chosen the smaller one to retain maximum number of degree of freedom.$\delta_i$andγ_i are the coefficients of lagged value of LIQ and SENT and the respective error terms are represented by u_t and v_t. Based on the standard approach of Granger-causality test, the causality may be unidirectional, or bidirectional or no causality in either directions. Moreover, to establish a clearer picture between the relationship of stock market liquidity and investor sentiment, the impulse response functions analysis is carried out. IRF traces the impact of a unit shock applied on one of the endogenous variables on the current and future values of other endogenous variables. In this study, the IRF traces out the response of stock market liquidity for one positive shock applied upon the residuals of investor sentiment. IRF helps to capture the sign, magnitude, and persistence of responses of stock market liquidity measures to shocks in investor sentiment variables.

5.2 Time Series Regression

In this section we explain the set of time series models used to examine the effect of investor sentiment on stock market liquidity. We infer from Figure 2 that the monthly changes of liquidity exhibit a clear seasonal pattern. To capture this regularity, we include eleven-monthly dummies in the regression that represents one for each month from April to February. The model is specified as follows:

$$LIQ_t = \alpha_0 + \alpha_1 D_{1t} + \alpha_2 D_{2t} + \alpha_3 D_{3t} + \alpha_4 D_{4t} + \alpha_5 D_{5t} + \alpha_6 D_{6t} + \alpha_7 D_{7t} + \alpha_8 D_{8t} + \alpha_9 D_{9t} + \alpha_{10} D_{10t} + \alpha_{11} D_{11t} + \varepsilon_1 \text{ --------------- } (6)$$

In equation (3), the LIQ stands for stock market liquidity measures such as TV, TR, ILLIQ and HLS, all D_is represent the monthly dummies and α_is represent the respective coefficients of dummy variables. The study of Chordia et al. (2001) and Goyenko and Ukhov (2009) advocate the role of macroeconomic and market related variables to influence stock market liquidity. Motivated from their findings, we include the following macroeconomic and market control variables such as RM, TS, IP, IR, FII, and STDV and RET in the equation (6) and specify the model as follows:

$$LIQ_t = \gamma_0 + \gamma_1 D_{1t} + \gamma_2 D_{2t} + \gamma_3 D_{3t} + \gamma_4 D_{4t} + \gamma_5 D_{5t} + \gamma_6 D_{6t} + \gamma_7 D_{7t} + \gamma_8 D_{8t} + \gamma_9 D_{9t} + \gamma_{10} D_{10t} + \gamma_{11} D_{11t} + \gamma_{12} RM_t + \gamma_{13} TS_t + \gamma_{14} IP_t + \gamma_{15} IR_t + \gamma_{16} FII_t + \gamma_{17} STDV_t + \gamma_{18} RET_t + \varepsilon_2 \text{-} (7)$$

Equation (6) and (7) essentially help to document the impact of monthly variation in liquidity and the impact of macroeconomic and market specific control variables on stock market liquidity (LIQ). Following the equation (6) and (7), we shift our focus to examine the impact of local investor sentiment on LIQ. We add the SENT variable in the equation (6) and reframe the model as:

$$LIQ_t = \beta_0 + \beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} + \beta_6 D_{6t} + \beta_7 D_{7t} + \beta_8 D_{8t} + \beta_9 D_{9t} + \beta_{10} D_{10t} + \beta_{11} D_{11t} + \beta_{12} SENT_{t-1} + \varepsilon_3 \text{ --------------- } (8)$$

We have added one time lag value of the SENT in the equation (8), which is consistent with the hypothesis that the current sentiment may influence future liquidity. Furthermore, we reframe the equation (8) by adding the SENT variable along with monthly dummies, macroeconomic and market variables, which is represented as equation (9).

$$LIQ_t = \delta_0 + \delta_1 D_{1t} + \delta_2 D_{2t} + \delta_3 D_{3t} + \delta_4 D_{4t} + \delta_5 D_{5t} + \delta_6 D_{6t} + \delta_7 D_{7t} + \delta_8 D_{8t} + \delta_9 D_{9t} + \delta_{10} D_{10t} + \delta_{11} D_{11t} + \delta_{12} RM_t + \delta_{13} TS_t + \delta_{14} IP_t + \delta_{15} IR_t + \delta_{16} FII_t + \delta_{17} STDV_t + \delta_{18} RET_t + \delta_{19} SENT_{t-1} + \varepsilon_4 \text{ --------------- } (9)$$

Since Indian stock market has experienced a great dominance of foreign players in last two decades and their role has been crucial for determining the liquidity of stock market. We can hypothesize that their sentiment might be playing an important role to understand liquidity dynamics of stock market. Based on this argument we include four global investor sentiment measures such as BWSI, EUROSI, AAIISI and EMSI along with domestic investor sentiment and other control variables in our model. The equations are as follows:

$$LIQ_t = \emptyset_0 + \emptyset_1 BWSI_{t-1} + \emptyset_2 SENT_{t-1} + \emptyset_3 RM_t + \emptyset_4 TS_t + \emptyset_5 IP_t + \emptyset_6 IR_t + \emptyset_7 FII_t + \emptyset_8 STDV_t + \emptyset_9 RET_t + \varepsilon_5 \quad (10)$$

$$LIQ_t = \mu_0 + \mu_1 EUROSI_{t-1} + \mu_2 SENT_{t-1} + \mu_3 RM_t + \mu_4 TS_t + \mu_5 IP_t + \mu_6 IR_t + \mu_7 FII_t + \mu_8 STDV_t + \mu_9 RET_t + \varepsilon_6 \quad (11)$$

$$LIQ_t = \varphi_0 + \varphi_1 AAIISI_{t-1} + \varphi_2 SENT_{t-1} + \varphi_3 RM_t + \varphi_4 TS_t + \varphi_5 IP_t + \varphi_6 IR_t + \varphi_7 FII_t + \varphi_8 STDV_t + \varphi_9 RET_t + \varepsilon_7 \quad (12)$$

$$LIQ_t = \psi_0 + \psi_1 EMSI_{t-1} + \psi_2 SENT_{t-1} + \psi_3 RM_t + \psi_4 TS_t + \psi_5 IP_t + \psi_6 IR_t + \psi_7 FII_t + \psi_8 STDV_t + \psi_9 RET_t + \varepsilon_8 \quad (13)$$

Following Liu (2015), the above time-series regression equations are estimated using OLS method and the autocorrelation in the error term are corrected using Newey and West (1987) corrections with 12 lags.

6. Results Discussion

We present the empirical results in six sub-sections. To start with we present the test statistics for unit root tests. Second sub-section discusses the Granger-causality test. Third sub-section presents impulse response functions (IRF) analysis. In fourth and fifth sub-sections, we elaborate time series regression results for examining the effect of local and global investor sentiment on stock market liquidity respectively and sixth sub-section discusses additional robustness tests.

6.1 Unit Root Test Statistics

Following the standard procedure, we first check the stationarity of the time series employed in our model. We conduct augmented Dickey-Fuller (ADF) (1981), Phillips Perron (PP) (1988) and Kwiatkowski et al. (KPSS) (1992) unit root tests. The tests examine the null hypothesis of a unit root against the stationary alternative.

{Insert of Table 3 here}

The unit root test statistics, as reported in Table 3, reveals that the null of the unit root is rejected for liquidity measures, sentiment variables, and control variables at first difference (with and without intercept and trend). We infer from the unit root analysis that most of the liquidity variables are stationary at first difference; hence we have reported the unit root test statistics at the first difference only. Also, the use of variables in their first difference in our model is motivated by Wooldridge (2002), which asserts that it reduces the problem of serial correlation and trending of data to a larger extent. We also conducted Inclan and Tiao (1994) structural break test to know whether any sudden shifts or trend break has occurred during the study period. The test results do not document any breaks in the time series. For brevity, we have not reported the structural break test results.

