How Foreign Trades Affect Domestic Market Liquidity: A Transaction Level Analysis

Yessy Arnold Peranginangin

A thesis submitted to the School of Accounting and Finance, The University of Adelaide, in fulfilment of the requirements for the degree of Doctor of Philosophy

December 2013

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

The extant literature has documented the significance of foreign trades on domestic markets as well as the importance of commonality in liquidity in a market, but it seems to be silent on how foreign trades affect commonality in liquidity, especially at the transaction level. The lack of research that investigates this line of enquiry provides the overarching research theme for this thesis.

To investigate the research theme I use transaction data from the Indonesian Stock Exchange (IDX) that allows me to identify the trading activities of foreign-versus-domestic investors on a trade-by-trade basis. I find that foreign investors enhance commonality in spread when they initiate trades on both sides of the market which are motivated either by differences in interpreting information or by the desire to trade immediately, but not by information asymmetry. This finding is surprising given the prevalence of asymmetric information evidence surrounding domestic and foreign interaction and the proposition of Chordia, Roll and Subrahmanyam (2000) suggesting that information asymmetry could induce commonality in liquidity. The lack of evidence to link information asymmetry between domestic and foreign investors and commonality in liquidity, along with the findings indicating that foreigners trade more aggressively than locals, lead me to raise and investigate a follow up research question. This second research question is why do foreigners have a propensity to place more aggressive orders as costs associated with these trades are higher?

Investigating the second research question, I find more evidence to exclude information asymmetry as the channel through which foreigners affect commonality in liquidity and

find more evidence to support the finding that foreigners affect commonality in liquidity through their desire to trade immediately. This finding implies that an inventory risks explanation is more appropriate in explaining the impact of foreign trades on commonality in liquidity. Given that foreign trades are aggressive and this affects commonality in liquidity, I then examine whether their trades are motivated by information advantage. Using price discovery analysis, I find that domestic investors make a greater contribution to the price discovery process compared to foreign investors and the contribution of domestic investors to the price discovery process can be explained by domestic and foreign interactions.

Furthermore, analysing the information types that are reflected in domestic and foreign price series, I find that domestic prices reflect firm-specific information while foreign price series reflect systematic information. These findings, along with the findings on the price discovery analysis, seem to suggest that the low contribution of foreign investors to the price discovery process could be due to the fact that they base their investment decisions on systematic information, rather than firm-specific information.

In summary, I find evidence suggesting that foreign investors affect commonality in liquidity through their needs of immediacy rather than information asymmetry. The evidence also suggests that there is a mutually-beneficial relationship between foreign (net) liquidity demanders and domestic (net) liquidity suppliers. This enduring relationship holds up very well during the 2008 financial crisis, demonstrating its resilience.

DECLARATION

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

I give consent to this copy of my thesis, when deposited in the University Library, being made available for loan and photocopying, subject to the provisions of the Copyright Act 1968. I also give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library catalogue and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

Signature ______________________________ Date:

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my principal supervisor Prof. Ralf Zurbrugg for his unreserved attention and guidance. I am so grateful of his support and motivation. I would like to thank my co-supervisor, Dr. Syed Ali, for the enthusiastic and stimulating discussions. I would also like to thank my co-supervisor, Prof. Paul Brockman for his wisdom and guidance. It is no exaggeration to say that this thesis would not have been completed without their kind help, support and guidance.

I would like to thank AusAid for the Australian Leadership Award Scholarship that enables me to undertake a PhD. My sincere gratitude goes to Dr. Zaafri Husodo. I am greatly indebted to him for the transaction data used in this thesis. I would also like to acknowledge the kind assistance of Mr. Syafruddin of KSEI in obtaining the ownership data.

Many thanks go to the staffs as well as PhD candidates at the School of Accounting and Finance, I thank them for the stimulating discussions, assistance and encouragements. I would like to express my sincere gratitude to Dr. Chee Cheong for his moral support and guidance.

I would like to express my love and gratitude to my lovely wife and daughter who have been so patient with the ups and downs of my PhD years. I could not get to the end without their continuous prayer, love and support. I am also grateful of the support and prayer of the Peranginangin and Ginting Suka family. Lastly, I would like to thank our friends in Adelaide. Their great help, hospitality and encouragements make living in Adelaide a lot easier.

CHAPTER 1: INTRODUCTION

1.1. BACKGROUND TO THE THESIS

Foreign trades have been widely investigated in the literature because these trades influence prices and have the potential to destabilise domestic markets. So far, research that investigates domestic and foreign interaction has focused on the risk and return aspects of this interaction with less effort having been made on investigating the liquidity aspects. The literature has also documented the existence and importance of commonality in liquidity, which refers to the systematic movements of liquidity across stocks. This systematic component is important to investors because stocks that have low exposure to systematic liquidity (i.e. low commonality in liquidity) provide investors the ability to liquidate their positions when market liquidity is low.

The extant literature has documented the significance of foreign trades on domestic markets as well as the importance of commonality in liquidity in a market, but it seems to be silent on how foreign trades affect commonality in liquidity, especially at the transaction level. The lack of research that investigates this line of enquiry provides the overarching research theme for this thesis. The result of investigating this research theme could contribute to a significant policy debate about the impact of foreign investors on domestic stock market liquidity. The fundamental controversy of this debate lies in the mixed empirical evidence to date regarding the relation between foreign trades and domestic market liquidity. Some studies find a net liquidity benefit to such trades, while others find a net cost. One common feature of all previous studies is that they lack the data granularity to identify foreign-initiated versus domestic-initiated trades at the transaction level. This thesis uses transaction data from the Indonesian Stock Exchange (IDX) to identify foreign-versus-domestic investor trading activity on a trade-by-trade basis. It thus allows a closer examination of the mechanisms through which foreign trades affect commonality in liquidity at the transaction level, which to my knowledge has not been done by other studies. In addition, the investigation of this research theme would contribute to the bigger debate of whether foreign presence benefits domestic financial markets or not, from the perspective of market liquidity. The next section will introduce the research questions of this thesis.

1.2. RESEARCH QUESTIONS

This thesis aims to contribute to the literature by asking the question:

How do foreign trades affect commonality in liquidity of domestic markets at the transaction level?

The answer to this question will fill the gap in the literature by providing evidence on the mechanisms through which foreign investors affect commonality in liquidity of domestic markets at the transaction level. The findings suggest that domestic and foreign investors have a relatively similar impact on commonality in liquidity except when foreign trades become two-sided. Commonality in spread increases as foreign investors initiate buys and sells. The increase in commonality in spread implies that foreign investors induce higher liquidity risks in domestic markets when they are uncertain on how to react to an information set or when they need immediacy. The findings also suggest that foreign trades tend to be more aggressive and that foreign investors tend to be the demanders of liquidity while domestic investors tend to supply liquidity.

Taking these findings together, I then ask a follow up question:

Why do foreigners have a propensity to place more aggressive orders as costs associated with these trades are higher?

The answer to this question will provide a complete understanding of how foreign trades affect commonality in liquidity. Foreign investors could induce commonality in liquidity through information asymmetry or inventory risks. Given the overwhelming evidence on the presence of information asymmetry in domestic markets, the investigation of whether foreign trades are more informed would provide a complete understanding of how exactly foreign trades induce commonality in liquidity.

A detailed discussion on the major research question will be provided in Chapter 3, while the detailed discussion of the follow up research question will be provided at the beginning of Chapter 6. Given the research questions of this thesis, the next section outlines the research agenda and how this agenda will answer these research questions.

1.3. RESEARCH AGENDA

In order to answer the first research question, I examine four different aspects of initiated trades that come from domestic and foreign investors. I focus on initiated trades because these trades consume liquidity and might capture different investment strategies of domestic and foreign investors. Even though the research question only focuses on investigating the impact of foreign trades on commonality in liquidity, I include initiated trades from domestic investors to control for different types of investors in the market. Given that the data comes from a market where institutional investors dominate ownership and trades, a comparison of how domestic and foreign initiated trades affect commonality ensures that it is investors' domicile which explains the different impact of initiated trades on commonality in liquidity not investors' type (i.e. individual or institutional).

The four aspects of initiated trades are as follows. First, I calculate change in the volume of initiated trades that come from domestic and foreign investors and use this variable to investigate whether domestic and foreign trades affect commonality in liquidity differently. The change in the volume of initiated trades would serve as a proxy for the changes in the desire to trade, which is proposed as one of the demand factors of commonality in liquidity (Coughenour and Saad (2004)). Second, using a measure of market sidedness that is proposed by Sarkar and Schwartz (2009), I examine whether market sidedness of domestic and foreign investors has a different impact on commonality in liquidity. Sarkar and Schwartz (2009) suggest that one- sided trades would reflect information asymmetry while two sided trades would reflect differences in interpreting information or the need of immediacy. This exercise will examine whether commonality in liquidity is induced by asymmetric information or inventory risks. Third, I estimate the degree of correlated trades across domestic and foreign investors and examine whether the impact of correlated trades on commonality in liquidity that is documented by Coughenour and Saad (2004) and Karolyi, Lee and van Dijk (2012) would be different when investors are grouped into domestic and foreign. Last, I use net flows (initiated buys minus initiated sells) to examine whether the net flows of domestic and foreign investors affect commonality in liquidity differently.

Using net flows as one of the explanatory variables would supplement the investigation of whether commonality in liquidity arises from asymmetric information between domestic and foreign investors or not. While net flows of foreign investors do not measure the degree of information asymmetry between domestic and foreign investors, researchers often use this variable to measure how foreign investors respond to the asymmetric information that they are exposed to.

Under the regression framework of Chordia, et al. (2000), the contribution of different aspects of domestic and foreign initiated trades to commonality in liquidity would be captured by estimating the interaction variable between market liquidity and these aspects of initiated trades. The regressions are estimated using liquidity measures and transaction data that are aggregated at daily intervals to control for the intraday seasonality. The two liquidity measures used are relative spread and depth in number of shares. Trade directions of domestic and foreign investors can be observed from the data set without the need to infer these directions. The intraday data observation of initiated trades is then aggregated at daily intervals to form the four aspects of initiated trades, which would be the explanatory variables of the commonality regressions.

The second research question of why foreigners have a propensity to place more aggressive orders is investigated through price discovery analysis and through the examination of return synchronicity. These methodologies analyse domestic and foreign price series that are constructed from domestic and foreign initiated trades. I will estimate the contribution of domestic and foreign investors to the price discovery process using the information leadership shares (ILS) of Putniņš (2013). This price discovery metric combines the two widely used price discovery metrics, namely, the information shares of Hasbrouck (1995) and the component shares of Gonzalo and Granger (1995). Putniņš (2013) suggests that the ILS is superior to the other two measures because the impact of noise on the price discovery estimates would be minimised. Further analysis is performed to examine whether the contribution of domestic investors to price discovery can be explained by the domestic and foreign interaction in the market. To investigate this possibility, I estimate a regression model inspired by Eun and Sabherwal (2003). This model aims to examine the contributing factors that explain the different contribution of price discovery across two markets for dual listed stocks. Higher contribution to price discovery does not necessarily imply that an investor group is more informed. Thus, further analysis is required to determine whether the different contribution to price discovery could be attributed to the different information set that an investors' group uses to make investment decisions.

To investigate this line of enquiry, I apply the return synchronicity method to the price series that comes from domestic and foreign initiated trades, aggregated at daily intervals. The return synchronicity framework aims to estimate the systematic component of a price series. This method has been used by Morck, Yeung and Yu (2000) to estimate the systematic component of price series in various markets. A more detailed description of research methodologies employed to answer the first research question will be presented in Chapter 4, while the methodologies used to answer the second research question will be presented in Chapter 6 and 7.

CHAPTER 2: LITERATURE REVIEW

The focus of this thesis is to investigate the impact of domestic and foreign interaction on commonality in liquidity at the transaction level. To the best of my knowledge, there has not been any study that investigates such an issue at the transaction level. Thus, the literature review chapter will cover two aspects surrounding the focus of this thesis. First, I will start the chapter by reviewing the research on foreign investment in domestic markets. Second, I will provide a review of literature on liquidity and commonality in liquidity to discuss the theories and technical terms that will be used in this thesis. As a subset of the discussion on liquidity and commonality in liquidity, a review of the studies that investigate the impact of foreign trades on the liquidity and commonality in the liquidity of domestic markets will close the literature review chapter.

2.1. THE INTERACTION OF DOMESTIC AND FOREIGN INVESTORS

The theoretical prediction of Stulz (1999) suggests that when financial markets lower their barriers to foreign investors, the cost of capital in these markets decreases. This decrease is possible through two mechanisms. First, investors lower their expected returns because they can allocate investment across multiple markets and gain benefit from international diversification. Second, the presence of foreign investors in domestic markets promotes better monitoring of management and controlling shareholders which reduces monitoring costs and increases the available cash flows for stockholders.

Confirming the prediction of Stulz (1999), Henry (2000) finds that the value of equity in emerging markets, measured by the aggregate equity index, increases by 27% after market liberalisation. In addition, Bekaert and Harvey (2000) also find that the cost of capital across emerging markets decreases between 5 to 75 basis points after market liberalisation. However, Bekaert and Harvey (2000) note that the decrease in the cost of capital should be greater and that home bias prevents foreign investors from investing in the emerging markets. Home bias refers to investors' preference to invest in a market where they are familiar with the environment. This preference prevents them gaining the optimum benefit of international diversification. Karolyi and Stulz (2003) suggest that the home bias that is prevalent across foreign investors could not be attributed to the explicit barriers to foreign investors because these barriers have diminished substantially over time. Karolyi and Stulz (2003) suggest that implicit barriers, for example information asymmetry, could play an important role in preventing foreign investors investing in international markets.

The literature agrees on the existence of information asymmetry between domestic and foreign investors, but is undecided on whether it is domestic or foreign investors who have the information advantage. The theoretical framework of Brennan, Henry Cao, Strong and Xu (2005) suggests that if domestic investors had the information advantage, there would be a positive correlation between foreign net flows and market returns of the host market. The behaviour of foreign investors in international markets seems to induce the positive correlation between foreign net flows and host market returns (Bohn and Tesar (1996), Choe, Kho and Stulz (1999), and Froot, O'Connell and Seasholes (2001)). Furthermore, in their empirical analysis, Brennan, et al. (2005) find that foreign purchase by U.S. investors in developed foreign markets is associated with an increase in market returns for these foreign markets and this finding is driven by the information advantage of domestic investors rather than the price impact of U.S.

investors' trades. In line with the proposition of Brennan, et al. (2005), several studies find that domestic investors are more informed (Choe, Kho and Stulz (2005), Dvorak (2005), and Agarwal, Faircloth, Liu and Ghon Rhee (2009)). However, several studies find that foreign investors have better trade performance compared to domestic investors (Grinblatt and Keloharju (2000), Froot and Ramadorai (2001), and Froot and Ramadorai (2008)), which would indicate that foreign investors are better informed than domestic investors.

Choe, et al. (2005) suggest that the better trade performance of foreign investors should not necessarily be concluded to be evidence of foreign investors having the informational advantage. They propose that it is necessary to control for risks on the performance differential between domestic and foreign investors in order to come to the conclusion of who is more informed. Choe, et al. (2005) argue that without controlling for investment risks, the superior performance of foreign investors could also be due to the sophistication of foreign investors[1]. Using 120 days of estimation period, Grinblatt and Keloharju (2000) find that the superior trade performance of foreign investors can be attributed to their sophistication and ability to implement momentum strategy where they buy past winners and sell past losers. They also find that trade performance is positively related to how close an investor group follows momentum strategy. Foreign investors have the best trade performance because they follow momentum strategy, while domestic individual investors who engage in contrarian strategy perform the worst. The trade performance of domestic institutions is in between foreign and

[1] Several studies suggest that foreign investors' sophistication plays an important role in assisting foreign investors to outperform domestic investors (Grinblatt and Keloharju (2000), Froot and Ramadorai (2008), Albuquerque, H. Bauer and Schneider (2009), Chen, Johnson, Lin and Liu (2009), and Huang and Cheng-Yi (2009))

domestic individual investors because they engage in a trading strategy that is in between momentum and contrarian. Froot and Ramadorai (2008) suggest a different explanation of the better trade performance of foreign investors. They suggest that foreign investors perform better compared to domestic investors because their investment decisions are based on the systematic component of returns, while domestic investors base their investment decisions on firm specific information.

With regard to the superior trade performance of domestic investors, Choe, et al. (2005) find that, compared to foreign investors, domestic investors pay less when they buy securities and receive more when they sell. The superior performance of domestic investors is because asset prices move against foreign investors before they trade. Choe, et al. (2005) argue that their findings do not rely on the different risks that domestic and foreign investors are exposed to. Thus, the differential performance of domestic and foreign investors' trade could be attributed to the fact that domestic investors are more informed than foreign investors. Applying the methodology of Choe, et al. (2005) in transaction data, Dvorak (2005) and Agarwal, et al. (2009) document similar findings. These studies find that domestic investors are more informed than foreign investors. However, Dvorak (2005) suggests that domestic investors' dominance is not significant at a weekly interval because foreign investors have better skills in interpreting information at a longer time interval.

The use of transaction data could reveal additional dynamics in the interaction between domestic and foreign investors. However, studies that use this high frequency data cannot reveal the reasons why foreign investors are still attracted to emerging markets given the presence of explicit and implicit trade barriers. Using monthly data of foreign ownership in Taiwan, Huang and Cheng-Yi (2009) find that foreign presence can generate a premium that enable them to outperform domestic investors in the longer investment horizon. They find that a foreign premium exists across stocks that have high foreign ownership. They argue that this premium can be attributed to better monitoring activities by foreign investors. Furthermore, Huang and Cheng-Yi (2009) find that firms with high foreign ownership can be associated with increased R&D (research and development) expenditures and performance.

2.2. MARKET MICROSTRUCTURE

2.2.1. Liquidity

Finance literature suggests that liquidity reflects the ability to buy or sell an asset at any quantity without affecting the asset's price significantly. While the definition of liquidity is straightforward, researchers have long recognised that liquidity is a slippery concept (Hicks (1962) and Kyle (1985)). Hicks (1962) suggests that the slipperiness of liquidity is partially due to its use in various fields (for example in accounting, government and academia work) that attracts multiple interpretations of the term. To add to this confusion, liquidity itself is considered to be a complicated concept because it incorporates multiple aspects of stock trading. Initial attempts to study liquidity benefit from a simple trading model that is proposed by Bagehot (1971). He suggests that market makers, who have pivotal roles in creating liquidity, have to transact with two types of traders, namely informed traders and noise traders. These market makers will gain profit when they trade with noise traders but experience loss when they trade with informed traders.

Kyle (1985) extends the trading framework in Bagehot (1971) and introduces a dynamic, sequential, equilibrium model where market liquidity holds an important role in determining how informed traders will trade. There are three dimensions of liquidity that informed traders must assess. The first dimension is tightness. Tightness reflects the cost of buying or selling assets immediately which is when buyers (sellers) have to cross from bid (ask) price to ask (bid) price. The second dimension is depth. This dimension expresses the additional quantity of an order that is required to change the price of an asset. The third dimension is resiliency. This dimension captures the speed that is required for the price of assets to recover from a random and non-informative shock. In a more recent work, Harris (2003) highlights the fact that when investors engage in the search of liquidity, there are trade-offs among the three dimensions of liquidity and investors cannot minimise their liquidity exposures across the three dimensions.

The three dimensions of liquidity assist researchers to propose liquidity measures that would capture one or several dimensions of liquidity. Early works to measure liquidity use a readily available liquidity measure, namely trading volume. Trading volume represents the number of stocks that are traded at a particular time. Intuitively, as the trading volume of a stock increases so does the stock's liquidity. However, Easley and O'Hara (2003) suggest that volume or volume-related liquidity measures, contain information of the true value of stocks, thus the ability of volume to explain the variation of return (Campbell, Grossman and Wang (1993) and Conrad, Hameed and Niden (1994)) cannot be attributed to liquidity. Even though trading volume cannot measure liquidity perfectly, it has the ability to explain several phenomena in the equity markets.

Amihud and Mendelson (1986) suggest that the bid-ask spread contains premium for immediate transaction and could capture the tightness dimension of liquidity. Bid (ask) price contains concession for selling (buying) securities immediately; as the concession for immediacy gets smaller, the market is more liquid. The ability to record the bid-ask spread at the transaction level generates more understanding on how intra-day liquidity is priced (Chalmers and Kadlec (1998) and on how intra-day liquidity evolves (Admati and Pfleiderer (1988) and Lee, Mucklow and Ready (1993)). Besides bid-ask spread, there are several intra-day liquidity measures that can be calculated from transaction data, namely depth and imbalance of depth. Depth is the number of stocks that is available at a certain level of bid or ask price. Imbalance of depth describes the imbalance of liquidity supply at the best bid and ask price. These transaction-based liquidity measures can be calculated at the best bid-ask prices or can be extended beyond the best bid-ask prices to take into account large trades (Aitken and Comerton-Forde (2003), Kempf and Mayston (2008), and Pukthuanthong-Le and Visaltanachoti (2009)).

Research conducted at intra-day intervals enhances our understanding of how the stock markets operate at a finer time grid. However, it is suggested that the development of low frequency measures of liquidity would benefit the literature since liquidity could impact portfolio formation, capital structure, security issuance (Amihud and Mendelson (1988), Amihud and Mendelson (1991), Goyenko, Holden and Trzcinka (2009)) and cross markets liquidity (Lesmond (2005), Bekaert, Harvey and Lundblad (2007)). Table 1 presents the low-frequency liquidity measures in the literature as investigated in Goyenko, et al. (2009).

Table 1: Low frequency liquidity measures
This table summarises the major low-frequency liquidity measures examined in Goyenko, et al. (2009). They grouped the liquidity measures based on the aspect of liquidity that these measures attempt to capture. Panel A presents the liquidity measures that capture the tightness dimension of liquidity and Panel B shows the measures that capture the depth dimension of liquidity.

Measures	**Description**
Panel A: tightness dimension of liquidity	
Roll Roll (1984)	Estimate of effective spread using the covariance of the changes in price
Effective Tick Holden (2009)	Proxy of effective spread that takes into account the price clustering phenomenon.
Holden Holden (2009)	Estimate of effective spread that is nested on Roll (1984) and Effective Tick.
Gibbs Hasbrouck (2004)	Gibbs sampler estimates of Roll (1984) measure.
LOT Lesmond, Lesmond, Ogden, Ogden, Trzcinka and Trzcinka (1999)	Proportional transaction costs for buying and selling in the presence (absence) of informed traders during zero return days (non-zero trading days).
Zeros Lesmond, et al. (1999)	Proportion of the number of days with zero return throughout the observation period (i.e. weekly or monthly)
Panel B: depth dimension of liquidity	
Illiquidity Amihud (2002)	Absolute daily return over dollar trading volume; relates daily changes in prices to the dollar volume.
Gamma Pastor and Stambaugh (2003)	Measures liquidity based on the strength of volume related return reversal.
Amivest	The inverse of illiquidity measure; measures the dollar value of trading required to change 1% of stock return.

Goyenko, et al. (2009) provide an excellent summary of the low frequency liquidity measures, propose modifications of the existing measures and conduct comprehensive tests on the performance of these liquidity measures. They examine the performance of twenty four low-frequency spread based and price impact based liquidity measures against the aggregated intra-day spread and price impact benchmarks, respectively. The low frequency liquidity measures are calculated at monthly and yearly intervals. Goyenko, et al. (2009) find that the spread based measures, calculated at the low frequency, track the aggregated intra-day benchmarks very well. However, the price impact measures do not perform as well as their spread based counterparts. Goyenko, et al. (2009) suggest that the illiquidity measure Amihud (2002) and any of the spread based measures standardised with volume should perform sufficiently well in tracking the aggregated intra-day benchmark for price impact measures. The Goyenko, et al. (2009) study justifies the strand of literature that investigates the properties of liquidity using the low-frequency spread measures. However, they note that the results of this study are sensitive to the sample selection and hence similar results would be less likely to be obtained when one extends this study to a different set of stocks or markets.

An attempt to propose a new measure of liquidity comes from Chordia, Huh and Subrahmanyam (2009). They suggest that the inconsistent evidence surrounding liquidity pricing literature is partly due to the lack of theoretical support for the liquidity measures employed and the endogeneity property of liquidity in the process of stock trading. They suggest that liquidity is an endogenous variable in pricing because its relationship to stock return is indirect (for example, through trading volume). Chordia, et al. (2009) extend the lambda (price impact measure) that is proposed by Kyle (1985) and propose a closed form solution of lambda under two conditions. The first condition is the absence of noise in the signals and the second condition is where noisy signals exist. Chordia, et al. (2009) find that the theoretical measures of liquidity perform as well as the other liquidity measures and contribute to the literature by supplying economic justification for liquidity studies through the use of theoretically derived liquidity measures. A more recent attempt to measure bid-ask spread at low frequency comes from Corwin and Schultz (2012). They propose the use of daily high and low prices to measure bid-ask spread. They suggest that their measure outperforms the other low frequency bid-ask spread measures in tracking the intraday bid-ask spread.

Studies have found that liquidity is a pricing factor since investors value liquid stocks higher than the illiquid ones (Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Eleswarapu (1997), Chalmers and Kadlec (1998), Amihud (2002)). An early study that attempts to investigate how liquidity affects asset pricing was conducted by Amihud and Mendelson (1986). They use bid-ask spread as a measure of liquidity and propose that the clientele effect leads to the existence of the negative relationship between liquidity and return. The clientele effect suggests that investors in general would prefer liquid assets despite their investment horizon. However, investors who have a long investment horizon can be induced to hold illiquid assets in their portfolios if they receive liquidity premium for holding illiquid assets. Moreover, there are studies that support the notion that liquidity significantly influences asset returns (and Brennan and Subrahmanyam (1996), Eleswarapu (1997), Chalmers and Kadlec (1998), Amihud (2002)) and there are studies that go against the notion (Eleswarapu and Reinganum (1993) and Easley and O'Hara (2003)).

One of the critiques in Easley and O'Hara (2003) is whether the negative relationship between liquidity and return only holds for bid-ask spread. Thus, this negative relationship between liquidity and return might not hold for other liquidity measures. However, Korajczyk and Sadka (2008) and Amihud (2002) find the liquidity and return relationship holds for other different measures of liquidity. To consolidate the different use of liquidity measures when investigating the liquidity and return relationship, Korajczyk and Sadka (2008) develop a latent liquidity variable that represents eight different measures of liquidity and find that this latent variable is a pricing factor. Their finding suggests that the liquidity and return relationship holds regardless of the liquidity measures.

2.2.2. Commonality in liquidity

Commonality in liquidity refers to the proposition that liquidity across stocks moves systematically. Research on commonality in liquidity was motivated by the lack of study that investigates the interactions of market microstructure variables across stocks. Most of the intra-day studies focussed on idiosyncratic liquidity and documented the intra-day seasonality in trading volume and spread (Admati and Pfleiderer (1988), Jones, Kaul and Lipson (1994), Ahn and Cheung (1999), and Husodo and Henker (2009), among others). More recent studies in the market microstructure field investigate the properties of cross-stock interactions and find a strong evidence of commonality in liquidity (Chordia, et al. (2000) and Huberman and Halka (2001)), but Hasbrouck and Seppi (2001) document a relatively weak evidence of commonality in liquidity in their study due to differences in their sample and methodology. Chordia, et al. (2000) implement the market model regressions framework into the liquidity context to examine the existence of commonality in liquidity in the NYSE, while Huberman and Halka (2001) find commonality evidence in the NYSE through the correlated innovation of liquidity. Hasbrouck and Seppi (2001), who examine commonality using principal component analysis and canonical correlation, find less convincing evidence of commonality in the thirty Dow stocks on the NYSE. They find that commonality in liquidity diminishes when the time-of-day effect is removed.

Chordia, et al. (2000) and Huberman and Halka (2001) suggest that there are several reasons to justify the existence of commonality in liquidity in the stock markets. Firstly, commonality in liquidity arises because dealers (whose role is to provide liquidity in the market) trade to achieve their optimal inventory in response to trading volume dynamics. Secondly, similarities in trading strategies among institutional investors (for example, indexation, hedging strategy) would lead these institutional investors to trade similar stocks and these trades result in the existence of commonality in liquidity. In addition, it has been observed that the magnitude of commonality in liquidity is greater during crises periods than during normal periods (Chordia, et al. (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001)). The existence of commonality in liquidity brings different implications for regulators and investors. Chordia, et al. (2000) and Huberman and Halka (2001) suggest that several puzzling crises were marked by a significant decrease in systematic liquidity and commonality in liquidity could serve as an early warning indicator for regulators. Additionally, given the existence of systematic liquidity, a diversified portfolio in the context of market return (i.e. systematic risk) would not necessarily be a diversified portfolio in the context of systematic liquidity (Domowitz, Hansch and Wang (2005) and Lee (2011)).

Several studies attempt to examine the existence of commonality in liquidity in order-driven markets because initial studies on commonality in liquidity were conducted in a quote-driven market. These studies mainly investigate whether commonality in liquidity is a common phenomenon or a property of a quote-driven market structure. The main difference between a quote-driven and order-driven market structure is the presence of designated market makers in the quote-driven markets. Designated market makers exist in a quote-driven market structure and they play a central role in providing liquidity to investors as they are obliged to supply liquidity. On the other hand, an order-driven market structure does not have designated market makers and liquidity in this market structure is provided by limit orders that are submitted into the trading platform of the exchange.

Brockman and Chung (2002) extend the research on commonality in liquidity to an order-driven market and suggest that commonality in liquidity in the order-driven markets could be more pronounced or less pronounced than the commonality in liquidity in the quote-driven markets. They suggest that commonality in liquidity in the order-driven markets could be more pervasive because liquidity providers have no obligation to supply liquidity. Thus, they have a free-exit situation that allows them to withdraw liquidity from the market during liquidity shocks. On the other hand, commonality in liquidity could be less pronounced as liquidity providers in the order-driven market also face a free-entry situation where higher liquidity needs can be distributed across independent liquidity providers. Brockman and Chung (2002) find that the magnitude of commonality in liquidity in the Stock Exchange of Hong Kong (SEHK) is less than the one reported in NYSE by Chordia, et al. (2000) and they suggest that the free-entry hypothesis could explain the lower magnitude of commonality in liquidity in the order-driven markets.

Another attempt to investigate commonality in liquidity in an order-driven market was conducted by Fabre and Frino (2004). They investigate commonality in liquidity in the Australian Stock Exchange (ASX) and find weaker evidence of commonality in liquidity compared to that documented by Chordia, et al. (2000). The findings of Brockman and Chung (2002) and Fabre and Frino (2004) suggest that information asymmetry across industry and markets lead to commonality in liquidity. A more recent attempt to examine the impact of different market structures towards commonality in liquidity comes from Galariotis and Giouvris (2007). They investigated commonality in the London Stock Exchange when the market experienced changes in its trading regime.

Using FTSE 100 stocks as their sample, Galariotis and Giouvris (2007) found that commonality in liquidity exists across different trading regimes.

Another extension of research on commonality in liquidity is one which investigates commonality in liquidity beyond the best bid-ask quotes. The use of liquidity measures that go beyond the best quotes is an attempt to accommodate large trades that are conducted by institutional investors (Aitken and Comerton-Forde (2003), Kempf and Mayston (2008), and Pukthuanthong-Le and Visaltanachoti (2009)). Kempf and Mayston (2008) investigate commonality in liquidity beyond the best bid-ask spread in the Frankfurt Stock Exchange and find that the degree of commonality in liquidity is stronger when it includes the second and third best quotes. However, Pukthuanthong-Le and Visaltanachoti (2009) provide less convincing evidence on the stronger commonality in liquidity beyond the best quotes in the Stock Exchange of Thailand (SET).

Furthermore, Chordia, et al. (2000) document that commonality in liquidity is stronger across large capitalisation stocks. They argue that the positive relationship between commonality in liquidity and size is due to institutional investors exhibiting stronger herding behaviour when they trade large stocks and less when they trade small stocks. Thus, as dealers systematically adjust their spread for large stocks to anticipate the trading volume of institutional herding, commonality in liquidity is stronger for large capitalisation stocks than for small stocks.

However, research that investigates commonality in liquidity in other markets fails to find a similar positive relationship between commonality in spread and size. Instead, these studies find a negative relationship between commonality in liquidity and size (Brockman and Chung (2002), Fabre and Frino (2004), Pukthuanthong-Le and Visaltanachoti (2009)). This negative relationship is not due to differences in market structure but rather to different market conditions. Cao and Wei (2010) document a negative relationship between commonality in liquidity and size in a quote-driven market. They report that the positive relationship between commonality in liquidity and size is subject to the changes in market dynamics. More specifically, they find that the positive relationship between commonality in spread and size is supported during the first four years of their sample. However, this positive relationship between commonality and size turns into a negative one during the last four years of their sample.

Despite the ample evidence of commonality in liquidity across different market structures, commonality in liquidity still lacks theoretical supports. Hence, little is known about the source of commonality in liquidity. In their attempt to identify the source of commonality in liquidity, Chordia, et al. (2000) find that commonality in liquidity is driven by dealers' actions to minimise their inventory risk rather than market-wide or industry-wide information asymmetry. This conclusion by Chordia, et al. (2000) is supported by Coughenour and Saad (2004) as they find that commonality is induced by the similarities of the environment where dealers operate. Coughenour and Saad (2004) suggest that when dealers perform their roles as liquidity providers, they are exposed to capital constraints and the risk of providing liquidity (i.e. holding non-optimal inventory). In addition, these exposures are assumed to be not diverse across dealers since dealers share similar pools of funds and information that would affect their optimal inventory and profit. Hence, dealers' responses to the changes in their capital constraints and/or risk to provide liquidity would induce commonality in liquidity.

Furthermore, Coughenour and Saad (2004) propose a general framework to determine the two factors that induce commonality in liquidity. First, they suggest that supply factors could induce commonality in liquidity through the changes in systematic costs to provide liquidity. Second, demand perspective could induce commonality in liquidity through the movements in the systematic desire to transact. Coughenour and Saad (2004) suggest that these two perspectives are highly likely to be affected by the same factors (for example, changes in interest rate). Hence, even though each perspective offers different explanations for the source of commonality, the task to decompose which factor is actually at work would be a challenging one.

Several studies also attempt to investigate the source of commonality in liquidity in the order-driven markets. Brockman and Chung (2002) find that commonality in the SEHK can be explained by the trading pattern of informed traders across the market. A more recent attempt to decompose commonality in liquidity in the order-driven markets comes from Domowitz, et al. (2005). They find that co-movements in order types (market orders or limit orders) induce commonality in liquidity because limit (market) order supplies (consumes) liquidity. Thus, order type co-movements would induce commonality in liquidity.

The existence of commonality in liquidity raises the additional question of whether the sensitivity of a stock's liquidity towards the market liquidity would influence how the stock is priced. The existence of commonality in liquidity raises two questions, namely whether the sensitivity of a stock's liquidity towards the market liquidity is priced and whether the dynamic of market liquidity is priced. Brennan and Subrahmanyam (1996) and Sadka (2006) investigate the properties of market liquidity. These studies implement the Glosten and Harris (1988) methodology to decompose the fixed and the variable components of liquidity given the adverse selection problem that the market makers have to deal with when they trade with informed traders. Brennan and Subrahmanyam (1996) use the illiquidity measure proposed by Amihud (2002) to proxy for liquidity and find that the fixed component of systematic liquidity is priced but fail to find sufficient evidence to support the existence of seasonality in the fixed component of systematic liquidity.

Furthermore, using a longer and more recent sample than Brennan and Subrahmanyam (1996), Sadka (2006) finds that the variable component of liquidity is priced. In other words, Sadka (2006) finds that the unexpected systematic liquidity is priced rather than the fixed systematic liquidity. Interestingly, Acharya and Pedersen (2005) provide a unifying model to resemble the different findings in Brennan and Subrahmanyam (1996) and Sadka (2006). Acharya and Pedersen (2005) suggest that liquidity influences returns through the changes in the liquidity of the assets, the liquidity risk of the assets and the market risk of the assets. Moreover, similar to Sadka (2006), Acharya and Pedersen (2005) find that the innovation of market liquidity is priced.

An attempt to investigate the second question, whether the dynamics of commonality in liquidity is priced, comes from Pastor and Stambaugh (2003). They examine the relationship between the sensitivity of a stock's liquidity towards the market liquidity (liquidity beta) and its expected return. They specify market liquidity as a state variable and find that stocks with a high liquidity beta (i.e. more sensitive to the changes of market liquidity) have a higher expected return. Pastor and Stambaugh (2003) suggest that investors demand a higher expected return for investing in stocks with a high liquidity beta since these investors will be exposed to a higher liquidity risk when they want to liquidate their position and this liquidation would be likely to happen when the market is illiquid.

Watanabe and Watanabe (2008) extend the work of Pastor and Stambaugh (2003) by allowing the liquidity beta and the liquidity risk premium to be time-varying. Watanabe and Watanabe (2008) suggest that investors experience changes in their level of preference towards uncertainty and these changes would create a time-varying liquidity beta and liquidity risk premium. They find that the cross-sectional dynamic of the liquidity beta exists and the illiquid stocks are more sensitive to the changes of preference towards uncertainty than the liquid ones. In addition, they find that the liquidity premium varies with time and is priced.

The conclusion that commonality in liquidity is a pricing factor is not without critique. Asparouhova, Bessembinder and Kalcheva (2010) suggest that microstructure bias leads both to an overestimated liquidity premium and to the premium for commonality in liquidity being insignificant. However, Han and Lesmond (2011) take into account the microstructure bias suggested in Asparouhova, et al. (2010) and find that idiosyncratic volatility is priced. Han and Lesmond (2011) suggest that idiosyncratic volatility is priced through commonality in liquidity, as idiosyncratic volatility is co-integrated with commonality in liquidity. Thus, commonality in liquidity is still a significant pricing factor. In addition, Lee (2011) applies the liquidity pricing framework in Acharya and

Pedersen (2005) and finds that commonality in liquidity is a significant pricing factor in international markets.

2.2.3. The impact of foreign trades on the liquidity and commonality in liquidity of domestic markets

There are only a few studies that investigate the impact of domestic and foreign interaction on the liquidity of emerging markets. Interestingly, these studies use low frequency data mainly because of the lack of access to transaction data in emerging markets. Lesmond (2005) uses quarterly liquidity measures to investigate which liquidity measures perform best in emerging markets and the cross sectional determinants of liquidity in emerging markets. Lesmond (2005) underlines the importance of liquidity for foreign investors because the high returns of emerging markets come with high liquidity risks. One of the key findings of Lesmond (2005) is that political risk seems to be a key driver of liquidity risks in emerging markets. Examining the pricing of liquidity in emerging markets, Bekaert, et al. (2007) find that foreign investors value the ability to exit a market during liquidity shocks. In other words, commonality in liquidity is an important pricing factor in emerging markets.

An attempt to investigate how foreign trades affect the liquidity of emerging markets comes from the work of Rhee and Wang (2009). Using foreign ownership as a direct measure of foreign investors' presence, they find that liquidity in general improves as foreign investors increase their participation. However, they also find that foreign investors take away liquidity through the following plausible mechanisms. First, foreign ownership enhances information asymmetry in a market. Second, foreign investors have a tendency to trade in large quantities. Thus, these trades induce volatility in the market and create higher inventory risks for liquidity suppliers. Third, as foreign investors trade in large quantities, they could be dominant traders who decrease the competition of liquidity supply. Finally, foreign investors could be implementing a buy and hold strategy. Hence, the stocks that have high foreign ownership will be less traded and less liquid.

Research by Karolyi, et al. (2012) is the only study that investigates the role of foreign investors on the commonality in liquidity of various markets. While they have excellent coverage of markets, their data consists of daily observation of liquidity that is aggregated into monthly measures of commonality in liquidity. Karolyi, et al. (2012) offer a comprehensive examination of the determinants of commonality in liquidity across various markets. Their findings suggest that institutional investors have a significant role in inducing commonality in liquidity. They suggest two lines of explanation for this finding. First, institutional investors induce commonality in liquidity because they have relatively similar trading patterns (Chordia, et al. (2000), Kamara, Lou and Sadka (2008), Koch, Ruenzi and Starks (2011), Karolyi, et al. (2012)). Second, institutional investors are more likely to invest in a basket of securities rather than an individual security (Gorton and Pennacchi (1993)).They also document relatively weak evidence suggesting foreign investors' trades induce commonality in liquidity. Based on their findings, Karolyi, et al. (2012) conclude that demand factors are more consistent in explaining commonality in liquidity across different markets.

CHAPTER 3: PRIMARY RESEARCH QUESTION

The previous chapter discussed the literature that is directly related to this thesis. As was shown, the literature has been silent on how foreign trades affect the commonality in liquidity of a domestic market at the transaction level. Thus, this thesis asks the question:

How do foreign trades affect the commonality in liquidity of a domestic market at the transaction level?

The answer to this question will facilitate the debate on whether the presence of foreign investors is beneficial or not to domestic financial markets. In particular, there are four primary ways in which the answer to this research question can contribute to the debate.

First, it will be beneficial for market regulators as they can decide whether there is a need to monitor foreign transactions and/or to impose capital restrictions on foreign investment. Several studies have documented that crisis periods are associated with the disappearance of liquidity in financial markets (Hameed, Kang and Viswanathan (2010), Karolyi, et al. (2012), among others). In addition, foreign investors are suspected of worsening the impact of a crisis in domestic markets. Thus, if foreign trades enhance commonality in liquidity in domestic markets, these trades potentially contribute to the liquidity dry-up and market regulators might want to impose a monitoring and/or controlling mechanism over these trades.

Second, the investigation of how foreign trades affect the commonality in liquidity of domestic markets at a transaction level would interest foreign investors because they value the ability to enter and exit a market quickly and cheaply. The closest attempt to examine how foreign trades affect commonality in liquidity comes from Karolyi, et al. (2012). They find relatively weak evidence that foreign investors enhance the commonality in liquidity of domestic markets. Their investigation was conducted using monthly data and hence there could be some dynamics that could not be captured in that time interval. Rhee and Wang (2009) suggest that the interaction between domestic and foreign investors would materialise in a longer term rather than at the transaction level. However, liquidity issues are closely related to the ability to enter and leave a market. Thus, capturing how foreign trades affect commonality in liquidity at the transaction level would be beneficial to this group of investors.

Third, as the data set allows a precise identification of domestic and foreign initiated trades, I will further examine how foreign trades affect commonality in liquidity of domestic markets. I will examine how domestic and foreign initiated trades affect commonality in liquidity in four ways. First, I will examine whether domestic and foreign initiated trades affect commonality in liquidity differently. Domestic and foreign initiated trades can be seen as a proxy of the desire to trade of these investor groups. Current literature shows that investors' desire to trade is one of the demand factors that could explain commonality in liquidity (Coughenour and Saad (2004), Kamara, et al. (2008), Koch, et al. (2011), Karolyi, et al. (2012)). Second, I aim to investigate whether market-sidedness (Sarkar and Schwartz (2009)) affects commonality in liquidity. This analysis will provide initial evidence on whether market-sidedness affects commonality in liquidity and whether investors' origin matters in the way market-sidedness leads to commonality in liquidity. Third, I will examine whether correlated trading across domestic and foreign investors affects commonality in liquidity differently. The findings would complement earlier studies that document the correlated trading and commonality in liquidity relationship at quarterly intervals (Koch, et al. (2011)) and at monthly intervals (Karolyi, et al. (2012)). This examination is expected to capture shorter term dynamics by examining the impact of correlated trading on commonality in liquidity at a daily interval. Lastly, I will examine whether the net flows (buys minus sells) of domestic and foreign investors affect commonality in liquidity. Foreign net flows can affect commonality in liquidity because these flows create price pressure (Richards (2005)) and contain information asymmetry (Froot and Ramadorai (2001)). The examination of whether foreign net flows affect commonality in liquidity would provide corroborative evidence on the source of commonality in liquidity in domestic markets (i.e. inventory maintenance or information asymmetry hypothesis). In addition, the examination of how net flows affect commonality in liquidity would also complement the weak and positive relationship between foreign net flows and commonality in liquidity that is found in Karolyi, et al. (2012) at a monthly interval.

Finally, several studies have documented that institutional investors have a significant role in inducing commonality in liquidity (Coughenour and Saad (2004), Kamara, et al. (2008), Koch, et al. (2011), and Karolyi, et al. (2012)). Previous studies which investigate the interaction between domestic and foreign investors suggest that most foreign investors that invest in international markets are institutional. The data set of this thesis is capable of capturing the interaction between domestic institutional investors and foreign institutional investors. Thus, by investigating how foreign trades affect commonality in liquidity I can investigate whether the impact of foreign trades on commonality in liquidity is because they are institutional or because they are foreign. Furthermore, the ability to capture the impact of institutional investors' interaction on commonality in liquidity implies that the results of this thesis could be extended to different markets where institutional investors are dominant.

CHAPTER 4: DATA AND METHODOLOGY

This chapter presents the data and methodology of this thesis. The data section starts with the background and features of the Indonesian Stock Exchange, (IDX), where the data comes from. Next, the data description section describes the variables used in this thesis along with explanations on the construction of these variables. Subsequently, a summary statistics section will present the descriptive statistics of the variables as well as some relevant market indicators. This chapter ends with the methodology section, which will describe the econometrics model used to test the research question.

4.1. IDX BACKGROUND

The IDX was established on December 14, 1912 during the Dutch colonial era. After periods of intermittent trading, the IDX was revitalised in the 1980s by the establishment of the Surabaya Stock Exchange (SSX) and the Jakarta Stock Exchange (JSX), which went private in 1992. These two exchanges operated as Self Regulatory Institutions and managed the trading platform of stocks (JSX) and of bonds and derivatives (SSX). The two exchanges were consolidated into the IDX in 2007. Similar to the JSX, the IDX is an order-driven market that continuously matches limit orders based on price and time precedence. The limit orders can be of one session duration or of one day duration and they are matched by the JATS Next-G (Jakarta Automated Trading System Next Generation). This trading platform accommodates the trading of different securities (e.g. bonds, stocks and derivatives) and is able to process a larger number of quotes and transactions per day than the JATS (Jakarta Automated Trading System), which the JSX had used for stock trading from 1995 to 2007. The IDX has three market segments for stock trading: namely, the regular, cash and negotiation market.

The regular and cash market are continuous limit-order markets where, during the sample period, buyers and sellers have to trade in a rounded lot (one lot consists of 500 stocks) while the negotiated market operates on the basis of agreement between buyer and seller. Investors who want to trade in the negotiated market would have to find their trade counterpart either through direct communication or through advertisement of their offer on the trading board. Once agreement has been reached, or in the case of an advertised offer, a counterpart order has been posted, investors would have to report the trade to the exchange. Trading in the regular market takes place in both trading sessions while trading in the cash and negotiated markets only takes place in the first session (explanations on trading sessions in the IDX can be found in the subsequent paragraph). The regular market requires trades to be settled in three days while the cash market requires trades to be settled on the same day. Same day settlement in the cash markets is usually needed by investors who are short in securities for the settlement of their trade in the regular market. Trade settlement of a negotiated trade would be dependent on the agreement between the buyer and seller. The regular market makes up most of the total trade value throughout the sample of this study; this is also documented by Chang, Hanafi and Rhee (2000) and Dvorak (2005).

Trading in the IDX consists of two sessions: from Monday to Thursday, the first trading session starts from 09:30 to 12:00 and the second session starts from 13:30 to 16:00. Trading on Fridays starts from 09:30 to 11:30 (first session) and from 14:00 to 16:00 (second session). A pre-opening session was introduced in 2004 to form opening prices on the regular market. The pre-opening session starts at 09:10 and ends before the first trading session starts. When the pre-opening session starts, brokers enter their orders and then the JATS Next-G system formulates the opening price based on the matched bids and asks. If the pre-opening session fails to generate an opening price, the price from the previous trading session is used. There are four tick sizes on the IDX that correspond to the price range of the stocks. The price range is less than IDR200; between IDR200 and IDR500; between IDR500 and IDR2,500; between IDR2,500 and IDR5,000; and greater than IDR5,000. The corresponding tick sizes are IDR 1, 5, 10, 25 and 50, respectively.

During normal trading time, the IDX implements an auto rejection system where orders are automatically rejected if their price is beyond an acceptable price range. This acceptable range varies across price levels and is based on a reference price that comes from either the pre-opening session or the previous trading day. The acceptable price range during normal trading times is as follows: (1) 35% above or below the reference price for stocks that are priced from IDR50 to IDR200, (2) 25% above or below the reference price for stocks that are priced from IDR200 to IDR5,000, and (3) 20% above or below the reference price for stocks that are priced greater than IDR5,000. The impact of the GFC on the IDX was at its worst during the last quarter of 2008. The market regulator had to suspend three trading days (8-10 October 2008), implement a stricter auto rejection system and fully restrict short selling. After lifting the trade suspension, the IDX implemented stricter auto rejection from 12 October 2008, where the acceptable price range was set at 10% above or below the reference price for all stocks. On 30 October 2008, the IDX relaxed the auto rejection system by applying an asymmetrical auto rejection range where the acceptable price range was 20% above and

10% below the reference price for all stocks. The auto rejection system went back to normal (as above) on 19 January 2009.

Restrictions on foreign investors' ownership in the IDX have been relaxed over time. Prior to 1997, foreign ownership was limited to 49% of the total listed stocks. During this period, foreign investors could trade in the regular and/or in the foreign board as part of the negotiated market. Foreign investors could trade a stock in the regular market as long as foreign ownership of that particular stock was less than 49%. Once foreign investors' ownership in a stock exceeded the 49% ceiling, foreign investors could only trade this stock among themselves on the foreign board. The Minister of Finance of the Indonesian Republic then started to lift the restriction of foreign ownership in 1997 but still imposed foreign ownership restrictions for listed banks, where foreign ownership could not exceed 49% of the banks' paid-in capital. However, the restriction of foreign ownership in listed banks was significantly relaxed in 1999, when banks were allowed to list up to 99% of their total stocks and foreign investors were allowed to hold up to 100% of the listed stocks. Trading in the foreign board was trivial after 1997, as limits of foreign ownership began to be lifted. In addition, the foreign board no longer existed throughout the sample of this study but foreign investors could still trade in the negotiated market.

Foreign investors' trade is perceived to influence prices in emerging markets as their trade can be more informed (Grinblatt and Keloharju (2000), Froot and Ramadorai (2001)) or their trade creates price pressure (Richards (2005)). The unique feature of the IDX's trading platform is that investors can observe investor types (domestic or foreign) along with a broker's identity in every order that is submitted to the trading platform.

Thus, foreign investors' orders can be observed by market participants, thereby making daily interaction between domestic and foreign investors possible. In addition, order data that comes from the IDX not only contains investor identity but also contains unique quote identification. This quote identification also appears in trade data. Hence, trade direction from domestic and foreign investors can be observed without any risk of misclassification.

4.2. DESCRIPTION OF DATA

The transaction data comes from two sources and starts from January 2, 2008 until January 3, 2011. The first source of transaction data is the IDX. Order and trade data that comes from the IDX allows the observation of a broker's identity, trade direction and whether the trade is initiated by domestic or foreign investors. Order data that comes from the IDX contains a unique identification number, which is also reported for each trade. Hence, trade directions and trade initiators (domestic or foreign) can be extracted directly from the data. This data set has been explored in Agarwal, et al. (2009) when they investigated the underperformance of foreign investors in the JSX from May 1995 until 2003.

The second source of transaction data comes from the Thomson Reuter Tick History (TRTH) database that is available through the Securities Industry Research Centre of Asia Pacific (SIRCA). This database reports trade and orders that are entered into the trading platform stamped to the nearest 100th of the second. Even though the transaction data from the IDX contains greater details of information, the time stamp of orders data from the IDX is inconsistent because the exchange changed the way it recorded the time stamp of orders when they implemented the new trading system on

March 2, 2009. Under the new trading system, the time stamp of orders are updated with the trades' time stamp when these orders are executed. On the other hand, transaction data from TRTH reports consistent time stamps. Therefore, to ensure the reliability of the prevailing bid-ask prices and quantities, the liquidity measures will be calculated using the transaction data that comes from TRTH.

I also collect stock ownership data from Kustodian Sentral Efek Indonesia (KSEI) which provides the custodial service for the IDX. The data set contains end-of-month foreign and domestic ownership based on the total number of shares and total number of tradable shares. This thesis uses stock ownership based on the number of tradeable shares similar to Rhee and Wang (2009) when they investigated the role of foreign investors on the liquidity of the IDX.

There were 440 stocks listed in the IDX at the end of 2011. However, not all listed stocks will be included in the analysis as not all stocks on the IDX are frequently traded. The infrequently traded stocks would yield unreliable liquidity measures and hence will be excluded from the final sample (Chordia, et al. (2000)). I include stocks that have at least five orders from domestic and foreign investors on any day of the sample period. This data filter excludes the less frequently traded stocks as well as capturing the dynamics of foreign investors' trades in the IDX. A similar data filter has been applied in the IDX data by Agarwal, et al. (2009). Of the 440 stocks that are listed on the IDX in 2011, 101 are included in the final sample. The selected stocks account for more than 86% of the total market capitalisation of the IDX. Moreover, foreign ownership based on tradeable stocks of the selected stocks ranges from 10% to 78%.

Similar to Chordia, et al. (2000), liquidity measures are calculated at each trade, throughout normal trading time and then averaged at daily intervals. This daily aggregation ensures that the liquidity measures are not affected by intraday seasonality. There are two liquidity measures calculated for each trade, relative spread and depth in the number of shares. Relative spread is calculated as the bid-ask spread standardised by the mid-point price and depth is the average quantity available for the best bid and ask order. These liquidity measures are chosen to reflect the tightness and depth dimension of liquidity (Kyle (1985)) and to maintain comparability with previous research on commonality in liquidity. Liquidity measures that reflect tightness and depth have been consistently used when researchers investigate commonality in liquidity. The liquidity measures are winsorised at 98% percentile before they are aggregated at daily intervals to ensure the analysis results are not driven by outliers. However, using raw data would qualitatively give similar results to those reported in this thesis.

The examination of how foreign trades affect the commonality in liquidity of the domestic market will be conducted through four variables. First, I will examine whether the dollar volume of initiated trade by domestic and foreign investors could explain commonality in liquidity. The dollar volume of initiated trades will be measured using the daily aggregate volume of initiated trades that come from domestic and foreign investors. The dollar volume of domestic and foreign investors would capture similarities or differences of trading patterns across these two groups of investors. This examination would extend the literature that has documented the significant roles of institutional investors in inducing commonality in liquidity (Chordia, et al. (2000), Coughenour and Saad (2004), Kamara, et al. (2008), Koch, et al. (2011)) and would complement the findings of Karolyi, et al. (2012) on the roles of domestic institutional investors in inducing commonality in liquidity.

Second, I will examine whether the motives behind initiated trades coming from domestic and foreign investors would have a different impact on commonality in liquidity. Sarkar and Schwartz (2009) propose a measure of market sidedness to disentangle the determinants of trade initiations. They suggest that initiated trades could be motivated by information asymmetry, different beliefs or liquidity needs. They suggest that initiated trades that are motivated by information asymmetry would lead to one-sided initiated trades (buys or sells), while initiated trades that are motivated either by different beliefs or liquidity needs would lead to two-sided initiated trades (buys and sells). Market sidedness is estimated from the correlation between Z_{BUY} and Z_{SELL}, which will be calculated as follows:

$$Z_{BUY} = \frac{BUY - Mean(BUY)}{SD(BUY)} \tag{1}$$

$$Z_{SELL} = \frac{SELL - Mean(SELL)}{SD(SELL)} \tag{2}$$

where *BUY* (*SELL*) is the number of buyer (seller) initiated trades in a day. *Mean* and *SD* are the daily mean and daily standard deviation of *BUY* and *SELL*. If the correlation between Z_{BUY} and Z_{SELL} is high (low), then one can infer that the market is two- (one-) sided. Furthermore, to determine whether sidedness of domestic and foreign investors induces commonality, sidedness for domestic and foreign investors will be estimated. This examination will provide empirical support for the prediction of Chordia, et al. (2000) on the role of information asymmetry on commonality in liquidity.

Third, I will examine whether correlated trading coming from different investor types has a different impact on commonality in liquidity. Correlated trading is measured using the price synchronicity measure that is proposed by Morck, et al. (2000). They propose two ways to measure the systematic component of stock returns; firstly, through the estimated R^2 of a market model regression and secondly, through the price synchronicity measure. The price synchronicity measure is an estimate of the proportion of stock prices that move in the same direction in a given time period.

Karolyi, et al. (2012) apply the market model regression and price synchronicity method to estimate correlated trading in their study. They suggest that the systematic component of monthly stock turnover is a manifestation of correlated trading. This study will follow a similar line of thinking to Karolyi, et al. (2012). I extract the systematic component of initiated trading volume as a proxy of correlated trading in the IDX. As the data frequency of this study is daily, the market model method is not applicable. I will apply the price synchronicity method to measure correlated trading in the IDX at daily intervals. The degree of correlated trading will be measured by the proportion of stocks that have a similar direction of dollar volume of initiated trading in one day. Correlated trading will be calculated as follows:

$$f_{j,t} = \frac{max[n_{j,t}^{UP}, n_{j,t}^{DOWN}]}{n_{j,t}^{UP} + n_{j,t}^{DOWN}}$$

(3)

where $f_{j,t}$ is the fraction of stocks that have a similar direction of dollar volume of initiated trades for a group of investors (*j*) on day *t*. $n_{j,t}^{UP}$ and $n_{j,t}^{DOWN}$ are the number of stocks on day *t* that experience an increase and decrease in the dollar volume of initiated trades of a group of investors (*j*). Correlated trading is stronger when the fraction of stocks that have a similar direction of dollar volume of initiated trades increases. As foreign investors tend to invest in liquid and large stocks (Kang and Stulz (1997) and Huang and Cheng-Yi (2009), among others), I also estimate the correlated trading measure for stocks that are included in the Liquid 45 index[2] (LQ45) and for large stocks for robustness.

The investigation of demand factors of commonality in liquidity suggests that institutional investors' trade induces commonality in liquidity because they have similar trading patterns (Chordia, et al. (2000), Coughenour and Saad (2004), Kamara, et al. (2008), Koch, et al. (2011)), because their trades are correlated (Koch, et al. (2011), Karolyi, et al. (2012)), and they are more informed (Chordia, et al. (2000)). A recent study by Karolyi, et al. (2012) examines the role of foreign investors in inducing commonality in liquidity in emerging markets. However, they did not examine the role of domestic institutional investors. Given that stock ownership in the IDX is dominated

[2] Liquid 45 index (LQ45) is an index that consists of the 45 best performing and most liquid stocks in the IDX. To be included in the index, a stock has to perform well in the previous 3 months and has to be listed for at least one year. The IDX decides the constituents of the LQ45 index in January and July of each year.