6.2 Granger-Causality Tests

The correlation analysis presented in Panel (B) of Table 1 depicts a positive association between investor sentiment and stock market liquidity, but it does not establish any causal relationship between them. It is clearly inferred from the preliminary results, as reported in Table 1 and Table 2, that the liquidity of stock market is more when investor sentiment is higher. However, from these observations, we do not accumulate any information about the causality between stock market liquidity and investor sentiment. Also, the causal relationship among local and global investor sentiment is not clear. It may happen that the higher investor sentiment causes a greater liquid market, or market liquidity causes higher investor sentiment or both causes each other. Similarly, the causal relationship among the domestic as well as global investor sentiment measures may be unidirectional or bidirectional. To ascertain the direction of causality, we conduct Granger-causality test in a bivariate VAR framework. The Chi-square statistics of Granger-causality tests between local and global investor sentiment proxies are reported in Table4.It is evident from Panel (A) and Panel (B) of Table 4 that there exists bidirectional causality between sentiment of local and global investors. The results reveal that the global investors' sentiment causes local investors' sentiment and vice-versa. The global investor sentiment proxy AAIISI seems to have no impact on the local investor sentiment (SENT). This is intuitively appealing that AAIISI represents US retail investor's sentiment, which may not have a significant portfolio allocation exposure towards Indian stock market. Taking a cue from this result, we further try to investigate the causal relationship between stock market liquidity and global investor sentiment along with domestic investor sentiment.

{Insert of Table 4 here}

We report the Granger-causality tests statistics between liquidity variables and sentiment proxies in Table 5. Reported results in Panel (A) of Table 5 reveals that the domestic investor sentiment (SENT) significantly Granger-causes stock market liquidity and the causality is prominent in case of trading activity (TV, TR) and price impact dimensions (ILLIQ). Most of the global sentiment proxies (BWSI, EUROSI, and EMSI) are Granger-causing stock market liquidity except individual investor sentiment of US market. It is also evident that the causality of the investor sentiment of emerging markets (EMSI) is illustrious amongst other global sentiment proxies. We do not gather much evidence of the occurrence of reverse causality, i.e., stock market liquidity Granger-causes investor sentiment. Overall, consistent with the argument of

Huberman and Halka (2001), Liu (2015), and Debata et al (2017) our empirical findings document a flow of causality from investor sentiment to stock market liquidity.

{Insert of Table 5 here}

6.3 Impulse Response Functions (IRF) Analysis

To understand the dynamic interaction among the variables in the model, we also conduct IRF analysis. The IRF analysis helps capture response of stock market liquidity to a unit standard deviation innovation in the investor sentiment. Figure 2 demonstrates the response of stock market liquidity to a unit standard deviation change in local and global investor sentiment proxies (traced forward over a period of 24 months). For brevity, IRFs of SENT, BWSI and EMSI are only shown in Figure 2. We use standard Cholesky decomposition method keeping in mind the existence of a high correlation between investor sentiment innovations. A positive shock to investor sentiment increases traded value and stock turnover rate (TV and TR), and decreases spread and illiquidity ratio (HLS and ILLIQ). This indicates that a market is more liquid when investor sentiment is high.

{Insert of Figure 2 here}

6.4 Time Series Estimation: Local Investor Sentiment and Stock Market Liquidity

In this section we focus to evaluate the impact of local investor sentiment on stock market liquidity using time series regression analysis. The dependent variables are the four different stock market liquidity proxies, i.e., TV, TR, ILLIQ and HLS. The independent variables are the local investor sentiment (SENT) and set of macroeconomic and market related control variables i.e., RM, TS, IP, IR, FII, STDV and RET. We also included eleven-monthly dummies in our model to account for seasonal pattern the stock market liquidity depicts. In our unreported results the time series plots of liquidity proxies after first difference, we observe a clear seasonal pattern of stock market liquidity. In order to make a detail analysis, for each liquidity proxy we estimate four regressions (I, II, III and IV) using equation numbers (6), (7), (8) and (9). In the first estimation (I) we include eleven-monthly dummies. Considering the importance of macroeconomic and market conditions for determining the stock market liquidity, in the second estimation (II) we have added RM, TS, IP, IR, FII, STDV and RET along with eleven-monthly dummies. In the third estimation (III) we include SENT along with eleven-monthly dummies. Our fourth estimation (IV) includes all variables i.e., local sentiment proxy, control variables and monthly dummies. Table 6 reports the estimated coefficients and *t*-statistics. Reported results of the first estimation (I) for all the liquidity proxies reveal that the coefficients are significantly positive for April, June, August, September, October, December, January and February. The coefficient signs are observable negative and significant for the illiquidity proxies. This implies that stock market is more liquid in these months. Consistent with the findings of Chordia et al. (2005), DeGennaro et al. (2008) and Hong and Yu (2009), we observe that the overall stock market liquidity varies across months.

We derive the following observations from our second estimation (II) results. Our results reveal a positive and significant influence of RM on TV and TR. For the illiquidity proxies (ILLIQ and HLS) we observe a negative and significant coefficient. Consistent with the findings of Goyenko and Ukhov (2009) and Fernández-Amador et al. (2013) our results indicate that an expansionary monetary policy increases stock market liquidity. The negative coefficient of IR indicates that higher (lower) inflation is attributed to reduction (increase) in stock market liquidity (illiquidity).In line with the findings of Levine and Zervos (1998) and Henry (2000),we observe a significant impact of net fund flows from FII on stock market liquidity. Inconsistent with most of the related literature in the context of developed markets (for e.g., Amihud and Mendelson, 1989; Brennan et al., 1998; Datar et al., 1998) we document a positive relationship between stock return and liquidity. The dissimilarity of our findings could be due to the low degree of integration of emerging equity markets with the global economy (Bekaert and Harvey, 1997; Jun et al., 2003). Besides, we document a negative (positive) impact of STDV on stock market liquidity (illiquidity). The observed pattern of STDV impact on stock market liquidity is consistent with the findings of Wang and Yau (2000) which suggest that higher volatility results into higher spread and lower liquidity. Related study by Brunnermeier and Pedersen (2009) also suggest that higher volatility imposes constraint on the funding liquidity of financial intermediaries, which restrict their liquidity supply mechanism. The results of our third estimation (III) suggest that the coefficient of SENT turnout to be positive and significant for TV. Consistent with the findings of Odean (1998) and Liu (2015), our finding indicates that higher investor sentiment positively influence traded volume. Moreover, the adjusted R-square value increases from 0.32 to 0.38, while moving from the first estimation (I) to third estimation (III), which further strengthen the efficiency of the model. Our results do not reveal significant SENT coefficient for TR, ILLIQ, and HLS. Though there is negative association between local investor sentiment and stock market illiquidity, the coefficients do not shown statistical significance of their relationship. Fourth estimation (IV) including all the independent variables shows a similar positive and significant relationship between SENT and TV. The coefficient of SENT is 0.52, which shows that if the index increase by 1% then TV will increase by 0.52%. Consistent with the third estimation results, our fourth estimation also fails to establish a statistically significant relationship between SENT and other liquidity proxies (TR, ILLIQ and HLS).

{Insert of Table 6 here}

From these observations, we infer a moderate influence of investor sentiment on stock market liquidity in a pure order-driven emerging market like India, which is partially consistent the findings of Liu (2015) in the case of US stock market. There could be two possible explanations for such moderate relationship between investor sentiment and stock market liquidity. One of the plausible reasons could be the less participation of retail investors in the Indian stock market. Related literature suggest that cognitive biases and valuation errors are more commonly made by less sophisticated retail investors as compared to the informed institutional investors (Kumar and Lee, 2006; Verma and Verma, 2009). The aggregate investor sentiment is characterized by the inherent behavioral or cognitive biases of market participants.

Therefore, a high degree of retail investors' participation in a stock market may causes more sentiment risk as intuitional investors are less susceptible to psychological biases. Trading activity in the Indian stock market is dominated by institutional investors and exhibits a high promoter holding ownership structure, investor sentiment possesses a moderate predictability on aggregate stock market liquidity. Order-driven market structure may be the second reason to moderate the impact of investor sentiment on liquidity. Market structure determines how investors place their order, which subsequently transformed into trades and finally this transformation affects liquidity. Order-driven systems generate liquidity demand and supply schedules that more closely approximate equilibrium under perfect competition (Brockman and Chung, 2002).Since there are no market makers in an order-driven market, liquidity is essentially provided only by traders' unexecuted limit orders. The existence of multiple (independent) liquidity providers in an order driven market makes the market less susceptible to liquidity commonality (Brockman and Chung, 2002) and less liable to Baker and Stein (2004) irrational market makers noise trading hypothesis.