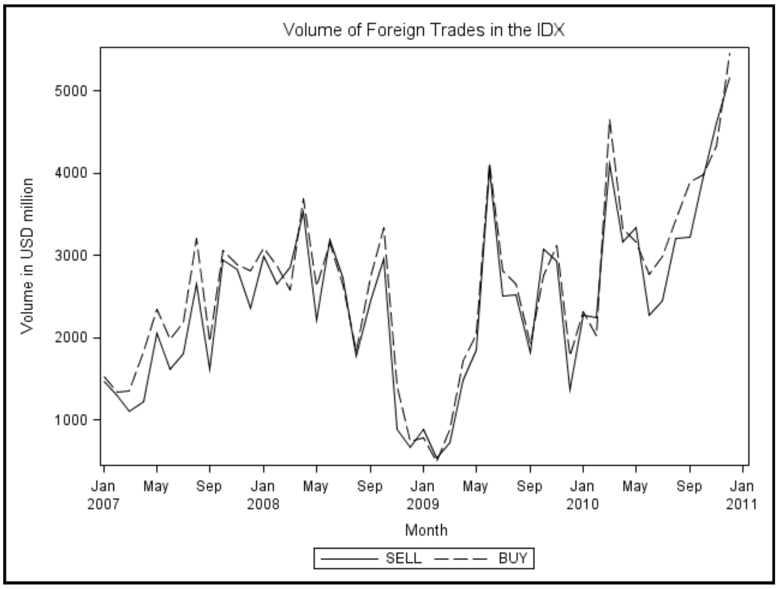
by institutional investors, both domestic and foreign, and the IDX does not limit stock ownership by foreign investors, I will examine whether the type of institutional investor (domestic or foreign) matters in the way that institutional investors induce commonality in liquidity.

Lastly, I will investigate the impact of domestic and foreign net flows on commonality in liquidity. Net flows are measured by taking the difference of the value of initiated buys and sells for domestic and foreign investors at daily intervals. The net flows data is then converted into US$ million.

4.3. SUMMARY STATISTICS

Before discussing the summary statistics of the variables that will be analysed in the data analysis, I present several preliminary statistics on foreign trades and ownership in the IDX. Figure 1 plots the volume of foreign trades in the IDX in million USD as well as the composite index performance of the market.

Figure 1: Foreign trades and the performance of composite index
The first graph plots the volume of foreign trades in the IDX in USD million against time. The conversion of IDR to USD was calculated using the average yearly middle rates as reported by Bank Indonesia (Indonesia's central bank). The second graph plots the level of the composite index of the IDX.



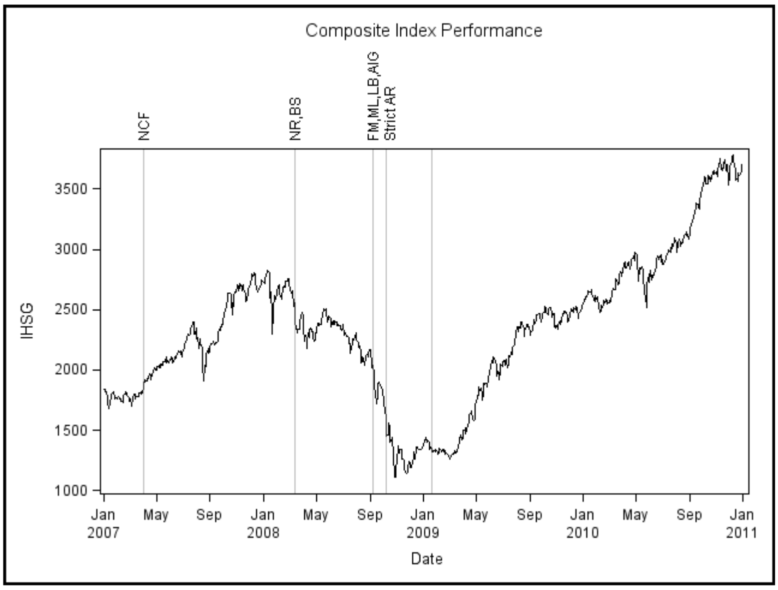


Figure 1 illustrates foreign investors' portfolio flows in the IDX along with the movements of the composite index of the IDX. Foreign buys and sells were at a minimum during the global financial crisis in November 2008. Although the bottom graph of Figure 1 shows a substantial decline in the index during the crisis, foreign trades were net buys and the IDX seemed to recover from the crisis relatively quicker compared to other equity markets. From early 2009 onwards, foreign trades picked up and continued to rise. At the end of 2010, foreign buys and sells were close to $5bn per month. Dominant foreign trades were from the US, Netherlands, France and Japan[3].

The crisis period in the IDX seemed to be from January 2008 to late October 2008. This crisis period was then followed by a quick recovery period that started in late 2008 and lasted until August 2011. The dating of the crisis period in the IDX seems to lag behind the crisis dating in the US and European markets, which started in early 2007. The crisis dating of this thesis is based on the performance of the IHSG (composite index of the IDX) during the series of events surrounding the GFC. The second graph of Figure 1 plots the level of IHSG from 2007 to August 2011 along with some reference to the key events of the global financial crisis in the US markets.

The US subprime mortgage crisis started to unfold in late 2007, but the composite index figure shows that the IDX performed fairly well in that year despite negative market sentiments in the US and European markets. In addition, the figure shows that the IDX performed very well when the New Financial Century Corp. (NCF), a financial institution that specialises in providing sub-prime loans, filed Chapter 11 bankruptcy. In fact, the IDX continued its good performance until the end of 2007.

The IDX started to react to the subprime mortgage crisis in early 2008. The market responded negatively following a series of government bailouts for major financial institutions that had been investing in subprime mortgage related securities. These

[3] Based on Bank Indonesia records – the central bank of Indonesia.

bailout episodes started with the nationalisation of Northern Rock by the British Government in February 2008 and the purchase of Bear Stern by J. P. Morgan in March 2008, a deal which was backed by the US Government. The IDX's composite index continued to plummet following another series of bailouts that happened in September 2008; the bailout of Fannie Mae and Freddie Mac by the US government, the purchase of Merrill Lynch by the Bank of America and the bailout of AIG by the US government. However, not all financial institutions were rescued by the US government. Lehman Brothers declared bankruptcy in mid September 2008 and this decision created a wave of nervousness across different markets around the globe. The panic wave led several major markets in the Asian region to stop their trading process as uncertainty in these markets was extreme.

The extreme uncertainty in the IDX led the market regulator to announce a trading halt from 8 to 10 October 2008. As mentioned earlier, the IDX implemented stricter auto rejection rules after it lifted the trade halt and these auto rejection rules were implemented until January 19, 2011. The lift of the strict auto rejection rule seems to mark the beginning of a recovery period for IDX that was followed by an episode of bullish price behaviour. Given the impact of GFC on the performance of the IDX, a crisis dummy will be included in the data analysis to ensure that the results are not driven by investors' behaviour during the crisis period. The crisis dummy will take the value of unity from October 12, 2008 to January 19, 2009, which represents the strict auto rejection period, and zero otherwise.

Figure 2 plots foreign ownership in the IDX during the sample period for the 30 smallest (size=1) and 30 largest (size=3) stocks. It is important to note that ownership in this graph is measured based on the number of tradeable stocks; thus, ownership greater than 51% is not necessarily translated into majority holding. While the 30 largest stocks would refer to the largest stocks in the exchange, the 30 smallest stocks are not necessarily the smallest stocks in the exchange, due to the sample selection criteria applied in this study. Furthermore, foreign holdings data used in Figure 2 excludes foreign ownership that is categorised as 'others' by KSEI due to being subsidiary holding companies and classified along with other entities owned by other foreign corporations.

Figure 2: Foreign ownership in the IDX
Figure 2 plots foreign ownership, based on tradeable stocks in the IDX, during crisis and post-crisis periods. Selected stocks with the smallest and largest market capitalisation are included in the group size=1 and size=3, respectively.

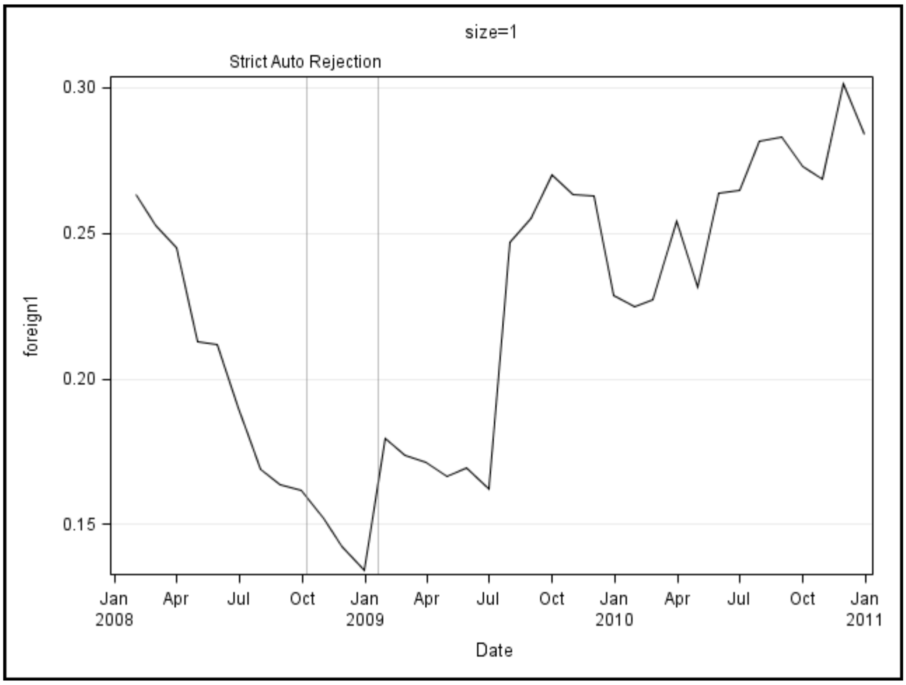
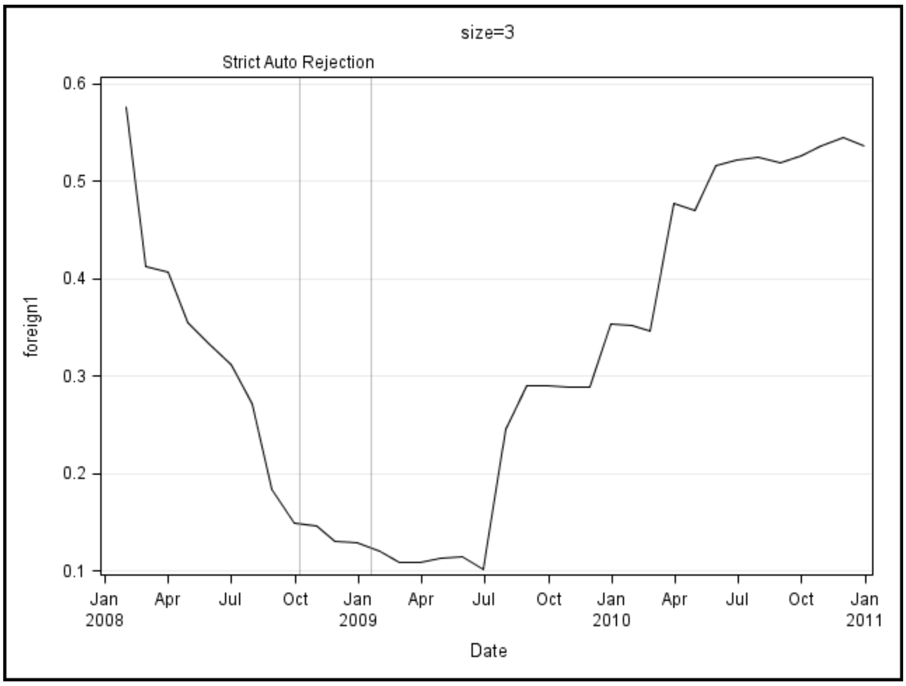


Figure 2 cont'd



In general, the graphs in Figure 2 suggest that foreign investors held more large stocks throughout the sample period. This is in line with the findings in Kang and Stulz (1997) and Huang and Cheng-Yi (2009). In addition, the graphs suggest that foreign investors started to liquidate their position from early 2008 until mid 2009 and they re-entered the market from mid 2009 onward. It is interesting to note that foreign ownership in large stocks declines at a greater rate than the rate of decline in the small stocks.

After presenting the dynamics of foreign trades and ownership, I will discuss the descriptive statistics of the variables that will be used in the data analysis. Table 2 presents the descriptive statistics of these variables.

Table 2: Descriptive statistics

The first panel of this table reports descriptive statistics for the whole market as well as the selected stocks. I calculate market liquidity by taking a simple average of daily liquidity of all stocks that are listed from 2008 to 2010. Relative spread and depth in number of shares are calculated at every trade and then averaged at daily intervals. Panel B reports stock ownership of domestic and foreign investors for tradeable stocks; volume of initiated trades (in US$) calculated on a daily basis; market sidedness (Sarkar and Schwartz (2009); and correlated trades estimated by the synchronicity measure proposed by Morck et al. (2000). To examine the aggressiveness of domestic and foreign investors, I also tabulate the proportion of the number of market to total number of executed orders, the time required for orders that do not initiate trades to be executed, and order execution rate. I follow the methodology in Agarwal et al. (2009) to calculate these aggressiveness metrics and I estimate these measures for all buy and sell orders.

Panel A. Market and sample descriptive statistics

Variable	Mean	Std Dev	Min	Max
Proportion of market capitalisation of the selected stocks	0.8643	0.0206	0.8432	0.8843
Market spread	0.0286	0.0377	0.0010	0.6917
Market depth (number of shares)	1.07E+06	4.47E+06	500	1.79E+08
Sample spread	0.0144	0.0136	0.0010	0.3333
Sample depth (number of shares)	1.92E+06	6.25E+06	750	1.79E+08
Price (IDR)	3,973.79	1,587.37	976.87	8,785.09
Price (US$)	0.3974	0.1587	0.0977	0.8785
Volume (number of shares)	60,404.39	26,928.1	23,689.41	337,821.85
Trade value (US$)	6,776	3,387	2,253	36,659

Panel B: Summary trading statistics by domestic and foreign investors

Variable	Domestic				Foreign			
	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
Stock ownership								
Total	0.4876	0.0245	0.4406	0.5295	0.5122	0.0245	0.4705	0.5594
Individual	0.1551	0.0245	0.1158	0.1850	0.0022	0.0005	0.0013	0.0032
Orders								
Bid price (IDR)	3,662	1,566	1,018	9,976	8,250	2,897	2,173	16,783
Ask price (IDR)	3,767	1,465	890	7,521	8,642	3,751	1,476	22,560
Bid size (# of shares)	88,457	39,046	33,385	444,176	177,552	120,799	18,954	812,254
Ask size (#of shares)	103,366	49,120	44,349	799,644	219,969	158,972	22,006	2,463,800
Bid frequency	41,709	15,308	119	122,134	3,772	3,377	12	30,605
Ask frequency	44,847	16,470	434	111,478	2,707	1,915	20	15,736
Initiated trades								
Frequency	26,695	10,823	8,549	79,193	3,058	2,558	348	21,531
Price (IDR)	3,423	1,406	940	8,370	8,261	2,844	2,229	16,738
Volume	45,295	18,743	16,437	152,535	63,277	39,432	8,943	282,322
Trade value (USD)	4,099	1,529	1,510	9,821	13,609	7,205	3,518	36,699

Table 2 cont'd

Variable	Domestic				Foreign			
	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
Volume of initiated trades (US$ thousands)								
	273	857	0	34,253	157	413	0	12,970
Market Sidedness	0.7209	0.1471	0.3464	0.9859	0.4056	0.1900	-0.1819	0.8968
Correlated trades	0.6119	0.0830	0.5000	0.9012	0.5872	0.0669	0.5000	0.8824
Net flows (US$ million)	7.7784	33.0374	-78.3752	108.8646	4.3558	24.1831	-72.0577	68.6151
Proportion of the number of market orders against the total number of executed orders								
All orders	0.4867	0.1157	0.0122	1.0000	0.5557	0.1977	0.0147	1.0000
Buy orders	0.4994	0.1863	0.0110	1.0000	0.5747	0.2219	0.0244	1.0000
Sell orders	0.4975	0.1799	0.0048	1.0000	0.5499	0.2214	0.0149	1.0000
Execution time for non-initiating trades (in minutes)								
All orders	63.62	57.02	0.00	389.95	40.36	55.85	0.00	389.98
Buy orders	58.87	58.43	0.00	389.87	39.15	55.74	0.00	389.93
Sell orders	52.19	61.47	0.00	389.95	36.69	57.77	0.00	389.98
Order execution rate								
All orders	0.6941	0.1625	0.0031	1.0000	0.8129	0.1698	0.0068	1.0000
Buy orders	0.7377	0.1534	0.0132	1.0000	0.8223	0.1736	0.0061	1.0000
Sell orders	0.6723	0.1766	0.0016	1.0000	0.8223	0.1794	0.0016	1.0000

Panel A of Table 1 reports that the selected sample in this thesis represents more than 86% of market capitalization in the IDX. Panel A also reports that the selected stocks are more liquid than whole market. The sample of stocks that is included in the data analysis exhibits tighter spreads (by 50%) and larger depth (by 80%) compared with the market. As mentioned earlier, tick size in the IDX is determined by five price intervals. As the price interval of a stock increases, so does its tick size. The descriptive statistics of stock price suggest that the tick size of the selected stocks ranges from IDR10 to IDR50, which suggests that the price level of the selected stocks belong to the three largest price intervals. Furthermore, sorting the descriptive statistics of stock prices with market capitalization, I find that there is a positive association of size and price intervals. The price of large stocks tends to be in the largest two price intervals and these stocks tend to have the largest tick size. The contrary happens for small stocks. The last two rows of Panel A provide information on the average daily volume of stocks as well as the average trade value in US$.

Panel B of Table 1 provides summary statistics of trades from domestic and foreign investors. Panel B suggests that the ownership of tradeable stocks in the sample is evenly divided between domestic (49%) and foreign investors (51%). Of those foreign holdings 24% are classified as institutional investors, although this number is likely to be much higher in realty as a remaining 27% of institutions are also categorized by KSEI as ‘others’ due to being subsidiary holding companies and classified along with other entities owned by other foreign corporations. The minimum and maximum ownership statistics also show that domestic and foreign ownership of tradeable stocks are evenly divided, although sometimes the market could be dominated by one type of investor. Similar to Rhee and Wang (2009), I find that ownership structure in the IDX is dominated by institutions. Individual investors account for less than 16% of ownership of tradeable stocks in the IDX.

Panel B also provides the descriptive statistics of orders and trades that come from domestic and foreign investors. On any given day, domestic investors dominate foreign investors in the frequency of orders submission. However, while foreign investors submit orders less frequently, they submit orders with higher quantity and value. A similar observation is obtained from the descriptive statistics of initiated trades:

domestic investors trade more frequently but the quantity and value of their trades is substantially smaller than the quantity and value of foreign trades. These findings suggest that foreign investors submit orders less often but with greater value, while domestic investors frequently submit orders but with smaller value. In addition, foreign trades concentrate on stocks with higher price levels, which indicate that foreign investors tend to invest in large stocks. This finding confirms the observation in Figure 2.

The next part of Panel B provides summary statistics of the explanatory variables that will be investigated later. While foreign investors dominate domestic investors in terms of average trade value, the daily volume of initiated trades (buy and sell initiated trades) from domestic investors is 73% more than the volume of foreign initiated trades. It seems that domestic investors initiate trade more often on both sides, compared to foreign investors on any given day. Thus, while the average value of initiated trades is higher for foreign investors, the average volume of initiated trades of domestic investors is not surprisingly, substantially higher than the volume of initiated trades from foreign investors.

Domestic investors tend to be two-sided while foreign trades tend to be one-sided. Foreign trades tend to be one-sided trades as they could be engaging in positive feedback trading as hypothesized by Froot and Ramadorai (2008). To further examine whether foreign investors pursue positive feedback trading, I examine the correlation of foreign net flows and market returns of the IDX as well as estimating a vector autoregressions model between foreign net flows and market returns. I find that foreign net flows and market returns are significantly and positively correlated and the estimated correlation coefficient is 0.56. Through the impulse response of the vector autoregressions[4], I find that foreign net flows and market returns respond significantly to each other's shocks. These findings indicate that foreign investors in the IDX engage in positive feedback trading and this behaviour could lead to one-sided trades.

The trades of domestic and foreign investors are correlated and there seems to be no difference in the degree of correlated trading of domestic and foreign investors. This finding is expected as the IDX is known to be dominated by institutional investors. The literature has documented that the trades of institutional investors tend to be correlated because they engage in equity basket trading (Gorton and Pennacchi (1993)) and this behaviour leads to the existence and dynamics of commonality in liquidity (Chordia, et al. (2000), Coughenour and Saad (2004), Kamara, et al. (2008), and Karolyi, et al. (2012)). The net flows of domestic and foreign investors seem to display a similar pattern of net flows as both investor groups are net buyers in the sample period. However, foreign net flows seem to have greater standard deviations from their mean compared to the standard deviations of domestic net flows. The greater standard deviations of foreign net flows could be the result of a substantial range between the minimum and maximum value of net flows.

Applying the order aggressiveness metrics of Agarwal et al. (2009) to foreign and domestic orders, I find that foreign investors are more aggressive than domestic investors. This finding is consistent with the findings of Agarwal et al. (2009) when they investigated foreign investors' underperformance in the IDX using an earlier sample period. The order aggressiveness measures in Panel B suggest that foreign

[4] Appendix 1 reports the full results of this analysis.

investors are more aggressive because they post more market orders (compared to their total orders) as well as posting aggressive limit orders that are executed faster. Investors that place market orders demand liquidity, which is fulfilled through limit orders posted by investors who provide the liquidity. As limit orders within the IDX are only good for the day, unless the order is cancelled or re-submitted at a better price, it will be the investors demanding liquidity who will push for faster execution, rather than the liquidity suppliers. I find that foreign investors are able to execute limit orders in two thirds of the time it takes for domestic investors (40.36 minutes compared with 63.62 minutes). Given the higher proportion of market orders by foreign investors and faster execution of limit orders, the completion rate for all foreign orders is higher than for domestic investors. This provides an indication that foreign investors are generally demanding liquidity, at least relative to the domestic investors

4.4. REGRESSIONS

To examine the impact that foreign and domestic investors have on commonality in liquidity, I start estimating the regression framework of Chordia, et al. (2000) as a benchmark against further analysis on commonality in liquidity. The regression model is as follows:

$$DLIQ_{i,t} = \propto_i + \beta_{1,i}DMLIQ_{i,t} + \beta_{2,i}DMLIQ_{i,t-1} + \beta_{3,i}DMLIQ_{i,t+1} + \beta_{4,i}MRET_t + \beta_{5,i}MRET_{t-1} + \beta_{6,i}MRET_{t+1} + \beta_{7,i}DVOLA_{i,t} + \beta_{8,i}CRISIS_t + \varepsilon_i \quad \textbf{(4)}$$

where the D that precedes all variables refers to the daily percentage change in the current day's measure from the previous trading day. $DLIQ_{i,t}$ is the daily percentage change in the liquidity variable of stock i at time t. There are two liquidity measures that will be used as the dependent variables, namely relative spread and depth in number of shares. The dependent variables are expressed in a percentage change format as the model aims to discover the co-movements of individual liquidity and the market liquidity. $DMLIQ_{i,t}$ is the daily percentage change in the concurrent market liquidity of stock i. $DMLIQ_{i,t-1}$ is the lag of concurrent market liquidity and $DMLIQ_{i,t+1}$ is the lead. $MRET_t$ is concurrent market returns, while $MRET_{t-1}$ and $MRET_{t+1}$ denote the lag and lead of market return, respectively. $DVOLA_{i,t}$ is the daily change of volatility of stock i at time t measured by squared return.

The market liquidity in equation 4 is an equally weighted index of individual liquidity. To avoid a misleading cross-section alignment of market liquidity to unity, stock i is excluded when calculating the market liquidity for that particular stock. This method yields slightly different market liquidity for each stock. Equation 4 includes the daily percentage change of lag and lead market liquidity to control the non-contemporaneous adjustment in liquidity that could arise from non-trading periods.

Following Chordia, et al. (2000), several control variables are included to anticipate the interaction of return and volatility with spread based liquidity measures. To control for the interaction between spread and market return, the concurrent, lead and lag of market returns are also included. Moreover, the contemporaneous change in the stock volatility, measured by squared returns, is also included to control for the impact of volatility on spread. These control variables ensure that the commonality findings are robust to market return and volatility dynamics. The time series regression is estimated for every liquidity measure and every stock.

I add a control variable to take into account the effects of the financial crisis by adding a dummy variable $CRISIS_t$. This dummy variable will take the value of 1 from October 12, 2008 to January 19, 2009, and zero otherwise. These dates represent a crisis period for the IDX as they coincide with the period when the market regulator implemented strict price rejection rules. During this period, investors were not allowed to submit orders with prices that were too far away from the prior market price of the stock. This regulation was implemented to limit volatility during the crisis period.

The examination of how domestic and foreign trades affect commonality in liquidity will be conducted by augmenting the regression framework of Chordia, et al. (2000) with the four variables mentioned earlier. To simplify notation, these variables will be represented as *EXPL* and the regression equation would take the following form:

$$\begin{aligned} DLIQ_{i,t} = \propto_i + \beta_{1,i} DMLIQ_{i,t} + \beta_{2,i} EXPL + \beta_{3,i}(EXPL \times DMLIQ_{i,t}) + \beta_{4,i} DMLIQ_{i,t-1} \\ + \beta_{5,i} DMLIQ_{i,t+1} + \beta_{6,i} MRET_t + \beta_{7,i} MRET_{t-1} + \beta_{8,i} MRET_{t+1} \\ + \beta_{9,i} DVOLA_{i,t} + \beta_{10,i} CRISIS_t + \varepsilon_i \end{aligned}$$

(5)

Because initiated trades are those that demand liquidity and may contain information, I augment Equation 4 with four explanatory variables (*EXPL*) that will capture different aspects of initiated trades across the market. These variables are as follows: (1) changes in the volume of initiated trades, (2) the level of market sidedness, (3) level of correlated trades, and (4) foreign net flows. These four measures are expressed through the explanatory variable, $EXPL$, in the model, as well as through its interaction with market liquidity $(EXPL \times DMLIQ_{i,t})$.

CHAPTER 5: EMPIRICAL RESULTS

5.1. REGRESSIONS RESULTS

Table 3 and 4 present the results of the regressions analysis for spread and depth, respectively. These tables report the averaged coefficient results from regressing equation (4) and (5) for each stock in the sample. Figures for market liquidity, $\hat{\beta}_1$, will be presented for both equations. Chordia, et al. (2000) suggests that commonality in liquidity is present when the cross-sectional average of $\hat{\beta}_1$ is significantly different from zero and the magnitude of commonality in liquidity would be reflected on the estimated cross-sectional average of $\hat{\beta}_1$. In addition, the cross-sectional average of the explanatory variable, $\hat{\beta}_2$, and the interaction term, $\hat{\beta}_3$, will be presented for equation (5). These results of estimating are tabulated along with their t-statistics. The tables also present the proportion of coefficients that are positive or negative, as well as the proportion that are significant in either direction under a 5% one-tail test. The standard error for each parameter is estimated using a Newey West correction (Newey and West (1987)). The parameter coefficients for the control variables are not presented in these tables, but are all significant with the expected signs[5].

[5] Appendix 2 presents the results of the control variables for Table 3 and 4.

Table 3: Commonality in spread

This table reports cross-section averages of the estimated parameters from the following regression that was run on each stock:

$$DLIQ_{i,t} = \propto_i + \beta_{1,i} DMLIQ_{i,t} + \beta_{2,i} EXPL + \beta_{3,i}\left(EXPL \times DMLIQ_{i,t}\right) + \beta_{4,i} DMLIQ_{i,t-1} + \beta_{5,i} DMLIQ_{i,t+1} + \beta_{6,i} MRET_{i,t} + \beta_{7,i} MRET_{i,t-1} + \beta_{8,i} MRET_{i,t+1} + \beta_{9,i} DVOLA_{i,t} + \beta_{10,i} CRISIS_t + \varepsilon_i$$

$DLIQ_{i,t}$ is the daily percentage change in the relative spread of stock i at time t. $DMLIQ_{i,t}$ is the daily percentage change of concurrent market liquidity present in stock i. $DMLIQ_{i,t-1}$ is the lag and $DMLIQ_{i,t+1}$ is the lead. $EXPL$ represents the four explanatory variables that I present results for. $MRET$ is the market return and $DVOLA_{i,t}$ is the daily change of volatility for each stock measured by its squared returns. $CRISIS$ is a dummy variable that takes the value of one from 12 October 2008 to 19 January 2009, and zero otherwise. The time series regression is estimated for each stock in the sample and the cross section average of the time series regressions' coefficients is reported with t-statistics in parentheses. '%pos' reports the proportion of positive regression coefficients and '%pos&sig' refers to the positive coefficients that are significant under a one-tail t-test at 5%. '%neg' and '%neg&sig' correspond to the proportion of negative regression coefficients and their significance, respectively. The standard error for each parameter is estimated using a Newey West correction (Newey and West, 1987). 'Sum' refers to the sum of concurrent, lag and lead coefficients of market liquidity. I only report the cross-section averages of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ for brevity. The first column, 'Benchmark', reports the results of estimating the regressions without any explanatory variables and their interaction with market liquidity. The remaining columns report the results of estimating the regressions for domestic, foreign and all investors using (i) the change in the volume of initiated trades; (ii) market sidedness; and (iii) correlated trading, as explanatory variables ($EXPL$). [a] and [b] denote significance at 1% and 5%, respectively.