6.5 Global Sentiment, Local Sentiment and Stock Market Liquidity

In this section we present time series estimation results of equation (10), (11), (12), (13) for examining the impact of global investor sentiment on stock market liquidity. BWSI proxy captures the aggregate sentiment of US stock markets, AAIISI represents the retail investors' sentiment of US stock market, EUROSI reflects the aggregate sentiment of euro area stock markets, and EMSI represents the aggregate investor sentiment index of emerging markets. For each liquidity proxy we make two estimations. In the first estimation we examine the impact of global investor sentiment on stock market liquidity. In the second estimation we control the impact of local investor sentiment

(SENT) while examining the impact of global investor sentiment. In both the estimations we control for macro-economic and market related control variables. Table 7 reports the estimated coefficients and corresponding t-statistics of the estimation results. Panel (A), (B), (C) and (D) of Table 7 document the impact of global investor sentiment proxies i.e., BWSI, AAIISI, EUROSI, EMSI on stock market liquidity respectively.

{Insert of Table 7 here}

Reported results in Panel (A) of Table 7 show an economically and statistically significant positive influence of BWSI on TV and TR liquidity proxies. We find a statistically significant and negative coefficient for the ILLIQ measure. This indicates that a higher (lower) aggregate sentiment of US stock market expedite trading activity and increases (decreases) liquidity of the Indian stock market. The BWSI coefficients for TV and TR reveal that one standard deviation increase in US investor sentiment increases the stock market liquidity by 39 and 34 percent respectively. In our second estimation (II) after controlling the effect of SENT, the significant effect of BWSI is observable in the case of TV, TR and ILLIQ. The Adjusted R2 value increases while moving from estimation (I) to estimation (II). The results are consistent across the two estimation and thus, validate our argument that global investor sentiment is an important parameter for emerging market liquidity. The finding that the market is more liquid (illiquid) when local and global investor sentiment is higher (lower) still persists even after controlling for the macro-economic and market related variables. Panel (B) of Table 7 does not reveal any statistically significant evidence towards the impact of AAIISI on stock market liquidity. We do not observe any improvement in the results after controlling local sentiment along with other independent variables. However, the economic sign of AAIISI coefficient remain consistent with BWSI. The individual investor sentiment of US does not account any crucial information to explain the liquidity variation in the Indian stock market. However, the aggregate investor sentiment of US stock market (BWSI) is turnout to be a good predictor of stock market liquidity. Panel (C) of Table 7 presents the empirical findings of the impact of EUROSI on stock market liquidity. The reported results reveal that the EUROSI is positively associated with market liquidity, though the effect is prominent only in the case of TV. This indicates that the effect is limited to trading activity only and do not affect the other dimensions of liquidity such as price impact and transaction costs. Even though the coefficients of EUROSI for other liquidity proxies are not statistically significant, they show economic sign consistent with the theoretical arguments. Thus, we document a moderate predictability of EUROSI and the effect remains unchanged even after controlling the effect of SENT. Panel (D) of Table 7 presents the estimated results of the impact of emerging market sentiment index (EMSI) on domestic stock market liquidity. The empirical results suggest that the investor sentiment of emerging markets plays a crucial role for determining the Indian stock market liquidity. Also, it is noteworthy to mention that all the market liquidity measures are significantly influenced by EMSI, which has not been observed in the case of any other sentiment measures. The results remain consistent even after controlling the effect of local sentiment. Overall, our results reveal that the global investor sentiment plays an important role for determining stock market liquidity of emerging market like India. Our results are consistent with related behavioural finance literature which ascertains that investor sentiment is having a contagious effect on stock return behavior of other markets (Aissia, 2016; Baker et al., 2012; Bathia et al., 2016; Hudson and Green, 2015). Our results also complements the liquidity commonality literature which emphasizes that global sources of commonality contribute a crucial portion of local (exchange-level) liquidity of emerging markets (Brockman et al., 2009). The documented results strengthen our argument that the local and global investor sentiment plays an important role for determining the exchange level liquidity.

6.6 Robustness Check

In view of the financial market integration and the contemporaneous effect of financial crisis on developed as well as emerging economies, we conduct Inclan and Tiao (1994) structural break test to know whether any shift or trend break has occurred in our sample period. The structural break test does not display any sudden shift or trend break in the time series. However, to check the consistency of our findings during normal market conditions and market turmoil we further divide our sample into two parts, i.e., January-2003 to July-2007, and August-2007 to March-2015. The division of the data period is based on the occurrences of financial market crises. The first part of sample period (January-2003 to July-2007) has not witnessed any major market crisis events. On the other hand, the second part (August-2007 to March-2015) has embraced a series of crises, such as global financial crisis (2007), European sovereign debt crisis (2010), Russian financial crisis (2014).

{Insert of Table 8 here}

We carry out this analysis in two steps. In the first step, we try to elicit the effect of SENT, BWSI, EUROSI, AAIISI and EMSI on stock market liquidity for the period ranging from January-2003 to July-2007. In the second step, the similar analysis has been carried out for the remaining period, i.e., August-2007 to March-2015. For brevity, we have only reported the estimated results of TV and ILLIQ in Table 8. Reported results in Table 8 suggest that the domestic investor sentiment is a crucial information variable to understand the variation is stock market liquidity. Its effect is more prominent in the crises period, i.e., August-2007 to March-2015. It has been observed that the SENT coefficients are significant for TV and ILLIQ. This indicates that the stock market liquidity is strengthened during the regime of higher investor sentiment and the impact of local investor sentiment is more prominent during the crisis period. It is also evident from our results that global sentiment measures such as BWSI, EUROSI and EMSI plays a vital role to determine domestic stock market liquidity. Besides, the monetary policy stance and inflationary conditions are turnout to be critical to influence market liquidity. Overall, we document a strong predictability of investor sentiment on stock market liquidity. The findings from sub-samples are consistent with the documented results for the whole sample period.

7. Summary and Conclusion

This paper examines the role of local and global investor sentiment to determine stock market liquidity in a pure order-driven Indian stock market. To capture the multidimensional nature of liquidity, we employ four different liquidity measures. We also construct a composite investor sentiment index for Indian stock market by considering various market related implicit sentiment proxies. Global investor sentiment is measured by four sentiment proxies derived from US, Europe and emerging markets. Our empirical analysis focuses on VAR-Granger causality test, impulse response functions analysis and time-series regression to examine the relationship between investor sentiment and stock market liquidity.

The Granger-causality test documents a significant flow of causality from investor sentiment to stock market liquidity. The direction of causality is also consistent for global investor sentiment proxies. Impulse response function analysis shows that the liquidity of stock market increases when investor sentiment is high. The results of time-series estimates suggest that market is more liquid when local and global investor sentiment is higher. The finding that market is more liquid when investor sentiment is higher persists even after controlling the effect of other control variables. The Baker and Wurgler (2006) sentiment index for US stock market and aggregate emerging market sentiment index found to be the most important source of global investor sentiment that can influence liquidity of the Indian stock market. The sub-sample periods robustness tests are consistent with the results of the whole sample period. Overall, we document a strong predictability of investor sentiment on stock liquidity. Therefore, investor sentiment may be used as a determinant of time-series variations of liquidity in the stock market. This finding is consistent with the argument that noise trading and sentiment induced trading behavior of investors is a relevant source of liquidity commonality (Huberman and Halka, 2001; Karolyi et al., 2012; Liu, 2015). Results are relevant for practitioners and policy makers. Market participants in the equity market can improve the liquidity forecast by considering investor sentiment along with macroeconomic conditions and market microstructure variables. One logical extension of our finding could be to identify channels through which local and global investor sentiment affects stock market liquidity.