	Benchmark	Change in volume of initiated trades			Market Sidedness			Correlated trades			Net flows		
		Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All
DMLIQ	0.0796	0.0721	0.0663	0.0693	-0.0356	-0.0023	-0.0002	0.1061	0.2036	0.1451	0.0729	0.0760	0.0732
(t-statistics)	(4.84)[a]	(4.38)[a]	(3.61)[a]	(4.11)[a]	(-0.45)	(-0.07)	(0.00)	(0.71)	(1.15)	(1.04)	(4.33)[a]	(4.46)[a]	(4.17)[a]
%pos	80.00%	76.47%	75.29%	76.47%	45.88%	49.41%	45.88%	50.59%	63.53%	55.29%	0.7647	0.7765	0.7765
%pos&sig	16.47%	18.82%	18.82%	17.65%	7.06%	7.06%	5.88%	5.88%	10.59%	8.24%	0.1882	0.1765	0.1765

Table 3 cont'd

	Benchmark	Change in volume of initiated trades			Market Sidedness			Correlated trades			Net flows		
		Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All
EXPL		-0.0195	-0.0077	-0.0180	-0.0106	-0.0117	-0.0080	0.0445	0.0023	0.0415	0.0000	0.0000	0.0000
(t-statistics)		(-3.12) [a]	(-1.67)	(-3.00) [a]	(-1.32)	(-1.33)	(-1.02)	(2.24) [b]	(0.1)	(2.18) [b]	(-1.09)	(1.44)	(-0.05)
%pos		29.41%	37.65%	28.24%	45.88%	29.41%	48.24%	61.18%	49.41%	56.47%	0.4824	0.5294	0.5412
%pos&sig		2.35%	2.35%	2.35%	4.71%	1.18%	3.53%	8.24%	8.24%	8.24%	0.0824	0.0824	0.0706
%neg		70.59%	62.35%	71.76%	54.12%	70.59%	51.76%	38.82%	50.59%	43.53%	0.5176	0.4706	0.4588
%neg&sig		20.00%	14.12%	18.82%	5.88%	5.88%	5.88%	2.35%	2.35%	3.53%	0.0353	0.0471	0.0235
DMLIQ*EXPL		0.0982	0.1350	0.1387	0.1574	0.1972	0.1054	-0.0419	-0.2124	-0.1087	0.0001	0.0001	0.0001
(t-statistics)		(2.00) [b]	(3.5) [a]	(2.98) [a]	(1.49)	(2.89) [a]	(0.9)	(-0.17)	(-0.72)	(-0.49)	(1.5)	(0.9)	(1.8)
%pos		67.06%	71.76%	71.76%	60.00%	64.71%	57.65%	51.76%	37.65%	48.24%	0.5765	0.5882	0.6235
%pos&sig		14.12%	14.12%	15.29%	8.24%	11.76%	7.06%	5.88%	5.88%	7.06%	0.0824	0.0824	0.0706
%neg		32.94%	28.24%	28.24%	40.00%	35.29%	42.35%	48.24%	62.35%	51.76%	0.4235	0.4118	0.3765
%neg&sig		4.71%	1.18%	4.71%	4.71%	0.00%	4.71%	5.88%	8.24%	7.06%	0.0235	0.0353	0.0235
Sum	0.1150	0.1008	0.0943	0.0953	0.0028	0.0341	0.0352	0.1421	0.2367	0.1777	0.1092	0.1129	0.1135
(t-statistics)	(3.38) [b]	(2.86) [b]	(2.77) [a]	(2.93) [a]	(0.04)	(0.72)	(0.44)	(0.92)	(1.37)	(1.24)	(3.13) [b]	(3.27) [b]	(3.22) [b]
Adjusted R^2 mean	0.0229	0.0262	0.0255	0.0261	0.0233	0.0231	0.0234	0.0236	0.0240	0.0235	0.0230	0.0227	0.0226

The first column of Table 3 sets a benchmark by presenting the results of performing the regression framework of Chordia, et al. (2000) for spread. The cross-sectional average of $\hat{\beta}_1$ is 0.0796 with the associated t-statistics of 4.84. The proportion of $\hat{\beta}_1$ that is positive and positive and significant is 80% and 16.5%, respectively. Although not reported, the cross-sectional average of lag and lead coefficients of market liquidity ($\hat{\beta}_2$ and $\hat{\beta}_3$ of Equation 4) is insignificant and this shows the lack of support for a non-contemporaneous adjustment process in commonality in liquidity.

Comparing my estimate of commonality in spread to the estimate of Brockman, Chung and Perignon (2009) for the same market, I find that my estimate is smaller than theirs. This difference could be due to the different market conditions that are captured during the period of estimation which is 4 years from my sample period. Cao and Wei (2010) note that market conditions have a significant impact on the dynamics of commonality in liquidity. It is interesting to note that my estimate for commonality in spread is less likely to be driven by large estimates of commonality in spread for each stock. The estimate of commonality in spread reported by Brockman, et al. (2009) seems to be driven by large values in the cross-sectional average of the estimated market liquidity coefficients, as indicated by the significant difference of the cross-sectional mean and median of the estimated parameters for market liquidity.

Moreover, the number of stocks that show a positive and significant parameter result for commonality in spread (16.5%) is greater than the one reported by Brockman, et al. (2009) for the IDX. Consistent with earlier studies, I find that commonality in order-driven markets is weaker than commonality in spread in quote-driven markets

(Brockman and Chung (2002), Fabre and Frino (2004), Pukthuanthong-Le and Visaltanachoti (2009).

The next three columns examine the impact of changes in the volume of initiated trades. I find that an increase in the volume of initiated trades decrease spread and enhances commonality in spread. The negative relationship between trading volume and spread comes from the trades of domestic investors. This negative relationship is compatible with the inventory explanation outlined in McInish and Wood (1992) where economies of scale materialise for liquidity suppliers as trading volume rise, which then enables them to attain better inventory levels. This finding is also consistent with the findings of Rhee and Wang (2009) that document a positive relationship between trading volume and liquidity in the IDX. Further, the rise in commonality in spread can be observed for the trades of domestic and foreign investors. The positive relationship between volume and commonality in liquidity can be justified from the inventory model of Huang and Stoll (1997) where liquidity suppliers employ a portfolio approach in their inventory and adjust quotes across stocks to hedge their inventory risks.

A slightly different story materialises when market sidedness is used as the explanatory variable. Here, only market sidedness from foreign investors has a positive and significant impact on commonality in spread. Although foreign investors tend to be one-sided, when they do become more two-sided, from either having greater heterogeneous opinions or disparity in trading motivations on whether to buy or sell, commonality in liquidity significantly grows. There is not enough evidence to conclude that market sidedness of domestic investors, which I already observe tends to be two-sided, affects commonality in spread. These findings are compatible with the portfolio approach of the Huang and Stoll (1997) inventory model. As volatility in stock prices increases due to the buys and sells of foreign investors, so does the inventory risks of liquidity suppliers. Thus, liquidity suppliers, whom I speculate to be the domestic investors, change their quotes systematically and this leads to an increase in commonality in liquidity.

In the case of correlated trades and net flows, none of the interaction terms is significant, although I do notice only domestic correlated trades increase their spread. This would be indicative of liquidity suppliers demanding higher liquidity premiums as trading activities of domestic investors increase across a larger range of stocks. This higher liquidity premium could be due to these domestic correlated trades moving liquidity suppliers away from their optimal inventory position (see Huang and Stoll (1997)).

Table 4 presents the results when depth is used to measure liquidity. The first column of Table 4 sets a benchmark. The cross-sectional average of $\hat{\beta}_1$ is 0.4826 with the associated t-statistics of 7.57. The proportion of $\hat{\beta}_1$ that is positive and positive and significant is 93% and 60%, respectively. Although not reported in Table 4, similar to the results in commonality in spread regressions, I fail to document evidence to support the non-contemporaneous adjustment process in commonality in liquidity.

Table 4: Commonality in depth

This table reports cross-section averages of the estimated parameters from the following regression that was run on each stock:

$$DLIQ_{i,t} = \propto_i + \beta_{1,i}DMLIQ_{i,t} + \beta_{2,i}EXPL + \beta_{3,i}(EXPL \times DMLIQ_{i,t}) + \beta_{4,i}DMLIQ_{i,t-1} + \beta_{5,i}DMLIQ_{i,t+1} + \beta_{6,i}MRET_{i,t} + \beta_{7,i}MRET_{i,t-1} + \beta_{8,i}MRET_{i,t+1} + \beta_{9,i}DVOLA_{i,t} + \beta_{10,i}CRISIS_t + \varepsilon_i$$

$DLIQ_{i,t}$ is the daily percentage change in the depth of stock i at time t. $DMLIQ_{i,t}$ is the daily percentage change of concurrent market liquidity present in stock i. $DMLIQ_{i,t-1}$ is the lag and $DMLIQ_{i,t+1}$ is the lead. $EXPL$ represents the three explanatory variables that I present results for. $MRET$ is the market return and $DVOLA_{i,t}$ is the daily change of volatility for each stock measured by its squared returns. $CRISIS$ is a dummy variable that takes the value of one from 12 October 2008 to 19 January 2009 and zero otherwise. The time series regression is estimated for each stock in the sample and the cross section average of the time series regressions' coefficients are reported with t-statistics in parentheses. '%pos' reports the proportion of positive regression coefficients and '%pos&sig' refers to the positive coefficients that are significant under a one-tail t-test at 5%. '%neg' and '%neg&sig' correspond to the proportion of negative regression coefficients and their significance, respectively. The standard error for each parameter is estimated using a Newey West correction (Newey and West, 1987). 'Sum' refers to the sum of concurrent, lag and lead coefficients of market liquidity. I only report the cross-section averages of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ for brevity. The first column, 'Benchmark', reports the results of estimating the regressions without any explanatory variables and their interaction with market liquidity. The remaining columns report the results of estimating the regressions for domestic, foreign and all investors using (i) the change in the volume of initiated trades; (ii) market sidedness; and (iii) correlated trading, as explanatory variables ($EXPL$). [a] and [b] denote significance at 1% and 5%, respectively.

	Benchmark	Change in the volume of initiated trade			Market sidedness			Correlated trade			Net flows		
		Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All
DMLIQ	0.4826	0.4748	0.4609	0.4673	1.0374	0.7504	1.1612	-0.1019	-0.0306	-0.0707	0.4947	0.4674	0.4928
(t-statistics)	(7.57) [a]	(6.72) [a]	(6.49) [a]	(6.55) [a]	(5.93) [a]	(5.92) [a]	(6.16) [a]	(-0.36)	(-0.05)	(-0.26)	(8.66) [a]	(6.63) [a]	(8.19) [a]
%pos	92.94%	90.59%	92.94%	91.76%	78.82%	84.71%	80.00%	51.76%	52.94%	54.12%	0.9176	0.9059	0.9294
%pos&sig	60.00%	56.47%	56.47%	57.65%	21.18%	41.18%	22.35%	3.53%	9.41%	4.71%	0.6118	0.6000	0.6000

Table 4 cont'd

	Benchmark	Change in the volume of initiated trade			Market sidedness			Correlated trade			Net flows		
		Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All	Domestic	Foreign	All
EXPL		0.1690	0.1938	0.2098	-0.0005	0.0503	0.0229	-0.2330	-0.1028	-0.1964	0.0000	0.0001	0.0000
(t-statistics)		(4.23) [a]	(4.9) [a]	(4.43) [a]	(-0.01)	(0.87)	(0.3)	(-2.32) [b]	(-0.59)	(-2.22) [b]	(-0.56)	(1.26)	(-0.15)
%pos		77.65%	81.18%	80.00%	41.18%	57.65%	42.35%	32.94%	47.06%	42.35%	0.5529	0.7412	0.6118
%pos&sig		29.41%	40.00%	37.65%	2.35%	3.53%	2.35%	2.35%	3.53%	0.00%	0.1059	0.1412	0.1647
%neg		22.35%	18.82%	20.00%	58.82%	42.35%	57.65%	67.06%	52.94%	57.65%	0.4471	0.2588	0.3882
%neg&sig		0.00%	0.00%	0.00%	14.12%	5.88%	14.12%	5.88%	3.53%	8.24%	0.0471	0.0118	0.0118
DMLIQ*EXPL		-0.2846	-0.2725	-0.3512	-0.7336	-0.6564	-0.8781	0.9410	0.8559	0.8858	0.0000	0.0000	0.0000
(t-statistics)		(-1.86)	(-1.53)	(-1.84)	(-2.91) [a]	(-1.89)	(-3.26) [a]	(2.36) [b]	(0.96)	(2.16) [b]	(0.44)	(0.16)	(0.27)
%pos		35.29%	41.18%	37.65%	30.59%	38.82%	27.06%	56.47%	61.18%	61.18%	0.4235	0.5294	0.3882
%pos&sig		4.71%	2.35%	3.53%	5.88%	1.18%	3.53%	10.59%	5.88%	8.24%	0.0471	0.0588	0.0588
%neg		64.71%	58.82%	62.35%	69.41%	61.18%	72.94%	43.53%	38.82%	38.82%	0.5765	0.4706	0.6118
%neg&sig		4.71%	4.71%	7.06%	5.88%	4.71%	8.24%	2.35%	5.88%	3.53%	0.0471	0.0588	0.0353
Sum	0.5739	0.5973	0.6073	0.6097	1.1384	0.8506	1.2627	-0.0002	0.0628	0.0263	0.5764	0.5437	0.5728
(t-statistics)	(3.39) [b]	(3.9) [b]	(3.82) [b]	(3.9) [b]	(5.87) [b]	(5.27) [b]	(6.18) [b]	(0.00)	(0.11)	(0.09)	(4.18) [b]	(3.66) [b]	(4.02) [b]
Adjusted R^2 mean	0.0459	0.0514	0.0532	0.0527	0.0468	0.0466	0.0470	0.0463	0.0472	0.0466	0.0469	0.0468	0.0478

Comparing my estimate of commonality in depth to the estimate of Brockman, et al. (2009) for the same market, I find that my estimate is greater than theirs. Similar to the results in commonality in spread, I find that the number of stocks that show a positive and significant parameter result for commonality in depth (60%) is greater than the one reported by Brockman, et al. (2009) for the IDX. Consistent with Chordia, et al. (2000), I find that commonality in depth to be stronger than commonality in spread.

Similar to the results in spread, I document a similar positive relationship between trading volume and liquidity. An increase in initiated trade volume would improve depth. Although none of the interaction terms are significant for change in initiated trade volume, I do see significant negative figures for domestic market sidedness. However, both the proportion of significantly positive (5.8%) and negative coefficient results (5.8%) are the same, indicating this particular result is very likely being driven by outliers and so I place some caution on this result.

The table also reveals that correlated trading from domestic investors has a negative and significant impact on depth, as well as a positive and significant impact on commonality in depth. As domestic investors trade across a larger range of stocks it will necessarily limit depth that may previously have existed in just a few stocks, thereby also leading to commonality in depth movements. As for the impact of foreign investors, given they tend to concentrate their trading on larger stocks with higher prices, the impact of their correlated trades is unlikely to be as great as the impact of domestic correlated trades.

5.1.1. Specification check

The results in the previous section are contingent on the validity of the cross-sectional t-statistics, and these are only reliable if the residuals across regressions are independent and do not omit any important variables. Therefore, as a specification check, I follow Chordia, et al. (2000) by taking the residuals from each regression and arranging them in alphabetical order using the stocks' tick code and estimating 100 time series regressions for every pair of the adjacent residuals for:

$$\varepsilon_{j+1,t} = \gamma_{j,0} + \gamma_{j,1}\varepsilon_{j,t} + \omega_{j,t}$$

$$j = 1, \ldots, 101 \tag{6}$$

where ε_j and ε_{j+1} are adjacent residuals, $\gamma_{j,0}$ and $\gamma_{j,1}$ are the estimated coefficients and $\omega_{j,t}$ is an error term. If there is any cross-equation dependence, it would show in the significance of $\hat{\gamma}_1$across the regressions. Table 5 shows little evidence of cross-equation dependence. The average correlation is close to zero for all regressions and the mean and median of t-statistics for $\widehat{\gamma_1}$ are less than 0.7.

Table 5: Specification check

This table reports a specification check for the cross-sectional t-statistics presented in tables 3 and 4. Cross section averages of $\widehat{\gamma_1}$ from the following equation:

$$\varepsilon_{j+1,t} = \gamma_{j,0} + \gamma_{j,1}\varepsilon_{j,t} + \omega_{j,t}$$
$$j = 1, \dots, 101$$

are tabulated where ε_j and ε_{j+1} are adjacent residuals of the regression in the equation and $\omega_{j,t}$ is an error term. There are 101 residuals estimated from each regression and these residuals are ordered based on the alphabetical order of the stocks' tick name. The time series regression is estimated for 100 residual pairs. The mean and median of the t-statistics are also reported in this table. In addition, using a two tail t-test, the proportion of the regression coefficients that are significant at the 5% and 10% levels are reported in the last two columns, respectively.

	Average Correlation	Average Slope	Mean-t	Median-t	sig 10%	sig 5%
Panel A: Relative spread						
A.1. Commonality in spread	0.0336	0.0246	0.6547	0.6258	0.22	0.16
A.2: Volume of initiated trades						
Domestic	0.0322	0.0233	0.6257	0.5996	0.21	0.15
Foreign	0.0325	0.0249	0.6284	0.6004	0.20	0.13
All	0.0324	0.0240	0.6290	0.6069	0.21	0.14
A.3: Market Sidedness						
Domestic	0.0336	0.0237	0.6575	0.6141	0.22	0.16
Foreign	0.0331	0.0237	0.6431	0.6204	0.22	0.15
All	0.0336	0.0237	0.6567	0.6079	0.22	0.17
A.4: Correlated trades						
Domestic	0.0327	0.0224	0.6398	0.5387	0.22	0.15
Foreign	0.0335	0.0220	0.6557	0.5969	0.21	0.16
All	0.0327	0.0226	0.6407	0.5691	0.22	0.15
A.4: Net flows						
Domestic	0.0336	0.0243	0.6553	0.6257	0.22	0.14
Foreign	0.0340	0.0250	0.6598	0.6309	0.22	0.15
All	0.0336	0.0246	0.6557	0.6269	0.22	0.15
Panel B: Depth						
B.1. Commonality in depth	0.0234	0.0178	0.4894	0.3940	0.13	0.10
B.2: Volume of initiated trades						
Domestic	0.0211	0.0144	0.4393	0.4295	0.12	0.09
Foreign	0.0198	0.0142	0.4109	0.4092	0.12	0.09
All	0.0200	0.0129	0.4171	0.3835	0.13	0.08
B.3: Market Sidedness						
Domestic	0.0225	0.0150	0.4747	0.4109	0.14	0.10
Foreign	0.0225	0.0158	0.4745	0.4259	0.14	0.11
All	0.0224	0.0152	0.4708	0.3937	0.15	0.10

Table 5 cont'd

	Average Correlation	Average Slope	Mean-t	Median-t	sig 10%	sig 5%
B.4: Correlated trades						
Domestic	0.0236	0.0171	0.4915	0.4314	0.13	0.10
Foreign	0.0244	0.0188	0.5094	0.4895	0.14	0.09
All	0.0236	0.0173	0.4924	0.4349	0.13	0.09
B.4: Net flows						
Domestic	0.0245	0.0187	0.5075	0.4508	0.14	0.09
Foreign	0.0247	0.0180	0.5104	0.4106	0.14	0.09
All	0.0230	0.0169	0.4859	0.4034	0.14	0.09

The proportion of significant t-statistics for relative spread and depth at the 5% significance level ranges from 9% to 17%. These figures seem to be greater than suggested by a normal distribution and are slightly higher than the figures reported in Chordia, et al. (2000), who find that 6% to 9% of the t-statistics are significant. However, these proportions are relatively similar to the findings in Coughenour and Saad (2004) who report significant t-statistics that can be as high as 21.56% for high-volume portfolios. Given that the sample of this study comes from the most active stocks in the IDX, the 17% of significant t-statistics is probably not unexpected. In addition, the mean of t-statistics is less than 0.7 when the proportion of t-statistics is the highest (17%). Overall, the evidence suggests that the average cross-equation residuals are not significant.

5.1.2. Global financial crisis

As mentioned earlier, a crisis dummy is introduced to take into account bias that might arise from the crisis period. This section aims to present evidence on the sufficiency of the crisis dummy to control for the crisis impact. To conduct the analysis, I augment Equation 4 with the crisis dummy and its interaction with market liquidity. The model specification is as follows:

$$
\begin{aligned}
DLIQ_{i,t} = \propto_i + \beta_{1,i} DMLIQ_{i,t} \\
+ \beta_{2,i} CRISIS + \beta_{3,i}\left(CRISIS \times DMLIQ_{i,t}\right) + \beta_{4,i} DMLIQ_{i,t-1} \\
+ \beta_{5,i} DMLIQ_{i,t+1} + \beta_{6,i} MRET_t + \beta_{7,i} MRET_{t-1} + \beta_{8,i} MRET_{t+1} \\
+ \beta_{9,i} DVOLA_{i,t} + \varepsilon_i
\end{aligned}
\tag{7}
$$

Table 6 presents the results of estimating this regression for both liquidity measures. I find that spread and depth increase during the crisis period, as reflected in the positive estimates for the $CRISIS$ dummy. On the surface, these results seem to be inconsistent. However, they are consistent with previous research. It is well documented that volatility increases during a crisis period due to the increased uncertainly in the market. During a period when volatility is high, spread is expected to increase because liquidity suppliers would charge additional premiums for the inventory risks that they face (see Huang and Stoll (1997)). On the other hand, as volatility increases it has been documented that investors tend to submit limit order (Ahn, Bae and Chan (2001)). This tendency, thus, increases depth during a crisis period.

Table 6: The impact of the crisis on commonality in liquidity

This table reports cross-section averages of the estimated parameters from the following regression that was run on each stock:

$$DLIQ_{i,t} = \propto_i + \beta_{1,i} DMLIQ_{i,t} + \beta_{2,i} CRISIS + \beta_{3,i}(CRISIS \times DMLIQ_{i,t}) + \beta_{4,i} DMLIQ_{i,t-1} + \beta_{5,i} DMLIQ_{i,t+1} + \beta_{6,i} MRET_t + \beta_{7,i} MRET_{t-1} + \beta_{8,i} MRET_{t+1} + \beta_{9,i} DVOLA_{i,t} + \varepsilon_i$$

$DLIQ_{i,t}$ is the daily percentage change in the liquidity of stock i at time t. There are two liquidity measures used in the regressions. DRSPRD is the daily percentage change in spread and DDEPTH is the daily percentage change of depth in number of shares. $DMLIQ_{i,t}$ is the daily percentage change of concurrent market liquidity present in stock i. $DMLIQ_{i,t-1}$ is the lag and $DMLIQ_{i,t+1}$ is the lead. $CRISIS$ is a dummy variable that takes the value of one from 12 October 2008 to 19 January 2009, and zero otherwise. $MRET$ is the market return and $DVOLA_{i,t}$ is the daily change of volatility for each stock measured by its squared returns. The time series regression is estimated for each stock in the sample and the cross section average of the time series regressions' coefficients is reported with t-statistics in parentheses. Please refer to previous tables for the definition of '%pos', '%pos&sig', '%neg', '%neg&sig' and 'Sum'. I only report the cross-section averages of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ for brevity.

	DRSPRD	DDEPTH
DMLIQ	0.0334	0.7481
(t-statistics)	(2.69)	(7.35)
%pos	63.10%	94.05%
%pos&sig	11.90%	77.38%
CRISIS	0.0142	0.0920
(t-statistics)	(2.57)	(2.15)
%pos	75.00%	69.05%
%pos&sig	2.38%	9.52%
%neg	25.00%	30.95%
%neg&sig	2.38%	4.76%
DMLIQ*CRISIS	0.3408	-0.3350
(t-statistics)	(3.31)	(-1.44)
%pos	73.81%	39.29%
%pos&sig	21.43%	3.57%
%neg	26.19%	60.71%
%neg&sig	4.76%	19.05%
Sum	0.0599	1.0444
Adjusted R^2 mean	0.0313	0.0658

Furthermore, I find that only the interaction variable for spread is significant. This finding suggests that commonality in spread is higher during a crisis period. This finding is consistent with previous research that documents an increase in commonality in liquidity during market downturn (Coughenour and Saad (2004), Comerton-Forde, Hendershott, Jones, Moulton and Seasholes (2010), Hameed, et al. (2010)). However, I fail to document similar evidence on the interaction between the crisis dummy and market liquidity measured by depth. It seems that the increase in depth during the crisis period is not as systematic as the increase in spread. One plausible explanation for this finding is that liquidity suppliers do not have any obligation to provide liquidity in order driven markets. Given the above results, I believe the $CRISIS$ dummy can sufficiently capture the dynamics of the global financial crisis. Thus, adding this dummy variable into the commonality regressions ensures that the results are not driven by investors' behaviour during the crisis period.

In addition, in the earlier stage of my data analysis, I attempted to examine the impact of the GFC on the data analysis by estimating the regressions in two sub-samples. The first sub-sample is the crisis period that starts from January 2, 2008 until the day before the IDX announced a trade halt (October 6, 2008). The second sub-sample, the post-crisis period, starts from October 30, 2008 because this was the date when the IDX relaxed the strict auto rejection rules for the first time. The post-crisis period ends on January 2, 2011. In general the results suggest that commonality in liquidity is absent during the crisis period but present during the post-crisis period. I find that the absence of commonality in liquidity during the crisis period does not align well with the theoretical framework (Vayanos (2004) and Brunnermeier and Pedersen (2009)) and the empirical evidence (Coughenour and Saad (2004), Comerton-Forde, et al. (2010), Hameed, et al.

(2010), and Karolyi, et al. (2012)) that suggest commonality in liquidity would increase during a crisis period. It seems that the commonality regression framework of Chordia, et al. (2000) does not perform well in capturing the commonality in liquidity surrounding a crisis period. This insufficiency could potentially be due to either the lack of trading or high volatility surrounding this period.

Adding the $CRISIS$ dummy seems to capture the impact of the GFC better than conducting sub-sample analysis. In addition, the results of adding the dummy and its interaction with market liquidity into commonality regressions seem to align well with previous studies. These results provide justification of the use of this dummy variable in the commonality in liquidity regressions.

5.1.3. Size effect

Chordia, et al. (2000) find that commonality in liquidity has a positive relationship with size. They find that commonality in liquidity across large stocks is stronger compared to the commonality in liquidity across small stocks. Chordia, et al. (2000) argue that institutional investors' bias towards large stocks could explain this positive relationship. However, several studies find that commonality in liquidity of large stocks is not necessarily greater than that of small stocks (Brockman and Chung (2002), Fabre and Frino (2004), Sujoto, Kalev and Faff (2008), Brockman, et al. (2009), and Pukthuanthong-Le and Visaltanachoti (2009)). It is noteworthy that these studies are conducted in order-driven markets. Thus, the different results could be due to the differences in market structure. However, Cao and Wei (2010) could not find a similar positive relationship even though they conducted their research on a quote-driven market. Cao and Wei (2010) suggest that the positive relationship between commonality in spread and size is subject to the changes in market dynamics. In addition, they find that the positive relationship between commonality in spread and size is supported during the first four years of their sample but find that the positive relationship between commonality and size turns into a negative one during the last four years of their sample.

To examine whether the positive relationship between commonality in liquidity and size exists, I sort the results of the benchmark model in Table 3 and 4 into two size-based groups. The first group consists of the 30 smallest stocks and the second group consists of the 30 largest stocks in the sample. Table 7 reports the results. Generally speaking, I could not find convincing evidence of the positive relationship between commonality in liquidity and size. While Table 7 suggests that commonality in spread across large stocks is stronger (due to the insignificant commonality in spread across small stocks), commonality in depth across large stocks is not greater than commonality in depth across small stocks. The lack of support for the positive relationship is consistent with the findings of (Brockman and Chung (2002), Fabre and Frino (2004), Sujoto, et al. (2008), Brockman, et al. (2009), and Pukthuanthong-Le and Visaltanachoti (2009).