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Stock Market Liquidity: Implication of Local and Global Investor Sentiment

Table1: Summary Statistics and Correlation Matrix

Panel A: Summary Statistics																
	TV	TR	ILLIQ	HLS	SENT	BWSI	EUROSI	AAIISI	EMSI	RM	TS	IP	IR	FII	STDV	RET
Mean	0.757	0.83	0.444	0.014	6.236	0.004	0.184	-0.002	0.896	1.359	1.005	6.069	5.92	1.75	7.887	0.13
Median	0.694	0.92	0.274	0.013	6.050	0.015	0.200	0.008	0.889	1.516	0.978	6.056	6.00	1.36	7.735	0.15
Maximum	1.33	1.43	1.950	0.037	11.07	0.296	19.50	0.554	1.201	2.953	4.457	19.981	9.10	9.99	20.077	1.50
Minimum	0.04	0.158	0.001	0.006	0.730	-0.59	-21.10	-0.501	0.012	-2.167	-2.665	-7.242	-2.30	-5.49	1.109	-1.72
Std. Dev.	1.264	0.692	0.488	0.004	1.934	0.119	6.973	0.193	0.698	0.83	1.24	5.419	2.82	2.71	4.123	0.46
Skewness	-1.288	-0.760	1.560	1.790	0.339	-1.30	-0.158	-0.052	1.259	0.326	0.760	0.258	-0.45	0.37	0.926	-0.21
Kurtosis	4.033	3.575	4.805	5.269	3.813	7.696	3.229	2.786	3.225	2.660	2.457	3.046	3.14	3.40	4.304	4.79
Panel B: Correlation Matrix																
	TV	TR	ILLIQ	HLS	SENT	BWSI	EUROSI	AAIISI	EMSI	RM	TS	IP	IR	FII	STDV	RET
TV	1.000															
TR	0.860	1.000														
ILLIQ	-0.25	-0.24	1.000													
HLS	-0.41	-0.14	0.130	1.000												
SENT	0.383	0.26	-0.19	-0.10	1.000											
BWSI	0.297	0.520	-0.37	-0.06	0.401	1.000										
EUROSI	0.106	0.169	-0.31	-0.29	0.360	-0.10	1.000									
AAIISI	0.161	0.137	-0.32	-0.01	0.077	0.450	-0.008	1.000								
EMSI	0.489	0.394	-0.41	-0.10	0.789	0.521	0.231	0.001	1.000							
RM	0.73	0.153	-0.03	-0.05	0.206	0.001	0.003	0.005	0.256	1.000						
TS	-0.04	-0.18	0.05	0.017	-0.13	-0.17	0.020	-0.020	-0.29	-0.19	1.000					
IP	0.067	0.132	-0.02	-0.01	0.011	-0.04	0.034	-0.009	0.181	0.714	-0.22	1.000				
IR	-0.08	-0.01	0.016	0.012	-0.06	-0.18	-0.041	0.090	-0.31	-0.38	0.359	-0.16	1.00			
FII	0.253	0.580	-0.09	-0.21	0.230	0.413	0.31	0.002	0.393	0.052	0.156	0.161	-0.10	1.00		
STDV	-0.23	-0.460	0.19	0.21	-0.025	-0.11	-0.021	-0.090	-0.11	-0.03	0.172	0.003	0.01	-0.01	1.000	
RET	0.67	0.590	-0.28	-0.11	0.112	0.014	0.001	0.100	0.211	0.089	-0.46	0.049	-0.14	0.350	-0.39	1.00

Notes: This table presents the descriptive statistics and correlation matrix of liquidity variables i.e., traded value (TV), turnover rate (TR), illiquidity ratio (ILLIQ) and high-low spread (HLS); sentiment variables i.e., domestic investor sentiment index (SENT), Baker-Wurgler investor sentiment index (BWSI), European sentiment index (EUROSI), AAII individual investors sentiment index (AAIISI) and emerging market sentiment index (EMSI); macroeconomic control variables i.e.,reserve money growth rate (RM), term spread (TS), industrial production growth rate (IP), inflation rate (IR), the net funds flow from foreign institutional investors (FII); and market control variables i.e., the monthly market standard deviation (STDV) and the monthly market return (RET). Sample period consists of 147 monthly observations from January-2003 till March-2015.

Table 2: Stock Market Liquidity in High and Low Sentiment Periods

Sentiment Proxies	Sub-period	TV	TR	ILLIQ	HLS
SENT	Low {Mean}	15.49	0.33	0.06	10.44
	High {Mean}	16.23	0.47	0.05	10.11
	High-Low {Mean}	0.74 (5.95)	0.13 (2.25)	-0.01 (-1.05)	-0.33 (-3.19)
BWSI	Low {Mean}	15.76	0.25	0.06	10.43
	High {Mean}	15.98	0.55	0.04	10.12
	High-Low {Mean}	0.22 (4.44)	0.30 (4.90)	-0.02 (-1.56)	-0.31 (-2.99)
AAIISI	Low {Mean}	15.56	0.53	0.06	10.54
	High {Mean}	16.18	0.56	0.05	10.02
	High-Low {Mean}	0.62 (5.21)	0.03 (1.62)	-0.01 (-1.15)	-0.52 (-3.11)
EUROSI	Low {Mean}	15.72	0.33	0.05	10.34
	High {Mean}	16.00	0.46	0.05	10.20
	High-Low {Mean}	0.27 (4.92)	0.12 (2.01)	-0.00 (-0.15)	-0.14 (-1.98)
EMSI	Low {Mean}	15.72	0.40	0.04	10.35
	High {Mean}	15.90	0.41	0.05	10.20
	High-Low {Mean}	0.18 (2.21)	0.01 (0.68)	-0.01 (-0.98)	-0.15 (-2.22)

Notes: Table 2 presents the average stock market liquidity at high and lower sentiment periods. Sample period consists of 147 monthly observations from January-2003 till March-2015. The values in the bracket are t-statistics.

Table 3: Unit Root Tests Statistics

Variables	ADF		PP		KPSS	
	Intercept without trend	Intercept with trend	Intercept without trend	Intercept with trend	Intercept without trend	Intercept with trend
TV	-11.345***	-11.448***	-11.356***	-11.488***	0.68	0.61
TR	-13.25***	-13.18***	-13.12***	-13.10***	0.29	0.23
ILLIQ	-13.59***	-13.60***	-13.50***	-13.47***	0.12	0.13
HLS	-17.67***	-18.01***	-18.09***	-18.12***	0.23	0.19
SENT	-16.26***	-16.35***	-16.97***	-16.05***	0.46	0.38
BWSI	-14.12***	-14.01***	-13.91***	-13.99***	0.25	0.21
EUROSI	-15.72***	-15.63***	-14.99***	-14.90***	0.31	0.23
AAIISI	-12.56***	-12.42***	-12.11***	12.02***	0.25	0.19
EMSI	-11.99***	-11.85***	-10.56***	-10.62***	0.21	0.17
RM	-14.29***	-14.38***	-13.95***	-14.05***	0.36	0.29
TS	-13.78***	-13.66***	-13.43***	-13.50***	0.22	0.16
IP	-12.51***	-12.98***	-13.463***	-14.20***	0.26	0.16
IR	-12.87***	-12.68***	-12.546***	-12.254***	0.19	0.13
FII	-19.97***	-19.01***	-19.29***	-19.22***	0.13	0.11
STDV	-18.21***	-18.18***	-18.01***	-18.10***	0.59	0.53
RET	-17.11***	-17.21***	-17.01***	-17.09***	0.19	0.15

Notes: The table reports the ADF (Augmented Dickey-Fuller), PP (Phillips-Perron) and KPSS (Kwiatkowski-Phillips-Schmidt-Shin) tests statistics for the unit root test. The optimal lag for ADF test and truncation lag for PP test are selected based on the AIC and SIC criteria. For fixing the truncation lag for KPSS test, the Bartlett kernel method is selected as the spectral estimation methods, and the Newey–West method is employed for bandwidth. The KPSS test examines null of stationary. *** Significance at 1% level.

Table 4: Granger-Causality Tests between Local and Global Investor Sentiment

Panel (A): Granger-causality test: local investor sentiment and global investor sentiment measures (H_0: Local investor sentiment does not Granger-cause global investor sentiment measures)				
	BWSI	EUROSI	AAIISI	EMSI
SENT	19.11***	14.07**	7.49	20.55***

Panel (B): Granger-causality test: Global investor sentiment measures and local investor sentiment (H_0: Global investor sentiment does not Granger-cause local investor sentiment)	
	SENT
BWSI	17.66***
EUROSI	12.92*
AAIISI	6.13
EMSI	18.99***

Notes: This table presents $\chi 2$ statistics of pair wise Granger causality tests between the local investor sentiment (SENT) and global investor sentiment proxies (BWSI, EUROSI,AAIISI, EMSI). We test the null hypothesis that row variables do not Granger-cause column variables. Sample period consists of 147 monthly observations from January-2003 till March-2015. ***, ** and * indicate statistical significance at 1%, 5% and 10% level respectively.

Table 5: Granger-Causality Tests between Investor Sentiment and Stock Market Liquidity

Panel (A): Granger-causality test: investor sentiment and stock market liquidity
(H_0: Investor sentiment does not Granger-cause stock market liquidity)

	TV	TR	ILLIQ	HLS
SENT	17.52***	15.07**	14.49**	4.17
BWSI	19.66***	13.05**	15.89**	6.39
EUROSI	18.69***	12.69*	4.63	3.33
AAIISI	5.99	6.54	7.14	1.96
EMSI	18.47***	17.77**	15.58**	13.32*

Panel (B): Granger-causality test: stock market liquidity and investor sentiment
(H_0: Stock market liquidity does not Granger-cause investor sentiment)

	SENT	BWSI	EUROSI	AAIISI	EMSI
TV	0.46	3.21	5.25	2.39	0.56
TR	2.42	1.99	4.96	4.14	1.64
ILLIQ	0.13	4.45	0.32	3.01	11.65*
HLS	1.18	2.29	1.25	2.19	5.36

Notes: This table presents $\chi 2$ statistics of pair wise Granger causality tests between stock market liquidity and investor sentiment. We test the null hypothesis that row variables do not Granger-cause column variables. Sample period consists of 147 monthly observations from January-2003 till March-2015.***, ** and * indicate statistical significance at 1%, 5% and 10% level respectively.

Table 6: Local Investor Sentiment and Stock Market Liquidity

Variables		Traded Value (TV)			Turnover Rate (TR)				Illiquidity Ratio (ILLIQ)				High-Low Spread (HLS)			
Models	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
SENT			0.42 (3.36)	0.54 (4.15)			0.05 (1.28)	0.06 (1.64)			-0.04 (-1.56)	-0.04 (-1.64)			-0.01 (-0.71)	-0.01 (-0.95)
RM		0.03 (1.98)		0.03 (1.86)		0.04 (3.59)		0.03 (2.89)		-0.10 (-2.19)		-0.09 (-2.55)		-0.09 (-2.98)		-0.09 (-2.71)
TS		-0.02 (-0.05)		-0.01 (-1.85)		-0.02 (-0.54)		-0.03 (-0.63)		0.13 (1.48)		0.13 (1.41)		0.11 (1.36)		0.19 (1.53)
IP		0.03 (2.75)		0.03 (2.09)		0.01 (2.35)		0.01 (2.41)		-0.01 (-0.06)		-0.01 (-0.08)		-0.03 (-2.06)		-0.08 (-2.82)
IR		-0.03 (-0.12)		-0.01 (0.83)		-0.03 (-1.35)		-0.03 (-1.58)		0.03 (0.48)		0.02 (0.33)		0.04 (1.68)		0.09 (1.98)
FII		0.93 (4.56)		0.01 (2.54)		0.02 (2.78)		0.02 (2.31)		-0.05 (-3.42)		-0.08 (-4.52)		-0.03 (-2.40)		-0.04 (-2.81)
STDV		-0.21 (-4.05)		-0.21 (-4.12)		-0.16 (-4.10)		-0.17 (-4.21)		0.26 (3.81)		0.27 (3.95)		0.16 (2.81)		0.26 (3.67)
RET		0.05 (5.26)		0.05 (4.65)		0.05 (6.07)		0.04 (5.32)		-0.04 (-2.49)		-0.05 (-2.61)		-0.10 (-3.19)		-0.17 (-5.11)
April	0.37 (2.95)	0.33 (2.61)	0.50 (3.39)	0.35 (2.70)	0.42 (3.58)	0.55 (5.74)	0.44 (3.81)	0.57 (5.87)	-0.32 (-2.53)	-0.41 (-1.92)	-0.32 (-2.52)	-0.43 (-1.96)	-0.91 (-4.81)	-0.92 (-4.26)	-0.96 (-4.96)	-0.23 (-2.21)
May	0.20 (1.46)	0.18 (1.47)	0.27 (2.10)	0.18 (1.46)	0.13 (1.16)	0.13 (1.43)	0.14 (1.17)	0.12 (1.30)	0.09 (0.45)	0.10 (0.47)	0.04 (0.17)	0.07 (0.31)	0.01 (-0.44)	-0.09 (-0.67)	0.01 (-0.14)	0.01 (-0.52)
June	0.26 (1.85)	0.25 (2.09)	0.24 (1.73)	0.24 (1.94)	0.47 (4.09)	0.49 (5.29)	0.45 (3.95)	0.47 (5.07)	-0.63 (-3.12)	-0.71 (-3.42)	-0.63 (-3.10)	-0.69 (-3.30)	0.17 (2.58)	0.16 (1.98)	0.20 (2.78)	0.04 (1.83)
July	0.17 (1.19)	0.22 (1.80)	0.17 (1.22)	0.22 (1.81)	0.24 (2.12)	0.29 (3.15)	0.24 (2.16)	0.29 (3.18)	-0.42 (-2.61)	-0.22 (-1.10)	-0.12 (-0.61)	-0.22 (-1.10)	-0.27 (-1.98)	-0.34 (-2.21)	-0.28 (-2.01)	-0.32 (-2.10)
Aug	0.27 (1.93)	0.31 (2.56)	0.26 (1.86)	0.31 (2.59)	0.35 (3.08)	0.40 (4.32)	0.36 (3.20)	0.40 (4.37)	-0.40 (-2.25)	-0.42 (-2.07)	-0.40 (-1.95)	-0.43 (-2.09)	-0.30 (-2.91)	-0.28 (-2.72)	-0.31 (-2.91)	-0.23 (-2.51)
Sept	0.30 (2.11)	0.35 (2.94)	0.30 (2.16)	0.36 (2.94)	0.30 (2.61)	0.37 (4.08)	0.30 (2.68)	0.37 (4.09)	-0.26 (-1.27)	-0.33 (-1.61)	-0.26 (-1.26)	-0.33 (-1.61)	-0.19 (-2.15)	-0.23 (-2.59)	-0.21 (-2.45)	-0.56 (-3.36)
Oct	0.32 (2.31)	0.26 (2.16)	0.32 (2.32)	0.25 (2.12)	0.38 (1.00)	0.32 (3.52)	0.38 (3.35)	0.31 (3.47)	-0.32 (-2.19)	-0.21 (-1.02)	-0.24 (-1.19)	-0.20 (-0.99)	-0.31 (-2.92)	-0.35 (3.19)	-0.33 (-3.01)	0.42 (4.17)
Nov	0.11 (0.77)	0.19 (1.54)	0.17 (1.15)	0.22 (1.77)	0.11 (2.54)	0.20 (2.19)	0.17 (1.48)	0.23 (2.47)	0.04 (0.21)	-0.13 (-0.65)	-0.04 (-0.19)	-0.18 (-0.83)	-0.01 (-1.90)	-0.02 (-1.99)	-0.01 (-1.21)	-0.10 (-2.39)
Dec	0.27 (2.23)	0.23 (1.87)	0.22 (1.96)	0.27 (2.34)	0.29 (3.41)	0.32 (3.53)	0.24 (2.06)	0.29 (3.08)	-0.47 (-2.31)	-0.56 (-2.75)	-0.47 (-2.24)	-0.52 (-2.46)	-0.01 (-1.21)	0.01 (-1.20)	-0.02 (-2.09)	0.01 (-1.41)
Jan	0.31 (2.17)	0.23 (1.95)	0.32 (2.27)	0.24 (1.96)	0.39 (1.92)	0.33 (3.66)	0.40 (3.54)	0.33 (3.67)	-0.10 (-0.48)	-0.05 (-0.25)	-0.10 (-0.48)	-0.05 (-0.26)	-0.02 (-2.02)	-0.06 (-2.69)	-0.02 (-1.65)	0.04 (-2.55)
Feb	0.27 (1.92)	0.27 (2.19)	0.28 (2.01)	0.27 (2.17)	0.37 (3.21)	0.40 (4.24)	0.38 (3.34)	0.39 (4.21)	-0.36 (-2.77)	-0.39 (-1.87)	-0.36 (-1.77)	-0.39 (-1.86)	-0.01 (-0.65)	-0.10 (-1.85)	-0.09 (-1.43)	-0.19 (-2.01)
Intercept	-0.18 (-1.80)	-0.20 (-2.37)	-0.18 (-1.85)	-0.20 (-2.36)	-0.27 (-3.39)	-0.30 (-4.72)	-0.28 (-3.47)	-0.30 (-4.70)	0.37 (2.05)	0.36 (2.61)	0.39 (2.65)	0.41 (3.22)	0.32 (2.28)	0.31 (2.16)	0.33 (2.39)	0.35 (2.75)
Adj. R2	0.32	0.30	0.38	0.41	0.35	0.39	0.33	0.45	0.41	0.39	0.47	0.49	0.37	0.33	0.39	0.42

Notes: Table 6 presents the time-series regression results of the impact of local investor sentiment on stock market liquidity. Sample period spans from January-2003 to March-2015 (147 monthly observations).The values in the parenthesis are t-statistics.