Table 7: Commonality in liquidity sorted by size

This table reports cross-section averages of the estimated parameters from the following regression that was run on each stock:

$$DLIQ_{i,t} = \propto_i + \beta_{1,i} DMLIQ_{i,t} + \beta_{2,i} DMLIQ_{i,t-1} + \beta_{3,i} DMLIQ_{i,t+1} + \beta_{4,i} MRET_{i,t} + \beta_{5,i} MRET_{i,t-1} + \beta_{6,i} MRET_{i,t+1} + \beta_{7,i} DVOLA_{i,t} + \beta_{8,i} CRISIS_t + \varepsilon_i,$$

$DLIQ_{i,t}$ is the daily percentage change in liquidity of stock i at time t. There are two liquidity measures used in the regressions. DRSPRD is the daily percentage change in spread and DDEPTH is the daily percentage change of depth in number of shares. $DMLIQ_{i,t}$ is the daily percentage change of concurrent market liquidity present in stock i. $DMLIQ_{i,t-1}$ is the lag and $DMLIQ_{i,t+1}$ is the lead. $CRISIS$ is a dummy variable that takes the value of one from 12 October 2008 to 19 January 2009, and zero otherwise. $MRET$ is the market return and $DVOLA_{i,t}$ is the daily change of volatility for each stock measured by its squared returns. 'Small' and 'Large' refers to the stocks with small and large market capitalization, respectively. The time series regression is estimated for each stock in the sample and the cross section average of the time series regressions' coefficients is reported with t-statistics in parentheses. Please refer to previous tables for the definition of '%pos', '%pos&sig', '%neg', '%neg&sig' and 'Sum'. I only report the cross-section averages of $\hat{\beta}_1$ for brevity. [a] and [b] denote significance at 1% and 5%, respectively.

	DRSPRD		DDEPTH	
	Small	Large	Small	Large
DMLIQ	0.0899	0.0821	0.5896	0.4259
(t-statistics)	(1.75)	(4.49) [a]	(2.45) [b]	(8.79) [a]
%pos	0.8000	0.8667	0.8500	0.9667
%pos&sig	0.1000	0.1333	0.4000	0.7000
Sum	0.1448	0.1319	0.9097	0.2971
Adjusted R^2 mean	0.0281	0.0237	0.0329	0.0488

To further examine whether the results in Table 3 and 4 are consistent across stocks with different market capitalization, I sort the results in Table 3 and 4 based on small and large capitalization groups. Table 8 and 9 present the results.

Table 8: Commonality in spread sorted by size

This table reports cross-section averages of the estimated parameters from the following regression that was run on each stock:

$$DLIQ_{i,t} = \propto_i + \beta_{1,i}DMLIQ_{i,t} + \beta_{2,i}EXPL + \beta_{3,i}\left(EXPL \times DMLIQ_{i,t}\right) + \beta_{4,i}DMLIQ_{i,t-1} + \beta_{5,i}DMLIQ_{i,t+1} + \beta_{6,i}MRET_t + \beta_{7,i}MRET_{t-1} + \beta_{8,i}MRET_{t+1} + \beta_{9,i}DVOLA_{i,t} + \beta_{10,i}CRISIS_t + \varepsilon_i$$

$DLIQ_{i,t}$ is the daily percentage change in spread of stock i at time t. $DMLIQ_{i,t}$ is the daily percentage change of concurrent market liquidity present in stock i. $DMLIQ_{i,t-1}$ is the lag and $DMLIQ_{i,t+1}$ is the lead. $CRISIS$ is a dummy variable that takes the value of one from 12 October 2008 to 19 January 2009, and zero otherwise. $MRET$ is the market return and $DVOLA_{i,t}$ is the daily change of volatility for each stock measured by its squared returns. 'Small' and 'Large' refers to the stocks with small and large market capitalisation, respectively. The time series regression is estimated for each stock in the sample and the cross section average of the time series regressions' coefficients is reported with t-statistics in parentheses. Please refer to previous tables for the definition of '%pos', '%pos&sig', '%neg', '%neg&sig' and 'Sum'. I only report the cross-section averages of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ for brevity. The remaining columns report the results of estimating the regressions for domestic, foreign and all investors using (i) the change in the volume of initiated trades; (ii) market sidedness; and (iii) correlated trading, as explanatory variables ($EXPL$). [a] and [b] denote significance at 1% and 5%, respectively.

	Change in volume of initiated trade				Market sidedness				Correlated trade				Net flows			
	Domestic		Foreign		Domestic		Foreign		Domestic		Foreign		Domestic		Foreign	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
DMLIQ	0.0717	0.0719	0.0691	0.0696	-0.0785	-0.0065	-0.0104	0.0177	0.1276	-0.0125	-0.3106	0.2314	0.0592	0.0825	0.0808	0.0793
(t-statistics)	(1.35)	(3.74)[a]	(1.11)	(3.79)[a]	(-0.31)	(-0.06)	(-0.09)	(0.56)	(0.28)	(-0.15)	(-0.6)	(1.45)	(1.12)	(4.88)[a]	(1.48)	(4.37)[a]
%pos	0.7000	0.8333	0.7000	0.8000	0.4000	0.5000	0.5500	0.5333	0.7000	0.4667	0.4000	0.7000	0.6500	0.8667	0.6500	0.9000
%pos&sig	0.0500	0.1667	0.0500	0.1667	0.1500	0.0667	0.1000	0.0667	0.1000	0.0000	0.0500	0.1333	0.1000	0.1667	0.0500	0.1333
EXPL	-0.0387	-0.0243	-0.0040	-0.0168	-0.0292	-0.0079	0.0094	-0.0110	0.1307	0.0082	-0.0471	0.0056	0.0000	0.0000	0.0000	0.0000
(t-statistics)	(-1.68)	(-4.84)[a]	(-0.25)	(-3.71)[a]	(-1.11)	(-1.1)	(0.28)	(-1.34)	(2.00)	(0.40)	(-0.70)	(0.24)	(-1.71)	(0.05)	(0.95)	(0.65)
%pos	0.2500	0.2000	0.4500	0.2667	0.4500	0.4333	0.4000	0.3000	0.8000	0.5667	0.5000	0.4000	0.3000	0.6000	0.4500	0.5000
%pos&sig	0.0000	0.0000	0.0500	0.0000	0.1000	0.0333	0.0500	0.0000	0.0500	0.0667	0.0500	0.1000	0.0000	0.1333	0.0000	0.1000
%neg	0.7500	0.8000	0.5500	0.7333	0.5500	0.5667	0.6000	0.7000	0.2000	0.4333	0.5000	0.6000	0.7000	0.4000	0.5500	0.5000
%neg&sig	0.2500	0.2333	0.1000	0.2333	0.1000	0.0333	0.0000	0.1000	0.0000	0.0000	0.0500	0.0000	0.0000	0.0333	0.0000	0.0333

Table 8 cont'd

	Change in volume of initiated trade				Market sidedness				Correlated trade				Net flows			
	Domestic		Foreign		Domestic		Foreign		Domestic		Foreign		Domestic		Foreign	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
DMLIQ*EXPL	0.2347	0.1519	0.2543	0.1404	0.2279	0.1217	0.2433	0.1545	-0.0555	0.1516	0.6775	-0.2579	0.0003	0.0000	0.0001	0.0001
(t-statistics)	(1.54)	(4.34)[a]	(1.85)	(5.09)[a]	(0.68)	(0.91)	(1.12)	(2.31)[b]	(-0.08)	(1.16)	(0.82)	(-1.01)	(2.49)[b]	(0.07)	(0.56)	(1.71)
%pos	0.6000	0.8000	0.7000	0.8000	0.7000	0.5667	0.5500	0.6333	0.3000	0.5667	0.6000	0.3000	0.6000	0.6333	0.7000	0.5667
%pos&sig	0.1500	0.1667	0.2500	0.1667	0.0000	0.0667	0.0500	0.1333	0.0500	0.0333	0.1000	0.0000	0.1500	0.1000	0.1000	0.0667
%neg	0.4000	0.2000	0.3000	0.2000	0.3000	0.4333	0.4500	0.3667	0.7000	0.4333	0.4000	0.7000	0.4000	0.3667	0.3000	0.4333
%neg&sig	0.0000	0.0000	0.0000	0.0000	0.1500	0.0333	0.0000	0.0000	0.0500	0.0000	0.0500	0.1000	0.0000	0.0667	0.0500	0.0000
Sum	0.1146	0.1123	0.1212	0.1063	-0.0223	0.0458	0.0588	0.0661	0.1819	0.0363	-0.2518	0.2780	0.1144	0.1328	0.1342	0.1344
Adj R^2 mean	0.0308	0.0277	0.0305	0.0268	0.0272	0.0242	0.0274	0.0238	0.0285	0.0234	0.0288	0.0241	0.0276	0.0242	0.0275	0.0239

Table 9: Commonality in depth sorted by size

This table reports cross-section averages of the estimated parameters from the following regression that was run on each stock:

$$DLIQ_{i,t} = \propto_i + \beta_{1,i} DMLIQ_{i,t} + \beta_{2,i} EXPL + \beta_{3,i}(EXPL \times DMLIQ_{i,t}) + \beta_{4,i} DMLIQ_{i,t-1} + \beta_{5,i} DMLIQ_{i,t+1} + \beta_{6,i} MRET_t + \beta_{7,i} MRET_{t-1} + \beta_{8,i} MRET_{t+1} + \beta_{9,i} DVOLA_{i,t} + \beta_{10,i} CRISIS_t + \varepsilon_i$$

$DLIQ_{i,t}$ is the daily percentage change in depth of stock i at time t. $DMLIQ_{i,t}$ is the daily percentage change of concurrent market liquidity present in stock i. $DMLIQ_{i,t-1}$ is the lag and $DMLIQ_{i,t+1}$ is the lead. $CRISIS$ is a dummy variable that takes the value of one from 12 October 2008 to 19 January 2009, and zero otherwise. $MRET$ is the market return and $DVOLA_{i,t}$ is the daily change of volatility for each stock measured by its squared returns. 'Small' and 'Large' refers to the stocks with small and large market capitalisation, respectively. The time series regression is estimated for each stock in the sample and the cross section average of the time series regressions' coefficients is reported with t-statistics in parentheses. Please refer to previous tables for the definition of '%pos', '%pos&sig', '%neg', '%neg&sig' and 'Sum'. I only report the cross-section averages of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ for brevity. The remaining columns report the results of estimating the regressions for domestic, foreign and all investors using (i) the change in the volume of initiated trades; (ii) market sidedness; and (iii) correlated trading, as explanatory variables ($EXPL$). [a] and [b] denote significance at 1% and 5%, respectively.

	Change in volume of initiated trade				Market sidedness				Correlated trade				Net flows			
	Domestic		Foreign		Domestic		Foreign		Domestic		Foreign		Domestic		Foreign	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
DMLIQ	0.6770	0.3828	0.6522	0.3561	1.8992	1.0051	1.0492	0.4717	0.4670	-0.6372	1.0846	-0.7525	0.6322	0.4229	0.6476	0.3811
(t-statistics)	(2.52)[b]	(6.75)[a]	(2.45)[b]	(7.5)[a]	(3.86)[a]	(4.82)[a]	(3.30)[b]	(4.25)[a]	(0.50)	(-2.27)[b]	(1.05)	(-2.53)[b]	(2.90)[a]	(8.85)[a]	(2.44)[b]	(7.35)[a]
%pos	0.8500	0.8667	0.8500	0.9333	0.8500	0.8000	0.8500	0.9333	0.5500	0.4000	0.7000	0.2000	0.8500	0.9000	0.8500	0.9000
%pos&sig	0.4000	0.6333	0.4500	0.6000	0.1000	0.3333	0.3500	0.3000	0.0000	0.0000	0.1000	0.0000	0.4000	0.7000	0.4000	0.7333
EXPL	0.0487	0.1963	0.1390	0.2487	-0.0605	-0.0841	-0.0056	-0.0183	-0.7198	0.0696	-0.7407	0.3025	-0.0001	0.0000	0.0000	0.0001
(t-statistics)	(1.14)	(4.72)[a]	(2.17)[b]	(7.97)[a]	(-0.34)	(-2.38)[b]	(-0.04)	(-0.49)	(-2.29)[b]	(0.74)	(-1.67)	(1.90)	(-1.19)	(0.91)	(0.51)	(3.02)[a]
%pos	0.7500	0.9000	0.7500	1.0000	0.3000	0.3667	0.6000	0.5333	0.2000	0.4000	0.3500	0.5333	0.4000	0.5000	0.6500	0.7667
%pos&sig	0.0500	0.4333	0.1000	0.7667	0.0000	0.0000	0.0500	0.0333	0.0000	0.0667	0.0000	0.0667	0.0000	0.1333	0.0500	0.1333
%neg	0.2500	0.1000	0.2500	0.0000	0.7000	0.6333	0.4000	0.4667	0.8000	0.6000	0.6500	0.4667	0.6000	0.5000	0.3500	0.2333
%neg&sig	0.0000	0.0000	0.0000	0.0000	0.2500	0.2000	0.0500	0.0667	0.1000	0.0000	0.0500	0.0000	0.0000	0.0667	0.0000	0.0000

Table 9 cont'd

	Change in volume of initiated trade				Market sidedness				Correlated trade				Net flows			
	Domestic		Foreign		Domestic		Foreign		Domestic		Foreign		Domestic		Foreign	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
DMLIQ*EXPL	-0.5679	-0.0616	-0.4824	0.0240	-1.7434	-0.7803	-1.1062	-0.1160	0.2451	1.6662	-0.8165	1.9518	-0.0001	0.0000	-0.0010	0.0004
(t-statistics)	(-2.14)[b]	(-0.6)	(-1.81)	(0.21)	(-2.12)[b]	(-2.92)[a]	(-1.23)	(-0.6)	(0.19)	(4.11)[a]	(-0.53)	(3.92)[a]	(-0.27)	(-0.13)	(-1.76)	(2.82)[a]
%pos	0.3000	0.3667	0.3000	0.5000	0.2000	0.2667	0.3000	0.4333	0.4500	0.7333	0.4500	0.9333	0.3000	0.4667	0.4000	0.7333
%pos&sig	0.0000	0.0333	0.0000	0.0000	0.0000	0.0667	0.0000	0.0000	0.2000	0.1000	0.1000	0.0667	0.0000	0.0000	0.0000	0.1000
%neg	0.7000	0.6333	0.7000	0.5000	0.8000	0.7333	0.7000	0.5667	0.5500	0.2667	0.5500	0.0667	0.7000	0.5333	0.6000	0.2667
%neg&sig	0.1000	0.0000	0.1000	0.0000	0.0500	0.0667	0.0000	0.0333	0.0000	0.0000	0.0500	0.0000	0.0000	0.1000	0.1500	0.0000
Sum	1.0244	0.2817	1.0501	0.2829	2.2412	0.8824	1.3949	0.3428	0.8025	-0.7608	1.3862	-0.8737	0.9428	0.2949	0.9474	0.2411
Adj R^2 mean	0.0318	0.0573	0.0332	0.0643	0.0342	0.0497	0.0335	0.0486	0.0323	0.0489	0.0325	0.0502	0.0307	0.0495	0.0314	0.0491

Table 8 and 9 reveal additional dynamics concerning the positive relationship between the volume of initiated trades and liquidity. The tables show that the positive impact of volume on liquidity is stronger across large stocks. An increase in the volume of initiated trades from domestic and foreign investors decreases spread and increases depth. As for the negative relationship between correlated trades of domestic investors and liquidity, Table 8 shows that the correlated trade of domestic investors does not have any impact on the spread of either small or large stocks. However, Table 9 suggests that these correlated trades decrease the depth of small stocks. A new result materialises for foreign net flows in Table 9 where foreign net flows increase the depth of large stocks as well as their commonality.

Table 8 and 9 reveal additional dynamics in the way initiated trades affect commonality in liquidity. The positive impact of change in volume of initiated trades on commonality in spread appears to materialise across large stocks. Change in volume of initiated trades of domestic investors appears to take away commonality in depth across small stocks. This result is driven by 3 stocks that have negative and significant estimates of the interaction variable. Thus, I put caution on the interpretation of this result. The positive impact of foreign investors' market sidedness on commonality in spread seems to concentrate across large stocks. In addition, the negative impact of domestic investors' sidedness on commonality in depth seems to be driven by outliers of the estimates which seem to be similarly distributed across the two groups of stocks. Furthermore, the positive impact of correlated trading on commonality in depth can also be observed across large stocks. Overall, the results suggest that the contribution of the different aspects of initiated trades on commonality in liquidity is more pronounced across large stocks rather than small stocks.

5.2. ROBUSTNESS TESTS

This section provides robustness analysis in two aspects. First, I examine whether the positive relationship between correlated trades and commonality in depth is dependent on the measurement of correlated trades. Second, whether negotiated trades have an additional impact on how the trades of foreign investors affect commonality in liquidity.

5.2.1. Different correlated trades measure

Karolyi, et al. (2012) suggest that correlated trading from institutional investors would manifest itself in commonality in turnover, as these institutional investors trade in a similar fashion. Thus, an increase in commonality in turnover would increase commonality in liquidity, and vice versa. Karolyi, et al. (2012) suggest that supply side factors could affect the trading pattern of institutional investors; therefore, they orthogonalise their commonality in the turnover measure against supply side factors.

To examine whether these variables could explain commonality in liquidity, Equation 5 is re-estimated by replacing correlated trading with commonality in turnover. Commonality in turnover is estimated using the first component of the principal component analysis of the daily turnover data and also the synchronicity in turnover. The first component of the principal component analysis is expected to capture commonality in turnover as earlier studies use it as a measure of commonality in liquidity (Hasbrouck and Seppi (2001) and Corwin and Lipson (2011)). The second way to estimate commonality in turnover is by implementing the price synchronicity measure of Morck, et al. (2000) into stock turnover data. Table 10 reports the results of this exercise.

Table 10: Commonality in liquidity with different measures of correlated trades

This table reports the results of re-estimating Equation 5 with different proxies of correlated trades. Correlated trades is measured with correlated trading (measured using synchronicity method), commonality in turnover measured using principal component analysis (PCA) and synchronicity measure. Time series regressions are estimated for each stock where the daily percentage change of individual stock's liquidity is regressed against the daily percentage change of equally-weighted market liquidity. There are two liquidity measures used in this study. *RSPRD* is relative spread. *DEPTH* is depth. The *D* that precedes the liquidity variables acronym refers to the daily percentage change in today's liquidity measure from the previous trading day. The cross section-average of the time series regressions' coefficients is reported with t-statistics in parentheses. '%pos' reports the proportion of positive regression coefficients and '%pos&sig' refers to the positive coefficients that are significant under the one-tail t-test at 5%. The standard error for each regression is estimated using Newey West correction (Newey and West (1987)). 'Sum' refers to the sum of Concurrent, Lag and Lead coefficients of market liquidity. The time series regressions include the concurrent, lag and lead of market returns and the daily percentage change of returns' volatility (measured by squared returns). The coefficients of these additional regressors are not reported. I only report the cross-section averages of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ for brevity. [a] and [b] denote significance at 1% and 5%, respectively.

	Correlated trading (Synchronicity)		Commonality in T/O (PCA)		Commonality in T/O (Synchronicity)	
	DRSPRD	DDEPTH	DRSPRD	DDEPTH	DRSPRD	DDEPTH
DMLIQ	0.1236	-0.2020	0.0447	0.7120	0.1767	-0.5249
(t-statistics)	(0.91)	(-0.65)	(2.64)[b]	(8.58)[a]	(1.34)	(-1.39)
%pos	59.41%	48.51%	72.28%	90.10%	56.44%	41.58%
%pos&sig	6.93%	3.96%	13.86%	63.37%	7.92%	1.98%
EXPL	0.0251	-0.0606	0.0004	0.0011	0.0166	0.0414
(t-statistics)	(0.92)	(-0.46)	(0.49)	(0.38)	(0.84)	(0.3)
%pos	56.44%	41.58%	52.48%	62.38%	58.42%	46.53%
%pos&sig	7.92%	0.99%	5.94%	11.88%	4.95%	3.96%
%neg	43.56%	58.42%	47.52%	37.62%	41.58%	53.47%
%neg&sig	2.97%	6.93%	7.92%	2.97%	2.97%	4.95%
DMLIQ*EXPL	-0.1069	1.4753	0.0041	-0.0284	-0.1915	1.9707
(t-statistics)	(-0.5)	(3.25)[a]	(0.72)	(-1.06)	(-0.95)	(3.46)[a]
%pos	49.50%	67.33%	57.43%	53.47%	46.53%	71.29%
%pos&sig	5.94%	12.87%	9.90%	6.93%	3.96%	16.83%
%neg	50.50%	32.67%	42.57%	46.53%	53.47%	28.71%
%neg&sig	6.93%	1.98%	1.98%	7.92%	6.93%	0.99%
Sum	0.1199	0.1429	0.0434	1.0529	0.1752	-0.1842
Adjusted R^2 mean	0.0252	0.0589	0.0252	0.0597	0.0245	0.0587

Table 10 reports that correlated trading, estimated through commonality in turnover, provides similar results to correlated trading measures. These two measures report a significant impact of correlated trading on commonality in depth and no significant impact of correlated trading on commonality in spread. These results suggest that the results documented earlier on correlated trading are robust.

Another robustness test that I perform is to estimate correlated trades across different sets of stocks because correlated trades could be stronger across more liquid or larger stocks. Following this line of argument I re-estimate correlated trades across different sets of stocks. The first group of stocks consists of the stocks that are included in LQ45 index, which represent the 45 stocks that are most liquid. The second group consists of the 30 largest stocks in the sample. Table 11 shows the results of estimating Equation 5 using these two measures of correlated trades as the explanatory variables.

Table 11: The impact of correlated trading on commonality in liquidity

This table reports the results of re-estimating Equation 5 with correlated trades as the explanatory variable. Correlated trades is measured across the 45 most liquid stocks (LQ) and across 30 largest capitalisation stocks (LARGE). Time series regressions are estimated for each stock where the daily percentage change of individual stock's liquidity is regressed against the daily percentage change of equally-weighted market liquidity. There are two liquidity measures used in this study. *RSPRD* is relative spread. *DEPTH* is depth. The *D* that precedes the liquidity variables acronym refers to the daily percentage change in today's liquidity measure from the previous trading day. The cross section-average of the time series regressions' coefficients is reported with t-statistics in parentheses. '%pos' reports the proportion of positive regression coefficients and '%pos&sig' refers to the positive coefficients that are significant under the one-tail t-test at 5%. The standard error for each regression is estimated using Newey West correction (Newey and West (1987)). 'Sum' refers to the sum of Concurrent, Lag and Lead coefficients of market liquidity. The time series regressions include the concurrent, lag and lead of market returns and the daily percentage change of returns' volatility (measured by squared returns). The coefficients of these additional regressors are not reported. I only report the cross-section averages of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ for brevity. [a] and [b] denote significance at 1% and 5%, respectively.

Variable	LQ45						LARGE					
	DRSPRD			DDEPTH			DRSPRD			DDEPTH		
	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR
DMLIQ	-0.1870	-0.0993	-0.0918	0.2918	0.1077	0.2464	-0.0048	-0.0165	-0.1339	0.1818	0.0501	0.0378
(t-statistics)	(-1.90)	(-1.17)	(-0.94)	(1.03)	(0.37)	(1.06)	(-0.05)	(-0.18)	(-1.1)	(0.57)	(0.17)	(0.12)
%pos	39.60%	43.56%	44.55%	60.40%	56.44%	60.40%	49.50%	48.51%	47.52%	55.45%	51.49%	59.41%
%pos&sig	4.95%	4.95%	3.96%	13.86%	8.91%	11.88%	3.96%	2.97%	4.95%	7.92%	10.89%	10.89%
CORRT	0.0132	0.0252	0.0025	0.0879	-0.0097	0.1924	-0.0019	0.0005	-0.0142	-0.0182	-0.0477	-0.0474
(t-statistics)	(1.00)	(1.74)	(0.1)	(1.48)	(-0.1)	(1.35)	(-0.08)	(0.02)	(-0.94)	(-0.2)	(-0.54)	(-0.47)
%pos	54.46%	58.42%	54.46%	53.47%	47.52%	52.48%	52.48%	49.50%	42.57%	55.45%	49.50%	57.43%
%pos&sig	6.93%	10.89%	6.93%	3.96%	2.97%	2.97%	4.95%	7.92%	2.97%	1.98%	3.96%	4.95%
%neg	45.54%	41.58%	45.54%	46.53%	52.48%	47.52%	47.52%	50.50%	57.43%	44.55%	50.50%	42.57%
%neg&sig	0.99%	3.96%	1.98%	5.94%	1.98%	2.97%	3.96%	4.95%	2.97%	1.98%	0.99%	2.97%

Table 11 cont'd

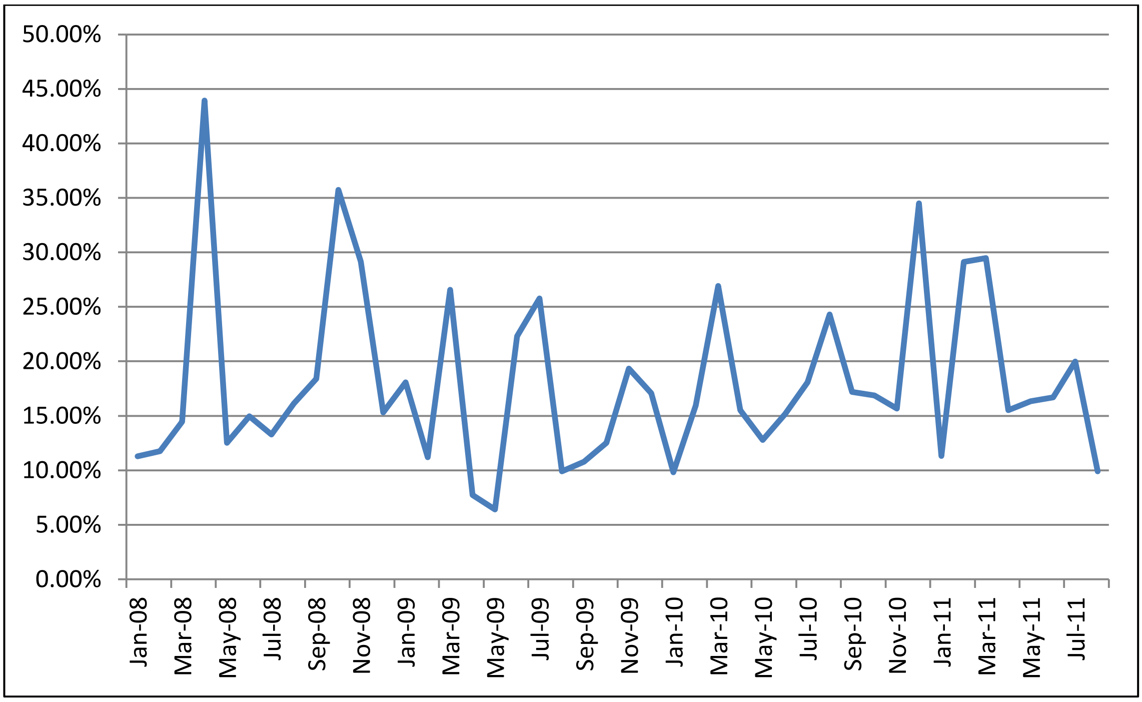
Variable	LQ45						LARGE					
	DRSPRD			DDEPTH			DRSPRD			DDEPTH		
	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR
DMLIQ* CORRT	0.3560	0.2350	0.2314	0.6271	0.8809	0.7256	0.0933	0.1111	0.3038	0.8147	1.0128	1.0797
(t-statistics)	(2.61)[a]	(1.94)	(1.62)	(1.71)	(2.25)[a]	(2.03)[a]	(0.72)	(0.78)	(1.67)	(1.92)	(2.51)[a]	(2.22)[a]
%pos	64.36%	60.40%	57.43%	67.33%	64.36%	60.40%	53.47%	56.44%	56.44%	67.33%	62.38%	62.38%
%pos&sig	9.90%	12.87%	9.90%	9.90%	17.82%	15.84%	5.94%	7.92%	6.93%	11.88%	14.85%	12.87%
%neg	35.64%	39.60%	42.57%	32.67%	35.64%	39.60%	46.53%	43.56%	43.56%	32.67%	37.62%	37.62%
%neg&sig	3.96%	2.97%	2.97%	2.97%	2.97%	2.97%	3.96%	1.98%	2.97%	4.95%	1.98%	3.96%
Sum	-0.1935	-0.1005	-0.0881	0.6265	0.4508	0.5729	-0.0068	-0.0210	-0.1303	0.5120	0.3875	0.3717
Adjusted R^2 mean	0.0251	0.0259	0.0253	0.0598	0.0603	0.0580	0.0248	0.0256	0.0244	0.0593	0.0590	0.0582

Table 11 shows that the negative impact of correlated trades on liquidity becomes insignificant. This finding indicates that the negative and significant impact of domestic correlated trades documented earlier is indeed because of the span of domestic investors' correlated trades. As the span of correlated trades decreases so does the significance of domestic correlated trades on depth. It is interesting to note that foreign correlated trades show significant contribution to commonality in depth when correlated trades is measured using a smaller number of stocks. Furthermore, the contribution of domestic correlated trades on commonality in depth seems to be relatively similar to the one that is estimated earlier in Table 4.

5.2.2. Negotiated trades

Figure 3 plots the proportion of negotiated trades against total trades in value measured at monthly intervals from January 2008 to August 2011. The figure shows that the proportion of negotiated trades in the IDX is not that small. The average value of negotiated trades in the sample is around 18%. The proportion of negotiated trades' value was at its highest in April 2008, about 42% of the total trade value in that particular month. While the magnitude of negotiated trades looks relatively similar in later months, negotiated trades in 2008 were mostly sells and the negotiated trades after 2008 are mostly buys.

Figure 3: Proportion of negotiated trades' value in the IDX
This figure plots the proportion of the monthly value of trade in the negotiated market against the monthly value of trade in the regular and the negotiated market from January 2008 to August 2011



Given the prevalence of negotiated sells of foreign investors around the GFC period, I attempt to analyse further whether these negotiated sells have additional impact on how the trades of foreign investors affect commonality in liquidity. I re-estimated Equation 5 to include the daily value of negotiated trades into the volume of initiated trades (DVOL) but I failed to document any significance for the interaction variable. I also estimate Equation 5 using only the daily volume of negotiated trades instead of volume of initiated trades, but this also did not yield significant results for the interaction variable. Although I cannot rule negotiated trades out completely, I have not been able to find any substantial impact of these trades on commonality in liquidity.

5.3. CONCLUSIONS

The results indicate that foreign investors are more aggressive than domestic investors because foreign investors tend to submit market orders more often and tend to submit more aggressive limit orders than domestic investors. The aggressive trades of foreign investors increase commonality in spread as these trades increase in volume and become more two-sided. While the volume of domestic initiated trades also has a positive and significant relationship with commonality in spread, market sidedness of domestic investors does not have any significant impact on commonality in spread.

I find that the correlated trades of domestic and foreign investors enhance commonality in depth. This result is robust for different measures of correlated trades. Net flows of domestic and foreign investors seem to have no impact on commonality in liquidity. In general, I find no support for the size effect on the commonality findings. However, it is noteworthy that the impact of initiated trades on commonality in liquidity is stronger across large stocks.

To conclude, domestic and foreign investors induce commonality in liquidity in different ways. Foreign sidedness enhances commonality in spread. Taking this conclusion along with the fact that foreign investors trade aggressively, I then ask a further question: given the high trade cost and the impact of foreign trades on commonality in liquidity, why do foreign investors trade more aggressively? This question will be examined in the next two chapters.

CHAPTER 6: PRICE DISCOVERY OF DOMESTIC AND FOREIGN INVESTORS

The results in the previous chapter indicate that foreigners take on higher costs when trading. This comes from their tendency to post market orders as well as their being more aggressive in their limit orders than domestic investors. At the same time, as foreign initiated trades increase in volume and become more two-sided, commonality in spread increases, exacerbating the systematic effect of liquidity on the market. The following question then arises:

Why do foreigners have a propensity to place more aggressive orders as costs associated with these trades are higher?

The answer to this provides a complete answer to how foreign trades impact commonality in liquidity. Chordia, et al. (2000) propose that commonality in liquidity emerges because of inventory risks or information asymmetry. Given the prevalent evidence of asymmetric information between domestic and foreign investors (Grinblatt and Keloharju (2000), Froot and Ramadorai (2001), Choe, et al. (2005), Dvorak (2005), Froot and Ramadorai (2008), and Agarwal, et al. (2009)), one would conveniently expect that information asymmetry is the driver that causes foreign trades to have an impact on commonality in liquidity. However, I do not find convincing evidence that net flows of domestic and foreign investors, which are seen as investors' response to asymmetric information, affect commonality in liquidity. Given this evidence, it is imperative to examine further whether aggressive orders that foreign investors submit which affect commonality in liquidity, are motivated by information or not.

Furthermore, the investigation of whether information asymmetry motivates foreign investors to submit aggressive orders would contribute to the investors' aggressiveness literature by investigating the determinants of order aggressiveness across domestic and foreign investors. Research on order aggressiveness mainly focuses on the determinants and impact of aggressive orders. Griffiths, Smith, Turnbull and White (2000) and Ranaldo (2004) investigate the determinants and impact of aggressive orders on several market indicators using order aggressiveness metrics proposed by Biais, Hillion and Spatt (1995). The closest research that investigates order aggressiveness of specific groups of investors comes from Aitken, Almeida, deB. Harris and McInish (2007) and Duong, Kalev and Krishnamurti (2009). These studies investigate the determinants of order aggressiveness for institutional and individual investors.

If foreign investors' tendency to submit aggressive orders is due to them having an information advantage, either in terms of possessing better information or a better ability to process and utilise relevant information, this may lead to more informative, aggressive trades. However, it could also be the case that foreign institutional investors who place funds in Indonesia are simply focused on portfolio capital flow allocations, in which case aggressive trades could simply be indicative of foreign preferences to trade on demand, with the speed at which transactions are settled being of concern. Domestic investors would provide liquidity in their role as non-designated market-makers, given that they would likely have a greater willingness to carry inventory in the local market.

If the former argument holds, then I should expect that the incorporation of relevant information for pricing shares to arise partly from foreign trades. On the other hand, if the latter case is true then trades that lead to price discovery would be dominated by domestic investors, with very little contribution coming from foreign investors. By providing liquidity to foreign portfolio investors who seek immediacy in their trades, domestic investors can not only earn liquidity rents, but also benefit from the opportunity to re-allocate their own funds to better valued stocks, thereby driving the price discovery process in the Indonesian market.

In order to investigate the contribution to price discovery that comes from domestic and foreign investors, I examine information leadership shares (ILS). ILS stems from a modification Putniņš (2013) makes of work by Yan and Zivot (2010) that combines the two well known measures of price discovery; namely the information share (IS) of Hasbrouck (1995) and the component share (CS) of Gonzalo and Granger (1995). Putniņš (2013) argues that the combination of these two measures yields a better estimate of price discovery as the impact of transitory shocks would be minimal, leaving the price discovery estimate to capture how price series respond to permanent shocks. I utilise ILS to attribute price discovery between domestic and foreign prices, which I construct from separating domestic and foreign initiated trades over various time intervals, ranging from 5 second up to 5 minutes. The next section provides a detailed discussion of the data and methodology.

6.1. DATA AND METHODOLOGY

I construct domestic and foreign price series from the initiated trades of domestic and foreign investors, respectively. I then align these price series at 5 second, 10 second, 15 second, 30 second, 1 minute and 5 minute intervals. I do not go beyond a 5 minute interval because a 5 minute interval sufficiently captures foreign trades that are less frequent compared to domestic trades. The average duration of domestic initiated trades is one minute and 30 seconds, while the average duration of foreign initiated trades is four minutes and 58 seconds. The alignment process takes the closest price to the specified time interval. As ILS methodology requires the two price series to be cointegrated, I conduct the Johansen cointegration test (Johansen (1995)) to examine whether domestic and foreign price series are cointegrated. I conduct the examination across the selected stocks on each trading day. The ILS will then be estimated for each stock and trading day where domestic and foreign price series are cointegrated.

The estimation process of ILS starts with obtaining information shares (IS) and component shares (CS) of domestic and foreign investors. Following the derivation outlined in Baillie, Geoffrey Booth, Tse and Zabotina (2002), consider two price series, domestic and foreign, which can be represented as $P_t = (p_{1t}, p_{2t})'$ with the cointegrating vector of $\beta = (1, -1)'$. The VECM for these price series would be:

$$\Delta P_t = \alpha\beta' Y_{t-1} + \sum_{j=1}^{k} A_j \Delta Y_{t-j} + e_t \tag{8}$$

where α is a vector of error correction and e_t is a zero mean vector of serially uncorrelated innovations. The CS can be estimated from the normalized matrix that is orthogonal to the vector of error correction coefficients. Given that $\alpha_{\perp} = (\gamma_1, \gamma_2)'$ the CS can be calculated as follows

$$CS_1 = \gamma_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}$$

(9)

$$CS_2 = \gamma_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2}$$

(10)

The covariance matrix Ω of the reduced form VECM is

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$$

(11)

and the Cholesky factorisation, $\Omega = MM'$, where

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$$

(12)

The IS can be calculated by

$$IS_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{12})^2}$$

(13)

$$IS_2 = \frac{(\gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{12})^2}$$

(14)

As IS can have different estimates due to different ordering of the two price series, I follow the approach suggested by Baillie, et al. (2002) to take the simple average of the estimates. After obtaining the estimates of CS and IS, the information leadership (IL) measure of Yan and Zivot (2010) can be calculated as following

$$IL_1 = \left|\frac{IS_1 CS_2}{IS_2 CS_1}\right| \tag{15}$$

$$IL_2 = \left|\frac{IS_2 CS_1}{IS_1 CS_2}\right| \tag{16}$$

Putniņš (2013) suggests that the IL metric provides a clean measure of relative contribution to price discovery (i.e. price leadership) because the combination of CS and IS takes out the relative level of noise. However, the IL metric is not expressed as shares and thus the sum of IL_1 and IL_2 is not equal to 1. Putniņš (2013) proposes ILS as a modification of IL so that the new measure is comparable against CS and IS. ILS can be calculated in the following way

$$ILS_1 = \frac{IL_1}{IL_1 + IL_2} \tag{17}$$

$$ILS_2 = \frac{IL_2}{IL_1 + IL_2} \tag{18}$$

To estimate the VECM model outlined in Equation 8, I apply the price discovery algorithms written by Joel Hasbrouck, which are available on his website.

6.2. RESULTS

This section starts with presenting the results of conducting the Johansen cointegration test (Johansen (1995)) on each trading day. To be included in the cointegration testing, a stock has to be traded at least 15 times by either domestic or foreign investors. Table 12 presents the results of this test for different time alignments of domestic and foreign price series. The two price series are aligned at 5 second, 10 second, 15 second, 30 second, 1 minute and 5 minute intervals.

Table 12: Johansen cointegration test

This table presents descriptive statistics of the cointegrated stocks against the number of stocks that are traded on each trading day. Cointegrated stocks are those where domestic and foreign prices are cointegrated.

Price series	Cointegration			
	Mean	Std Dev	Min	Max
5 sec	0.2176	0.0670	0.0732	0.5400
10 sec	0.2132	0.0674	0.0714	0.5500
15 sec	0.2096	0.0674	0.0667	0.5600
30 sec	0.2026	0.0664	0.0533	0.5600
1 min	0.1968	0.0655	0.0267	0.5500
5 min	0.1686	0.0582	0.0133	0.5700

Table 12 shows that of all stocks that are traded in any given day, cointegration between domestic and foreign prices exists in around 16% to 21% of these traded stocks. Note that in some trading days, stocks with cointegrated prices can be as high as 57%. The relatively low proportion of stocks with cointegrated prices could be due to the low trading frequency and to the lack of changes in the price series within a day.

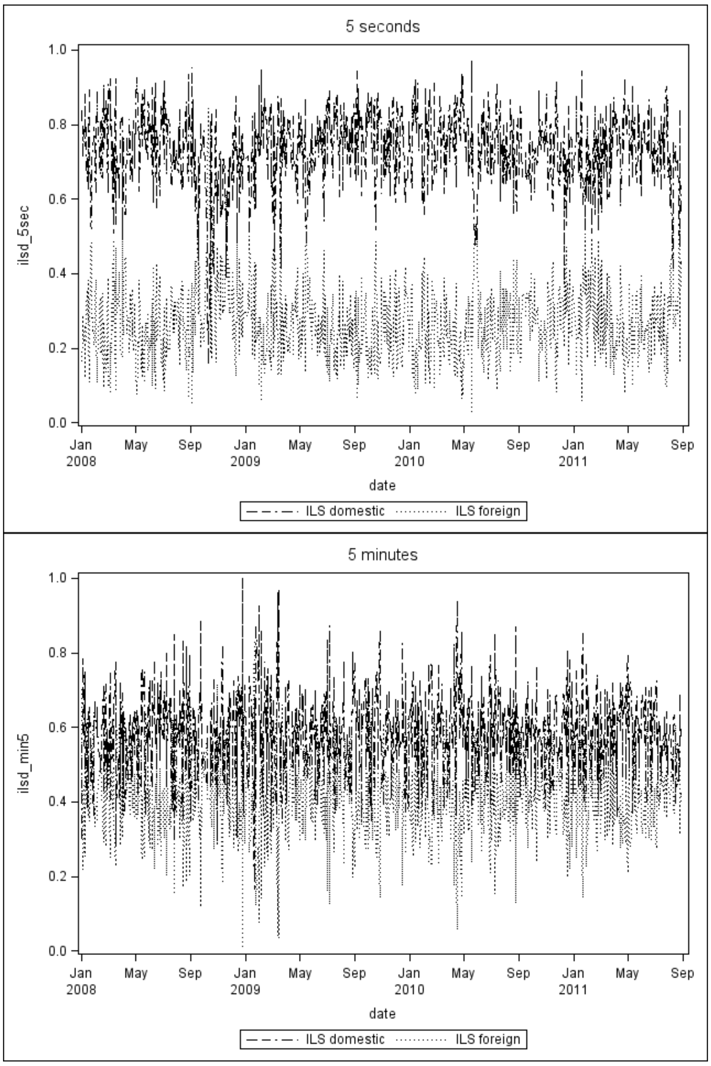
Given that I have identified the stocks with cointegrated prices, I then estimate the ILS of domestic and foreign investors for each stock on each trading day. The estimation is conducted using a different alignment of price series from 5 seconds to 5 minutes. Table 13 presents the daily cross-sectional average of ILS' estimates for domestic and foreign price series.

Table 13: Information leadership shares (ILS) of domestic and foreign investors
This table reports the cross-sectional average of domestic and foreign ILS. Price series are constructed from domestic and foreign initiated trades measured every 5, 10, 15, and 30 seconds, as well as every 1 and 5 minutes. 'Domestic-Foreign' provides the difference between the daily cross-sectional average of domestic and foreign ILS and the final column reports the t-statistic of this difference.

Price series	Domestic	Foreign	Domestic-Foreign	t-stat
5 second	0.7297	0.2703	0.4594	87.91
10 second	0.7080	0.2920	0.4160	77.01
15 second	0.6915	0.3085	0.3830	69.24
30 second	0.6580	0.3420	0.3160	54.53
1 minute	0.6240	0.3760	0.2481	41.34
5 minute	0.5746	0.4254	0.1491	22.64

The results presented in Table 13 show price discovery is predominately from domestic investors, with them explaining 73% of information leadership shares on a 5 second basis, and 57% over 5 minute intervals. The dominance of domestic price discovery is also prevalent across time. Figure 4 shows how over the entire sample period, on a 5 second basis, domestic investors hold higher information shares. Less than 2% of the sample shows periods where foreign information leadership shares are larger than for domestic investors. Domestic investors also dominate the price discovery process at 5 minutes intervals for 74% of the sample.

Figure 4: Information leadership shares (ILS)
These graphs show the contribution of domestic and foreign investors to price discovery using ILS, which is estimated from domestic and foreign price series that are aligned at 5 seconds and 5 minutes.



6.3. CONCLUSION

Using ILS to measure the contribution to price discovery, the results suggest that domestic investors lead foreign investors in the price discovery process. These results are consistent for different price series alignments starting from 5 seconds to 5 minutes. These findings indicate that information asymmetry is less likely to drive foreign investors' tendency to trade aggressively which affects commonality in liquidity.

Given these findings, the possibility that foreigners are trading primarily for speed in allocating funds in the market, as opposed to trading on information, grows. This may be further evidenced by examining in more detail the trading behaviour between foreign and domestic investors in explaining the above information shares. The next chapter will investigate this issue.

CHAPTER 7: ANALYSIS OF PRICE DISCOVERY AND INFORMATION TYPE

The findings in the previous chapter point to a conclusion that the aggressive trades of foreign investors are motivated by immediacy rather than information. However, the evidence from the price discovery analysis alone is not sufficient to support this conclusion. This chapter aims to provide additional evidence to support the immediacy motive conclusion in two ways. First, I will perform price discovery analysis where I examine whether the information leadership shares results can be explained by the trading behaviour of domestic and foreign investors. Second, I will investigate whether the return series of domestic and foreign investors are dominated by systematic or idiosyncratic components. This examination would reveal what potential information advantage domestic investors have.

7.1. METHODOLOGY FOR PRICE DISCOVERY ANALYSIS

To perform the price discovery analysis, I estimate a panel regression model adapted from Eun and Sabherwal (2003). The dependent variable is the ILS of domestic investors. As the value of ILS is bounded from zero to one, I implement a logistic transformation[6] following Eun and Sabherwal (2003). The panel regression aims to examine how the daily domestic information leadership shares, *PD*, for stock *i* can be explained by a number of independent variables. Specifically:

---

[6] $\ln\left(x/_{1-x}\right)$, where x is the dependent variable.

$$PD_{i,t} = \alpha_i + \beta_1 LARGE\_D_{i,t} + \beta_2 LARGE\_F_{i,t} + \beta_3 OID_{i,t} + \beta_4 OIF_{i,t} + \beta_5 MOF_t + \beta_6 SIDE\_D_t + \beta_7 SIDE\_F_t + \beta_8 CORRT\_D_t + \beta_9 CORRT\_F_t + \beta_{10} VOL\_IN\_F_t + \beta_{11} VOLATILITY_{i,t} + \beta_{12} MCAP_{i,t} + \beta_{13} MDEPTH_t + \beta_{14} MRSPRD_t + \beta_{15} VOLUME\_D_{i,t} \quad \textbf{(19)}$$

I include the proportion of large initiated trades[7] over all initiated trades during the day from domestic ($LARGE\_D$) and foreign ($LARGE\_F$) investors to capture the possibility of whether large trades are more informed. Hasbrouck (1995) and Eun and Sabherwal (2003) examine trade size and its relationship to price discovery, with arguments suggesting large trades are not the most informative as they reveal the identity of the trader. In the case of the IDX, regardless of trade size, the origin of the orders as either coming from foreign or domestic investors is immediately known. Hence, investors have less incentive to break their orders. I add order imbalance[8] of initiated trades for both domestic (OID) and foreign (OIF) investors to see if there is a difference between buys and sells in generating price discovery. I also include the ratio of market orders to total orders from foreign investors (*MOF*). If foreigners are indeed placing market orders to increase the immediacy of their trades, then this variable is expected to be insignificant as it will not contain any information content. On the other hand, if market orders are in some way related to information-induced trades then a significant and negative result should be expected. Additionally, I add the three explanatory factors for commonality used in Tables 3 and 4; being domestic ($SIDE\_D$) and foreign ($SIDE\_F$) market sidedness; domestic ($CORRT\_D$) and foreign ($CORRT\_F$) correlated trades and the change in foreign initiated trades (VOL_IN_F). I do not include a parameter for

[7] A large trade is identified as being in the top 25 percentile of trades, by investor group.

[8] Order imbalance is calculated for each investor group by netting total buy and sell trades.

domestic initiated trades given there is a high correlation between both series (above 0.6).

As control variables, I include $VOLATILITY$ measured as squared market returns, $MCAP$ measured as the natural log of market capitalisation, market depth (MDEPTH) and spread (MSPREAD), plus the volume of domestic initiated trades over total initiated trades (VDOM). The latter item is added to control for the fact that domestic investors make up the bulk of trading on the IDX.

7.2. RESULTS

Table 14 shows the results of estimating Equation 19 for the ILS of domestic investors that are estimated using 5, 10, 15, and 30 second, as well as at 1 and 5 minute price series. Focusing on the 5 second regression results, a picture emerges where activity from foreign investors leads to increased domestic investor price discovery. Large foreign trades do not seem to be information-induced trades as they actually increase domestic price discovery. Further, as the volume of foreign initiated trades increases it has a similar impact, and is in addition to their effect on increasing commonality in spread previously shown in Table 3. Evidence that foreign initiated trades are motivated by immediacy concerns rather than being related to information trading is further reinforced by the fact that the market to total orders coefficient is insignificant.

Table 14: Panel regressions for domestic ILS

This table reports panel regression results of the following regression specification:

$$PD_{i,t} = \alpha_i + \beta_1 LARGE\_D_{i,t} + \beta_2 LARGE\_F_{i,t} + \beta_3 OID_{i,t} + \beta_4 OIF_{i,t} + \beta_5 MOF_t + \beta_6 SIDE\_D_t + \beta_7 SIDE\_F_t + \beta_8 CORRT\_D_t + \beta_9 CORRT\_F_t + \beta_{10} VOL\_IN\_F_t + \beta_{11} VOLATILITY_{i,t} + \beta_{12} MCAP_{i,t} + \beta_{13} MDEPTH_t + \beta_{14} MRSPRD_t + \beta_{15} VOLUME\_D_{i,t}$$

where PD is the information leadership share of domestic investors in continuous form, $LRGD$ and $LRGF$ are the proportion of initiated trades that have a large number of shares against the total volume of initiated trades for domestic and foreign investors, respectively. OID and OIF are order imbalance in the number of initiated trades of domestic and foreign investors, respectively. MOF refers to the ratio of the number of market orders against the number of total orders submitted by foreign investors. $SIDE\_D$ and $SIDE\_F$ refer to market sidedness of domestic and foreign investors, respectively. $CORRT\_D$ and $CORRT\_F$ refer to correlated trading by domestic and foreign investors, respectively. VOL_IN_F refers to the change in the volume of initiated trades coming from foreign investors. $VOLATILITY$ is measured by squared returns. $MDEPTH$ and $MRSPRD$ are measures of market liquidity in depth and relative spread. Lastly, $VOLUME\_D$ is the proportion of the volume of domestic initiated trades against total initiated trades. I include stock and year fixed effects in the regressions. [a] and [b] denote significance at 1% and 5%, respectively.

	5 sec	10 sec	15 sec	30 sec	1 min	5 min
LARGE_D	0.6289	0.6079	0.7095	0.8419	0.9633	0.441
	(1.87)	(1.81)	(2.11)[b]	(2.48)[b]	(2.68)[a]	(1.23)
LARGE_F	9.2605	8.6973	7.6208	5.4998	3.3615	1.5637
	(11.82)[a]	(11.22)[a]	(9.95)[a]	(7.32)[a]	(4.62)[a]	(2.27)[b]
OID	-5.81E-06	-7.27E-06	-5.81E-06	-9.58E-06	-9.67E-06	-2.01E-06
	(2.08)[b]	(2.47)[b]	(1.99)[b]	(3.54)[a]	(3.58)[a]	-0.79
OIF	-2.05E-05	-2.05E-05	-1.90E-05	-1.70E-05	-1.53E-05	-1.25E-05
	(2.21)[b]	(2.18)[b]	(1.92)	(1.64)	(1.44)	(1.18)
MOF	0.4302	0.4294	0.344	0.0588	0.2898	-0.0046
	(1.67)	(1.65)	(1.30)	(0.22)	(1.05)	(0.02)
SIDE_D	-0.9859	-1.1376	-1.1977	-1.4288	-1.2023	-0.5382
	(3.57)[a]	(4.12)[a]	(4.29)[a]	(5.14)[a]	(4.15)[a]	(1.80)
SIDE_F	-0.4742	-0.5106	-0.4263	-0.4631	-0.6117	-0.5008
	(2.44)[b]	(2.65)[a]	(2.14)[b]	(2.28)[b]	(3.00)[a]	(2.40)[b]
CORRT_D	-0.6063	-0.4625	-0.532	-1.0919	-1.0792	-0.0077
	(1.22)	(0.92)	(1.05)	(2.14)[b]	(2.03)[b]	(0.01)
CORRT_F	1.2157	1.4414	1.6241	2.1593	1.8484	0.1161
	(1.97)[b]	(2.29)[b]	(2.59)[a]	(3.37)[a]	(2.82)[a]	(0.17)
VOL_IN_F	0.2011	0.0294	0.0462	-0.0637	0.0575	-0.0668
	(2.17)[b]	(0.31)	(0.48)	(0.64)	(0.59)	(0.67)
VOLATILITY	-83.73	-80.1616	-77.845	-67.0168	-53.6012	-26.7739
	(9.73)[a]	(8.74)[a]	(8.39)[a]	(8.08)[a]	(7.51)[a]	(5.25)[a]

Table 14 cont'd

	5 sec	10 sec	15 sec	30 sec	1 min	5 min
MCAP	-0.4604	-0.5092	-0.5404	-0.6456	-0.5627	-0.3711
	(4.47)[a]	(5.06)[a]	(5.13)[a]	(6.14)[a]	(5.12)[a]	(3.28)[a]
MDEPTH	1.4571	1.2866	1.3583	1.2066	0.9112	0.0826
	(10.13)[a]	(8.82)[a]	(9.40)[a]	(8.05)[a]	(5.77)[a]	(0.50)
MRSPRD	-0.8464	-1.1662	-1.0465	-1.0018	-0.9282	-0.9337
	(2.93)[a]	(3.92)[a]	(3.47)[a]	(3.26)[a]	(2.96)[a]	(2.96)[a]
VOLUME_D	10.0398	8.9193	7.4908	4.7628	3.0942	1.5095
	(12.62)[a]	(11.44)[a]	(9.64)[a]	(6.32)[a]	(4.25)[a]	(2.22)[b]
CRISIS	0.0311	-0.0688	0.002	0.1245	0.0769	-0.2607
	(0.16)	(0.33)	(0.01)	(0.57)	(0.34)	(1.10)
Stock fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.22	0.2	0.18	0.15	0.12	0.04
N	14,059	13,780	13,576	13,235	12,789	10,402

Also, when there is more selling pressure, from either domestic or foreign investors, domestic price discovery increases. This would be in alignment with the literature that shows sells tend to be more informative than buys (Chiyachantana, Jain, Jiang and Wood (2004)). A similar story exists with market sidedness, where one-sided trading from either foreign or domestic investors, which Sarkar and Schwartz (2009) indicate is potentially related to private information trades, leads to increased price discovery. In the case of foreign investors, I previously established that increased two-sidedness leads to a rise in commonality in spread. Combined with the fact this also diminishes domestic price discovery, my contention is that when foreigners are trading for immediacy (expressed as two-sided trading), domestic investors sit back posting less aggressive limit orders that lead to increased liquidity premiums. As foreigners are not posting information-induced orders, there would be no reason to suspect a benefit to domestic price discovery. On the other hand, regardless of whether they are domestic or foreign investors, one-sided trading potentially reveals information, although it only leads to an improvement in domestic investors driving prices.

Correlated trades also tell a story as there is a greater advantage to domestic investors in leading price movements when foreign investors trade across multiple stocks. Possibly because foreign correlated trades are representations of portfolio rebalancing activities, they are less likely to be informed. Domestic investors potentially lead the price discovery process by providing liquidity to foreign investors who seek immediacy in their trades. As one would expect when the frequency interval is reduced to 5 minute periods, a number of variables lose their significance. What remains significant though, is the impact from large foreign trades plus foreign market sidedness.

7.3. METHODOLOGY FOR INFORMATION TYPE ANALYSIS

Clearly, the evidence points to foreign investors being liquidity demanders, whilst domestic investors act as liquidity suppliers. However, the price discovery analysis itself does not explicitly highlight what potential information advantage domestic investors have. The obvious place to look for a domestic investor information advantage would be in their ability to impound local information better than foreign investors.

A strand of literature attempts to measure the systematic component of stock returns along with its determinants (Morck, et al. (2000), Piotroski and Roulstone (2004), Chan and Hameed (2006), and Gul, Kim and Qiu (2010)). These studies uses the coefficient of determination (R^2) that comes from market model regressions to measure the systematic component of stock returns, with $1 - R^2$ as the firm-specific component. Morck, et al. (2000) find that the systematic component of stock returns is greater across emerging markets compared to the developed markets because market frictions that are more pronounced in these markets prevent informed trades to impound firm specific information into stock returns. Extending the line of enquiry of Morck, et al. (2000), Piotroski and Roulstone (2004) and Chan and Hameed (2006) investigate whether different groups of sophisticated investors impound firm-specific information into return series differently. These two studies focus on the performance of stock analysts in impounding firm specific information compared to insiders. The findings of these studies suggest that stock analysts do not impound firm specific information as much as insiders. Extending this line of enquiry to domestic and foreign interaction, Gul, et al. (2010) find that the presence of foreigners lead stock returns to impound more firm-specific information, which could be attributed to higher corporate transparency and lower information asymmetry.

To examine the proportion of firm-specific information that is impounded in domestic and foreign returns, I estimate market model regressions for domestic and foreign return series that are calculated earlier for the price discovery analysis. However, I average the price series at daily intervals to construct daily return series to comply with the methodology of Morck, et al. (2000). They suggest that the coefficient of determination, R^2, of a market model regression captures the systematic component of stock returns, and that $1 - R^2$ would capture the firm-specific component of returns. The market model regression would take the following specification:

$$R_{i,t} = \alpha_{i,t} + \beta_i R_{M,t} + e_{i,t} \tag{20}$$

where $R_{i,t}$ is domestic and foreign return series for stock i on day t and $R_{M,t}$ is the market return on day t. These return series are calculated from intraday domestic and foreign initiated prices that are averaged at daily intervals.

7.4. RESULTS

Table 15 shows cross-section averages for the coefficient of determination obtained from estimating Equation 20. This equation is estimated for each stock from the market model regression of domestic and foreign returns series against market returns on a semi-annual basis for the length of the sample period. The last two columns show the difference in R^2 between the domestic and foreign investor regressions and t-statistics for a one-tail test of significance.

In all cases, the results suggest domestic investors impound more firm-specific information into their return series than foreign investors. This finding is in contrast to the findings of Gul, et al. (2010) that suggest foreigners promote more firm-specific information to be impounded into return series. This different finding could be due to my study capturing the domestic and foreign interaction at transaction level, while Gul, et al. (2010) captures similar interaction at a longer interval. The finding that domestic trades reflect more firm-specific information is therefore indicative of domestic investors utilising firm-specific information better than the foreign investors. The differential in synchronicity was also at a peak during the last part of 2008 and for 2009, when the impact of the global financial crisis was also at its height, with the likely benefit from local knowledge being of extra value.

Table 15: Price synchronicity of domestic versus foreign investors
This table reports the results of estimating market model regressions for domestic and foreign return series against market returns. Return series are calculated from domestic and foreign initiated trades that are averaged at daily intervals. R^2Domestic and R^2Foreign refer to the cross-section averages of the coefficient of determination for each regression on each stock. The last two columns report the difference of the cross-section averages between domestic and foreign investors, along with the corresponding t-statistics.