Table 7: Global Investor Sentiment, Local Investor Sentiment and Stock Market Liquidity

Panel (A): Baker and Wurgler sentiment index and stock market liquidity	TV		TR		ILLIQ		HLS	
BWSI	0.39 (2.89)	0.42 (2.91)	0.34 (2.79)	0.27 (2.43)	-0.65 (-2.69)	-0.58 (-2.51)	-0.01 (-0.31)	-0.01 (-1.12)
SENT		0.29 (2.15)		0.01 (1.49)		-0.68 (-3.47)		-0.01 (-1.02)
RM	0.04 (2.77)	0.01 (1.96)	0.05 (3.05)	0.06 (2.81)	-0.07 (-3.73)	-0.04 (-2.24)	-0.02 (-2.66)	-0.05 (-2.52)
TS	-0.01 (-1.49)	-0.04 (-1.79)	-0.01 (-1.79)	-0.05 (-1.97)	0.01 (0.39)	0.06 (2.11)	-0.06 (-1.05)	0.01 (0.64)
IP	0.01 (0.43)	0.01 (1.47)	0.02 (0.82)	-0.01 (-1.76)	-0.00 (-0.01)	-0.00 (-0.35)	-0.40 (-1.92)	-0.01 (-1.08)
IR	-0.01 (-0.7)	-0.02 (-0.55)	-0.01 (-2.1)	-0.03 (-0.97)	0.00 (0.31)	0.02 (2.15)	0.00 (0.34)	0.01 (1.79)
FII	0.44 (4.96)	0.03 (2.43)	0.72 (5.12)	0.04 (2.74)	0.10 (0.87)	-0.01 (-0.63)	-0.20 (-1.8)	-0.02 (-0.91)
STDV	-0.19 (-4.26)	-0.20 (-4.37)	-0.12 (-2.97)	-0.12 (-3.13)	0.07 (0.86)	0.18 (3.34)	0.06 (0.48)	0.02 (1.96)
RET	0.05 (5.39)	0.05 (4.88)	0.05 (5.28)	0.04 (4.82)	-0.04 (-4.33)	-0.05 (-4.86)	-0.05 (-5.42)	-0.04 (-5.11)
Adj. R^2	0.39	45	41	43	39	42	24	26
Panel (B): AAII sentiment index and stock market liquidity								
AAIISI	0.03 (1.08)	0.04 (0.78)	0.02 (1.42)	0.15 (1.27)	-0.01 (-1.66)	-0.01 (-0.88)	-0.00 (-0.48)	-0.00 (-1.09)
SENT		0.17 (3.65)		0.02 (1.19)		-0.02 (-1.99)		-0.01 (-1.11)
RM	0.01 (1.97)	0.03 (2.32)	0.23 (3.67)	0.06 (3.77)	-0.26 (-3.73)	-0.04 (-3.25)	-0.25 (-2.97)	-0.27 (-4.93)
TS	-0.03 (-0.65)	-0.03 (-0.66)	-0.04 (-0.97)	-0.04 (-0.98)	0.06 (0.94)	0.06 (1.22)	0.01 (0.65)	0.01 (0.56)
IP	0.08 (2.45)	0.01 (1.86)	0.07 (2.30)	0.01 (1.97)	-0.05 (-2.15)	-0.00 (-0.27)	-0.04 (-1.98)	-0.02 (-0.29)
IR	-0.02 (-1.84)	-0.03 (-1.93)	-0.03 (-1.96)	-0.03 (-2.27)	0.02 (1.82)	0.01 (0.16)	0.05 (1.97)	0.02 (1.09)
FII	0.01 (1.94)	0.01 (2.01)	0.02 (2.68)	0.02 (2.35)	-0.02 (-2.77)	-0.02 (-2.17)	-0.02 (-3.19)	-0.02 (-3.31)
STDV	-0.18 (-4.09)	-0.19 (-4.13)	-0.11 (-2.84)	-0.12 (-2.95)	0.19 (2.97)	0.02 (3.19)	0.20 (3.05)	0.15 (3.84)
RET	0.05 (5.21)	0.05 (4.81)	0.06 (5.28)	0.04 (4.77)	-0.04 (-2.18)	-0.05 (-4.96)	-0.06 (-5.41)	-0.06 (-5.81)
Adj. R^2	42	45	39	42	31	38	29	35

Panel (C): European sentiment index and stock market liquidity Variables	TV		TR		ILLIQ		HLS	
EUROSI	0.04 (2.18)	0.05 (2.65)	0.00 (0.87)	0.02 (1.39)	-0.01 (-0.79)	-0.00 (-0.79)	-0.01 (-1.76)	-0.01 (-1.77)
SENT		0.04 (2.11)		0.03 (1.24)		-0.08 (-1.66)		-0.00 (-1.03)
RM	0.02 (2.36)	0.03 (2.43)	0.06 (2.75)	0.07 (2.86)	-0.07 (-3.45)	-0.05 (-2.31)	-0.05 (-3.19)	-0.05 (-2.48)
TS	-0.04 (-1.73)	-0.04 (-1.53)	-0.05 (-2.02)	-0.05 (-1.73)	0.06 (2.68)	0.06 (1.97)	0.01 (0.66)	0.01 (1.59)
IP	0.01 (1.79)	0.01 (1.98)	0.01 (2.01)	0.01 (2.01)	-0.00 (-1.12)	0.00 (0.11)	-0.00 (-1.01)	-0.01 (1.61)
IR	-0.02 (-0.87)	-0.03 (-0.98)	-0.03 (-1.14)	-0.03 (-1.31)	0.02 (1.42)	0.01 (0.18)	0.05 (2.03)	0.02 (1.99)
FII	0.38 (2.99)	0.50 (3.08)	0.42 (2.41)	0.39 (2.09)	-0.01 (-0.65)	-0.38 (-1.98)	-0.00 (-0.45)	-0.39 (-2.23)
STDV	-0.18 (-3.97)	-0.19 (-4.04)	-0.11 (-2.76)	-0.12 (-2.89)	0.28 (3.04)	0.20 (2.99)	0.25 (2.56)	0.14 (2.38)
RET	0.05 (5.28)	0.04 (4.82)	0.06 (5.34)	0.04 (4.79)	-0.04 (-4.24)	-0.05 (-2.63)	-0.05 (-5.43)	-0.05 (-2.55)
Adj. R^2	40	42	38	40	39	41	32	34
Panel (D): Emerging market sentiment index and stock market liquidity								
EMSI	0.36 (7.88)	0.401 (8.18)	0.40 (8.55)	0.45 (9.37)	-0.15 (-2.92)	-0.22 (-3.99)	-0.19 (-3.27)	-0.34 (-4.21)
SENT		0.167 (3.89)		0.03 (1.27)		-0.02 (-1.89)		-0.00 (-0.98)
RM	0.20 (3.11)	0.322 (5.22)	0.27 (3.88)	0.26 (3.87)	-0.26 (-3.42)	-0.14 (-2.29)	-0.22 (-2.98)	-0.17 (-2.88)
TS	-0.03 (-0.75)	-0.031 (-0.78)	-0.05 (-1.12)	-0.04 (-1.18)	0.06 (0.99)	0.05 (1.45)	0.01 (0.69)	0.01 (1.16)
IP	0.01 (1.65)	0.012 (1.93)	0.01 (1.18)	0.01 (1.49)	-0.00 (-0.57)	-0.00 (-0.29)	-0.00 (-0.32)	-0.00 (-0.41)
IR	-0.10 (-4.44)	-0.091 (-2.82)	-0.09 (-3.11)	-0.07 (-2.56)	0.06 (2.55)	0.01 (0.66)	0.04 (2.08)	0.14 (5.58)
FII	0.02 (2.94)	0.021 (3.11)	0.02 (2.68)	0.02 (2.39)	-0.02 (-3.81)	-0.02 (-3.01)	-0.02 (-3.27)	-0.03 (-4.34)
STDV	-0.19 (-4.15)	-0.188 (-4.06)	-0.13 (-3.19)	-0.11 (-2.84)	0.22 (3.77)	0.19 (3.33)	0.11 (2.23)	0.16 (3.99)
RET	0.06 (5.65)	0.05 (4.95)	0.05 (5.33)	0.04 (4.68)	-0.04 (-3.23)	-0.05 (-4.87)	-0.07 (-5.99)	-0.06 (-5.98)
Adj. R^2	47	48	49	50	52	48	50	44

Notes: Table 7 presents the time-series regression results of the impact of global and local investor sentiment on stock market liquidity. Sample period spans from January-2003 to March-2015 (147 monthly observations).The values in the parenthesis are t-statistics.