	R^2Domestic	R^2Foreign	R^2Domestic - R^2Foreign	t-stat
Whole sample	0.0144	0.0273	-0.0129	-1.76
Six months intervals				
2008-1	0.1060	0.1483	-0.0543	-2.03
2008-2	0.0980	0.2209	-0.1228	-3.38
2009-1	0.1110	0.1639	-0.0830	-2.74
2009-2	0.0638	0.1262	-0.0726	-3.12
2010-1	0.0787	0.1139	-0.0475	-2.13
2010-2	0.0658	0.0913	-0.0334	-2.23
2011-1	0.0536	0.1034	-0.0501	-2.48

7.5. CONCLUSION

The results in this chapter complement and explain the potential differences in the motivation to trade between domestic and foreign investors. Foreigners would seem to be motivated to push for quicker executions to meet capital flow needs, thereby becoming liquidity demanders, whereas domestic investors act as suppliers of liquidity whilst utilizing firm-specific information better in driving market prices forward.

CHAPTER 8: THESIS CONCLUSION

8.1. CONTRIBUTION OF THE THESIS

This thesis aims to address the gap in the literature on the impact of foreign trades on commonality in liquidity of the domestic market at a transaction level. Capturing the interaction between domestic and foreign investors in a market where foreign participation is not restricted, I find that foreign investors significantly affect commonality in liquidity. Investigating the research questions using transaction data reveals additional dynamics in the way foreign trades affect commonality in liquidity that has not been documented in earlier studies.

I find that foreign investors enhance commonality in spread when they initiate trades on both sides of the market which are motivated either by differences in interpreting information or by immediacy needs but not by information asymmetry. This finding is surprising given the prevalence of asymmetric information evidence surrounding domestic and foreign interaction and the proposition of Chordia, et al. (2000) suggesting that information asymmetry could induce commonality in liquidity. The lack of evidence to link information asymmetry between domestic and foreign investors and commonality in liquidity, along with the findings indicating that foreigners trade more aggressively than the locals, lead me to raise and investigate a follow up research question.

Investigating the second research question, I find more evidence to exclude information asymmetry as the channel through which foreigners affect commonality in liquidity and find more evidence to support the finding that foreigners affect commonality in liquidity through their needs of immediacy. This finding implies that an inventory risks explanation is more appropriate in explaining the impact of foreign trades on commonality in liquidity. Given that foreign trades are aggressive and this affects commonality in liquidity, I then examine whether their trades are motivated by information advantage. Using price discovery analysis, I find that domestic investors make a greater contribution to the price discovery process compared to foreign investors and the contribution of domestic investors to the price discovery process can be explained by domestic and foreign interactions.

Furthermore, analysing the information types that are reflected in domestic and foreign price series, I find that domestic prices reflect firm-specific information while foreign price series reflect systematic information. Taking these findings along with the findings in the price discovery analysis seem to suggest that the low contribution of foreign investors to the price discovery process could be due to the fact that they base their investment decisions on systematic information, rather than firm-specific information.

To summarise, the evidence suggests that foreign investors affect commonality in liquidity through their needs of immediacy rather than information asymmetry. The evidence also suggests that there is a mutually-beneficial relationship between foreign (net) liquidity demanders and domestic (net) liquidity suppliers. This enduring relationship held up very well during the 2008 financial crisis, demonstrating its resilience.

8.1.1. Contribution to Knowledge

This thesis contributes to knowledge by providing new evidence on domestic and foreign interaction at a higher frequency, investigated from the perspective of liquidity. More specifically, there are three ways in which this thesis contributes to knowledge.

First, this thesis provides evidence that foreign investors affect commonality in liquidity in different ways compared to domestic investors. I extend the current literature by providing evidence that foreign investors affect commonality in liquidity because they are foreign and not because they are institutional.

Second, the thesis provides evidence of the mechanisms through which foreign trades affect commonality in liquidity. The evidence suggests that inventory explanations could explain how foreign trades affect commonality in liquidity rather than information asymmetry.

Last, this thesis provides evidence that a symbiotic relationship exists between domestic and foreign investors and that the relationship held up fairly well even in a crisis period. This evidence provides a new insight on the impact of foreign presence in domestic markets as domestic investors could gain benefit from supplying liquidity for foreign investors.

8.1.2. Contribution to Practice

This thesis also contributes to practitioners in two ways. First, foreign investors could benefit from this thesis because the results show the mechanisms through which foreign trades affect commonality in liquidity in domestic markets. Second, market regulators could also benefit from this thesis. Foreign investors are suspected of exerting a bad influence on domestic markets. Thus, there has been a policy debate on whether regulators should put a control on foreign trades. The sample of this thesis covers a crisis period and the evidence seems to suggest that liquidity supply and demand can be organised fairly well across domestic and foreign investors. The absence of designated market makers does not impair supply of liquidity during a crisis period. On the other hand, taking the perspective of crisis management, regulators are still required to implement deregulations during crisis periods. These deregulations are required to prevent market movements that are predominantly influenced by panic reactions. The IDX's decision to stop trading and to implement a strict auto rejection could be two contributing factors that caused the market to survive the GFC shocks.

8.2. LIMITATIONS

There are three major limitations to this thesis. First, I aggregate domestic individual trades and domestic institutional trades as domestic trades in the analysis. However, the inclusion of domestic individual trades in the analysis would not significantly change the results because, as mentioned earlier, domestic institutional investors dominate transaction and ownership in the IDX. In addition, looking at the average trade size in the data, individual domestic investors are less likely to actively provide liquidity for foreign investors. If anything, the inclusion of domestic individual trades would slightly dilute the change in the initiated trade measures.

Second, even though the investigation of commonality in liquidity at intraday intervals would offer interesting insights, the current methodology only allows the investigation of commonality in liquidity using transaction data that is aggregated at daily intervals.

This limitation in the methodology prevents the investigation of commonalty in liquidity at intraday intervals.

Third, this thesis perceives institutional investors to have homogenous behaviour. However, the literature has documented that the behaviour of institutional investors is not homogenous. For example, pension funds and insurance funds tend to be passive investors while hedge funds tend to be active. The absence of transaction data that is grouped by different types of institutions prevents this thesis from investigating whether different types of institutional investors affect commonality in liquidity differently. In addition, this data limitation leads the thesis to assume that institutional investors behave similarly.

8.3. AREAS FOR FUTURE RESEARCH

The research questions of this thesis have been fully addressed by the empirical results. In addition, the process of investigating the research questions also points to several directions of potential research, which will be highlighted as follows. First, as mentioned earlier, institutional investors behaviour is heterogeneous. Thus, if data permits, it would be interesting to examine whether different institutional investors affect commonality in liquidity differently. Second, the information type analysis suggests that domestic and foreign investors base their investment decisions on a different information set. Extending this analysis to observe how domestic and foreign investors respond to similar information set, at a finer time interval, would be another possible extension. This line of enquiry would be interesting because holding the information set similar, the results could verify whether domestic and foreign investors respond to information differently.

REFERENCES

Acharya, Viral V., and Lasse Heje Pedersen, 2005, Asset Pricing with Liquidity Risk, *Journal of Financial Economics* 77, 375-410.

Admati, Anat R., and Paul Pfleiderer, 1988, A Theory of Intraday Patterns: Volume and Price Variability, *Review of Financial Studies* 1.

Agarwal, Sumit, Sheri Faircloth, Chunlin Liu, and S. Ghon Rhee, 2009, Why Do Foreign Investors Underperform Domestic Investors in Trading Activities? Evidence from Indonesia, *Journal of Financial Markets* 12, 32-53.

Ahn, Hee-Joon, Kee-Hong Bae, and Kalok Chan, 2001, Limit Orders, Depth, and Volatility: Evidence from the Stock Exchange of Hong Kong, *The Journal of Finance* 56, 767-788.

Ahn, Hee-Joon, and Yan-Leung Cheung, 1999, The Intraday Patterns of the Spread and Depth in a Market without Market Makers: The Stock Exchange of Hong Kong, *Pacific-Basin Finance Journal* 7, 539-556.

Aitken, Michael, Niall Almeida, Frederick H. deB. Harris, and Thomas H. McInish, 2007, Liquidity Supply in Electronic Markets, *Journal of Financial Markets* 10, 144-168.

Aitken, Michael, and Carole Comerton-Forde, 2003, How Should Liquidity Be Measured?, *Pacific-Basin Finance Journal* 11, 45.

Albuquerque, Rui, Gregory H. Bauer, and Martin Schneider, 2009, Global Private Information in International Equity Markets, *Journal of Financial Economics* 94, 18-46.

Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets* 5, 31-56.

Amihud, Yakov, and Haim Mendelson, 1986, Asset Pricing and the Bid-Ask Spread, *Journal of Financial Economics* 17, 223-249.

Amihud, Yakov, and Haim Mendelson, 1988, Liquidity and Asset Prices: Financial Management Implications, *Financial Management* 17, 5-15.

Amihud, Yakov, and Haim Mendelson, 1991, Liquidity, Asset Prices and Financial Policy, *Financial Analysts Journal* 47, 56-66.

Asparouhova, Elena, Hendrik Bessembinder, and Ivalina Kalcheva, 2010, Liquidity Biases in Asset Pricing Tests, *Journal of Financial Economics* 96, 215-237.

Bagehot, Walter, 1971, The Only Game in Town, *Financial Analysts Journal* 27, 12-22.

Baillie, Richard T., G. Geoffrey Booth, Yiuman Tse, and Tatyana Zabotina, 2002, Price Discovery and Common Factor Models, *Journal of Financial Markets* 5, 309-321.

Bekaert, Geert, and Campbell R. Harvey, 2000, Foreign Speculators and Emerging Equity Markets, *The Journal of Finance* 55, 565-613.

Bekaert, Geert, Campbell R. Harvey, and Christian Lundblad, 2007, Liquidity and Expected Returns: Lessons from Emerging Markets, *Review of Financial Studies* 20, 1783-1831.

Biais, Bruno, Pierre Hillion, and Chester Spatt, 1995, An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse, *The Journal of Finance* 50, 1655-1689.

Bohn, Henning, and Linda L. Tesar, 1996, U.S. Equity Investment in Foreign Markets: Portfolio Rebalancing or Return Chasing?, *The American Economic Review* 86, 77-81.

Brennan, Michael J., H. Henry Cao, Norman Strong, and Xinzhong Xu, 2005, The Dynamics of International Equity Market Expectations, *Journal of Financial Economics* 77, 257-288.

Brennan, Michael J., and Avanidhar Subrahmanyam, 1996, Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns, *Journal of Financial Economics* 41, 441-464.

Brockman, P., D. Y. Chung, and C. Perignon, 2009, Commonality in Liquidity: A Global Perspective, *Journal of Financial and Quantitative Analysis* 44, 851-882.

Brockman, Paul, and Dennis Y. Chung, 2002, Commonality in Liquidity: Evidence from an Order-Driven Market Structure *Journal of Financial Research* 25, 521-539.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2009, Market Liquidity and Funding Liquidity, *Review of Financial Studies* 22, 2201-2238.

Campbell, John Y., Sanford J. Grossman, and Jiang Wang, 1993, Trading Volume and Serial Correlation in Stock Returns *Quarterly Journal of Economics* 108, 905-939.

Cao, Melanie, and Jason Wei, 2010, Option Market Liquidity: Commonality and Other Characteristics, *Journal of Financial Markets* 13, 20-48.

Chalmers, John M. R., and Gregory B. Kadlec, 1998, An Empirical Examination of the Amortized Spread, *Journal of Financial Economics* 48, 159-188.

Chan, Kalok, and Allaudeen Hameed, 2006, Stock Price Synchronicity and Analyst Coverage in Emerging Markets, *Journal of Financial Economics* 80, 115-147.

Chang, Rosita P., Mamduh Hanafi, and S. Ghon Rhee, 2000, Price Discovery Process on Regular Trade and Cross Trade Markets: Empirical Evidence from the Jakarta Stock Exchange, K.J. Luke Working Paper (Asia-Pacific Financial Markets Research Center).

Chen, Li-Wen, Shane A. Johnson, Ji-Chai Lin, and Yu-Jane Liu, 2009, Information, Sophistication, and Foreign Versus Domestic Investors' Performance, *Journal of Banking & Finance* 33, 1636-1651.

Chiyachantana, Chiraphol N., Pankaj K. Jain, Christine Jiang, and Robert A. Wood, 2004, International Evidence on Institutional Trading Behavior and Price Impact, *The Journal of Finance* 59, 869-898.

Choe, Hyuk, Bong-Chan Kho, and René M. Stulz, 1999, Do Foreign Investors Destabilize Stock Markets? The Korean Experience in 1997, *Journal of Financial Economics* 54, 227-264.

Choe, Hyuk, Bong-Chan Kho, and René M. Stulz, 2005, Do Domestic Investors Have an Edge? The Trading Experience of Foreign Investors in Korea, *Review of Financial Studies* 18, 795-829.

Chordia, T., S. W. Huh, and A. Subrahmanyam, 2009, Theory-Based Illiquidity and Asset Pricing, *Review of Financial Studies* 22, 3629-3668.

Chordia, T., R. Roll, and A. Subrahmanyam, 2000, Commonality in Liquidity, *Journal of Financial Economics* 56, 3-28.

Comerton-Forde, C., T. Hendershott, C. M. Jones, P. C. Moulton, and M. S. Seasholes, 2010, Time Variation in Liquidity: The Role of Market-Maker Inventories and Revenues, *Journal of Finance* 65, 295-331.

Conrad, Jennifer S., Allauden Hameed, and Cathy Niden, 1994, Volume and Autocovariances in Short-Horizon Individual Security Returns, *Journal of Finance* 49, 1305-1329.
Corwin, Shane A., and Marc L. Lipson, 2011, Order Characteristics and the Sources of Commonality in Prices and Liquidity, *Journal of Financial Markets* 14, 47-81.
Corwin, Shane A., and Paul Schultz, 2012, A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices, *The Journal of Finance* 67, 719-760.
Coughenour, J. F., and M. M. Saad, 2004, Common Market Makers and Commonality in Liquidity, *Journal of Financial Economics* 73, 37-69.
Domowitz, Ian, Oliver Hansch, and Xiaoxin Wang, 2005, Liquidity Commonality and Return Co-Movement, *Journal of Financial Markets* 8, 351-376.
Duong, Huu Nhan, Petko S. Kalev, and Chandrasekhar Krishnamurti, 2009, Order Aggressiveness of Institutional and Individual Investors, *Pacific-Basin Finance Journal* 17, 533-546.
Dvorak, Tomas, 2005, Do Domestic Investors Have an Information Advantage? Evidence from Indonesia, *Journal of Finance* 60, 817-839.
Easley, David, and Maureen O'Hara, 2003, Chapter 17 Microstructure and Asset Pricing, in M. Harris G.M. Constantinides, and R. M. Stulz, eds.: *Handbook of the Economics of Finance* (Elsevier).
Eleswarapu, Venkat R., 1997, Cost of Transacting and Expected Returns in the Nasdaq Market, *The Journal of Finance* 52, 2113-2127.
Eleswarapu, Venkat R., and Marc R. Reinganum, 1993, The Seasonal Behavior of the Liquidity Premium in Asset Pricing, *Journal of Financial Economics* 34, 373-386.
Eun, Cheol S., and Sanjiv Sabherwal, 2003, Cross-Border Listings and Price Discovery: Evidence from U.S.-Listed Canadian Stocks, *The Journal of Finance* 58, 549-576.
Fabre, Joel, and Alex Frino, 2004, Commonality in Liquidity: Evidence from the Australian Stock Exchange, *Accounting & Finance* 44, 357-368.
Froot, Kenneth A., Paul G. J. O'Connell, and Mark S. Seasholes, 2001, The Portfolio Flows of International Investors, *Journal of Financial Economics* 59, 151-193.
Froot, Kenneth A., and Tarun Ramadorai, 2008, Institutional Portfolio Flows and International Investments, *Review of Financial Studies* 21, 937-971.
Froot, Kenneth, and Tarun Ramadorai, 2001, The Information Content of International Portfolio Flows, (National Bureau of Economic Research).
Galariotis, Emilios C., and Evangelos Giouvris, 2007, Liquidity Commonality in the London Stock Exchange, *Journal of Business Finance & Accounting* 34, 374-388.
Glosten, Lawrence R., and Lawrence E. Harris, 1988, Estimating the Components of the Bid/Ask Spread, *Journal of Financial Economics* 21, 123-142.
Gonzalo, Jesus, and Clive Granger, 1995, Estimation of Common Long-Memory Components in Cointegrated Systems, *Journal of Business & Economic Statistics* 13, 27-35.
Gorton, Gary B., and George G. Pennacchi, 1993, Security Baskets and Index-Linked Securities, *The Journal of Business* 66, 1-27.
Goyenko, R. Y., C. W. Holden, and C. A. Trzcinka, 2009, Do Liquidity Measures Measure Liquidity?, *Journal of Financial Economics* 92, 153-181.

Griffiths, Mark D., Brian F. Smith, D. Alasdair S. Turnbull, and Robert W. White, 2000, The Costs and Determinants of Order Aggressiveness, *Journal of Financial Economics* 56, 65-88.

Grinblatt, Mark, and Matti Keloharju, 2000, The Investment Behavior and Performance of Various Investor Types: A Study of Finland's Unique Data Set, *Journal of Financial Economics* 55, 43-67.

Gul, Ferdinand A., Jeong-Bon Kim, and Annie A. Qiu, 2010, Ownership Concentration, Foreign Shareholding, Audit Quality, and Stock Price Synchronicity: Evidence from China, *Journal of Financial Economics* 95, 425-442.

Hameed, Allaudeen, Wenjin Kang, and S. Viswanathan, 2010, Stock Market Declines and Liquidity, *Journal of Finance* 65, 257-293.

Han, Yufeng, and David Lesmond, 2011, Liquidity Biases and the Pricing of Cross-Sectional Idiosyncratic Volatility, *Review of Financial Studies* 24, 1590-1629.

Harris, Larry, 2003. *Trading and Exchanges: Market Microstructure for Practitioners* (Oxford University Press, New York).

Hasbrouck, Joel, 1995, One Security, Many Markets: Determining the Contributions to Price Discovery, *The Journal of Finance* 50, 1175-1199.

Hasbrouck, Joel, 2004, Liquidity in the Futures Pits: Inferring Market Dynamics from Incomplete Data, *Journal of Financial & Quantitative Analysis* 39, 305-326.

Hasbrouck, Joel, and Duane J. Seppi, 2001, Common Factors in Prices, Order Flows, and Liquidity, *Journal of Financial Economics* 59, 383-411.

Henry, Peter Blair, 2000, Stock Market Liberalization, Economic Reform, and Emerging Market Equity Prices, *The Journal of Finance* 55, 529-564.

Hicks, J. R., 1962, Liquidity, *Economic Journal* 72, 787-802.

Holden, Craig W., 2009, New Low-Frequency Spread Measures, *Journal of Financial Markets* 12, 778-813.

Huang, RD, and HR Stoll, 1997, The Components of the Bid-Ask Spread: A General Approach, *Review of Financial Studies* 10, 995-1034.

Huang, Roger D., and Shiu Cheng-Yi, 2009, Local Effects of Foreign Ownership in an Emerging Financial Market: Evidence from Qualified Foreign Institutional Investors in Taiwan, *Financial Management (Blackwell Publishing Limited)* 38, 567-602.

Huberman, Gur, and Dominika Halka, 2001, Systematic Liquidity, *Journal of Financial Research* 24, 161.

Husodo, Zaafri, and Thomas Henker, 2009, Intraday Pattern and Speed of Adjustment in the Jakarta Stock Exchange, *Indonesian Capital Market Review* 1.

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

Jones, C. M., G. Kaul, and M. L. Lipson, 1994, Transactions, Volume, and Volatility, *Review of Financial Studies* 7.

Kamara, Avraham, Xiaoxia Lou, and Ronnie Sadka, 2008, The Divergence of Liquidity Commonality in the Cross-Section of Stocks, *Journal of Financial Economics* 89, 444-466.

Kang, Jun-Koo, and Rene´M Stulz, 1997, Why Is There a Home Bias? An Analysis of Foreign Portfolio Equity Ownership in Japan, *Journal of Financial Economics* 46, 3-28.

Karolyi, G. Andrew, Kuan-Hui Lee, and Mathijs A. van Dijk, 2012, Understanding Commonality in Liquidity around the World, *Journal of Financial Economics* 105, 82-112.

Karolyi, G. Andrew, and René M. Stulz, 2003, Chapter 16 Are Financial Assets Priced Locally or Globally?, in M. Harris G.M. Constantinides, and R. M. Stulz, eds.: *Handbook of the Economics of Finance* (Elsevier).

Kempf, Alexander, and Daniel Mayston, 2008, Liquidity Commonality Beyond Best Prices, *Journal of Financial Research* 31, 25-40.

Koch, Andy, Stefan Ruenzi, and Laura Starks, 2011, Commonality in Liquidity: A Demand-Side Explanation, Working Paper (University of Texas at Austin and University of Manheim).

Korajczyk, R. A., and R. Sadka, 2008, Pricing the Commonality across Alternative Measures of Liquidity, *Journal of Financial Economics* 87, 45-72.

Kyle, Albert S., 1985, Continuous Auctions and Insider Trading *Econometrica* 53, 1315-1335.

Lee, C. M. C., B. Mucklow, and M. J. Ready, 1993, Spreads, Depths, and the Impact of Earnings Information: An Intraday Analysis, *Review of Financial Studies* 6, 345.

Lee, Kuan-Hui, 2011, The World Price of Liquidity Risk, *Journal of Financial Economics* 99, 136-161.

Lesmond, D. A., David A. Lesmond, J. P. Ogden, Joseph P. Ogden, C. A. Trzcinka, and Charles A. Trzcinka, 1999, A New Estimate of Transaction Costs, *Review of Financial Studies* 12.

Lesmond, David A., 2005, Liquidity of Emerging Markets, *Journal of Financial Economics* 77, 411-452.

McInish, Thomas H., and Robert A. Wood, 1992, An Analysis of Intraday Patterns in Bid/Ask Spreads for Nyse Stocks, *The Journal of Finance* 47, 753-764.

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements?, *Journal of Financial Economics* 58, 215-260.

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703-708.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642-685.

Piotroski, Joseph D., and Darren T. Roulstone, 2004, The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices, *The Accounting Review* 79, 1119-1151.

Pukthuanthong-Le, Kuntara, and Nuttawat Visaltanachoti, 2009, Commonality in Liquidity: Evidence from the Stock Exchange of Thailand, *Pacific-Basin Finance Journal* 17, 80-99.

Putniņš, Tālis J., 2013, What Do Price Discovery Metrics Really Measure?, *Journal of Empirical Finance* 23, 68-83.

Ranaldo, Angelo, 2004, Order Aggressiveness in Limit Order Book Markets, *Journal of Financial Markets* 7, 53-74.

Rhee, S. Ghon, and Jianxin Wang, 2009, Foreign Institutional Ownership and Stock Market Liquidity: Evidence from Indonesia, *Journal of Banking & Finance* 33, 1312-1324.

Richards, Anthony, 2005, Big Fish in Small Ponds: The Trading Behavior and Price Impact of Foreign Investors in Asian Emerging Equity Markets, *The Journal of Financial and Quantitative Analysis* 40, 1-27.

Roll, Richard, 1984, A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market, *Journal of Finance* 39, 1127-1139.

Sadka, Ronnie, 2006, Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk, *Journal of Financial Economics* 80, 309-349.

Sarkar, Asani, and Robert A. Schwartz, 2009, Market Sidedness: Insights into Motives for Trade Initiation, *The Journal of Finance* 64, 375-423.

Stulz, Rene, 1999, Globalization of Equity Markets and the Cost of Capital, (National Bureau of Economic Research).

Sujoto, C., P. S. Kalev, and R. W. Faff, 2008, An Examination of Commonality in Liquidity: New Evidence from the Australian Stock Exchange, *Journal for Studies in Economics and Econometrics* 32, 55-79.

Vayanos, Dimitri, 2004, Flight to Quality, Flight to Liquidity and the Pricing of Risk, *NBER working paper*.

Watanabe, Akiko, and Masahiro Watanabe, 2008, Time-Varying Liquidity Risk and the Cross Section of Stock Returns, *Review of Financial Studies* 21, 2449-2486.

Yan, Bingcheng, and Eric Zivot, 2010, A Structural Analysis of Price Discovery Measures, *Journal of Financial Markets* 13, 1-19.

APPENDICES

APPENDIX 1: VECTOR AUTOREGRESSION ANALYSIS OF FOREIGN NET FLOWS AND DOMESTIC MARKET RETURNS

This appendix presents a detailed examination of the positive feedback trading behaviour of foreign investors in the IDX. Froot, et al. (2001) and Brennan, et al. (2005) capture positive feedback trading through positive correlation between foreign net flows and market returns and the ability of past returns to explain foreign net flows. I find initial evidence on the positive feedback trading behaviour of foreign investors in the IDX through the positive and significant correlation (0.56) between foreign net flows and market return. In addition, to examine the ability of past market return to explain foreign net flows, I estimate a bi-variate vector autoregressions (VAR) between foreign net flows (in IDR million) and market return.

The bi-variate VAR is inspired by Froot, et al. (2001) and takes the following specification:

$$f_t = \alpha_F + \sum_{p=1}^{P} \Pi_{11p} f_{t-p} + \sum_{p=1}^{P} \Pi_{12p} r_{t-p} + \varepsilon_{t,F}$$

$$r_t = \alpha_R + \sum_{p=1}^{P} \Pi_{21p} f_{t-p} + \sum_{p=1}^{P} \Pi_{22p} r_{t-p} + \varepsilon_{t,F}$$

(21)

where f_t and r_t are the foreign net flows and market return, respectively. The number of lags (P) will be determined using Akaike Information Criterion. To take into account different results that come from different variable ordering, I will estimate another bi-variate VAR with market return as the first variable.

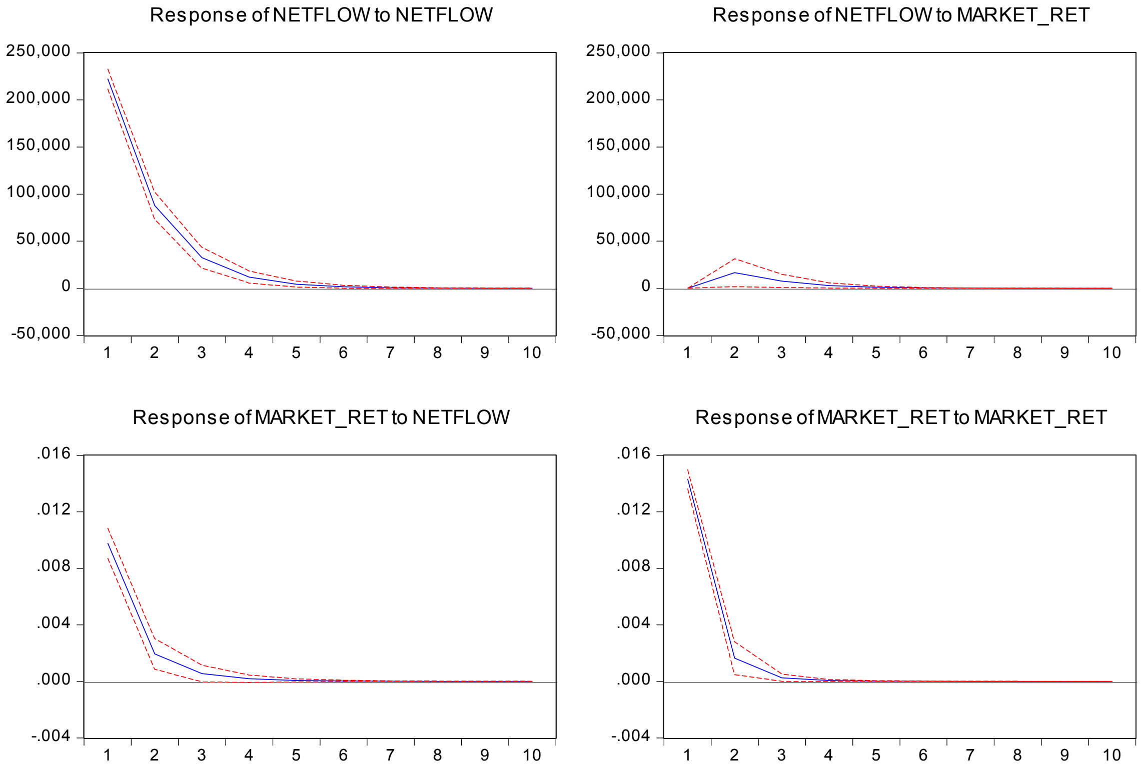
Table A.16 presents the results of estimating the bi-variate VAR specified in Equation 1 with one lag as suggested by the Akaike Information Criteria. The results of Table A.16 suggest that foreign net flows are persistent as well as can be explained by lag market returns. These findings are consistent with Froot, et al. (2001) and confirm that foreign investor engage in positive feedback trading. As I obtain similar results when estimating the bi-variate VAR with market returns as the first variable, the subsequent results come from estimating the bi-variate VAR with foreign net flows as the first variable.

Table A.16: Estimated coefficients of bi-variate VAR
This table presents the estimated coefficients of the bi-variate VAR specified in Equation 1. Only one lag is included in the model as suggested by the Akaike Information Criteria.