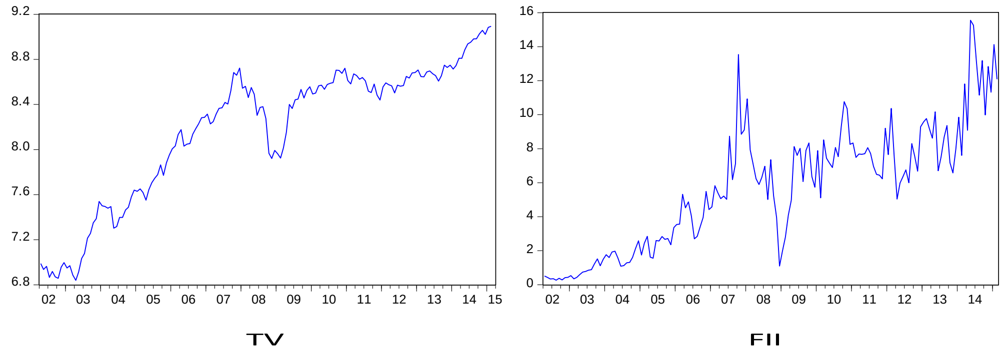
Table 8: Investor Sentiment and Liquidity: With and Without Financial Crisis

Panel (A): Investor sentiment and stock market liquidity for the period January-2003 to July-2007										
Variables	TV					ILLIQ				
SENT	0.341 (3.22)					-0.041 (-0.91)				
BWSI		0.487 (3.98)					-0.437 (-3.18)			
EUROSI			0.089 (3.01)					-0.001 (-0.78)		
AAIISI				0.001 (0.34)					-0.000 (-0.19)	
EMSI					0.379 (5.56)					-0.312 (-4.96)
RM	0.039 (2.77)	0.047 (3.05)	0.026 (1.93)	0.021 (1.86)	0.065 (4.22)	-0.023 (-2.36)	-0.063 (-3.80)	-0.038 (-2.74)	-0.002 (-0.52)	-0.041 (-3.66)
TS	-0.011 (-1.49)	-0.011 (-1.79)	-0.005 (-1.39)	-0.003 (-1.05)	-0.001 (-0.96)	0.040 (0.79)	0.048 (1.07)	0.064 (0.71)	0.000 (0.14)	0.002 (1.21)
IP	0.012 (0.43)	0.021 (0.82)	0.073 (1.01)	-0.004 (-1.92)	0.025 (1.66)	-0.010 (-1.47)	-0.011 (-1.76)	-0.004 (-0.35)	-0.010 (-1.08)	-0.018 (-1.51)
IR	-0.015 (-2.7)	-0.004 (-1.1)	-0.004 (-1.21)	-0.001 (-0.94)	-0.002 (-1.23)	0.016 (2.55)	0.025 (2.97)	0.007 (0.75)	0.000 (0.59)	0.025 (3.44)
FII	0.411 (2.96)	0.322 (2.12)	0.210 (1.87)	0.120 (1.81)	0.522 (3.23)	0.034 (2.43)	-0.012 (-1.74)	0.008 (0.63)	-0.001 (-0.11)	-0.395 (-2.09)
STDV	-0.190 (-4.26)	-0.116 (-2.97)	-0.068 (-1.96)	-0.001 (-0.48)	-0.212 (-4.79)	0.196 (4.37)	0.123 (3.13)	0.083 (1.04)	0.000 (0.36)	0.215 (4.83)
RET	0.053 (5.39)	0.047 (5.28)	0.041 (4.33)	0.045 (5.42)	0.046 (4.56)	-0.050 (-4.88)	-0.043 (-4.82)	-0.048 (-4.66)	-0.0004 (-1.49)	-0.060 (-5.99)
Adj. R^2	47	44	40	31	45	45	43	37	28	44
Panel (B): Investor sentiment and stock market liquidity for the period August-2007 to March-2015										
Variables	TV					ILLIQ				
SENT	0.441 (4.98)					-0.411 (-3.91)				
BWSI		0.411 (2.28)					-0.411 (-3.02)			
EUROSI			0.009 (1.01)					-0.003 (-0.97)		
AAIISI				0.001 (0.34)					-0.000 (-0.21)	
EMSI					0.452 (6.92)					-0.386 (-5.26)
RM	0.099 (5.17)	0.077 (4.35)	0.063 (3.91)	0.053 (3.56)	0.089 (4.20)	-0.083 (-4.36)	-0.063 (-3.90)	-0.048 (-3.16)	-0.027 (-2.52)	-0.091 (-4.95)
TS	-0.021 (-1.99)	-0.018 (-1.77)	-0.003 (-1.22)	-0.002 (-1.15)	-0.006 (-1.11)	0.050 (1.25)	0.058 (1.33)	0.054 (0.83)	0.001 (1.12)	0.040 (1.15)
IP	0.042 (2.49)	0.091 (3.82)	0.073 (1.01)	-0.003 (-1.88)	0.031 (2.18)	-0.019 (-1.96)	-0.013 (-1.88)	-0.003 (-0.55)	-0.011 (-1.78)	-0.021 (-2.16)
IR	-0.025 (-3.57)	-0.029 (-3.99)	-0.024 (-3.22)	-0.021 (-2.94)	-0.021 (-3.33)	0.015 (2.58)	0.029 (3.77)	0.017 (2.75)	0.019 (2.89)	0.016 (2.77)
FII	0.421 (3.06)	0.422 (3.12)	0.220 (1.99)	0.020 (0.92)	0.455 (3.72)	0.044 (2.49)	-0.011 (-1.69)	-0.018 (-1.93)	-0.001 (-0.12)	0.034 (1.99)
STDV	-0.219 (-4.83)	-0.216 (-4.77)	-0.118 (-2.99)	-0.001 (-0.49)	-0.280 (-5.23)	0.296 (4.99)	0.143 (3.29)	0.183 (4.04)	0.020 (1.87)	0.361 (5.22)
RET	0.055 (5.44)	0.057 (5.88)	0.044 (4.33)	0.045 (4.49)	0.032 (4.94)	-0.030 (-4.27)	-0.023 (-3.12)	-0.028 (-3.61)	-0.003 (-1.99)	-0.037 (-4.88)
Adj. R^2	52	48	42	39	49	51	46	41	37	50

Notes: This table presents the time-series regression results of the impact of investor sentiment on stock market liquidity. The dependent variables are traded value (TV) and Amihud's (2002) illiquidity ratio (ILLIQ). The independent variables are as follows. The domestic investor sentiment (SENT), the Baker-Wurgler sentiment index (BWSI), the European investor sentiment index (EUROSI), the index of AAII (AAIISI), investor sentiment index of emerging markets (EMSI), the rolling twelve-months growth rate of reserve money (RM), term spread (TS), the growth rate of industrial production (IP), inflation growth rate (IR), net funds flow from foreign institutional investors (FII), the monthly market volatility (STDV) and the market return (RET). Panel A reports the OLS estimated results the sample period ranging from January-2003 to July-2007. And, the Panel B presents OLS estimated results for the sample period, i.e., August-2007 to March-2015. The values in the parenthesis are t-statistics.