Variables	Foreign net flows	Market return
Lag of foreign net flows	0.3435	3.69E-09
	(9.16)	(1.26)
Lag of market return	1.15E+06	0.1141
	(2.23)	(2.83)

Figure A.5 shows the impulse response function of the estimated VAR. The figure strengthens the findings documented earlier on the persistence of foreign net flows and the relationship between foreign net flows and market return. The top left figure shows that foreign net flows return to its initial condition in 4 days after a shock. The bottom left graph shows that a shock in foreign net flow would increase market returns by 80 basis points and it takes only 2 days to come back to its initial condition.

Figure A.5: Impulse response functions of foreign net flows and market return
This figure presents the impulse response of foreign net flows and market return when shocked by its own shocks and the shocks of the other variable.



APPENDIX 2: THE CONTROL VARIABLES OF COMMONALITY REGRESSIONS

Table A.17 and A.18 present the full results of estimating Equation 5 for spread and depth, respectively. The control variables include the lag and lead of market liquidity, crisis dummy, market return along with its lag and lead and change in volatility. The lag and lead of market liquidity are included in the model to take into account the possibility of having commonality in liquidity that is non-contemporaneous. The estimated coefficients of lag and lead market liquidity are not significant across the two liquidity measures. As for the *CRISIS* dummy, the results seem to suggest that the impact of crisis is not significant in spread but positive and significant for depth. This finding seems to be counterintuitive, but as explained earlier investors might deal with the uncertainties surrounding the crisis period by submitting more limit order, which is consistent with the findings of Ahn, et al. (2001).

Including market returns in the regressions seem to control for the positive relationship between market return and liquidity. The estimated coefficients for market returns are all significant and positive (negative) for depth (spread), signifying that these control variables are capable of capturing the positive relationship between market performance and liquidity. Non-contemporaneous adjustment of market performance and liquidity seems to be documented to exist across both liquidity measures. If anything, only the lead of market return is significant for spread while only the lag of market return is significant for depth.

The change in volatility seems to sufficiently control for the impact of volatility on liquidity. Change in volatility is highly significant and positive for both liquidity measures. These results lend additional support for the conjecture made earlier, suggesting that as volatility increases spread and depth tend to increase. The increase in spread could be attributed to the increase risks, while the increase in depth is due to investors tend to submit limit order to reduce their risks.

Table A.17: Full results of commonality regressions for spread

This table reports cross-section averages of the estimated parameters from the following regression that was run on each stock:

$$DLIQ_{i,t} = \propto_i + \beta_{1,i}DMLIQ_{i,t} + \beta_{2,i}EXPL + \beta_{3,i}\left(EXPL \times DMLIQ_{i,t}\right) + \beta_{4,i}DMLIQ_{i,t-1} + \beta_{5,i}DMLIQ_{i,t+1} + \beta_{6,i}MRET_{i,t} + \beta_{7,i}MRET_{i,t-1} + \beta_{8,i}MRET_{i,t+1} + \beta_{9,i}DVOLA_{i,t} + \beta_{10,i}CRISIS_t + \varepsilon_i$$

$DLIQ_{i,t}$ is the daily percentage change in the relative spread of stock i at time t. $DMLIQ_{i,t}$ is the daily percentage change of concurrent market liquidity present in stock i. $DMLIQ_{i,t-1}$ is the lag and $DMLIQ_{i,t+1}$ is the lead. $EXPL$ represents the four explanatory variables that I present results for. $MRET$ is the market return and $DVOLA_{i,t}$ is the daily change of volatility for each stock measured by its squared returns. $CRISIS$ is a dummy variable that takes the value of one from 12 October 2008 to 19 January 2009, and zero otherwise. The time series regression is estimated for each stock in the sample and the cross section average of the time series regressions' coefficients is reported with t-statistics in parentheses. '%pos' reports the proportion of positive regression coefficients and '%pos&sig' refers to the positive coefficients that are significant under a one-tail t-test at 5%. '%neg' and '%neg&sig' correspond to the proportion of negative regression coefficients and their significance, respectively. The standard error for each parameter is estimated using a Newey West correction (Newey and West, 1987). 'Sum' refers to the sum of concurrent, lag and lead coefficients of market liquidity. I only report the cross-section averages of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ for brevity. The first column, 'Benchmark', reports the results of estimating the regressions without any explanatory variables and their interaction with market liquidity. The remaining columns report the results of estimating the regressions for domestic, foreign and all investors using (i) the change in the volume of initiated trades; (ii) market sidedness; and (iii) correlated trading, as explanatory variables (*EXPL*). [a] and [b] denote significance at 1% and 5%, respectively.

	Benchmark	Change in volume of initiated trades			Market Sidedness			Correlated trades			Net flows		
		DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL
DMLIQ	0.0796	0.0721	0.0663	0.0693	-0.0356	-0.0023	-0.0002	0.1061	0.2036	0.1451	0.0729	0.0760	0.0732
(t-statistics)	(4.84)[a]	(4.38)[a]	(3.61)[a]	(4.11)[a]	(-0.45)	(-0.07)	(0.00)	(0.71)	(1.15)	(1.04)	(4.33)[a]	(4.46)[a]	(4.17)[a]
%pos	0.8000	0.7647	0.7529	0.7647	0.4588	0.4941	0.4588	0.5059	0.6353	0.5529	0.7647	0.7765	0.7765
%pos&sig	0.1647	0.1882	0.1882	0.1765	0.0706	0.0706	0.0588	0.0588	0.1059	0.0824	0.1882	0.1765	0.1765

Table A.17 cont'd

	Benchmark	Change in volume of initiated trades			Market Sidedness			Correlated trades			Net flows		
		DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL
DMLIQ (t-1)	0.0187	0.0158	0.0129	0.0131	0.0202	0.0175	0.0184	0.0205	0.0197	0.0191	0.0199	0.0189	0.0215
(t-statistics)	(1.1)	(0.89)	(0.78)	(0.75)	(1.17)	(0.98)	(1.06)	(1.22)	(1.17)	(1.13)	(1.22)	(1.1)	(1.33)
%pos	0.5059	0.5176	0.4941	0.4824	0.5176	0.5059	0.5176	0.5412	0.4941	0.5176	0.5059	0.5647	0.5412
%pos&sig	0.1294	0.0941	0.0706	0.0824	0.1176	0.1176	0.1176	0.1176	0.1294	0.1176	0.0941	0.1176	0.1176
DMLIQ (t+1)	0.0168	0.0129	0.0151	0.0129	0.0181	0.0189	0.0170	0.0156	0.0134	0.0135	0.0165	0.0180	0.0188
(t-statistics)	(1.14)	(0.87)	(1.1)	(0.89)	(1.25)	(1.3)	(1.16)	(1.06)	(0.89)	(0.91)	(1.1)	(1.24)	(1.27)
%pos	0.6118	0.5882	0.5765	0.5882	0.6118	0.6118	0.6118	0.6235	0.6000	0.6118	0.6118	0.6235	0.6235
%pos&sig	0.0941	0.0941	0.0824	0.0941	0.1059	0.0941	0.1059	0.0824	0.0824	0.0706	0.0824	0.0941	0.1059
EXPL		-0.0195	-0.0077	-0.0180	-0.0106	-0.0117	-0.0080	0.0445	0.0023	0.0415	0.0000	0.0000	0.0000
(t-statistics)		(-3.12) [a]	(-1.67)	(-3.00) [a]	(-1.32)	(-1.33)	(-1.02)	(2.24) [b]	(0.1)	(2.18) [b]	(-1.09)	(1.44)	(-0.05)
%pos		0.2941	0.3765	0.2824	0.4588	0.2941	0.4824	0.6118	0.4941	0.5647	0.4824	0.5294	0.5412
%pos&sig		0.0235	0.0235	0.0235	0.0471	0.0118	0.0353	0.0824	0.0824	0.0824	0.0824	0.0824	0.0706
%neg		0.7059	0.6235	0.7176	0.5412	0.7059	0.5176	0.3882	0.5059	0.4353	0.5176	0.4706	0.4588
%neg&sig		0.2000	0.1412	0.1882	0.0588	0.0588	0.0588	0.0235	0.0235	0.0353	0.0353	0.0471	0.0235
DMLIQ*EXPL		0.0982	0.1350	0.1387	0.1574	0.1972	0.1054	-0.0419	-0.2124	-0.1087	0.0001	0.0001	0.0001
(t-statistics)		(2.00) [b]	(3.5) [a]	(2.98) [a]	(1.49)	(2.89) [a]	(0.9)	(-0.17)	(-0.72)	(-0.49)	(1.5)	(0.9)	(1.8)
%pos		0.6706	0.7176	0.7176	0.6000	0.6471	0.5765	0.5176	0.3765	0.4824	0.5765	0.5882	0.6235
%pos&sig		0.1412	0.1412	0.1529	0.0824	0.1176	0.0706	0.0588	0.0588	0.0706	0.0824	0.0824	0.0706

Table A.17 cont'd

	Benchmark	Change in volume of initiated trades			Market Sidedness			Correlated trades			Net flows		
		DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL
%neg		0.3294	0.2824	0.2824	0.4000	0.3529	0.4235	0.4824	0.6235	0.5176	0.4235	0.4118	0.3765
%neg&sig		0.0471	0.0118	0.0471	0.0471	0.0000	0.0471	0.0588	0.0824	0.0706	0.0235	0.0353	0.0235
Crisis	0.0474	0.0493	0.0470	0.0488	0.0498	0.0465	0.0499	0.0456	0.0481	0.0459	0.0472	0.0482	0.0465
(t-statistics)	(1.33)	(1.38)	(1.33)	(1.37)	(1.34)	(1.41)	(1.34)	(1.31)	(1.36)	(1.32)	(1.32)	(1.33)	(1.3)
%pos	0.7529	0.7529	0.7412	0.7647	0.7176	0.7529	0.7412	0.7294	0.7294	0.7294	0.7529	0.7529	0.7529
%pos&sig	0.0353	0.0588	0.0353	0.0471	0.0471	0.0471	0.0471	0.0353	0.0353	0.0353	0.0353	0.0471	0.0471
%neg	0.2471	0.2471	0.2588	0.2353	0.2824	0.2471	0.2588	0.2706	0.2706	0.2706	0.2471	0.2471	0.2471
%neg&sig	0.2235	0.2353	0.2353	0.2118	0.2706	0.2235	0.2471	0.2588	0.2588	0.2588	0.2235	0.2353	0.2235
Market return	-1.0490	-0.9655	-1.0091	-0.9608	-1.0370	-1.0335	-1.0414	-1.0239	-1.0156	-1.0281	-1.0007	-1.1507	-1.0987
(t-statistics)	(-9.5)[a]	(-9.37)[a]	(-9.31)[a]	(-9.15)[a]	(-9.49)[a]	(-9.3)[a]	(-9.46)[a]	(-9.52)[a]	(-9.00)[a]	(-9.57)[a]	(-7.66)[a]	(-8.64)[a]	(-7.19)[a]
%pos	0.1412	0.1647	0.1647	0.1647	0.1412	0.1412	0.1412	0.1412	0.1412	0.1412	0.1529	0.1529	0.1529
%pos&sig	0.0000	0.0000	0.0000	0.0000	0.0118	0.0118	0.0118	0.0118	0.0118	0.0118	0.0000	0.0000	0.0000
%neg	0.8588	0.8353	0.8353	0.8353	0.8588	0.8588	0.8588	0.8588	0.8588	0.8588	0.8471	0.8471	0.8471
%neg&sig	0.3529	0.3882	0.3529	0.3765	0.3765	0.3647	0.3647	0.3647	0.3765	0.3765	0.4706	0.4235	0.4588
Market return (t-1)	-0.1164	-0.1307	-0.1261	-0.1333	-0.1314	-0.1149	-0.1309	-0.1313	-0.1580	-0.1332	-0.1491	-0.1680	-0.1373
(t-statistics)	(-1.28)	(-1.43)	(-1.36)	(-1.45)	(-1.42)	(-1.3)	(-1.41)	(-1.38)	(-1.52)	(-1.4)	(-1.56)	(-1.76)	(-1.5)
%pos	0.4118	0.4000	0.4000	0.4000	0.4235	0.4000	0.4235	0.4118	0.4000	0.4118	0.3882	0.3765	0.4118
%pos&sig	0.0471	0.0471	0.0471	0.0471	0.0588	0.0471	0.0471	0.0471	0.0471	0.0471	0.0471	0.0588	0.0471

Table A.17 cont'd

	Benchmark	Change in volume of initiated trades			Market Sidedness			Correlated trades			Net flows		
		DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL
%neg	0.5882	0.6000	0.6000	0.6000	0.5765	0.6000	0.5765	0.5882	0.6000	0.5882	0.6118	0.6235	0.5882
%neg&sig	0.4824	0.4824	0.5176	0.4941	0.4706	0.5059	0.4588	0.4941	0.4824	0.4824	0.5294	0.5294	0.4941
Market return (t+1)	0.1953	0.2063	0.2010	0.2066	0.1913	0.1772	0.1918	0.1921	0.1982	0.1925	0.2086	0.1797	0.2082
(t-statistics)	(2.39)[b]	(2.62)[b]	(2.5)[b]	(2.65)[a]	(2.37)[b]	(2.25)[b]	(2.37)[b]	(2.56)[b]	(2.41)[b]	(2.53)[b]	(2.51)[b]	(2.3)[b]	(2.52)[b]
%pos	0.7059	0.7294	0.7059	0.7294	0.7059	0.6824	0.6824	0.6941	0.6706	0.6941	0.6588	0.7059	0.6824
%pos&sig	0.0706	0.0941	0.0706	0.0941	0.0706	0.0824	0.0706	0.0824	0.1059	0.0941	0.0824	0.0706	0.0941
%neg	0.2941	0.2706	0.2941	0.2706	0.2941	0.3176	0.3176	0.3059	0.3294	0.3059	0.3412	0.2941	0.3176
%neg&sig	0.2824	0.2588	0.2824	0.2588	0.2824	0.2941	0.3059	0.2941	0.3176	0.2941	0.3294	0.2824	0.3059
Change in volatility	0.0006	0.0007	0.0006	0.0007	0.0007	0.0007	0.0007	0.0006	0.0006	0.0006	0.0007	0.0007	0.0007
(t-statistics)	(2.79)[a]	(2.91)[a]	(2.88)[a]	(2.93)[a]	(2.82)[a]	(2.82)[a]	(2.82)[a]	(2.91)a	(2.88)[a]	(2.95)[a]	(2.80)[a]	(2.81)[a]	(2.81)[a]
%pos	0.6588	0.6706	0.6706	0.6706	0.6588	0.6706	0.6588	0.6588	0.6824	0.6588	0.6706	0.6588	0.6706
%pos&sig	0.2118	0.2353	0.2118	0.2235	0.2118	0.2235	0.2235	0.2000	0.2235	0.2000	0.1882	0.2118	0.2118
%neg	0.3412	0.3294	0.3294	0.3294	0.3412	0.3294	0.3412	0.3412	0.3176	0.3412	0.3294	0.3412	0.3294
%neg&sig	0.2706	0.2706	0.2471	0.2588	0.2706	0.2706	0.2706	0.2706	0.2588	0.2706	0.2588	0.2706	0.2588
Sum	0.1150	0.1008	0.0943	0.0953	0.0028	0.0341	0.0352	0.1421	0.2367	0.1777	0.1092	0.1129	0.1135
(t-statistics)	(3.38)[b]	(2.86)[b]	(2.77)[a]	(2.93)[a]	(0.04)	(0.72)	(0.44)	(0.92)	(1.37)	(1.24)	(3.13)[b]	(3.27)[b]	(3.22)[b]
Adjusted R^2 mean	0.0229	0.0262	0.0255	0.0261	0.0233	0.0231	0.0234	0.0236	0.0240	0.0235	0.0230	0.0227	0.0226

Table A.18: Full results of commonality regressions for depth

This table reports cross-section averages of the estimated parameters from the following regression that was run on each stock:

$$DLIQ_{i,t} = \propto_i + \beta_{1,i}DMLIQ_{i,t} + \beta_{2,i}EXPL + \beta_{3,i}(EXPL \times DMLIQ_{i,t}) + \beta_{4,i}DMLIQ_{i,t-1} + \beta_{5,i}DMLIQ_{i,t+1} + \beta_{6,i}MRET_{i,t} + \beta_{7,i}MRET_{i,t-1} + \beta_{8,i}MRET_{i,t+1} + \beta_{9,i}DVOLA_{i,t} + \beta_{10,i}CRISIS_t + \varepsilon_i$$

$DLIQ_{i,t}$ is the daily percentage change in the depth of stock i at time t. $DMLIQ_{i,t}$ is the daily percentage change of concurrent market liquidity present in stock i. $DMLIQ_{i,t-1}$ is the lag and $DMLIQ_{i,t+1}$ is the lead. $EXPL$ represents the three explanatory variables that I present results for. $MRET$ is the market return and $DVOLA_{i,t}$ is the daily change of volatility for each stock measured by its squared returns. $CRISIS$ is a dummy variable that takes the value of one from 12 October 2008 to 19 January 2009 and zero otherwise. The time series regression is estimated for each stock in the sample and the cross section average of the time series regressions' coefficients are reported with t-statistics in parentheses. '%pos' reports the proportion of positive regression coefficients and '%pos&sig' refers to the positive coefficients that are significant under a one-tail t-test at 5%. '%neg' and '%neg&sig' correspond to the proportion of negative regression coefficients and their significance, respectively. The standard error for each parameter is estimated using a Newey West correction (Newey and West, 1987). 'Sum' refers to the sum of concurrent, lag and lead coefficients of market liquidity. I only report the cross-section averages of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ for brevity. The first column, 'Benchmark', reports the results of estimating the regressions without any explanatory variables and their interaction with market liquidity. The remaining columns report the results of estimating the regressions for domestic, foreign and all investors using (i) the change in the volume of initiated trades; (ii) market sidedness; and (iii) correlated trading, as explanatory variables (*EXPL*). [a] and [b] denote significance at 1% and 5%, respectively.

	Benchmark	Change in volume of initiated trades			Market Sidedness			Correlated trades			Net flows		
		DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL
DMLIQ	0.4826	0.4748	0.4609	0.4673	1.0374	0.7504	1.1612	-0.1019	-0.0306	-0.0707	0.4947	0.4674	0.4928
(t-statistics)	(7.57) [a]	(6.72) [a]	(6.49) [a]	(6.55) [a]	(5.93) [a]	(5.92) [a]	(6.16) [a]	(-0.36)	(-0.05)	(-0.26)	(8.66) [a]	(6.63) [a]	(8.19) [a]
%pos	0.9294	0.9059	0.9294	0.9176	0.7882	0.8471	0.8000	0.5176	0.5294	0.5412	0.9176	0.9059	0.9294
%pos&sig	0.6000	0.5647	0.5647	0.5765	0.2118	0.4118	0.2235	0.0353	0.0941	0.0471	0.6118	0.6000	0.6000

Table A.18 cont'd

	Benchmark	Change in volume of initiated trades			Market Sidedness			Correlated trades			Net flows		
		DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL
DMLIQ (t-1)	0.0343	0.0229	0.0380	0.0275	0.0352	0.0373	0.0368	0.0405	0.0308	0.0396	0.0315	0.0169	0.0315
(t-statistics)	(0.74)	(0.5)	(0.8)	(0.59)	(0.79)	(0.74)	(0.82)	(0.83)	(0.66)	(0.82)	(0.71)	(0.38)	(0.69)
%pos	0.4941	0.4941	0.5176	0.5059	0.4941	0.4941	0.5059	0.5059	0.4941	0.5059	0.4941	0.4941	0.4824
%pos&sig	0.0471	0.0471	0.0471	0.0471	0.0471	0.0235	0.0471	0.0471	0.0471	0.0471	0.0471	0.0353	0.0235
DMLIQ (t+1)	0.0570	0.0995	0.1085	0.1149	0.0658	0.0629	0.0647	0.0612	0.0625	0.0574	0.0501	0.0595	0.0485
(t-statistics)	(0.84)	(1.34)	(1.39)	(1.48)	(0.96)	(0.91)	(0.96)	(0.87)	(0.87)	(0.82)	(0.74)	(0.87)	(0.73)
%pos	0.4353	0.4941	0.5059	0.5059	0.4588	0.4353	0.4588	0.4353	0.4353	0.4353	0.4471	0.4353	0.4471
%pos&sig	0.0353	0.0353	0.0353	0.0471	0.0353	0.0235	0.0353	0.0353	0.0353	0.0235	0.0118	0.0353	0.0118
EXPL		0.1690	0.1938	0.2098	-0.0005	0.0503	0.0229	-0.2330	-0.1028	-0.1964	0.0000	0.0001	0.0000
(t-statistics)		(4.23) [a]	(4.9) [a]	(4.43) [a]	(-0.01)	(0.87)	(0.3)	(-2.32) [b]	(-0.59)	(-2.22) [b]	(-0.56)	(1.26)	(-0.15)
%pos		0.7765	0.8118	0.8000	0.4118	0.5765	0.4235	0.3294	0.4706	0.4235	0.5529	0.7412	0.6118
%pos&sig		0.2941	0.4000	0.3765	0.0235	0.0353	0.0235	0.0235	0.0353	0.0000	0.1059	0.1412	0.1647
%neg		0.2235	0.1882	0.2000	0.5882	0.4235	0.5765	0.6706	0.5294	0.5765	0.4471	0.2588	0.3882
%neg&sig		0.0000	0.0000	0.0000	0.1412	0.0588	0.1412	0.0588	0.0353	0.0824	0.0471	0.0118	0.0118
DMLIQ*EXPL		-0.2846	-0.2725	-0.3512	-0.7336	-0.6564	-0.8781	0.9410	0.8559	0.8858	0.0000	0.0000	0.0000
(t-statistics)		(-1.86)	(-1.53)	(-1.84)	(-2.91) [a]	(-1.89)	(-3.26) [a]	(2.36) [b]	(0.96)	(2.16) [b]	(0.44)	(0.16)	(0.27)
%pos		0.3529	0.4118	0.3765	0.3059	0.3882	0.2706	0.5647	0.6118	0.6118	0.4235	0.5294	0.3882
%pos&sig		0.0471	0.0235	0.0353	0.0588	0.0118	0.0353	0.1059	0.0588	0.0824	0.0471	0.0588	0.0588

Table A.18 cont'd

	Benchmark	Change in volume of initiated trades			Market Sidedness			Correlated trades			Net flows		
		DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL
%neg		0.6471	0.5882	0.6235	0.6941	0.6118	0.7294	0.4353	0.3882	0.3882	0.5765	0.4706	0.6118
%neg&sig		0.0471	0.0471	0.0706	0.0588	0.0471	0.0824	0.0235	0.0588	0.0353	0.0471	0.0588	0.0353
Crisis	0.1472	0.1255	0.1360	0.1259	0.1424	0.1432	0.1402	0.1398	0.1378	0.1430	0.1483	0.1547	0.1515
(t-statistics)	(3.69)[a]	(3.36)[a]	(3.44)[a]	(3.36)[a]	(4.11)[a]	(4.49)[a]	(4.16)[a]	(3.47)[a]	(3.25)[a]	(3.49)[a]	(3.48)[a]	(3.68)[a]	(3.52)[a]
%pos	0.8000	0.6941	0.7294	0.7176	0.8000	0.8000	0.8118	0.8000	0.8118	0.8118	0.8000	0.8118	0.7765
%pos&sig	0.1294	0.1412	0.1294	0.1412	0.1647	0.1059	0.1765	0.1412	0.1294	0.1529	0.1294	0.1412	0.1294
%neg	0.2000	0.3059	0.2706	0.2824	0.2000	0.2000	0.1882	0.2000	0.1882	0.1882	0.2000	0.1882	0.2235
%neg&sig	0.1882	0.2941	0.2588	0.2706	0.1647	0.1765	0.1529	0.1882	0.1765	0.1765	0.1765	0.1529	0.2118
Market return	3.1525	2.9848	3.0580	3.0123	3.1781	3.2909	3.1946	3.0107	3.1762	3.0115	3.3389	2.9561	3.3768
(t-statistics)	(6.4)[a]	(6.15)[a]	(5.73)[a]	(5.98)[a]	(6.48)[a]	(6.57)[a]	(6.53)[a]	(5.87)[a]	(6.28)[a]	(5.82)[a]	(4.69)[a]	(4.28)[a]	(2.85)[a]
%pos	0.8471	0.8235	0.8000	0.8118	0.8353	0.8471	0.8353	0.8235	0.8235	0.8235	0.7882	0.7882	0.7647
%pos&sig	0.4706	0.4353	0.4353	0.4353	0.4588	0.4706	0.4588	0.4588	0.4824	0.4588	0.3765	0.3647	0.3059
%neg	0.1529	0.1765	0.2000	0.1882	0.1647	0.1529	0.1647	0.1765	0.1765	0.1765	0.2118	0.2118	0.2353
%neg&sig	0.1412	0.1647	0.1882	0.1765	0.1529	0.1412	0.1529	0.1647	0.1647	0.1647	0.2000	0.1765	0.2118
Market return (t-1)	-1.7501	-1.3319	-1.2118	-1.2327	-1.7556	-1.6376	-1.7447	-1.7940	-1.6561	-1.8032	-1.7642	-1.6681	-1.5003
(t-statistics)	(-3.96)[a]	(-3.41)[a]	(-3.24)[a]	(-3.25)[a]	(-3.97)[a]	(-3.77)[a]	(-3.92)[a]	(-4.18)[a]	(-3.96)[a]	(-4.18)[a]	(-3.37)[a]	(-4.03)[a]	(-3.93)[a]
%pos	0.2000	0.2588	0.2588	0.2824	0.2118	0.2235	0.2000	0.2118	0.2000	0.2000	0.2235	0.2235	0.2118
%pos&sig	0.0235	0.0235	0.0235	0.0235	0.0235	0.0235	0.0235	0.0235	0.0235	0.0235	0.0235	0.0235	0.0235

Table A.18 cont'd

	Benchmark	Change in volume of initiated trades			Market Sidedness			Correlated trades			Net flows		
		DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL	DOM	FOR	ALL
%neg	0.8000	0.7412	0.7412	0.7176	0.7882	0.7765	0.8000	0.7882	0.8000	0.8000	0.7765	0.7765	0.7882
%neg&sig	0.6471	0.6118	0.6118	0.5882	0.6235	0.6118	0.6235	0.6353	0.6471	0.6471	0.6353	0.5765	0.6235
Market return (t+1)	-0.5092	-0.7248	-0.8922	-0.8433	-0.6332	-0.5767	-0.6386	-0.4841	-0.5429	-0.4277	-0.3393	-0.5952	-0.3386
(t-statistics)	(-0.63)	(-0.91)	(-1.06)	(-1.04)	(-0.77)	(-0.72)	(-0.78)	(-0.64)	(-0.69)	(-0.56)	(-0.42)	(-0.68)	(-0.41)
%pos	0.5412	0.4824	0.4824	0.4824	0.5176	0.5176	0.5059	0.5294	0.5412	0.5294	0.5529	0.5294	0.5412
%pos&sig	0.0471	0.0471	0.0588	0.0471	0.0471	0.0471	0.0471	0.0353	0.0471	0.0353	0.0353	0.0471	0.0471
%neg	0.4588	0.5176	0.5176	0.5176	0.4824	0.4824	0.4941	0.4706	0.4588	0.4706	0.4471	0.4706	0.4588
%neg&sig	0.4353	0.4941	0.4941	0.4941	0.4588	0.4588	0.4706	0.4471	0.4353	0.4588	0.4235	0.4471	0.4353
Change in volatility	0.0039	0.0037	0.0036	0.0037	0.0039	0.0041	0.0040	0.0038	0.0038	0.0038	0.0038	0.0038	0.0038
(t-statistics)	(4.89)[a]	(4.77)[a]	(4.54)[a]	(4.7)[a]	(5.06)[a]	(5.74)[a]	(5.08)[a]	(4.79)[a]	(4.65)[a]	(4.77)[a]	(4.84)[a]	(4.71)[a]	(4.76)[a]
%pos	0.8471	0.8471	0.8353	0.8353	0.8471	0.8471	0.8471	0.8471	0.8471	0.8471	0.8471	0.8471	0.8471
%pos&sig	0.4235	0.3882	0.3882	0.3765	0.4118	0.4353	0.4235	0.4235	0.4235	0.4235	0.4118	0.3882	0.4118
%neg	0.1529	0.1529	0.1647	0.1647	0.1529	0.1529	0.1529	0.1529	0.1529	0.1529	0.1529	0.1529	0.1529
%neg&sig	0.0824	0.0941	0.1059	0.1176	0.0824	0.0706	0.0824	0.0941	0.0824	0.0941	0.0824	0.0824	0.1059
Sum	0.5739	0.5973	0.6073	0.6097	1.1384	0.8506	1.2627	-0.0002	0.0628	0.0263	0.5764	0.5437	0.5728
(t-statistics)	(3.39)[b]	(3.9)[b]	(3.82)[b]	(3.9)[b]	(5.87)[b]	(5.27)[b]	(6.18)[b]	(0.00)	(0.11)	(0.09)	(4.18)[b]	(3.66)[b]	(4.02)[b]
Adjusted R^2 mean	0.0459	0.0514	0.0532	0.0527	0.0468	0.0466	0.0470	0.0463	0.0472	0.0466	0.0469	0.0468	0.0478