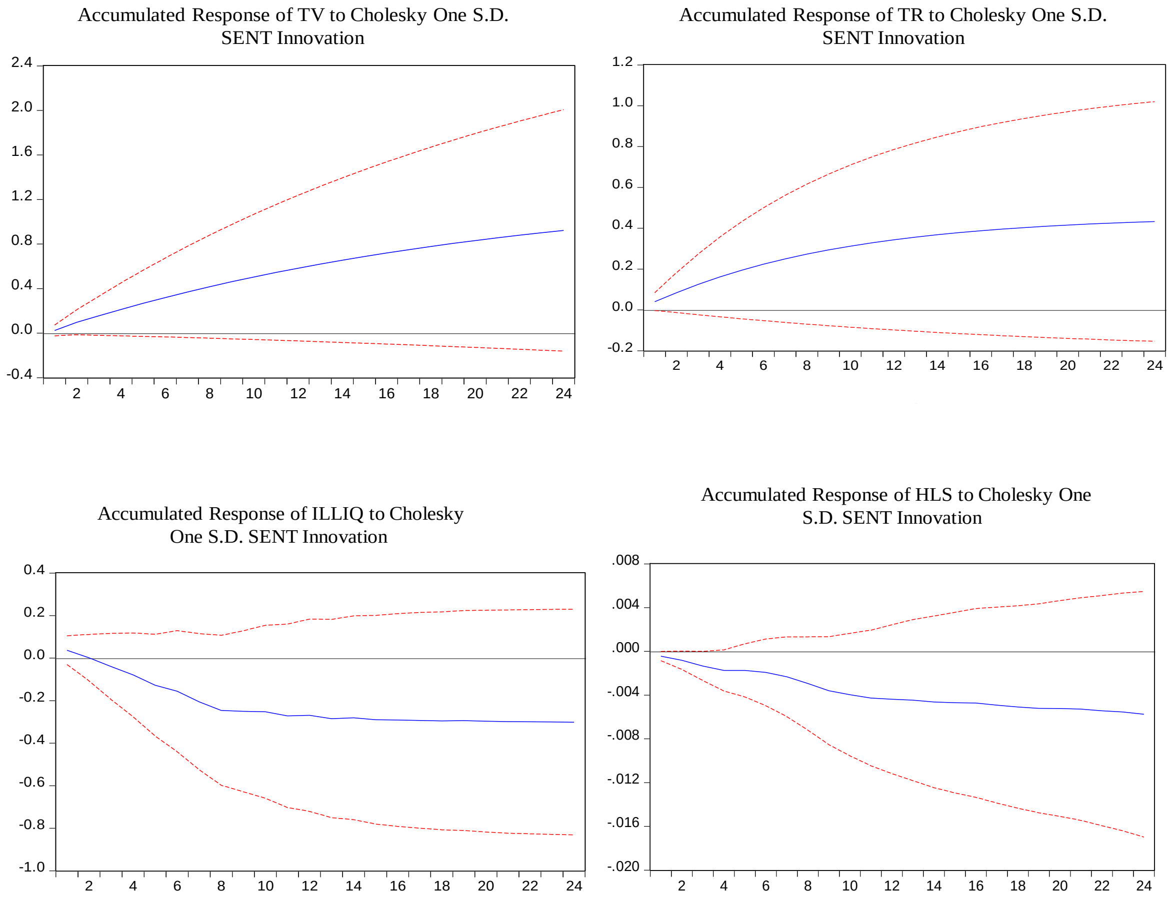
Stock Market Liquidity: Implication of Local and Global Investor Sentiment

Figure 1: Trends of stock market liquidity and foreign institutional investors' inflow

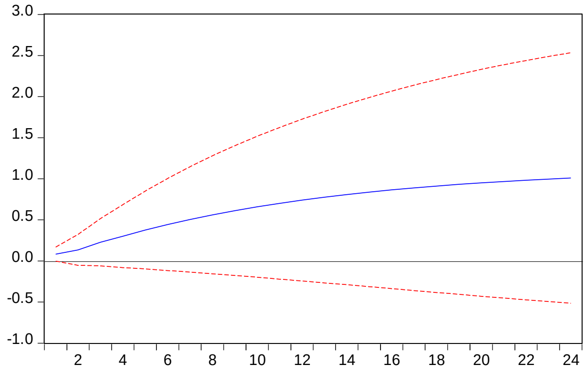


Note: Sample period consists of monthly observation from 2002 till 2015.

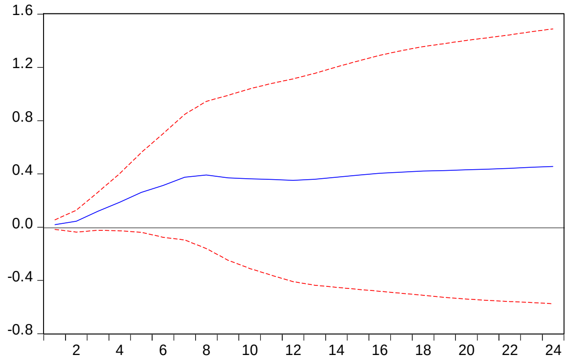
Figure 2: Response of market liquidity to a unit standard deviation innovation in the investor sentiment



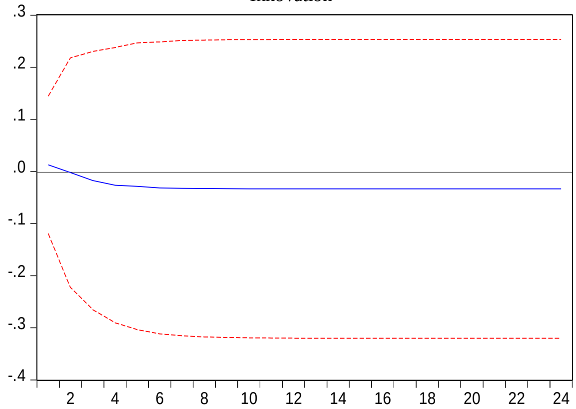
Accumulated Response of TV to Cholesky One S.D. BWSI Innovation



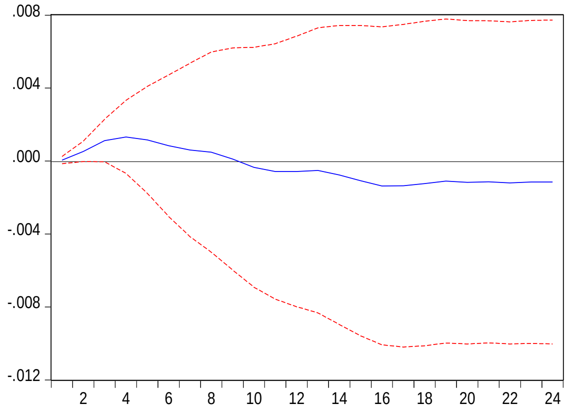
Accumulated Response of TR to Cholesky One S.D. BWSI Innovation



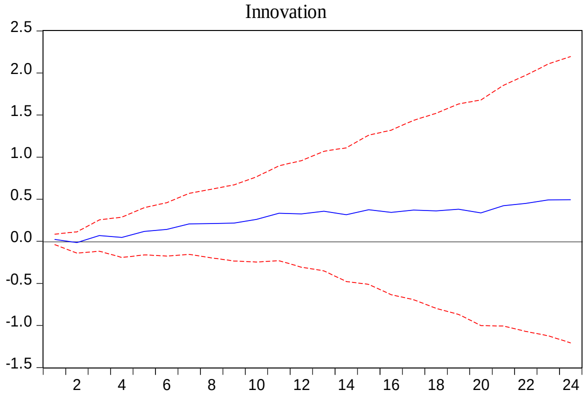
Accumulated Response of ILLIQ to Cholesky One S.D. BWSI Innovation



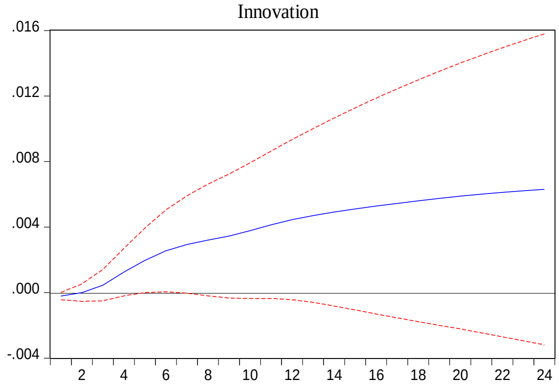
Accumulated Response of HLS to Cholesky One S.D. BWSI Innovation



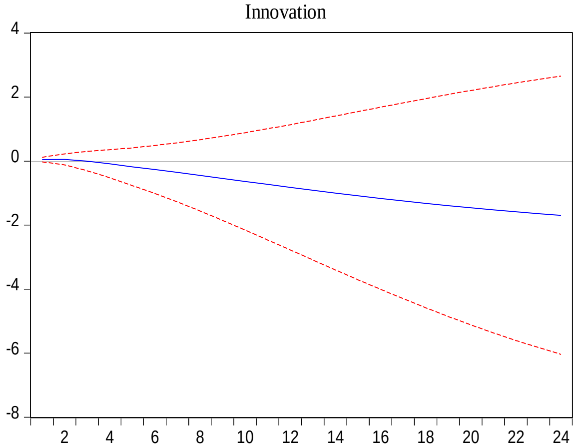
Accumulated Response of TV to Cholesky One S.D. EMSI Innovation



Accumulated Response of TR to Cholesky One S.D. EMSI Innovation



Accumulated Response of ILLIQ to Cholesky One S.D. EMSI Innovation



Accumulated Response of HLS to Cholesky One S.D. EMSI Innovation